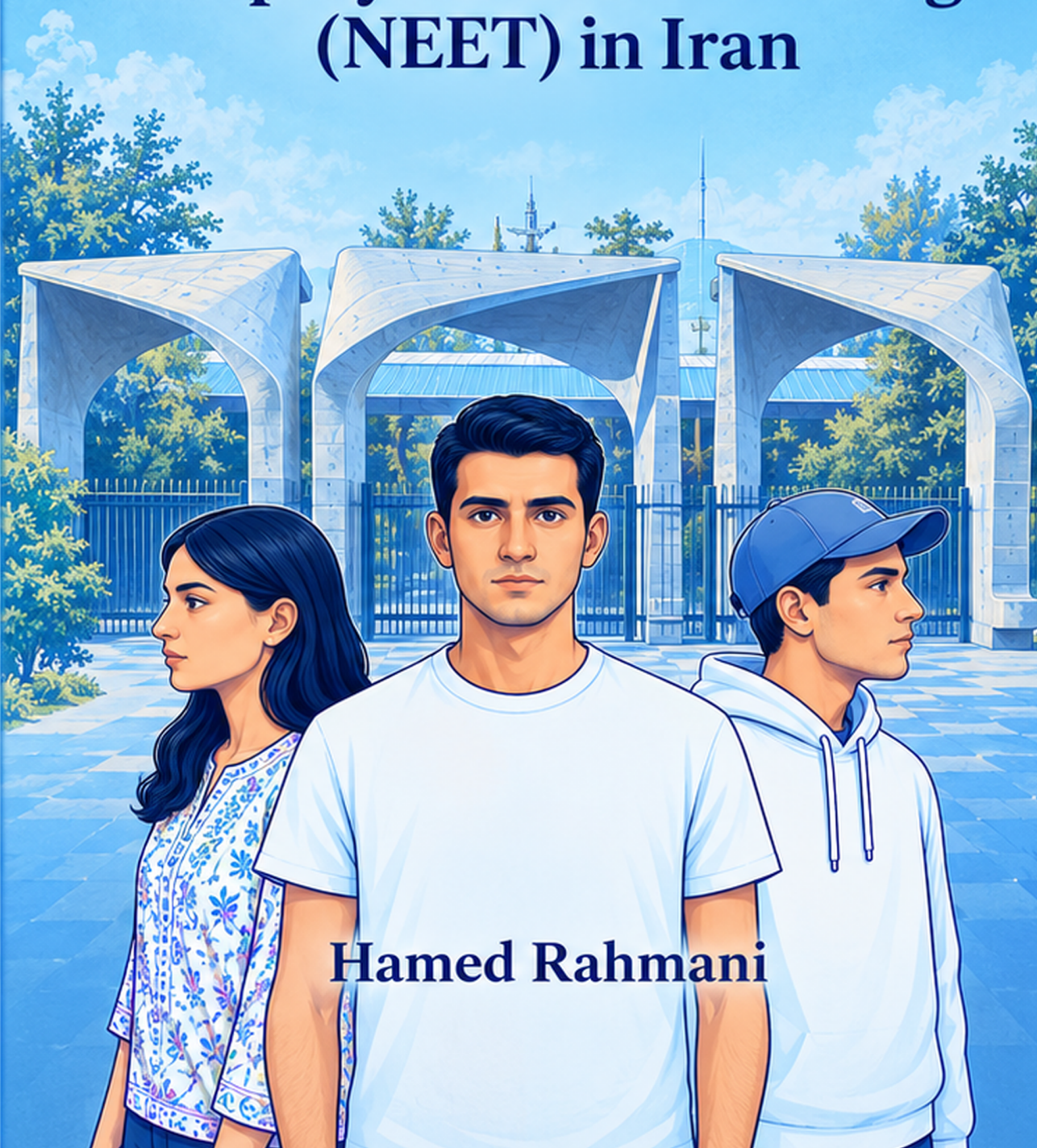
Risk factors of Being a Youth Not in Education, Employment or Training (NEET) in Iran



Hamed Rahmani

Proposition accompanying the Doctoral Thesis

Risk Factors of Being a Youth Not in Education, Employment, or Training (NEET) in Iran

1. NEET risk factor vary across contexts and no universal risk profile exists *(This dissertation).*
2. In Iran, a high NEET rate in one province reduces neighbouring provinces' rates through migration, not contagion. *(This dissertation)*
3. Above twenty hours of weekly housework, education loses its protective effect against NEET status *(This dissertation)*
4. Education reduces NEET risk only where the economy can absorb graduates. *(This dissertation)*
5. Iran's NEET crisis is structurally embedded in its political economy: economic recovery alone cannot resolve it *(This dissertation)*
6. Pooling male and female labour-market outcomes masks the gender-specific mechanisms driving NEET status, producing a coefficient that fits neither group.
7. A one-hour employment threshold, combined with widespread informal contracts, leads to misleading conclusions about youth NEET status.
8. Spatial econometric models developed for stable Western economies require context-specific adaptation, when applied to developing countries.
9. In data-constrained research environments, different methodological approaches is necessity.
10. When a country's most educated generation is also its most unemployed, the problem is not the graduates but the labour market.
11. In societies where women's domestic labour is invisible in national statistics, gender-neutral policy is not neutral at all.

Doctoral Thesis

Risk Factors of Being a Youth Not in Education, Employment, or Training (NEET) in Iran

Hamed Rahmani

2026



Risk Factors of Being a Youth Not in Education, Employment, or Training (NEET) in Iran

Dissertation

To obtain the degree of Doctor at Maastricht University,
on the authority of the Rector Magnificus of Prof. Dr. Pamela Habibović
in accordance with the decision of the Board of Deans,
to be defended in public on Monday,9th November 2026, at 16:00 hours

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List of abbreviations

ADF	Augmented Dickey-Fuller (test)
ADHD/ADD	Attention Deficit Hyperactivity Disorder / Attention Deficit Disorder
AIC	Akaike Information Criterion
AI	Artificial Intelligence
ALMP	Active Labour Market Policies
ARDL	Auto-Regressive Distributed Lag
AUC	Area Under the Curve
BIC	Bayesian Information Criterion
CART	Classification and Regression Tree
CD	Cross-sectional Dependence (test)
CI	Confidence Interval
COVID-19	Coronavirus Disease 2019
EA	Enumeration Area
DOR	Diagnostic Odds Ratio
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GVA	Gross Value Added
ILO	International Labour Organization
LM	Lagrange Multiplier (test)
MENA	Middle East and North Africa
NEET	Not in Education, Employment, or Training
NGO	Non-Governmental Organization
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
OR	Odds Ratio
PP	Percentage Point
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSU	Primary Sampling Unit
RVE	Robust Variance Estimation
SAR	Spatial Autoregressive (model)
SAC	Spatial Autoregressive Combined (model)
SDG	Sustainable Development Goals
SDM	Spatial Durbin Model
SEM	Spatial Error Model
VET	Vocational Education and Training
VIF	Variance Inflation Factor
WHO	World Health Organization

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Chapter 1

General Introduction

1.1. Introduction

A country's economic and social progress depends on its ability to engage and empower its youth, a group that holds the future, but is vulnerable to disengagement today. To ensure long-term, sustainable economic growth, youth must be integrated into the job market and the education system. Governments must consider population structure and dynamics in short- and long-term policies to achieve economic growth and well-being. Educating and training young people and integrating them into the workforce are the keys to achieving this goal (Geiger & Okpych, 2022).

NEET (Not in Education, Employment, or Training) has become a significant indicator of young people's disengagement from crucial areas of society. The term refers to young people aged 15-24 who are not engaged in education, employment, or training. These youth often lack qualifications, have limited access to professional training, and face barriers to meeting labour market demands (Schoon & Bynner, 2019). As a result of the 2008 recession, the term has gained popularity, highlighting the vulnerability of young people during economic instability. Many countries experienced dramatic increases in NEET rates during this period, rising steadily even as the economy recovered (Batini et al., 2017). Many organizations and governments have adopted the NEET indicator, which captures a broader range of youth disengagement than traditional youth unemployment or youth inactivity rates. Unlike the unemployment rate, which only includes young people actively seeking work, and the youth inactivity rate, which includes individuals still accumulating human capital through education or training, the NEET record includes those who are not engaged in employment, education or training, offering a view of youth's socioeconomic disadvantages and the resulting loss of human capital potential (Guido, 2015).

The NEET youth represent both a personal crisis and a broader societal challenge that threaten economic growth and social cohesion, and play an increasingly important role in policy discussions. NEET youth require targeted interventions due to their unique circumstances. To assist them in reintegrating into education or the job market, tailored support programs are needed (Mascherini et al., 2012).

A growing number of people are becoming NEETs, and society is facing the challenge of addressing the phenomenon. Emerging and developing countries have limited formal employment opportunities for all demographic groups. Many developing countries have a high percentage of NEET youth, underscoring the greater vulnerability of young people to economic downturns than older individuals (Aina et al., 2025). In 2023, one in five young people

worldwide was classified as NEET, with women accounting for two-thirds of this group (Kaya, 2023).

In many countries, NEET youth are regarded as a uniformly vulnerable category at risk of long-term socio-economic marginalization. NEET status has significant consequences for both individuals and society. However, treating NEETs as uniformly vulnerable overlooks important within-group diversity that shapes intervention effectiveness. Young people at risk of being permanently excluded from the job market may experience permanent poverty, social isolation, criminal behaviour, addiction, and mental disorders (Paabort et al., 2023).

Understanding NEET involves identifying unemployed or out-of-school youth and examining the socio-economic and cultural factors that lead to this situation. This approach must examine multiple subgroups within the NEET population, including those experiencing short- and long-term unemployment, re-entry, individuals with family responsibilities, those with health or disability challenges, and voluntary NEET youth (This will be explored in more detail in Chapter 2). For example, NEET youth who are caregivers may permanently disengage due to ongoing family responsibilities. In contrast, those with health challenges may face barriers associated with physical restrictions or mental health issues, and those who may voluntarily choose NEET status due to personal preferences or circumstances (such as taking a gap year, travelling, or participating in other activities). Several factors contribute to youth becoming NEETs, including gender discrimination, low wages, instability at work, inefficient school-to-work transitions, and insufficient skill training (Mascherini et al., 2012). COVID-19 has further complicated these dynamics by causing job losses and preventing education and training.

Despite the issue's importance, existing NEET studies have some notable limitations. They frequently overlook the diversity within this demographic group, ignoring the patterns, causes, and consequences of NEET status. The oversimplification of the NEET phenomenon may lead to inadequate policy responses and interventions, potentially extending the disengagement cycle for many young people (Mascherini et al., 2012). Iran is particularly affected, with NEET rates higher than in many lower-income and neighbouring countries. NEET rates in Iran are high for a variety of reasons, including persistent macroeconomic instability, economic stagnation, high and volatile inflation, currency devaluation, budget deficits, fluctuating oil revenues, economic recession, sanctions, institutional gender inequality, and a lack of strategic planning. Consequently, the NEET problem has been compounded, transforming what could have been an economic advantage into a social problem (Eslamian et al., 2024).

The NEET challenge in Iran differs fundamentally from the European contexts that dominate existing research. Systematic research on Iranian NEET patterns remains limited. Studies examining youth labour market outcomes (Salehi-Isfahani & Egel, 2007) address related issues, such as unemployment and gender gaps, but do not specifically analyze NEET status or its distinct risk factors. No study has examined how individual characteristics, family circumstances, and regional factors influence NEET status within Iran's specific institutional environment.

There are real consequences to this research gap. Policymakers cannot target interventions effectively without knowing which factors drive NEET patterns in Iran. The programs developed for European welfare states might not work in contexts with different labour market structures, family systems, and institutions.

In this dissertation, we identify risk factors that predict NEET status among Iranian youth and examine how these factors vary across individuals, regions, and time. This analysis combines international evidence synthesis with Iranian-specific empirical research to identify which global patterns work here and which need adaptation. Based on these findings, policy design can be adapted to Iran's unique socioeconomic realities rather than importing frameworks from other countries.

1.2. NEET: understanding complex concepts through an interdisciplinary lens

NEET (Not in Education, Employment, or Training) refers to young people aged 15-24 who are neither in paid employment (including part-time or full-time work), formal education (such as schools, colleges, or universities), nor in vocational training or apprenticeships (Abayasekara & Gunasekara, 2019).

NEETs encompass both unemployed and inactive youth, including those seeking employment but unable to find it, as well as those neither engaged in the labour market nor pursuing education. Among these challenges can be caring responsibilities, health issues, or discouragement due to repeated failures to obtain employment or educational opportunities (for more details, see Chapter 2).

This disengagement can have major long-term consequences, resulting in what are known as "scarring effects[1]" in which early experiences of unemployment or inactivity have long-term

[1] Refer to the long-term negative impacts of early periods of unemployment on an individual's future earnings, employability, and career stability.

adverse effects and lead to repeated periods of unemployment, lower lifetime earnings, and limited social mobility (Groot, 1990; Mühlböck et al., 2022a)

The NEET population is not a homogeneous group. It encompasses individuals from diverse backgrounds and varying living circumstances. Some NEET youth, for example, may be out of school or unemployed for a short time as they transition between life stages. Others may face long-term exclusion owing to socio-economic disadvantages or structural barriers to employment. This heterogeneity within the NEET group presents a challenge for policy, as attempts to address NEET status must be tailored to each subgroup's specific requirements and circumstances (Paabort et al., 2023).

Additionally, the NEET concept has evolved over time. Originally defined as young people aged 16 to 18, the age range has been broadened to encompass individuals up to 24 years old, and in certain circumstances, older age groups (up to 35 years old) (Chen, 2011). As a result of this development, the NEET community has become more diverse, making it more challenging to draw general conclusions about the causes and consequences of NEET status. This dissertation defines NEETs as young people aged 15-24 who are not in education, employment, or training. The range is aligned with ILO and OECD standards, ensuring comparability with international research, and any use of broader age ranges, such as 15 to 29, is explicitly stated and justified based on data constraints.

Despite its broad applicability, the NEET concept has also been criticized for excluding disadvantaged individuals, such as those working in low-wage jobs or in short-term training programs that do not lead to long-term employment. Figure 1.1 illustrates the composition of the NEET indicator for the youth population. Despite these drawbacks, NEET remains useful for determining and quantifying youth disengagement and for guiding policy decisions (Pennoni & Bal-Domańska, 2022).

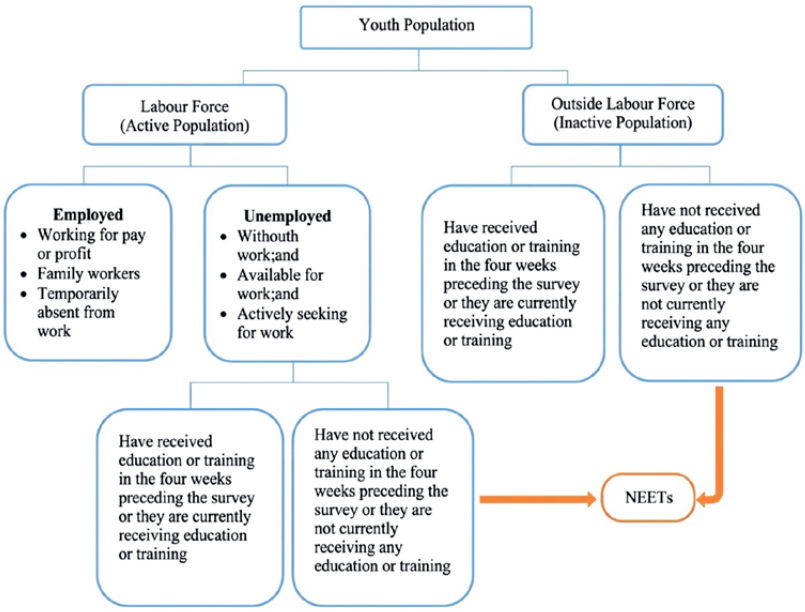

Figure 1.1. Composition of NEET indicators. Source: Bardak et al. (2015).

1.3. NEET in Iran

Iran's unique socioeconomic and political characteristics offer a critical context for understanding the NEET phenomenon. Iran's NEET rate stood at 30% in 2020, substantially higher than the global average of 22.1%, and this trend of high rates is also seen in neighbouring countries such as Turkey (24.4%), Pakistan (31%), and Arab countries (33.4%) (ILO, 2021). This represents a large percentage of 15-24-year-olds who do not participate in education, skill training, or employment, straining their households and communities. The scale of disengagement threatens both individual life prospects and national development capacity (Eslamian et al., 2024).

The magnitude of the challenge becomes clearer when examining trends over time. The Iranian youth active population decreased from 8 million in 2011 to 5.6 million in 2020. A lack of employment growth, economic constraints, and a high emigration rate among educated individuals could all contribute to the decrease (Vakili & Mobini, 2023). With 16.6 million working-age youth in 2019, Iran possesses substantial demographic potential. However, the country's demographic dividend[2] is not being harnessed from the millions of NEET youth;

[2] Describes the economic growth potential that arises from a shift in a population's age structure, typically when the working-age population grows larger than the dependent young and elderly populations.

only 1.2 million unemployed individuals received targeted support in 2020, revealing a substantial policy gap in addressing broader youth employment challenges. The current system ignores NEET young people, rendering them invisible and further exacerbating their exclusion from targeted interventions (Ministry of Cooperatives, Labour and Social Welfare, 2020).

More than 73% of NEETs in Iran are women, making them the most visible group among NEETs. This disparity is largely due to social expectations and cultural norms that emphasize women's roles in the family and the heavy burden of housework and caregiving. This will be explored in more detail in Chapter 4. Geographically, NEET rates vary substantially in rural areas, the NEET rate is higher (over 41% among 15-24-year-olds) than in urban areas (37%). There is a wide variation in NEET rates across provinces; some areas have extremely high rates. For instance, the Sistan-Baluchistan province has a NEET rate of approximately 48.2% among the other provinces with a high NEET rate are Golestan (44%), Hormozgan (43.8%), Kermanshah (42.8%), Lorestan (42.1%), and West Azerbaijan (41.7%). There is a significant loss of potential that could have contributed to Iran's economic and social development (Mir Mohamad Tabar & Noghani, 2019). These geographic disparities stem from deeper structural failures in Iran's school-to-work transition system, which is inefficient and contributes to the problem of NEETs. The education system often fails to equip young people with marketable skills, leading to a mismatch between job seekers' qualifications and labour market demands (Nazarzadeh Zare & Parvin, 2024). This mismatch is especially problematic because 42.8% of Iran's unemployed youth hold higher education degrees, and many educated women in rural areas are unable to find suitable employment. The labour market, characterized by informality, low wages, and job insecurity, makes it even more challenging for graduates to find stable employment (for more details, see Chapter 4). Iranian unemployment rates by sex and age are shown in Figures 1.2 and 1.3. Figure 1.2 reveals that women consistently face higher unemployment rates than men across all years, while Figure 1.3 shows that youth (15-24) experience unemployment rates nearly twice those of older age groups.

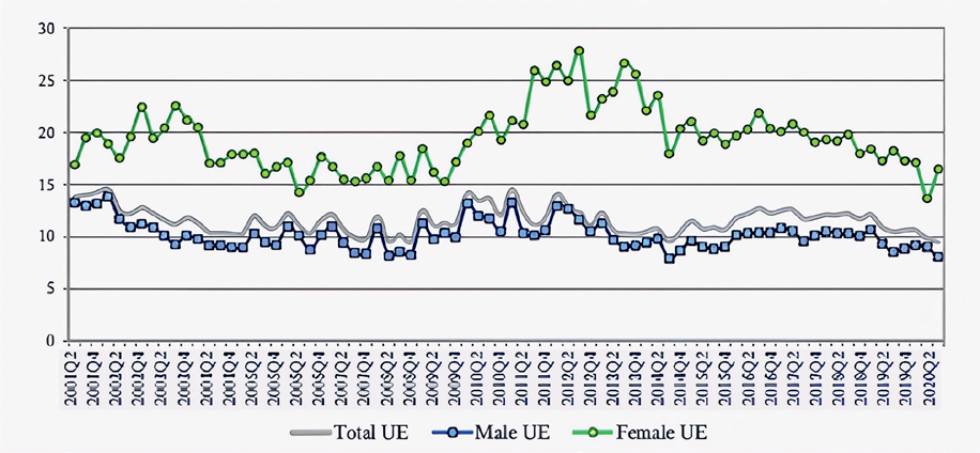

Figure 1.2. The unemployment rate by gender. Source: Statistical Centre of Iran.

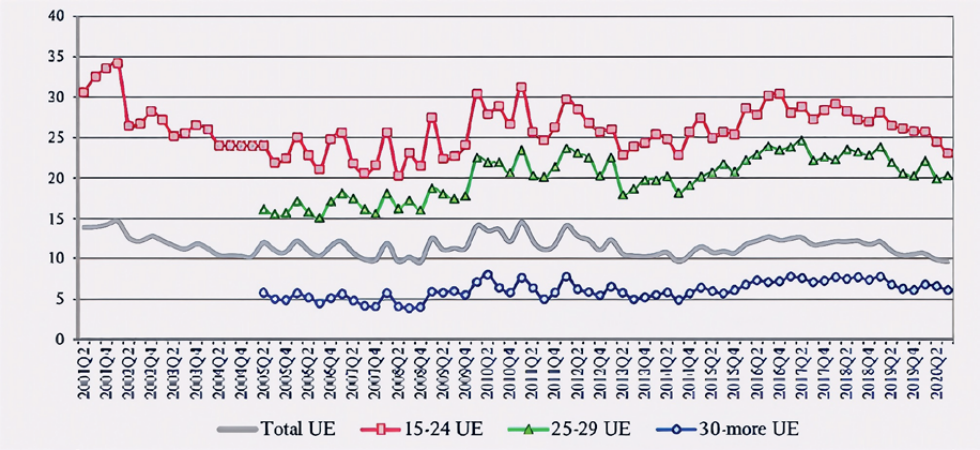

Figure 1.3. The unemployment rate by age group. Source: Statistical Centre of Iran.

NEET youth who do find work are often employed in unregulated, informal, and unsatisfactory jobs. Approximately 70% of Iranian youth workers are employed and have informal contracts, and many temporary jobs discourage young people from pursuing long-term employment. Low pay in these sectors limits motivation to work, and the commercialization of education limits social mobility by preventing lower-income families from obtaining higher-paying jobs (Esfahani & Shajari, 2012).

The economic constraints in Iran have severely limited job creation, making Iran's demographic window a challenge rather than an opportunity. Several factors, including economic sanctions, macroeconomic instability, and limited access to international markets, have restricted oil exports and foreign exchange access since 2012, intensifying economic

isolation and exacerbating the country's NEET crisis. It is impossible to separate Iran's NEET crisis from its economic-political structure, which limits youth employment through three reinforcing channels. The first is the sanctions; as a result of international sanctions imposed in 2012 on Iran's oil exports and banking sector, partially lifted under the JCPOA in 2015, and reimposed more broadly in 2018, the economy has consistently been unable to create formal jobs. Revenues from oil fell from roughly $118 billion in 2011 to $52 billion in 2013, recovered to $64 billion in 2017, then collapsed again to $19 billion in 2019 (Pescatori & Nazer, 2022). Each contraction reduced foreign exchange, depressed private investment, and restricted imports of capital goods on which Iran's manufacturing sector depends (Farzanegan & Krieger, 2019). For youth entering the labour market during these episodes, the result was fewer formal openings and accelerating inflation that reduced real wages.

The second is the dual public–private economy. The public sector absorbs many university graduates but cannot expand at the pace demographic growth demands, constrained as it is by oil-dependent revenues and sanctions pressure. The private sector, small-scale, informal, and concentrated in services and construction, generates precarious, low-wage jobs with limited career prospects (Salehi-Isfahani & Egel, 2007). Educated youth are caught between queuing for scarce public-sector positions and accepting informal work that underutilises their qualifications.

The third is inflation-induced discouragement. Sanctions pressure interacting with domestic monetary policy produced severe currency devaluation: the rial lost approximately 60% of its value between 2018 and 2020, generating cost-push inflation that disproportionately affects lower-income households and discourages labour force participation among youth whose potential earnings fall below subsistence thresholds.

These three mechanisms operate simultaneously, producing an environment in which high NEET rates are structurally embedded rather than merely cyclical.

Despite government promises to create jobs, youth unemployment remains high. As of the third quarter of 2024, Iran's youth unemployment rate (ages 15-24) stands at 19.4%, down from a record high of 30.4% in 2016 (Cheratian et al., 2023). Figure 1.4 shows the NEET rate in Iran by gender.

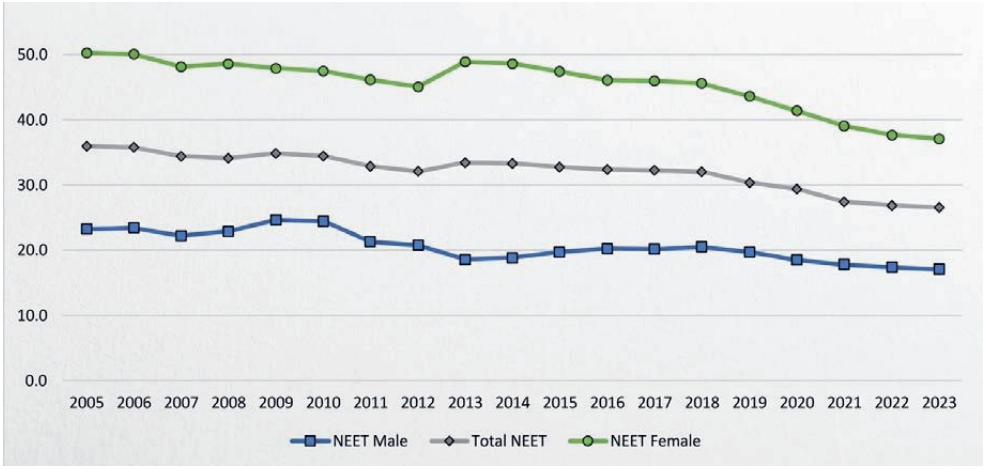

Figure 1.4. The NEET rate in Iran by gender. Source: World Bank (2024).

There are cultural and institutional barriers that prevent women from accessing the labour market in Iran, especially in rural areas with low educational attainment and limited economic opportunities. Iranian youth face distinct challenges in finding stable employment due to the commercialization of education and the prevalence of informal employment (Farzanegan & Krieger, 2019). Effective interventions must account for Iran's economic, social, and cultural landscape, combining global best practices with local expertise to overcome structural constraints.

NEET youth in Iran form heterogeneous subgroups, including unemployed job seekers, inactive caregivers, discouraged workers, and short-term transitional cases, and these pathways imply different mechanisms and policy needs. In the Iranian context, available survey and administrative data do not allow a clean and fully reliable separation of these subgroups into mutually exclusive categories. For this reason, the empirical chapters treat NEET as an umbrella outcome while using theory-to-measurement mapping to approximate dominant pathways through observable indicators, such as education and work experience for employability, unpaid housework and caregiving for inactivity constraints, and regional labour market conditions for discouragement. This approach acknowledges the conceptual distinction between NEET subgroups while remaining transparent about data limitations and avoiding overinterpretation of subgroup-specific mechanisms where direct identification is not feasible.

1.4. Theoretical background and conceptual framework

1.4.1. Theoretical Background

Studying NEET requires an interdisciplinary approach that draws on sociology, labour economics, and education. No single theory can fully account for why some young people end up disconnected from both work and education, while others facing similar conditions do not. What follows is a brief overview of the main theoretical perspectives that inform this dissertation, organized not as isolated summaries but as a cumulative argument about how individual, institutional, and structural forces interact to produce NEET status.

The starting point for most economic analyses of youth disconnection is human capital theory. Becker (1964) argued that individuals invest in education and skills to raise their productivity and, by extension, their earnings. In this perspective, NEET periods are costly because they prevent young people from acquiring the skills and credentials they need to compete in the job market. According to the theory, young people cannot build human capital when educational infrastructure is weak or financially out of reach. This type of barrier is created in Iran by an uneven distribution of educational resources across provinces. During economic downturns, the problem becomes more acute. Kelly and McGuinness (2015) show that when job prospects decline, young people become discouraged from investing in further education or job search, and NEET rates surge as a result. Human capital theory treats the labour market as if it rewarded skills straightforwardly.

Matching theory complicates this picture. Thurow (1975) and Kalleberg and Sorensen (1979) shifted attention from what workers can do to how employers select them. Hiring decisions rely on signals: credentials, work experience, and social networks. Young people who have spent time as NEETs lack these signals, making it difficult for them to access higher-skilled jobs regardless of their actual abilities. The result is a sorting mechanism that pushes NEET youth toward the bottom of the job queue, concentrating them in low-skilled segments of the labour market and denying them access to the kinds of first jobs that build careers.

Labour market segmentation theories formalize this dynamic. Doeringer and Piore (1971) and Lutz and Sengenberger (1974) described labour markets as divided into distinct segments that offer very different prospects. Primary sector jobs provide stability, decent wages, and room for advancement. Secondary sector jobs are precarious, poorly paid, and lead nowhere. Young people without vocational credentials or workplace connections typically enter the secondary sector, if they find employment at all. In highly segmented markets, the barriers between these

sectors become nearly impossible to cross, trapping NEET youth in unstable job or shutting them out of formal employment entirely.

Do these divisions persist for a reason? Lindbeck and Snower (1989) offer an explanation based on insider-outsider theory. Workers already employed accumulate firm-specific skills, union protections, and bargaining power that make them expensive to replace. Unemployed youth and new labour market entrants lack these advantages. They are, in effect, outsiders in a system that structurally favours those already inside it. This framework is useful because it shifts the explanation for NEET status away from individual deficits. The problem is not that young people lack motivation or talent; it is that labour market institutions are designed in ways that systematically disadvantage newcomers.

These economic theories, taken together, explain a great deal about how labour markets generate and sustain youth exclusion. They are, however, less equipped to account for why NEET risk falls unevenly across social groups. Social stratification theory (Ballantine et al., 2009) fills this gap by highlighting the roles of family background, social class, immigration status, and health in shaping educational and employment outcomes. Young people from low-income families or immigrant communities face compounded disadvantages that increase their chances of becoming NEET. Educational institutions play a part here too. Tracking systems, credential hierarchies, and monitoring practices sort students into different opportunity pathways, and these sorting mechanisms tend to reproduce existing inequalities rather than offset them.

Each of these perspectives captures something real, but each also operates at a single level of analysis. Bronfenbrenner's ecological systems theory (1979, 1994) provides a framework for connecting them. The theory organizes youth outcomes into layers based on influences. Microsystems consist of the immediate environments in which young people are directly involved: family dynamics, peer relationships, and school environments. A mesosystem captures how these settings interact with each other, for example, how parental involvement in education affects the educational engagement of a young person. Exosystems also include indirect factors, such as parental employment stability and community resources. The macrosystem is composed of cultural norms, policy frameworks, and economic structures. A chronosystem incorporates policy changes, historical periods, and developmental transitions.

Using the ecological model is particularly valuable for NEET research because it emphasizes that outcomes arise from the interaction among these layers, not from any one of them alone.

A young woman in a rural Iranian province may simultaneously face limited human capital, poor signal quality for employers, a segmented local labour market, outsider disadvantage, and stratified social conditions. Her NEET status is not reducible to any one of these forces. Effective intervention, by the same logic, cannot target only one level. It must address individual vulnerabilities, institutional barriers, and structural constraints at the same time.

These theoretical perspectives provide the multi-level foundation for this dissertation's empirical analyses. Each explains distinct mechanisms, operates at a distinct level, and points to distinct intervention targets. The integrated conceptual model of youth transitions from school to work is presented in Figure 1.5.

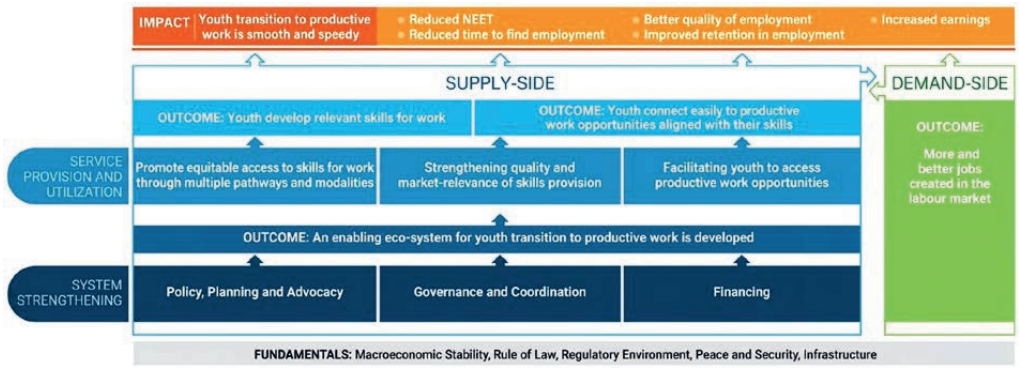

Figure 1.5. School-to-Work Transition for Young People, Conceptual Framework.

1.4.2. Conceptual Framework

The conceptual framework organizes this theoretical complexity into three analytical dimensions that correspond to the policy cycle: identifying the population, diagnosing causes, and evaluating responses. This structure guides both empirical analysis and policy assessment.

1. **Characteristics of the Target Group**

   NEET youth represent a heterogeneous group of students with different educational levels, skills, and life circumstances (Schneider & Ingram, 1993). Some possess secondary or tertiary credentials but cannot find appropriate employment; others left school early due to family obligations, health issues, or educational disengagement. Some actively seek work; others have withdrawn entirely from the labour market. Some people live in urban centres with a wide range of opportunities, while others live in rural areas with fewer opportunities. Understanding this diversity is crucial to developing effective policies rather

than treating NEETs as a monolithic group. Subpopulations face different barriers and require different interventions.

2. **Causes Underlying the NEET Issue**

   NEET status results from structural factors operating at multiple levels (Siraj et al., 2014). Labour market segmentation limits access to stable employment. Educational systems produce mismatches between credentials and employer requirements. Socioeconomic inequalities concentrate disadvantage among particular communities. Regional economic disparities create geography-specific barriers. Women and men are constrained differently by gender norms and family expectations. National policies determine whether these risks intensify or diminish. Causation requires examining how individual characteristics interact with institutional arrangements and structural conditions.

3. **Characteristics of National Policy Responses**

   Various countries address NEET challenges differently, depending on their institutional contexts, resources, and political priorities (Heidenreich & Zeitlin, 2009). The key to building human capital is training and education. In other cases, job creation or employment subsidies are used to expand opportunities. Some organizations provide income support to young people while they search for jobs. The effectiveness of a policy depends on its fit with local conditions. Interventions that are effective in contexts with strong vocational systems may not work in contexts with weak educational institutions. In this dimension, we map the policy landscape to identify which approaches show promise for addressing Iran's specific challenges related to NEETs, including regional disparities, gender inequalities, and substantial informal employment.

This framework challenges universal recommendations by highlighting how NEET patterns and appropriate responses vary across contexts. Iran's unique configuration of highly educated youth facing employment scarcity, gender segregation in labour markets, regional economic disparities, a substantial informal sector, and rapid demographic shifts requires a contextually grounded analysis rather than the importation of Western European labour-market frameworks. The theoretical perspectives outlined above provide conceptual tools, but their application must account for Iran's specific socioeconomic, political, and cultural realities.

Conceptual mechanisms and observable indicators are linked in theory to guide empirical analysis. Each theoretical framework is mapped to specific variables and expected relationships in Appendix 1.1, showing how abstract concepts can be translated into measurable constructs.

1.4.3. Integrative Approach

This dissertation draws on three disciplinary traditions to understand NEET youth in Iran. Sociology provides frameworks for examining social stratification, gender inequality, and the institutional barriers that structure young people's opportunities. Labour economics explains education-employment transitions, skill formation processes, and labour market dynamics. Education research illuminates how schooling systems, credential hierarchies, and school-to-work pathways affect young people's trajectory, including how educational institutions themselves can produce disengagement and dropout that lead to NEET status. Together, these perspectives inform social policy research that translates empirical findings into actionable intervention strategies. This interdisciplinary approach is essential because NEET status operates simultaneously as an economic outcome (labour force non-participation), a social position (exclusion from key developmental institutions), an educational challenge (reflecting both system failures and individual disengagement), and a policy problem (requiring coordinated intervention across multiple systems). These three perspectives converge through Bronfenbrenner's ecological systems theory, which organizes the analysis around nested layers of influence, from individual characteristics to family and community contexts, to regional and national structures. Figure 1.6 illustrates how these ecological systems shape youth outcomes. The framework positions NEET status as an overlapping area of influence that either facilitates or constrains young people's transition back into education and employment, rather than simply an individual failure. Every level of analysis draws from a specific disciplinary tradition, while remaining informed by others as well. Education, skills, and employability shape an individual's employment prospects at the micro level through human capital theory and job-matching models. Educational psychology and student engagement research reveal how individual learning experiences, academic self-efficacy, and school attachment influence educational persistence. At the meso level, labour market segmentation and insider-outsider theories reveal how institutional arrangements, such as labour laws, hiring practices, and credential requirements, create barriers that prevent young people from accessing stable employment regardless of their qualifications. Educational institutional analysis exposes how school organization, tracking systems, and vocational education structures channel students into different opportunity pathways. At the macro level, social stratification frameworks and regional economic analysis expose how structural inequalities based on geography, social class, and gender systematically produce differential NEET risks across Iranian provinces. The framework attends to both temporal and spatial dynamics. Young people move into and out of

NEET status over time, and these transitions vary markedly across Iran's diverse regional contexts. Provincial labour markets, shaped by local industrial structures and demographic compositions, create distinct opportunity environments. Similarly, regional variation in educational infrastructure, from university access to vocational training quality, shapes the pathways available to young people in different provinces. Understanding how NEET prevalence varies across space, time, and demographic groups requires connecting regional economic structures with local educational systems and socio-economic conditions, a perspective that bridges economics, education, and geography. This theoretical integration informs the dissertation's methodological approach. The empirical chapters employ systematic and scoping reviews from the social sciences and education literature, machine learning and probit modelling grounded in economic theory, and spatial panel data analysis to capture geographic variation in NEET patterns. The dissertation provides a comprehensive analysis of NEET patterns in Iran by combining complementary methods and focusing on individual experiences. It provides insight into the multidimensional challenges young Iranians face as they transition to economic independence and ultimately guides the evaluation of NEET initiatives, programs, and policies.

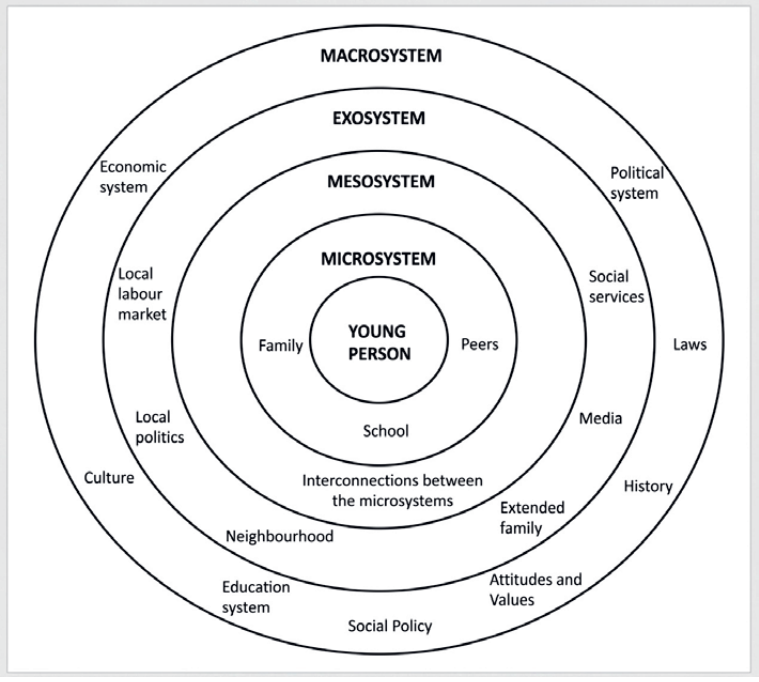

Figure 1.6. Model of Bronfenbrenner's Ecological Systems.

1.5. Problem statement and aim of the dissertation

Approximately three million Iranian youth were classified as NEET in 2022, with a disproportionately high number of them being young women (Ministry of Cooperatives, 2022). The NEET rate is unevenly distributed across the country due to low educational attainment, economic instability, and inadequate infrastructure for job creation and skill development, resulting in higher rates in some regions. The disparities indicate that a one-size-fits-all policy is insufficient to address Iran's NEET problem. The regional variation in NEET rates demonstrates that local socioeconomic conditions, cultural characteristics, and available resources all play a significant role in determining the effectiveness of policy measures. Therefore, spatially informed research is essential for the design of region-specific policies. Understanding the spatial dynamics and interconnections among surrounding regions enables policymakers to develop more effective measures to reduce NEET rates and promote equitable economic growth across all provinces.

Gender is a key component in understanding the NEET phenomenon in Iran. Women are more likely to be NEET than men, not only because of unemployment but also because they are less likely to be active in the labour market. Inactivity is often the result of social restrictions, caregiving responsibilities, and systemic barriers within the labour market that restrict their access to education and employment. Young women in Iran face unique issues that require distinct approaches to address.

During the COVID-19 pandemic, job losses and educational barriers caused an increase in the number of NEET youth. NEET rates have declined since 2021, but the recovery has been inconsistent. Furthermore, the economic recovery has had only a limited impact on many regions, especially rural areas, and young women (Simões, 2024).

The lack of research and effective policies tailored to Iran's unique socioeconomic conditions has limited progress in resolving this issue, putting many young Iranians at risk of long-term marginalization. Furthermore, the NEET problem can influence larger societal processes such as migration, marriage, divorce, and reproduction, as well as contribute to harmful behaviours such as crime, depression, and substance abuse (Zīlīte, 2020).

Three decades of NEET research have focused overwhelmingly on European welfare states, leaving unanswered fundamental questions about youth disconnection in developing economies. Iran presents a sharply different configuration, with highly educated youth facing severe employment scarcity, gender-segregated labour markets, rapid demographic shifts,

extensive informal employment, and regional disparities that exceed those in European contexts. However, systematic research on Iranian NEET patterns remains limited. There are only a few studies that offer national analyses rather than snapshots of specific provinces or demographic groups.

The majority of NEET research employs a single methodological approach, capturing only partial perspectives. Qualitative studies can illuminate individual experiences, but they cannot estimate prevalence at the population level. Econometric analyses may miss unexpected patterns because they test specific hypotheses. The distinction between robust phenomena and method-specific artifacts remains unclear because no studies have triangulated results across multiple methods.

There is a particular lack of development in spatial analysis. While literature acknowledges that NEET rates vary by region, it treats location as a control variable rather than examining how regional structures affect NEET rates.

Theoretically, disciplinary divisions limit explanatory power. Sociologists emphasize institutional barriers, economists focus on human capital, and education researchers examine school disengagement. Despite their differences, these perspectives illuminate different mechanisms. Individual characteristics, institutional arrangements, and structural conditions interact to produce NEET status, requiring an integrated analysis across traditions.

Finally, policy frameworks developed for European contexts may not transfer to settings lacking comprehensive welfare systems, where informal employment dominates, and where cultural norms create distinct constraints on youth transitions.

NEET status in Iran is influenced by unique risk factors that need to be identified before developing strategies to reduce it. This dissertation aims to examine the factors that lead young people to become NEET and understand how these factors vary across demographic, socioeconomic, and regional contexts. The purpose is to fill these gaps by applying an integrated empirical analysis that combines scoping review, meta-analysis, machine learning, and spatial panel methods. This study aims to provide new insights into how individual characteristics, institutional contexts, and regional structures interact to influence NEET experiences.

This dissertation addresses the research gaps identified above through an integrated approach. Meta-analyses and scoping reviews are used to synthesize global evidence. Iranian data reveals context-specific patterns through machine learning. Spatial panel analysis examines regional

variation over time. These approaches provide a comprehensive understanding of NEET patterns in Iran while contributing methodological innovations applicable to other developing economies.

The study contributes empirically by providing a national-level analysis of Iranian NEETs. It shows how triangulation across approaches strengthens inference beyond what a single method could provide. It generates evidence-based, regionally tailored policy recommendations based on Iran's specific institutional realities. This dissertation builds a replicable framework for analyzing NEET dynamics in developing countries by integrating advanced methodologies. The study addresses these challenges with a view to developing regionally tailored, evidence-based policies to reduce NEET rates in Iran and to provide actionable solutions for other contexts.

1.6. Methodology Overview

This dissertation employs a comprehensive, sequential methodology integrating four distinct analytical approaches to examine NEET patterns in Iran. The research design recognizes that no single method can adequately capture the complexity of youth disconnection across individual, demographic, and regional dimensions.

The research begins with a scoping review to map which risk factors have been investigated across different groups and settings. The purpose of a scoping review is to gather all available information and identify characteristics that are consistent across studies, as well as those that warrant further research. A methodical approach considers all possible factors, not just those that fit into a specific theoretical framework. A meta-analysis enhances evidence synthesis by separating robust predictors from context-dependent correlations based on empirical weights. A factor that shows large, consistent effect sizes across different populations and situations is a theoretically sound concept that can explain a lot, rather than being just an artifact of a single study. Based on meta-analysis estimates, machine learning risk profiling models are selected. A risk profiling model based on CART (Classification and Regression Trees) is used to estimate the likelihood of Iranian youth becoming NEETs. Probability models allow the identification of average relationships consistent with theory, with marginal effects and coefficients that make sense. CART can detect nonlinear relationships, interaction patterns, and threshold effects that are not captured by standard regression equations. This combination does not aim to understand how things work; instead, it serves a policy goal by sorting and ranking young people by their expected NEET risk for screening and targeting. Based on theoretical frameworks, NEET risk

is caused by factors that operate differently for different groups. Using algorithms to find complex patterns can help us better understand how risk is created.

A regional analysis focuses on connecting regions instead of treating them as separate entities. Youth outcomes are closely linked across provinces due to interprovincial labour markets, migration flows, and public policies. As a result of this spatial dependence, the model fits better and supports the idea that NEET is a phenomenon driven by local opportunities and spillover effects in a particular place. Spatial approaches examine whether geographic clustering is driven by compositional sorting (people at risk tend to live in certain areas) or by contextual mechanisms (places themselves cause different outcomes). This difference is important in theory because compositional effects require treatments specific to each person, while contextual effects require changes to the system's policies.

Each method has a specific goal. A scoping review and meta-analysis examine all available data to determine which risk factors are consistently associated with NEET status across contexts. These chapters sort the data and compare sizes, but they do not make any claims about causation because the studies were too different in design, measurement, and context to support causal pooling. The individual-level models examine how youth and household factors are related to NEET status, enabling us to identify who is at highest risk. The spatial panel models examine relationships among provinces and how they are connected at the regional level. They focus on structural patterns instead of figuring out what causes them.

This dissertation utilizes complementary analytical strategies, each possessing unique analytical advantages. Cross-sectional analyses (Chapters 2, 3, and 4) reveal significant correlations between risk factors and NEET status, measure effect sizes, and delineate non-linear thresholds. When stronger causal claims are needed, the Heckman selection correction for unobserved confounding (Chapter 4) or temporal lags to reduce reverse-causal concerns (Chapter 5) are used, but their limits are also recognized. Experimental data would enhance causal inference, but these are difficult to obtain. However, triangulation across methodologies offers convergent evidence that specific factors, including education, work experience, domestic responsibilities, and provincial GDP, reliably predict NEET outcomes across various samples, statistical techniques, and analytical frameworks. When the same variables show significance in meta-analysis (combining different studies), in individual-level models (accounting for selection and interactions), and in spatial panel analysis (controlling for regional fixed effects and temporal dynamics), it is less likely that these relationships are due

solely to confounding. Without experimental variation, this multimethod convergence, alongside theoretical foundations in Human Capital Theory and the Capability Approach, establishes a solid basis for evidence-based policy interventions.

1.7. Research Questions

In countries with high youth disengagement rates, such as Iran, understanding the NEET phenomenon is vital to improving social inclusion and economic stability (Aina et al., 2025). However, effective interventions require an understanding of the socioeconomic, educational, and regional factors that contribute to NEET status. Tailored, context-specific policies are necessary to address the diverse needs and circumstances of NEET youth, rather than treating them as a homogeneous group. Addressing youth disengagement is vital because these young individuals often struggle to reintegrate into the education system and the labour market, thereby decreasing national productivity and growth.

Iran faces several challenges, including gender inequality, regional disparities, limited employment opportunities, and unstable economic conditions. To identify the most important risk factors influencing NEET youth and understand how these factors vary across demographic, socioeconomic, and regional contexts, this dissertation addresses four research questions:

RQ1: What are the key individual, familial, socioeconomic, educational, health, addiction, social, and environmental risk factors that contribute to youth becoming NEET?

Chapter 2 examines the various individual, familial, socioeconomic, and psychological factors that contribute to NEET status through a systematic scoping review. This chapter identifies key risk factors for NEET status, including educational achievement, mental health, parental background, and socioeconomic status, and identifies the primary risk factors for youth disengagement and the areas where interventions are most needed.

RQ2: What are the primary risk factors contributing to NEET status among youth, how do these factors vary across different demographic groups, and which factors demonstrate the strongest associations with NEET status to inform targeted, evidence-based interventions?

Chapter 3 presents a systematic review and meta-analysis, concentrating on demographic differences, including gender and age group. This chapter examines how risk factors, such as

education, mental health, and unemployment history, differ in their influence across subgroups. This question seeks to quantify the role of structural and systemic factors in NEET vulnerability.

RQ3: What are the key risk factors associated with NEET status among Iranian youth, and how can econometric and machine learning classification methods be combined to identify high-risk profiles and gender-specific patterns?

Chapter 4 employs Probit and Classification and Regression Tree (CART) models to analyze key variables, including educational attainment, work experience, and family background, using cross-sectional data from Iran's labour force surveys. These models provide an empirical basis for proactive interventions and serve as a risk screening framework to identify at-risk youth, enabling more targeted, customized policy responses.

RQ4: How can macroeconomic conditions and structural disparities explain regional and demographic variations in NEET outcomes across Iran, and how can these insights lead to more regionally tailored and gender-sensitive policy responses?

Chapter 5 examines regional and demographic variations in relation to youth exclusion from education and employment. This chapter examines NEET outcomes in light of existing economic structures and institutional arrangements. Several factors influence the distribution of NEETs, including regional economic capacity, employment opportunities, and disparities in social infrastructure. Based on these findings, regionally adaptive and gender-responsive strategies can better support youth at risk of long-term disengagement.

1.8. Dissertation outline

This dissertation consists of six chapters that proceed from a global evidence synthesis to an Iranian-specific empirical analysis.

According to PRISMA guidelines, Chapter 2 presents a systematic scoping review of NEET youth in the global context. The chapter evaluates findings across eight primary risk domains, including individual characteristics, education, employment, health, addiction, social factors, family, and environment, based on databases such as Scopus, PsycINFO, and ERIC. This chapter summarizes 91 peer-reviewed studies from 2000 to June 2022. This review identifies several major factors contributing to NEET status, including insufficient education, unemployment, and socioeconomic disadvantage. It provides a disciplined basis for selecting

variables in subsequent empirical chapters by identifying factors that appear consistently across studies.

Chapter 3 builds on the findings of Chapter 2, undertaking a systematic review and meta-analysis to quantify the impact of key risk factors on NEET status. In Chapter 3, odds ratios and robust variance estimation (RVE) are used to account for statistical dependencies and improve the precision of effect-size estimates. Higher levels of education significantly reduce the likelihood of being NEET, while unemployment and socioeconomic concerns increase it.

While the scoping review in Chapter 2 mapped the full landscape of NEET risk factors of diverse designs, it could not determine the relative magnitude of different risk factors or assess whether observed associations are statistically robust when pooled across studies. This chapter addresses that limitation through a meta-analysis restricted to reporting quantifiable effect sizes (odds ratios). The quantified effect sizes also serve a direct practical function: they inform the variable selection for the Iranian classification model in Chapter 4.

Chapter 4 presents the results of pooling estimations to select machine learning models and applies these insights to Iranian household survey data, developing risk profiling models using probit regression and classification and regression trees (CART) to assess individual NEET risk. Key predictors include education, employment experience, and household activities. Where Chapter 3 establishes which factors matter globally, Chapter 4 reveals how they operate within Iran's specific institutional context. NEET status is strongly influenced by low educational attainment, lack of work experience, and household responsibilities.

In Chapter 5, the spatial analysis is based on provincial data and macroeconomic factors. This chapter uses spatial panel methods to examine how demographic disparities and regional differences affect young people's disengagement from education and employment across Iranian provinces over the period 2004-2022. The spatial econometric analysis indicates strong spatial correlation among provinces, suggesting that elevated NEET rates in one region tend to spread to other regions. Economic growth (measured by GDP per capita) and government spending were associated with lower NEET rates, while inflation and labour market congestion reversed this trend. In this chapter, we distinguish compositional effects (clustering at-risk individuals) from contextual effects (place-based factors operating independently). We then decide whether interventions should focus on individual characteristics or structural conditions.

Chapter 6 synthesizes findings across methods to identify robust intervention targets. Factors demonstrating significance across meta-analysis, individual risk profiling models, and spatial

analysis provide the most secure foundations for policy recommendations. The chapter discusses the importance of the results for both research and policy, demonstrating how insights from the scoping review, meta-analysis, machine learning models, and spatial panel data can guide future actions. It recommends refining policy and enhancing support mechanisms for at-risk NEET youth, with particular attention to gender-specific issues and regional disparities.

Figure 1.7 visualizes the structure of the dissertation.



Figure 1.7. presents the dissertation's overall structure.


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Chapter 2

Risk Factors of Being a Youth Not in Education, Employment or Training (NEET): A Scoping Review

This chapter draws upon: Rahmani, H., & Groot, W. (2023). Risk factors of being a youth not in education, employment or training (NEET): A scoping review. **International Journal of Educational Research**, 120, 102198. https://doi.org/10.1016/j.ijer.2023.102198

Abstract

In recent years, concerns over youth unemployment have broadened to those about youth not in Education, Employment, or Training (NEET). The appeal of the "NEET" concept comes from its alleged ability to address a wide range of vulnerabilities among youth, including concerns about unemployment, early school leaving, and labour market discouragement. These concerns require attention as youth face the effects of economic crises, especially in industrial economies, as well as global crises such as the COVID-19 pandemic.

Based on the PRISMA criteria, this scoping review identifies and maps the evidence on the risk factors of NEET youth. We included articles published between 2000 and June 2022, which resulted in 91 included papers. We categorized all the risk factors into eight major groups: individual characteristics, education and school, work, health, addiction, social factors, family, and environment.

Overall, the findings indicate that education and family-related variables have a crucial influence on NEET youth. The most critical indicators were education level, work experience and skill, physical and mental health, marital status, poverty and social inequalities, living situation, parents' income, education, and job status. In addition, the review identifies various knowledge gaps regarding relevant risk factors. More research is needed to address these gaps and evaluate each risk factor's influence on NEET youth.

2.1. Introduction

As explained in Chapter 1, the proportion of youth in the population who are neither employed nor in education or training (the so-called "NEET rate") is a relatively new measure gaining popularity in policy and the media. The proportion of NEET youth increased among males from 13.1% in 2019 to 15.3% in 2020, and among females from 30.3% in 2019 to 31.1% in 2020 (ILO, 2020). Furthermore, the number of NEET youth and those in precarious jobs appears to have increased, and the shock of the COVID-19 epidemic has aggravated this issue. These trends underscore the urgent need to understand which factors predict NEET status (ILO, 2021). Many youth are not counted in these numbers because they have fallen out or never joined an unemployment scheme (Abayasekara & Gunasekara, 2019).

In 2021, youth employment fell by 8.7% globally. The drop in employment among adults was less dramatic, at 3.7% (ILO, 2021). This disparity demonstrates the pandemic's economic effects on youth. According to the International Labour Organization, unless action is taken to address this issue, it will harm youth's employment prospects, and many of them may continue to feel its impact for a long time. Furthermore, in developing countries, NEET rates are lower because youth cannot afford to remain jobless without well-developed social security systems, forcing them to frequently take insecure, low-paying jobs in the informal sector (ILO, 2017).

Identifying the risk factors and determinants of NEET status is crucial to develop effective strategies to ensure that young people are productively engaged and do not become disconnected from education or employment. So far, the policy emphasis has mainly been centered on European and other developed countries (Abayasekara & Gunasekara, 2019).

Much of the literature analyzing the NEET problem has been produced by local governments, educational institutions, and central government agencies. The literature on NEET youth portrays the situation as problematic, with NEET individuals often seen as either victims or lacking the agency to change their circumstances. The literature demonstrates various interventions, including knowledge, a guidance counsellor (CEDEFOP, 2010), support and self-esteem boosting (LGA, 2009), informal learning programs (Taylor & Evans, 2009), and volunteering programs and job experience (Grist et al., 2011) to insert NEET youth into the labour market, education, or training.

This Chapter aims to identify and map the evidence on the risk factors of NEET youth. This only includes youth who are not in education, employment, or training. We also identify

research gaps by mapping to prevent NEET youth from disappearing from 'the radar,' thereby obstructing effective school-to-work transitions.

Previous systematic reviews and meta-analyses have concentrated on NEET youth demographics and particular determinants. For example, Gariépy et al. (2021) investigated the association between NEET status and youth mental health and substance use problems. This study emphasized that mental health issues at a young age increase the risk of becoming NEET. There are two other systematic reviews, one demonstrating a relationship between poor mental health and poor physical health (Hale et al., 2015) and the other showing a negative association between youth depression and education and job outcomes (Clayborne et al., 2019). Also, Lindhardt et al. (2022) have reported psychosis among NEET youth. These systematic reviews demonstrate the growing recognition of the critical role of mental health in shaping young people's educational and economic paths. However, they did not investigate the impact of other factors, such as family, environment, or social factors, on NEET.

Filges et al. (2022) conducted a systematic review examining the impact of service-learning on NEET status, post-compulsory school academic achievement, personal and social skills, and risk behaviours (alcohol and drug use, aggressive behaviour, sexual risk-taking). Mawn et al. (2017) analyzed the impact of various interventions, such as employment, earnings, welfare receipt, health, and education, in their systematic review and meta-analysis. Employment and earnings were the most commonly used intervention outcomes, underscoring the imperative to design and assess initiatives that facilitate job transitions for individuals currently jobless. Furthermore, they emphasize the importance of providing mental health and emotional support to this demographic group (Mawn et al., 2017; Oliver et al., 2014). While these reviews examined specific aspects, there has been no systematic review, scoping review, or synthesis of data to date with in-depth information on significant individual, social, family, environmental characteristics, and other important aspects and factors related to NEET.

This scoping review compares the risk factors and characteristics of youth who are not in education, employment, or training. The results of this Chapter may help practitioners and policymakers identify who is at risk of becoming NEET. Also, this study may help develop early intervention programs targeting at-risk youth to prevent NEET. Furthermore, awareness of these characteristics may increase the demand for an evidence-based assessment tool to identify these risks. The argument presented here advocates a comprehensive solution to the "issue" of NEET youth. It is primarily concerned with addressing the needs of young people in an open, meaningful, and long-term way rather than with lowering unemployment statistics in

the near term for political reasons. This scoping review reports on the difficulties and methods of addressing the NEET problem.

2.2. Methods

This study follows a scoping review methodology in accordance with the framework proposed by Arksey and O'Malley (2005) and the PRISMA Extension for Scoping Reviews (PRISMA-ScR) reporting guidelines (Tricco et al., 2018). Scoping reviews differ from systematic reviews in that they aim to map the breadth of literature on a topic, identify key concepts and research gaps, and include diverse study designs without conducting risk-of-bias assessments or requiring inter-rater reliability protocols (Munn et al., 2018). The purpose of this approach is to comprehensively identify the range of risk factors associated with NEET status across international contexts. It takes a broader perspective and includes research with experimental and quasi-experimental designs (Arksey & O'Malley, 2005) as well as research with other designs (Ahn & Kang, 2018). Therefore, the synthesis is narrative and descriptive rather than statistical (Tricco et al., 2018).

2.2.1. Search strategy

The review was limited to English-language peer-reviewed articles published from 2000 to June 2022. We conducted electronic searches on several bibliographic databases: Scopus, PsycINFO, ERIC, British Education Index, Social Science Citation Index, Conference Proceedings Index, and grey literature collections (e.g., GLADNET, OATD, ProQuest) and IEEE Xplore, SpringerLink, and ScienceDirect using the search criteria, and Google Scholar was used as a supplementary source. Each database's export function in CSV format was used to retain results (for Scopus, PsycINFO, ERIC, and SpringerLink) and in BibTeX format (for IEEE Xplore and ScienceDirect). The open-source bibliographic reference manager JadRef was used to convert BibTeX to CSV. The citation data for all publications were finally collected and extracted into EndNote X9.

Additional articles were found by searching the reference lists of the included articles. Hand searching and online searches were used to augment the database searches. The PICO (population, intervention, comparison, and outcomes) criteria defined the eligibility criteria (Ahn & Kang, 2018; Nsanzumuhire & Groot, 2020).

Population

The target population consisted of youth aged 15 to 24 years old who were not in education, employment, or training. Studies including respondents aged 12 to 35 years and those presenting analyses for subgroups of NEET participants in the whole population from all countries were also considered.

Risk Factors and Determinants (Intervention)

All individual, family, community, and structural-level factors are hypothesized to influence NEET status (e.g., education level, mental health, household income, labour market conditions). Any programmatic or policy actions explicitly tested for their effect on reducing NEET rates (e.g., vocational training, outreach counseling, conditional cash transfers).

Study Characteristics Extracted (Comparison)

For studies that assessed the efficacy of risk variables, we extracted methodological and contextual characteristics to enable comparison across studies.

Outcome

Outcomes include any risk factors and other behaviours that may be used to determine whether or not someone is a NEET, including those in which they are involved. The effects of single and multiple risk factors on being NEET were assessed.

2.2.2. Types of studies

Prospective and retrospective cohort studies, case-control studies, time-series studies, and analytical cross-sectional studies with cases and comparators on risk factors affecting NEET are included in this review. The search terms listed in Table 2.1 were used in each database, with different Boolean operators, wildcard symbols, and field indexes, as required by each database. Search terms related to risk factors, determinants, interventions, and related topics were included.

Table 2.1. Search terms used for this scoping article

Population	(youth*OR Adolescent* OR young OR Juvenile OR school ADJ student* OR NEETs OR NEET).TI, AB. AND
Intervention	(youth ADJ engag* OR youth ADJ Unemploy* OR youth ADJ activism OR youth ADJ development OR youth ADJ inclusion OR community ADJ service OR after ADJ school OR afterschool OR youth ADJ1 decision-making OR Out of work OR youth ADJ adult ADJ partnership* OR youth/adult ADJ partnership* OR youth-adult ADJ partnership* OR youth ADJ action OR youth ADJ1 involvement OR youth ADJ participation OR young ADJ people* participation OR Socially excluded OR Not in work OR service ADJ learning OR Not in Employment OR Not in education OR non-formal ADJ education OR non-formal ADJ education OR informal ADJ education OR Not in train OR participatory ADJ research). TI, AB. AND
Comparison	(risk factor OR determinants OR intervention OR control* OR random* OR trial* OR effectiveness OR efficacy OR compar* OR experiment* OR impact ADJ evaluation OR impact ADJ study OR impact ADJ assessment OR outcome ADJ evaluation OR outcome study OR outcome ADJ assessment) af.

We applied the inclusion criteria to screen articles. We analyzed and synthesized our articles regarding the dimensions and features mentioned in Table 2.2.

Table 2.2. Admission criteria.

Article feature	**Specific factors**
Database	Scopus, Medline, Embase, PsycINFO, ERIC,….
Main field	NEET
Source type	Journal
Document type	Articles
Publication stage	Final
Type of journals	Peer-reviewed journals
Coverage periods	2000-2022
Language	English

Several study types were excluded because they did not meet the objectives of our scoping review. We excluded purely theoretical or conceptual papers without empirical data, as we sought to identify evidence-based risk factors rather than theoretical frameworks. We also excluded studies that focused solely on intervention effectiveness without reporting baseline risk factors or NEET determinants; these studies increased our understanding of solutions but did not contribute to our understanding of the underlying causes. We excluded conference abstracts, book chapters, dissertations, and non-peer-reviewed sources to ensure quality and accessibility (though we searched grey literature databases as a supplementary source). Additionally, studies that reported only aggregate national statistics without analyzing individual or group-level risk factors were excluded, since they lacked the granularity required for a thematic synthesis. Lastly, we excluded studies in which NEET status was not the primary outcome or was combined with other outcomes (e.g., "unemployed or NEET" without separate analysis), as these may obscure NEET-specific patterns.

2.2.3. Study selection and quality appraisal

EndNote X9.0 was used to import search results and exclude duplicates. After eliminating duplicate citations, two authors independently evaluated titles and abstracts against the inclusion criteria. Full-text articles were acquired for research that could not be ruled out during the first title and abstract screening. The search results, screening findings, and selection choices were recorded and displayed in a flow diagram. Reviewers extracted data from each study, which was then cross-checked for correctness. The first filter involved reviewing titles and abstracts for clues that the item was about NEET. The second filter evaluated the titles and abstracts of articles that passed the first filter to determine whether they were related to NEET risk factors and determinants. The third filter involved reading the full texts of articles that had passed the first and second filters to determine whether they met our inclusion and exclusion criteria and were related to our crucial issue. The reviewers examined their results and agreed on a consolidated list of publications.

2.2.4. Data analysis and synthesis

We categorized the information from the selected studies as follows: 'authors', 'year of publication', 'study location',' sample size', 'main study objective', 'study design' (i.e. study population, survey type, year of data collection), 'risk factors targeted', 'methodological approach used in data analysis and outcomes(including outcome measures). The data from

quantitative studies were further broken down into explanatory factors employed and statistical relationships with outcome measures (Gholizadeh & Mohammadkazemi, 2022).

After the first screening, we analyzed the results to summarize the extant literature on risk factors for NEET youth. We focused on literature that provides unique insights into risk factors and determinants, building on existing research. Appendix 2.1 presents the unique features of each incorporated publication in tabular form. Finally, we summarize and explain the results of the scoping reviews for each selected application area.

2.3. Results

2.3.1. Aims and design

Because the first search returned many irrelevant publications, an additional search was conducted to improve the relevance of the results (by including specific phrases in the title or designating essential topic headings). A "relevancy forcing search set" guaranteed that all relevant articles were included. The search returned 2435 articles, of which 1573 were eliminated after duplicate screening. After duplicates were removed, 865 articles were evaluated for eligibility; 708 were rejected because their inclusion criteria were unsatisfactory. The most often cited reason for exclusion was that the publication did not analyze or provide data for the NEET population. Based on this, 74 papers remain to be reviewed. Additional publications were identified through reference checking and by reviewing relevant handbooks, key journals, and specific publications, using a snowball approach. This resulted in 17 additional relevant studies. In total, 91 studies met the inclusion criteria and were mapped. Figure 2.1 shows a PRISMA flowchart of the search, screening, and selection outcomes. The growth trend in articles is shown in Figure A1 of Appendix 2.2.2

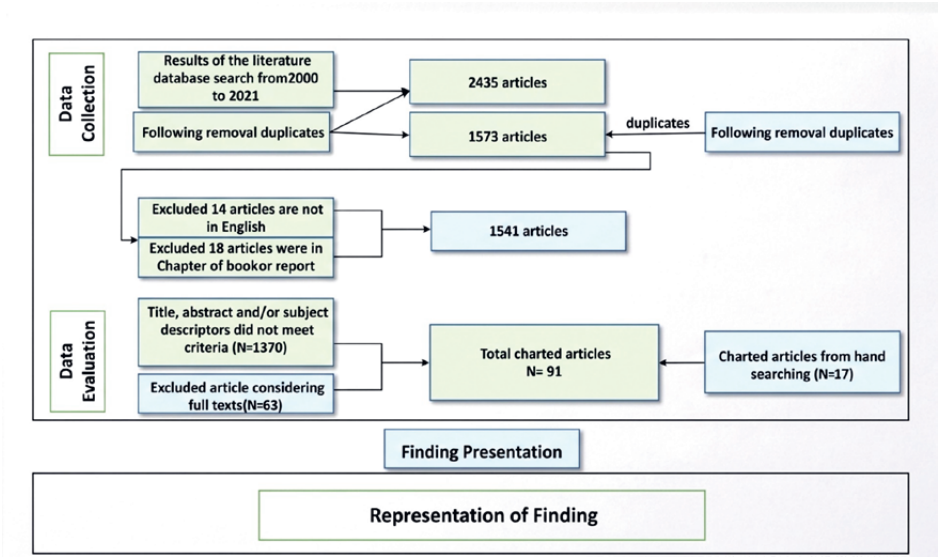


Figure 2.1. PRISMA flow chart of scoping review.

2.3.2. Participant characteristics

The 91 studies comprised a total of 3,642,751 participants. Men accounted for 1,296,819 (35.6 %) of the total participants, while women accounted for 1,741,234 (47.8 %). This difference might result from larger studies specifically targeting young women or from an oversampling of female participants in NEET research, reflecting the higher NEET rates often observed among young women. Gender was not provided in 14/91 (15.4%) studies, comprising 859,689 (23.6%) unknown gender participants. The participants' average age was 24.2 years old. The largest proportion of research comes from Europe, encompassing 22 countries and regions. England (United Kingdom) is most frequently represented (16 studies), followed by Italy (6), Spain (5), and Finland (4). Additional European contexts include Austria, Norway, the Netherlands, Russia, Scotland, Sweden, Germany, Denmark, France, Portugal, Croatia, Switzerland, and Romania, as well as several cross-national pan-European analyses. The Asian region is represented by ten countries or territories, including multiple studies from China and Japan, two studies from South Korea, and individual studies from Singapore, Hong Kong, Taiwan, and a multi-country investigation covering Vietnam, Cambodia, and Nepal. Among the studies from Africa are those from South Africa, Senegal, and Morocco, as well as broader studies involving African countries as a whole. The Oceania region is represented by three studies, mainly from Australia and New Zealand. Finally, six global or multi-regional analyses synthesize evidence from diverse international samples, including OECD member states and

emerging economies, further highlighting the international dimension of NEET youth issues and highlighting significant regional variations in risk profiles.

2.3.3. Classification of studies

The elements considered significant are categorized into eight primary groups: individual characteristics; education and school; work; health; addiction; social; family; and environment. Their reported effect is addressed in Appendix 2.3 (with positive and negative notations indicating correlations), along with the papers that address it. A positive notation suggests a positive association with being NEET; greater values of the variable are connected with a higher likelihood, while a negative notation denotes a negative relationship with being NEET.

2.3.4. Individual characteristics

Sixteen individual characteristics are identified as risk factors for being NEET. These were examined in 45 included articles (see the references table in Appendix 2.4). There is consistent evidence that characteristics like aspirations and expectations (Alvarado et al., 2020b; de Almeida & Simões, 2020; Gutman & Schoon, 2018; Schoon, 2014; Schoon & Lyons-Amos, 2017; Su et al., 2022; Tayfur et al., 2022), autonomy (Alfieri et al., 2015), IQ (Hegelund et al., 2018), self-esteem (LIEW et al., 2021; Ose & Jensen, 2017; Tayfur et al., 2022) and self-confidence (de Almeida & Simões, 2020), and skills (Fakih et al., 2020; Jongbloed & Giret, 2021; Kevelson et al., 2020) influence to not being NEET. In addition, there is consistent evidence from seven studies that time use (Salvà-Mut et al., 2018; Su et al., 2022), age (Abayasekara & Gunasekara, 2019; Akinyemi & Mushunje, 2017; Alvarado et al., 2020b; Bacher et al., 2017; Cabral, 2018; Chen, 2018; de Almeida & Simões, 2020; Fakih et al., 2020; Flynn & Tessier, 2011; Genda, 2007; Kevelson et al., 2020; Lee & Kim, 2012; Luthra, 2019; C. Quintano et al., 2018; Román et al., 2022; Ruesga-Benito et al., 2018; Selenko & Pils, 2019; Su et al., 2022; Vancea & Utzet, 2018; Varshavskaia, 2017; Veldman et al., 2015; Yang, 2020), isolation (Maguire, 2018), and risky and aggressive behaviours (Karyda, 2020) are predictors of NEET. The gender gap in the NEET rate has been explained by various factors such as marital status, migration, ethnicity, time caring for children and/or other family members, parental joblessness, living with a single parent, early pregnancy, and place of residence. This increasing gender inequality in the labour market may also imply that the traditional notions of gendered labour still plays a critical role in determining the low labour force participation for young women (Abayasekara & Gunasekara, 2019; Akinyemi & Mushunje, 2017; Bacher et al., 2017; Bania et al., 2019; Caroleo et al., 2020; Contini et al., 2019; de Almeida & Simões, 2020;

Fakih et al., 2020; Flynn & Tessier, 2011; Giret et al., 2020; Kevelson et al., 2020; Luthra, 2019; Mansuy & Werquin, 2018; B. O'Dea et al., 2014; C. Quintano et al., 2018; Rodriguez-Modroño, 2019; Román et al., 2022; Salvà-Mut et al., 2016; Salvà-Mut et al., 2018; Schoon, 2014; Su et al., 2022; Tamesberger & Bacher, 2014; Vancea & Utzet, 2018; Varshavskaia, 2017; Yang, 2020; Zuccotti & O'Reilly, 2019). Three studies showed no effect on personality and character (Baggio et al., 2015; LIEW et al., 2021; Ringbom et al., 2022; Schoon, 2014). The evidence on life satisfaction (Schoon & Lyons-Amos, 2017) and self-dependency (Mizintseva et al., 2017) as predictors of NEET status was inconsistent, as these characteristics had been evaluated in only one study, and the data were deemed inadequate. Among these factors, skill, time spent, autonomy, aspirations, and expectations are practical and affect men and women differently. Individuals with low skill levels are more likely to report a NEET status (Apunyo et al., 2022; Kevelson et al., 2020). In recent cohorts, young women from less privileged backgrounds had stronger educational and life ambitions than men in similar circumstances (Ashby & Schoon, 2010). Autonomy affects men solely, negatively impacting their status as NEETs (Alfieri et al., 2015). Time spent on housework is almost twice as important in determining NEET status in women as in men. Each extra hour spent on household chores is associated with a higher likelihood of women adopting NEET status by 0.32%, but only 0.17% for men (Salvà-Mut et al., 2018). Appendix 2.1 provides more specific information on the research goals, the population, and the association estimates with 95% confidence intervals.

2.3.5. School and education characteristics

We identified eight school and education characteristics in the 58 articles included in this study (see Appendix 2.4). There is consistent evidence from nine studies that dropout (Alcazar et al., 2020; Avagianou et al., 2022; E. Ghignoni et al., 2019; Pennoni & Bal-Domańska, 2022; Salvà-Mut et al., 2018; Selenko & Pils, 2019), truancy (Sadler et al., 2015), and problem learning (Hakkarainen et al., 2016; Ringbom et al., 2022) are predictors of (earlier) NEET. In contrast, education level (Abayasekara & Gunasekara, 2019; Alcazar et al., 2020; Alvarado et al., 2020b; Anyanwu, 2013; Apunyo et al., 2022; Avagianou et al., 2022; Berloffa et al., 2017; Bojadjieva et al., 2022; Cabral, 2018; Caroleo et al., 2020; Chen, 2018; Contini et al., 2019; de Almeida & Simões, 2020; Fakih et al., 2020; Genda, 2007; Giret et al., 2020; Karyda, 2020; Kevelson et al., 2020; Lee & Kim, 2012; Mawn et al., 2017; Mizintseva et al., 2017; Nestić & Tomić, 2018; B. O'Dea et al., 2014; Odoardi, 2020; Ose & Jensen, 2017; Pemberton, 2008; C. Quintano et al., 2018; Rodriguez-Modroño, 2019; Román et al., 2022; Salvà-Mut et al., 2016; Salvà-Mut

et al., 2018; Sánchez-Soto & Bautista León, 2020; Shinozaki, 2012; Su et al., 2022; Sveinsdottir et al., 2018; Tamesberger & Bacher, 2014; Vancea & Utzet, 2018; Varshavskaia, 2017; Vasile & Anghel, 2015; Yang, 2020; Zhang et al., 2020; Zudina, 2022), qualification and school conditions (Dorsett & Lucchino, 2014; Duckworth & Schoon, 2012; Lallukka et al., 2019; Noh & Lee, 2017; L. Rodwell et al., 2018; Salvà-Mut et al., 2016; Schoon & Lyons-Amos, 2017), school performance (Lallukka et al., 2019; Plenty et al., 2021; Tayfur et al., 2022), field of study (Giret et al., 2020; Kevelson et al., 2020; C. Quintano et al., 2018; Claudio Quintano et al., 2018) negatively influence being NEET. Thirty-three studies argue that the education level is the most effective factor to preventing NEET and is a suitable intervention. Higher education is important for reducing the risk of becoming NEET. However, four studies (Dorsett & Lucchino, 2014; Duckworth & Schoon, 2012; Lallukka et al., 2019; Noh & Lee, 2017; L. Rodwell et al., 2018; Salvà-Mut et al., 2016; Schoon & Lyons-Amos, 2017) found that higher education is positively associated with NEET, whereas one study (Abayasekara & Gunasekara, 2019) found that higher education is not associated with NEET. The studies distinguish two reasons for being NEET with higher education. The first is that higher education improves employability but can cause jobless youth to become inactive rather than active job seekers (Lee & Kim, 2012). Some inactive youth with higher education may have families to take care of; others may not be able to find work related to their degree; and others may take a break after completing their studies to travel or engage in other constructive activities, such as art, music, or self-directed learning. These youth are either voluntary or involuntary NEETs (Eurofound, 2012). Second, a growing proportion of the labour force has a higher education, and in some cases, there is an oversupply of university graduates. The value of higher education is decreasing due to a structural (education-qualification) mismatch between the supply of young workers and their demand (e.g., in Macedonia and Egypt) or a transient macroeconomic crisis (e.g., in Greece, Spain, and Italy). A growing supply of graduates from low-quality higher education institutions may increase the risk of graduate unemployment due to a mismatch between graduates' qualifications and the skills required by the labour market (Zudina, 2022). The descriptive findings showed that the field of study might be an important factor among college-educated individuals. Youth who studied education, humanities, languages, and arts were more likely to be NEET. It was less prevalent among students of social sciences, business, law, or health and welfare (Claudio Quintano et al., 2018). Furthermore, women are more likely to have a "poor" job and low salaries, and they do worse when they drop out without a "fallback plan" (Emanuela Ghignoni et al., 2019).

The findings show that enhancing school motivation and educational engagement among youth, as well as school features, may provide a feasible lever for reducing the likelihood of becoming a NEET (Duckworth & Schoon, 2012). Mathematical and reading challenges, as well as socioemotional and behavioural issues, have a long-term impact on youths' educational careers (Hakkarainen et al., 2016).

2.3.6. Work characteristics

In total, eight factors related to work characteristics were investigated in 27 included articles (Appendix 2.4). Unemployment history (Genda, 2007; Salvà-Mut et al., 2018; Vancea & Utzet, 2018), low salary (Duckworth & Schoon, 2012; Maguire, 2018; Mawn et al., 2017; Mizintseva et al., 2017; Pennoni & Bal-Domańska, 2022; Sadler et al., 2015; Salvà-Mut et al., 2016), and minimum wage (Bacher et al., 2017; Dayioglu et al., 2022; Shinozaki, 2012) are predictors of NEET. There is consistent evidence from 10 studies that work history and experience (Apunyo et al., 2022; Mizintseva et al., 2017; Ose & Jensen, 2017; Pemberton, 2008; Rodriguez-Modroño, 2019; Salvà-Mut et al., 2018; Vancea & Utzet, 2018), career planning and aspiration (Gutman & Schoon, 2018; Maguire, 2018; Noh & Lee, 2017), and job training (Lee & Kim, 2012) are negatively influenced by being NEET.

NEET males aged 18–24 were less likely than non-NEET to have previous job experience (Vancea & Utzet, 2018). Furthermore, having care obligations and being unemployed increases women's likelihood of becoming NEET (Genda, 2007). Both males and females are more likely to be NEET if they have had past jobless experience and unemployed friends (Vancea & Utzet, 2018).

2.3.7. Health characteristics

In 33 studies, health characteristics were found to have a relationship with NEET (Appendix 2.4). Evidence from some studies shows that poor health (Alcazar et al., 2020; Dorsett & Lucchino, 2014; Flynn & Tessier, 2011; Hegelund et al., 2018; Kevelson et al., 2020; Lallukka et al., 2019; Maguire, 2018; Mawn et al., 2017; Mendolia & Walker, 2015; Bridianne O'Dea et al., 2014; Ose & Jensen, 2017; Sadler et al., 2015; Salvà-Mut et al., 2018; Su et al., 2022; Sveinsdottir et al., 2018; Veldman et al., 2015), disability (Cabral, 2018; Flynn & Tessier, 2011; Bridianne O'Dea et al., 2014; Sadler et al., 2015; Su et al., 2022; Sveinsdottir et al., 2018), psychiatric disorders (Egan et al., 2015; Gariépy et al., 2021; Lindhardt et al., 2022; Bridianne O'Dea et al., 2014; Ringbom et al., 2022), mental health (Baggio et al., 2015; Bania et al., 2019; Blajeski, 2020; Cabral, 2018; Gariépy et al., 2021; Ladhani et al., 2019; Lindhardt

et al., 2022; Maguire, 2018; Maraj et al., 2019; Bridianne O'Dea et al., 2014; Plenty et al., 2021; Ringbom et al., 2022; Veldman et al., 2015), depression (Gariépy et al., 2021; Bridianne O'Dea et al., 2014; Ose & Jensen, 2017; Ringbom et al., 2022; Sadler et al., 2015), sexual debut , bullying (Sveinsdottir et al., 2018; Tayfur et al., 2022), anxiety (Gariépy et al., 2021; LIEW et al., 2021; B. O'Dea et al., 2014; Ringbom et al., 2022), and illness (Tamesberger & Bacher, 2014) are predictors of being NEET. The evidence on sleeping problems was inconsistent (Ose & Jensen, 2017). Back discomfort, migraine/headache, pain, fibromyalgia, and other musculoskeletal issues, emotional disorders include attention deficit hyperactivity disorder (ADHD/ADD), bipolar disorder, social phobia, eating issues, obesity, or obsessive-compulsive disorder, autism, Asperger's syndrome, and Tourette's syndrome (a mood disorder or symptoms, a depressive disorder or symptoms) were all common health issues on NEET youth (Ose & Jensen, 2017). Only a few studies identified serious mental diseases like psychosis, schizophrenia, or major depression (Sveinsdottir et al., 2018). According to the findings, youth with a depression are more likely to leave school (Sadler et al., 2015). They have a lower chance of enrolling in university or other types of further education and have higher unemployment rates and early motherhood. This is hardly unexpected, given that people with depression may be more restless, have difficulties focusing, and cannot think about or prepare for the future (Sadler et al., 2015). Furthermore, there is a two-way interaction between unemployment and poor mental health and psychosocial maladjustment, and youths with mental health problems are more likely to be unemployed (Modini, Joyce, et al., 2016; Modini, Tan, et al., 2016; Paul & Moser, 2009) .

2.3.8. Addiction characteristics

Variables related to addiction were explored in 15 studies (Appendix 2.4). Two studies found that smoking cigarettes was not significantly associated with being NEET (Baggio et al., 2015; Dorsett & Lucchino, 2014). In contrast, two studies showed that tobacco use and smoking cigarettes positively correlate with NEET (Andrade & Jarvinen, 2017; B. O'Dea et al., 2014) Alcohol debut (Andrade & Jarvinen, 2017), binge drinking/drinking behaviour (Andrade & Jarvinen, 2017; Baggio et al., 2015; Gariépy et al., 2021; L. Rodwell et al., 2018; Sveinsdottir et al., 2018), cannabis use (Baggio et al., 2015; Gariépy et al., 2021; L. Rodwell et al., 2018), drug addiction (Gariépy et al., 2021; Su et al., 2022; Sveinsdottir et al., 2018; Tayfur et al., 2022; Zhang et al., 2020), soft drug (Flynn & Tessier, 2011), and misuse (Ladhani et al., 2019; Lin & Chiao, 2022; Bridianne O'Dea et al., 2014; Ringbom et al., 2022) significantly increased being NEET among youth. Drug addiction is the most influential variable (Zhang et al., 2020).

In all cross-sectional and longitudinal studies, alcohol use had distinct patterns and was not associated with NEET status (Compton et al., 2014). Some research on alcohol use and academic performance showed mixed findings, with some studies showing that alcohol consumption reduces the number of years of education and graduation (Balsa et al., 2011; Compton et al., 2014).

There have also been conflicting reports on the relationship between alcohol usage and unemployment (Baggio et al., 2015). Indeed, unemployment may raise alcohol use because individuals use alcohol to cope, but the income impact may also reduce alcohol consumption (Andrade & Jarvinen, 2017).

Although the impairment in cognitive function has mainly been acute, studies have shown that even after abstinence, frequent cannabis use impacts decision-making and planning (Andrade & Jarvinen, 2017). Cannabis users in adolescence have reported a drop in their interest in activities and a reduction in their energy levels (Palamar et al., 2014). Cannabis-induced "amotivational syndrome" has been identified as a cause of such declines in interest and energy (Andrade & Jarvinen, 2017).

2.3.9. Social characteristics

The influence of social characteristics on relationships with NEET youth was examined across 52 studies (Appendix 2.4). There is evidence from 24 studies that area and neighbourhood deprivation (Fakih et al., 2020; Karyda, 2020; Karyda & Jenkins, 2018; Sadler et al., 2015; Schoon, 2014; Shinozaki, 2012), criminal offenses and charges (Chen et al., 2016; Hakkarainen et al., 2016; Karyda & Jenkins, 2018; B. O'Dea et al., 2014), dwelling and living situation (Abayasekara & Gunasekara, 2019; Andrade & Jarvinen, 2017; Avagianou et al., 2022; Baggio et al., 2015; Contini et al., 2019; Duckworth & Schoon, 2012; Gutman & Schoon, 2018; Holloway et al., 2018; Mansuy & Werquin, 2018; Nestić & Tomić, 2018; Pitkänen et al., 2021; Schoon & Lyons-Amos, 2017; Simões et al., 2022; Tamesberger & Bacher, 2014; Tayfur et al., 2022), and country of origin (Bacher et al., 2017; Giret et al., 2020) are predictors of being NEET. Some studies reported that religion (Abayasekara & Gunasekara, 2019), immigration background, and migration (Alcazar et al., 2020; Caroleo et al., 2020; Chen et al., 2016; Giret et al., 2020; Kevelson et al., 2020; Luthra, 2019; Salvà-Mut et al., 2018; Tamesberger & Bacher, 2014; Yang, 2020) are associated exclusively with women being NEET (Abayasekara & Gunasekara, 2019; Basit, 2012a, 2012b). Also, generational effects depend on year and country (Shinozaki, 2012).

Eleven studies showed no relationship between birthplace (Salvà-Mut et al., 2016), residential area (Abayasekara & Gunasekara, 2019; Bania et al., 2019; Lee & Kim, 2012; Varshavskaia, 2017), minority (Maraj et al., 2019), indigenous background (Bridianne O'Dea et al., 2014), house price (Nestić & Tomić, 2018), housing type (Bradley & Crouchley, 2020; Dorsett & Lucchino, 2014; Genda, 2007; Lindemann & Gangl, 2019), civil status (Bacher et al., 2017; C. Quintano et al., 2018; Ruesga-Benito et al., 2018) country of origin (Giret et al., 2020; Karyda, 2020; C. Quintano et al., 2018; Rodriguez-Modroño, 2019; Selenko & Pils, 2019), and being NEET.

Some studies reported that community engagement (Kevelson et al., 2020; Vancea & Utzet, 2018) and party membership (Yang, 2020), citizenship (Bacher et al., 2017), and ethnicity (Abayasekara & Gunasekara, 2019; Bania et al., 2019; Dorsett & Lucchino, 2014; Duckworth & Schoon, 2012; Hegelund et al., 2018; Karyda, 2020; Karyda & Jenkins, 2018; Mendolia & Walker, 2015; Sadler et al., 2015; Schoon, 2014; Schoon & Lyons-Amos, 2017; Tayfur et al., 2022; Yang, 2020; Zuccotti & O'Reilly, 2019) negatively affect being NEET.

For males, migration is a protective factor against becoming a NEET. Migration, on the other hand, has the opposite impact on women. Further findings reveal that a lack of education is a substantial barrier to women's migration, leading them to become NEETs (Yang, 2020).

Ethnic minority members were less likely to become NEET after completing compulsory schooling (Yates et al., 2011). Moreover, research has shown that young people from minority groups who complete compulsory schooling are less likely to become NEETs (Karyda, 2020). The influence of ethnicity and religion also varies by gender, with female minorities more likely to become NEET than male minorities. This might be due to a greater proclivity among women of various races to serve as primary caregivers in the home (Abayasekara & Gunasekara, 2019).

2.3.10. Family characteristics

Family characteristics were investigated in 54 studies (Appendix 2.4). Of these 54 studies, 38 studies examined the parental characteristic of being NEET. Several studies provide evidence that parents who are divorced or separated (L. Rodwell et al., 2018; Zhang et al., 2020), living with a single parent (Luthra, 2019; Mendolia & Walker, 2015; Pitkänen et al., 2021), family composition/ household size (Berloffa et al., 2017; Contini et al., 2019; Maguire, 2018; Román et al., 2022; Salvà-Mut et al., 2016; Schoon & Lyons-Amos, 2017; Selenko & Pils, 2019; Sveinsdottir et al., 2018; Tayfur et al., 2022; Veldman et al., 2015; Yang, 2020), number of

children (Akinyemi & Mushunje, 2017), workless parent/family (Duckworth & Schoon, 2012; Pitkänen et al., 2021; Schoon, 2014), teenage parenthood (Alvarado et al., 2020b; Bacher et al., 2017; Duckworth & Schoon, 2012; Maguire, 2018; Mendolia & Walker, 2015), parent substance use (Pitkänen et al., 2021), dependent elder/kids (Abayasekara & Gunasekara, 2019), poor family background (Caroleo et al., 2020; Karyda & Jenkins, 2018), and family health issues (Lallukka et al., 2019; Pitkänen et al., 2021) are positively associated with (earlier) NEET. The evidence on family/household income (Alvarado et al., 2020b; Avagianou et al., 2022; Dorsett & Lucchino, 2014; Genda, 2007; Mansuy & Werquin, 2018; Mendolia & Walker, 2015; Noh & Lee, 2017; Pitkänen et al., 2021; Rodriguez-Modroño, 2019; Román et al., 2022; Schoon & Lyons-Amos, 2017; Shinozaki, 2012; Vancea & Utzet, 2018; Yang, 2020; Zhang et al., 2020), support (Alfieri et al., 2015; Blajeski, 2020; Zhang et al., 2020), cohabitation alone (Luthra, 2019), parent education level (Alfieri et al., 2015; Bania et al., 2019; Cabral, 2018; de Almeida & Simões, 2020; Duckworth & Schoon, 2012; E. Ghignoni et al., 2019; Giret et al., 2020; Hakkarainen et al., 2016; Hegelund et al., 2018; Karyda & Jenkins, 2018; Kevelson et al., 2020; Lallukka et al., 2019; Lee & Kim, 2012; Lindemann & Gangl, 2019; Maguire, 2018; Mansuy & Werquin, 2018; Mendolia & Walker, 2015; Odoardi, 2020; Pitkänen et al., 2021; C. Quintano et al., 2018; L. Rodwell et al., 2018; Salvà-Mut et al., 2018; Sánchez-Soto & Bautista León, 2020; Schoon, 2014; Schoon & Lyons-Amos, 2017; Shinozaki, 2012; Tamesberger & Bacher, 2014; Vancea & Utzet, 2018; Veldman et al., 2015; Yang, 2020; Zhang et al., 2020), parent occupation (Abayasekara & Gunasekara, 2019; Berloffa et al., 2017; Bradley & Crouchley, 2020; Cabral, 2018; Dorsett & Lucchino, 2014; E. Ghignoni et al., 2019; Lee & Kim, 2012; Lindemann & Gangl, 2019; Mansuy & Werquin, 2018; Pitkänen et al., 2021; Sadler et al., 2015; Salvà-Mut et al., 2018; Schoon, 2014; Selenko & Pils, 2019; Shinozaki, 2012), sibling work status (Dorsett & Lucchino, 2014), and relationship quality (Alfieri et al., 2015; Sánchez-Soto & Bautista León, 2020; Selenko & Pils, 2019) are negatively related to being NEET. The evidence suggests that parental death (in one study) (Pitkänen et al., 2021) and the number of siblings, older siblings, and sibling rank (Mansuy & Werquin, 2018; Mendolia & Walker, 2015; Selenko & Pils, 2019) do not affect being NEET.

Marital status (Abayasekara & Gunasekara, 2019; Akinyemi & Mushunje, 2017; Caroleo et al., 2020; Fakih et al., 2020; Lallukka et al., 2019; Lee & Kim, 2012; Luthra, 2019; Mendolia & Walker, 2015; Odoardi, 2020; Román et al., 2022; Sveinsdottir et al., 2018; Vancea & Utzet, 2018; Varshavskaia, 2017; Yang, 2020), care responsibility (Alcazar et al., 2020; Maguire, 2018; Su et al., 2022; Tamesberger & Bacher, 2014; Tayfur et al., 2022; Vancea & Utzet, 2018)

and having children (Maguire, 2018; Salvà-Mut et al., 2016; Sveinsdottir et al., 2018; Vancea & Utzet, 2018) negatively affects men and increases the chance of women becoming a NEET.

NEET seems to be linked to the household socioeconomic background and poverty status (Odoardi, 2020). There is evidence that family poverty and intrusive parenting are more harmful to females, whereas living in a single-parent household is more harmful to men (Pitkänen et al., 2021). Furthermore, parent mental health and substance abuse, out-of-home placement, and living in a single-parent household increase the probability of becoming NEET compared to persons who are not exposed to these events (Pitkänen, 2018; Pitkänen et al., 2021). The marital status of the household's head is also an important factor. When females live in a household with a female head, their likelihood of becoming NEET decreases; however, this factor does not affect men. On the other hand, belonging to a family with a divorced head increases a young man's chances of becoming a NEET (Cabral, 2018). In terms of location, being a family member whose head is divorced increases the likelihood of becoming a NEET in rural areas(Abayasekara & Gunasekara, 2019) .

The quality of a relationship does not affect the likelihood of becoming unemployed but increases the chance of dropout (Selenko & Pils, 2019); however, intrusiveness affects women only. The greater the parental involvement in a young woman's life, the more likely she will become a NEET (Addabbo et al., 2017; Alfieri et al., 2015). Additionally, parents' educational level has a greater impact on the status of NEETs among women than among men (C. Quintano et al., 2018). Having tertiary-educated parents was associated with a lower risk of becoming a NEET among men than among women. A lower probability of NEET among men with tertiary-educated parents may be related to gender roles, which may lead to more achievement-driven goals for their children (Pitkänen et al., 2021). In comparison, the head of household's lack of education increases the chance of women becoming a NEET, while the head of household's lack of employment increases the risk for men (Cabral, 2018).

Having children at a young age makes pursuing employment, education, or training difficult, especially for young mothers. Teen pregnancies and motherhood substantially impact NEET status among women, who are more likely to stay NEET than men (Sadler et al., 2015).

2.3.11. Environment characteristics

35 studies examined the influence of environmental factors on NEET status (Appendix 2.4). In these studies, college funding cuts (McMurray, 2019), economic and social inequalities (Apunyo et al., 2022; Karyda, 2020; Maguire, 2021; B. O'Dea et al., 2014; Zuccotti & O'Reilly,

2019), inaccessibility of information (Mizintseva et al., 2017), inadequate infrastructure (Anyanwu, 2013; Fakih et al., 2020), economic hardship (B. O'Dea et al., 2014), poverty (Alcazar et al., 2020; Blajeski, 2020; Odoardi, 2020), welfare receipt (Apunyo et al., 2022; Maguire, 2018; Mawn et al., 2017), social exclusion and deprivation (de Almeida & Simões, 2020; Karyda, 2020), difficulties in finding jobs (Mizintseva et al., 2017), shortage of jobs (Mansuy & Werquin, 2018; Mizintseva et al., 2017) and global crisis like the COVID-19 pandemic (Crismon et al., 2021) appear to have a positive relationship with being NEET. There is evidence from nine studies that the regional employment rate (Giret et al., 2020; Mansuy & Werquin, 2018; Pennoni & Bal-Domańska, 2022; Shinozaki, 2012), social support (Mizintseva et al., 2017; B. O'Dea et al., 2014; Sveinsdottir et al., 2018), and receiving educational grants (Akinyemi & Mushunje, 2017; Dorsett & Lucchino, 2014) are not predictors of being NEET. The evidence on economic condition and crisis (Bacher et al., 2017; Caroleo et al., 2020; Ruesga-Benito et al., 2018; Salvà-Mut et al., 2018) and population (Anyanwu, 2013; Chen et al., 2016; Sadler et al., 2015; Tamesberger & Bacher, 2014) predictors for NEET were inconsistent. Exclusion and poverty are more important factors in being a NEET than a poor economic situation (Ruesga-Benito et al., 2018). Some policies aimed at boosting social cohesion and sustainability may prevent an increase in the number of NEETs (Ruesga-Benito et al., 2018).

The qualities of an area may have a substantial impact on the lives of youth. Lower achievement orientation and academic performance have been linked to being in poor neighbourhoods, particularly in urban regions (characterized by high unemployment, violence, and a lack of community resources) (Schoon & Lyons-Amos, 2017), as well as an increased likelihood of risky work transitions, such as prolonged spells of unemployment (Schoon, 2014). Compared with individuals residing in less impoverished regions, youth living in high-crime areas are more likely to become NEETs (Karyda & Jenkins, 2018).

The global financial crisis has a well-documented effect on youth in high-income countries, leading to disengagement from school and the labour market, making adulthood more difficult and raising the possibility of intergenerational transfer of vulnerabilities (Richardson et al., 2020). Consequently, the lost education and job experience associated with COVID-19 (due to school lockdowns and economic repercussions combined) will have a long-term impact on young people (Crismon et al., 2021). Table 2.3 summarise all the top risk factors and key gaps and number of studies they explored these risk factors.

Table 2.3. Summary of top risk factors and number of studies in each category.

Domain	Top Risk Factors	Key gaps	Domain
Individual	• Low academic aspirations/self-confidence • Poor time-use skills • Older age (20–24, 25–29)	Psychological mechanisms; intervention malleability; resilience factors	45
Education & School	• Early school leaving/truancy • Low qualifications • Poor school performance	Field of study effects; vocational pathway effectiveness	58
Work Experience	• Prior unemployment spells (scarring effects) • Lack of job training • Low-paid/temporary work	Employer demand-side factors; skill-training matching; credential inflation effects	27
Health & Well-Being	• Mental health problems (depression, anxiety) • Chronic physical illness/disability	Mental health underrepresented (13 studies only); disability pathways; early intervention timing	33
Addiction	• Drug addiction (hard drugs) • Binge drinking/cannabis use	only 15 studies despite theoretical importance; causal mechanisms; comorbidity with mental health	15
Family	• Parental unemployment/low income • Single-parent household • Low parental education	Longitudinal family trajectories; intergenerational transmission mechanisms	54
Environmental	• Poverty and neighbourhood deprivation • Regional unemployment rate • COVID-19 economic shock	Mechanism of macro influence; regional policy variation; climate/disaster effects	35
Social & Cultural	• Criminal involvement/peer networks • Migrant/ethnic minority status (gender-specific effects)	Causal mechanisms; cross-national comparisons; intersectionality	52

2.4. Discussion

This scoping review examined 91 studies over 22 years (2000-2022) on risk factors for NEET status. Individual characteristics, education, work experience, health, addiction, social factors, family background, and environmental conditions were identified as the eight primary risk domains.

The most consistently identified risk factor across virtually all studies is education. NEET status was largely influenced by low educational attainment, early school leaving, and lack of vocational qualifications.

According to 54 studies, family background was associated with robust effects. Youth NEET risk was consistently predicted by parental education, household income, family structure, and

parental employment. Socioeconomic disadvantage significantly increased the likelihood of becoming a NEET.

In most contexts, the NEET rate was higher for young women, particularly in developing countries where caregiving responsibilities concentrated risk among women.

Health factors remain underexplored despite their apparent significance. According to 33 studies, mental health conditions (depression, anxiety) were more likely to predict NEET status than physical health limitations.

Work experience had a protective effect. A lack of work experience created a vicious cycle of unemployment, while work experience reduced the likelihood of becoming a NEET.

NEET pathways are influenced by environmental factors (regional unemployment and labour market conditions) and social factors (neighborhood deprivation and peer networks).

The review's conclusions are somewhat limited by significant variation in study methodologies, sample characteristics, measurement methods, the uniformity with which results are reported, and the conclusions of different investigations. However, the wide variety of research examined revealed certain common factors. Research on structural factors, such as labour market policies, welfare system design, and regional economic disparities, is relatively limited compared to individual-level determinants. Figure. A4 in Appendix 2.2 shows a radar graph of risk factors for each category.

Another element to consider in NEET research is the unemployed youths studied. The field seems to be heavily influenced by models and ideas developed for unemployment situations. According to the diverse range of themes studied, NEET studies are characterized by methodological diversity. However, the majority (67%) of the publications examined here used quantitative methodologies. Table A2 in Appendix 2.2 presents the methodologies and their numbers. While non-experimental research approaches are more prevalent in both High-Income and Upper Middle-Income countries, experimental studies were mostly undertaken in Lower-Income and Lower Middle-Income countries (see details in Table A3 in Appendix 2.2). Although evidence of intervention efficacy was scarce, some articles in our study provided such evidence; however, they often relied on small samples. Overall, the area seems to have weak to middling methodological rigour.

As a result, the methodologies used may have significantly impacted the results. Furthermore, the data acquired are often of a restricted demographic character, as they are widely accessible, focused on applying analytics to databases, and centred on quantitative variables (e.g., study level and previous work experience). NEET phenomena, on the other hand, are generally qualitative and complicated. As a result, NEET studies often lack information on critical socio-

psychological causes and consequences (e.g., personal problems, worklessness, and parental conditions).

More qualitative studies are required to investigate the youth's (care responsibility, professional skills, psychosis, poverty) experience and the multiplicity of factors, as the literature has largely ignored these factors. Some major intervention subcategories are underrepresented: older youth, youth in fragile situations, war, and violent contexts, or humanitarian settings, ethnic minorities, decent work legislation, and those with a criminal history are the least researched.

However, gathering qualitative data on NEET is more challenging. Additional quantitative studies with standardized scales and large samples should be examined to supplement the more qualitative investigations.

NEET-related issues are complicated, necessitating precise definitions. In that way, the field is nearly anarchic. Most of the publications examined did not provide a precise definition; when they did, they often did not use previously established definitions. Furthermore, some definitions are specific, while others are broad and ambiguous, and the majority are used interchangeably.

They should take age diversity into account across different countries. There is a tendency to generalize the phenomenon. Furthermore, different classifications are used. For example, Eurostat presents a breakdown of the EU-28 NEET population between the ages of 15 and 34 (Eurostat, 2018), while the OECD focuses on the 15-29 age range (OECD, 2018), in Italy, Spain, and Mexico, the NEET population falls within the 15-29 years old age group, while in Japan and South Korea, it ranges from 15 to 34 years old. In America, Australia, and Northern Ireland, the NEET population is aged 16-24 years old, while in South Africa it falls within the 18-24 years old range (Batini et al., 2017). It is clear that age limits, which should serve as the basis for nations to agree on the definition of NEET, are insufficient because they do not accurately capture the transition period between professional training and the world of work. This difference refers to the number of years of compulsory education or training across countries. Cultural differences also lead to variations in how the NEET population is measured, particularly in how females are included in the statistics (Maguire, 2021). This poses a significant difficulty for NEET studies; they need to be generalizable, abundant, and use exact definitions, but they also require context-dependent, adaptable definitions to address contextual interventions.

Raffe (2003) distinguished between what they referred to as "wide" and "limited" definitions of NEET. The wide description includes two subgroups: unemployed NEETs, those enjoying a lengthy vacation, performing volunteer work, or working part-time (the more privileged

group, who may have more options), and those who were jobless, ill or disabled, or caring for children or family (inactive NEETs). These characteristics generally imply a voluntary component in the NEET phenomenon. It is likely that these youth are traveling or participating in other activities, such as pursuing art or music, engaging in self-directed learning, or adopting alternative lifestyles, and are reliant on their families' financial support rather than facing employment-related obstacles (voluntary NEET status). The population aged 15 to 29 years who are not involved in any form of education, training, or employment and who have ceased seeking work or do not intend to do so are classified as NEET according to the restricted definition. As a result, NEET youth are often characterized by inactivity. Some writers define "levels" of being NEET based on the chronology of belonging to the NEET group, such as "only young individuals who have been categorized as NEET for at least 6 months are those of level 0" (Batini et al., 2017).

The vast majority of the studies in our sample focused on NEET reasons regarding the topics investigated. More focus should be placed on intervention and strategy research, especially through cost-benefit analysis and rigorous impact assessment, the development of research methodologies and equipment, and the integration of the many subjects into a cohesive theoretical and empirical collection.

The study of NEET predictive variables was the only general pattern identified in the field; 77.5% of the studies examined various components. So, NEET is produced by a complex combination of characteristics that vary depending on the circumstances. There is disagreement about which factors are most important in predicting NEET status. Consequently, research has shown a lack of consistent hypotheses regarding the causes of NEET. Because of the complexity of NEET phenomena, developing a cohesive theory or paradigm is either impossible or utopian.

Some research attempted to create prediction models by including several parameters, which is commendable (Bruno et al., 2014; Dietrich, 2013; Jongbloed & Giret, 2022; Mendolia & Walker, 2015; Pattinasarany, 2019; Plenty et al., 2021; Ruesga-Benito et al., 2018; Tamesberger & Bacher, 2014; Zuccotti & O'Reilly, 2019). When earlier models are used in the literature, they are frequently extremely obsolete. That exemplifies one of the field's most pressing issues: transferring (old) ideas and procedures from the NEET literature and context to an entirely new set of factors. Classical definitions and methodologies are considerably more challenging to apply to NEET, which should always be kept in mind. As a result, future NEET research should strive to develop more comprehensive models that yield more successful therapies. NEET has different meanings for different people in different contexts (e.g.,

unemployed and inactive NEETs) and across age groups, depending on country, region, and labour-market context.

Individual, family, and educational characteristics (sex, education, age, parents' occupation, and parents' education) are key determinants of whether a young person becomes a NEET. Education is the most significant determinant of the likelihood of becoming NEET, at both the individual and family levels. Furthermore, living in rural places and having a disadvantage, such as a disability or immigrant origin, significantly increases the likelihood of being NEET (Mascherini, 2019; C. Quintano et al., 2018). The role of family background in raising the likelihood of becoming a NEET is reaffirmed (Karyda & Jenkins, 2018). Youth from troubled families, such as divorced parents or parents with a history of unemployment, are more likely to be NEET (Shinozaki, 2012).

Furthermore, low skill level, the inadequacy of skilling to labour market needs, labour market passivity, insecure financial conditions, low or no social support, and inadequate or missing institutional support were identified as critical elements contributing to youths' susceptibility to social exclusion in the labour market (Cace et al., 2021). The findings show that low skill levels and poor educational attainment greatly enhance the likelihood of reporting long-term NEET status, with highly statistically significant odds ratios across models. Early school leavers are disadvantaged because they lack the skills necessary for the labour market, lack of access to job search channels, and the social and cultural capital needed to compete (Erdoğan et al., 2017). Many respondents stated that their lack of educational credentials, particularly a passing grade in English and arithmetic, was a major factor in their difficulty pursuing additional education, training, or a job (Hakkarainen et al., 2016). The dangers of exclusion and poverty are also more important than a poor economic environment in becoming a NEET (Ruesga-Benito et al., 2018).

The likelihood of becoming a NEET grows considerably with age. Compared to the 15–19 age range, the increase in the NEET rate is more pronounced between the ages of 20 and 24, when young people have finished upper secondary and/or postsecondary school. The number of NEETs rises considerably between the ages of 25 and 29, which appears to be driven by the large proportion of women who leave the labour force after 24 (generally linked to marriage) (Buheji, 2019).

Furthermore, the cost of learning while not working increases with age, as the opportunity cost rises with constraints on educational access. Age is correlated with choices for economic independence, fertility, and hazardous conduct (e.g., smoking, drug use, and unprotected sex) concerning NEET (Alvarado et al., 2020a). Gender is a crucial factor in becoming a NEET.

Married women and migrant women are much more likely to be NEET than their male counterparts (Lüküslü & Çelik, 2022). In most nations, female unemployment rates are greater than male unemployment rates. Many women are inactive outside of school and do not seek work. They get disguised under the inactive group, which is subsequently included in the NEET rate (Vancea & Utzet, 2018).

Long-term unemployment has major consequences for young people, as it prevents them from gaining job experience, resulting in negative impacts on lifetime income, career options, and later unemployment incidence, known as the "scarring effects" of youth unemployment (Mühlböck et al., 2022b). This is also connected to employers' reluctance to recruit young individuals with little job experience. Youths who become jobless are more likely to remain long-term unemployed or have low income for the rest of their lives.

Many NEET youth indicated that school was tough or monotonous, that they did not work hard enough, that they lacked motivation, and that they did not receive the support they believed they needed from school and instructors. Some students struggled to engage with the school's teaching and learning style, and there were reports of negative relationships with teachers (Chen, 2011).

According to the findings, growing up with long-term health issues significantly impacts a youth's educational and occupational achievements as they enter early adulthood (Rasalingam et al., 2021). Physical and mental health issues, such as depression and panic attacks, were significant personal risk factors that reduced educational performance and led to young people becoming NEET (Rasalingam et al., 2021; L. Rodwell et al., 2018). This might be connected to the fact that persons suffering from depression report increased restlessness, difficulty focusing, and an inability to think about or prepare for the future. An adolescent's depression is often accompanied by negative social, family, and personal factors, resulting in the manifestation of such symptoms (Sadler et al., 2015).

Early drug and binge alcohol usage raises the chance of poor school achievement and, particularly, school dropout. Adolescent drug use has been linked to an increased risk of unemployment, low income, and reliance on social welfare assistance in adulthood (Andrade & Järvinen, 2017).

Exposure to violent behaviour, anti-social activities, and being in trouble with the police were all linked to an increased likelihood of becoming a NEET. Youths who spend a lot of time in a disorganized environment and are part of a deviant peer group are more likely to engage in anti-social or criminal behaviour, which may affect their self-esteem and educational and professional objectives, increasing their chances of becoming NEET (Karyda, 2020).

Family status is another factor that influences a young person's likelihood of being in a NEET situation. Youths from lower-income families are less likely to finish school and lack the networks to secure suitable careers. Joblessness, poor income, low levels of education, lone motherhood, big families living in leased housing, and parental ill-health all contribute to socioeconomic family hardship that impacts youth's development and adjustment (Holloway et al., 2018).

Youths with highly educated parents are often less pressured to find work, since a better education generally correlates with a higher quality of life, enabling students to complete their studies or wait for more qualified employees (C. Quintano et al., 2018). Also, people with a college degree may be affected by having less-educated parents, demonstrating the permanent consequences of socioeconomic disadvantage (Odoardi, 2020).

The long-term effects of early parenting appear comparable to those of unemployment. These include diminished life prospects, psychological disadvantage, and greater welfare dependency (Laura Rodwell et al., 2018). One argument against categorizing young people with children under 5 years old as NEETs is that parenthood comes with a level of responsibility that may limit a youth's ability to pursue a job or education, particularly for females.

The global recession and the Covid-19 pandemic revealed how economic insecurity causes young people to postpone their transition from school to the Labour market. During the pandemic, how education is delivered (for example, the move to online learning) may affect young people's decisions to begin or complete an education program, influencing the NEET rate (Aina et al., 2021). For some youth, online learning has made education more accessible and convenient, allowing them to continue their studies despite the challenges posed by the COVID-19 pandemic. However, the transition to online learning has been more difficult for others, leading to increased stress and decreased motivation. This may result in some young people dropping out of education or choosing not to start one in the first place (Nambiar, 2020). Furthermore, the economic fallout from the pandemic has resulted in job losses and financial insecurity for many families. This may make it harder for some young people to pursue education, as they may need to work to support themselves or their families. In some cases, young people may even be forced to abandon their education altogether (Goldschmidt, 2020).

The COVID-19 pandemic has had a significant impact on job losses and economic growth. The measures implemented to curb the spread of the virus have hindered business operations, causing many companies to go bankrupt and exacerbating the already high unemployment rate, particularly among young people (Lambovska et al., 2021). Unlike the 2008 financial crisis, which was structural and primarily economic, the COVID-19 issue is external and has

permeated all aspects of life. As a result, it is plausible to consider the latter impact to be relatively short-term (i.e., lasting for a shorter time). During the pandemic, some believed the world would look vastly different afterward, with even fewer job opportunities available (Fenga & Son-Turan, 2020). Further analysis emphasizes that young people, especially women in urban areas, have been more affected by the pandemic than older people. This is due to several reasons, including high NEET rates among this group, temporary contracts, over-representation in sectors that were shut down during the lockdown, and employment in sectors where social distancing measures will structurally change (Fiaschi & Tealdi, 2022).

2.4.1. Policy and Practice Implications

Evidence suggests that NEET status is influenced by low educational attainment, limited work experience, mental and physical health challenges, family socioeconomic disadvantage, and systemic inequalities. Education, employment, health, and social welfare need to be included in multi-sectoral strategies. A proactive approach is crucial to identifying at-risk youth before they become disengaged. To prevent dropouts, schools and communities should implement early warning systems to identify academic underachievement, disengagement, and mental health issues. By developing evidence-based assessment tools, we can identify vulnerable individuals and provide targeted early interventions to keep them in school, training, or employment. Rather than providing one-size-fits-all solutions for NEET youth, policies should recognize their heterogeneity. "Voluntary" and "involuntary" NEETs require different approaches. Individuals with less ambition may benefit from career guidance, volunteer work, or upskilling opportunities, whereas those with more challenges may benefit from remedial education, psychosocial counselling, apprenticeships, and job placement programs.

As a result of the interplay of factors, an integrated model of service delivery is necessary. Education, employment, health, and social services should collaborate to provide coordinated, one-stop support for young people. New cross-sector partnerships are reconnecting NEET youth to education and employment.

There is a growing consensus that siloed interventions are insufficient. A holistic service hub can provide tailored pathways for remedial education, vocational training, mental health care, and social support.

The structural inequalities that perpetuate NEET status must also be addressed in global strategies. Reforms must address labour market segmentation and gender inequality. To bridge skills gaps, educational curricula should be aligned with labour market needs, and quality vocational training should be expanded. It is equally imperative to address gender gaps: young

women often experience disproportionate rates of NEET as a result of their care responsibilities and limited opportunities. It is crucial to support childcare, enforce anti-discrimination laws, and promote female participation in education and STEM fields. Anti-poverty measures and community development initiatives can mitigate socioeconomic and regional disparities that put certain youth at risk.

It is important to note that effective strategies for addressing NEET status must be explicitly gender-responsive; for instance, offering childcare and reentry programs to young mothers, as well as mentoring or targeted employment interventions for young men from single-parent households.

A high-impact global response to the NEET challenge would combine early, individualized intervention with integrated service delivery and structural reform. Policymakers can significantly improve the prospects of NEET youth and foster their inclusion in education and employment by prioritizing early risk detection, tailoring support to youth's diverse circumstances, coordinating efforts across sectors, and dismantling systemic barriers.

Several substantive gaps were identified in the review. There were only 15 studies that examined causal mechanisms and mental health comorbidities associated with addiction and substance use, despite their theoretical importance. It is important to note that only 13 studies examined mental health in a broader sense, leaving little evidence of bidirectional relationships or early intervention. Youth from underrepresented groups, such as older youth (25-29), ethnic minorities, youth with disabilities, and conflict-affected communities, should be investigated more closely.

Methodologically, 67% of studies employed cross-sectional designs, which limit causal inferences about entry, duration, and exit patterns of NEETs. Due to the geographic concentration of studies in European contexts (particularly Scandinavia and Southern Europe), findings may not be applicable to low- and middle-income countries, which accounted for only 10% of studies despite vastly different structural conditions. It was apparent that measurement inconsistency plagued the field: NEET definitions varied (ranging from 15-24 to 15-34 years), inclusion criteria differed, and few studies provided standardized effect sizes.

The field suffers from atheoretical empiricism. In most studies, predictors (77.5%) took precedence over intervention effectiveness, with minimal cost-benefit analysis or implementation research. There is a lack of research on lived experiences, meaning-making, and agency, hindering our understanding of the socio-psychological processes underlying NEET status.

2.4.2. Strengths and limitations

This study provides an overview of current evidence on the risk factors for NEET youth. Although the data were gathered systematically, a scoping review cannot provide a comprehensive quality assessment of the included studies. We only provided data from multivariate analyses that adjusted for potential confounders to avoid this.

Endogeneity is an important concern when examining the relationship between NEET status and various negative outcomes. For instance, factors such as involvement in criminal activities and substance abuse, low self-esteem, social exclusion, financial stress, and family conflict or dysfunction can serve both as antecedents and consequences of being NEET. Similarly, poor mental health, involvement in risky behaviours such as unsafe sexual behaviour, and lack of social support can all be factors that contribute to NEET status, while they are also potential consequences of being NEET. Therefore, it is important to take a nuanced approach when examining and interpreting the connections between being NEET and various negative outcomes and to consider the potential bidirectional relationships between these factors. Addressing NEET requires a comprehensive approach that considers the various factors that contribute to and result from it. This approach must take into account each individual's unique needs and circumstances.

Our review investigated variables across various research types and demographics, offering a "big picture" view of potential risk factor relationships. While the present review's 'large picture' perspective is a strength, it is also a weakness, as the available literature makes it difficult to combine data and draw general conclusions.

A review of longitudinal research aimed at evaluating moderators and mediators of the relevant risk variables, including NEET status, would have provided more extensive information on the processes underlying the relationship. However, due to the lack of longitudinal studies, cross-sectional studies were included to expand the scope of the study, avoid losing potentially relevant information, and provide initial insights into the link as a starting point for future research. Furthermore, most included research examined just a few associations between variables rather than assessing all relevant relationships, including potential interactions. Similarly, the demographic sample employed in each study varied greatly. This includes population-based samples, unemployed youth, illiterate youth, and age groups. Furthermore, several studies were underpowered to examine the factors relevant to our review, and effect sizes were inconsistently reported.

The vast majority of evidence comes from high-income countries, where data availability and research infrastructure are more developed. There is a limited representation of studies from low- to middle-income regions, including parts of Africa, Latin America, and Southeast Asia. Due to these differences, generalizations should be made with caution, as risk factors identified in wealthier nations may not necessarily translate to lower-income countries, where structural conditions, labour markets, and social norms vary widely. Future research should expand empirical studies in developing and emerging economies to determine if similar patterns hold or if unique regional determinants of NEET status exist.

2.4.3. Future research directions

Future NEET studies should focus on the aspects most closely related to NEET: demographic features, time and financial constraints, motivation, perfectionism, reduced work capacity, the possibility of work accommodations, and perceived injustice. Policies must differentiate between voluntary and involuntary NEET youth, and research must delineate their risk profiles accordingly. This is crucial because structural disadvantages, such as low educational attainment, household poverty, and poor physical or mental health, are likely more prevalent among involuntary NEET youth facing more severe challenges. In contrast, voluntary NEET youth, such as those taking a gap year or engaging in creative projects, demonstrate a markedly different risk pattern.

As NEET studies often reveal significant associations, meta-analyses should be conducted to confirm which components are most essential with greater precision. This is a topic for the next Chapter. New modes of intervention should also be attempted. More research is required using quantitative methodologies and large samples to provide evidence of intervention efficacy.

Current methodologies make it impossible to assess the intricate interconnections among macro-level labour-market institutional characteristics. As a result, the demand-side labour-market function in influencing the degree of signalling effects remains unknown in both the present study and the research literature to date. This is still an essential and fruitful subject for future study.

Further study should look into the significance of certain economic situations and how they affect the influence of personal attributes on the likelihood of becoming NEET. This is especially important in light of pandemics, natural disasters, and the Great Recession. As a result, although unemployment may lose its stigma for one generation, its cross-generational

consequences may become more significant. This will also be important in understanding the effects of the COVID-19 pandemic on youth.

Future research could pay more attention to underrepresented subgroups such as older youth (25–29), ethnic minorities, youth with disabilities or criminal records, and those living in conflict-affected or fragile environments. The challenges these populations face may not be adequately captured by existing NEET research, which is largely concentrated in more stable, high-income settings. The development of inclusive, context-sensitive interventions requires expanding empirical work to include these marginalized groups.

Using longitudinal or cross-sectional designs, future research could examine intersectional and interactive risk factors, such as gender, education, and family background. To achieve further advancements, integrative models based on system dynamics or machine learning could be proposed.

2.5. Conclusion

Research on determinants of NEET youth has increased dramatically in recent years, so finding the most effective risk factors is very important. This study tracked and synthesized 22 years of NEET research. Most research has been conducted in the Scandinavian nations, England, Italy, and Spain. The studies have examined various personal, work, educational, addictive, health, family, social, and environmental determinants.

In conclusion, findings suggest that education and family-related factors play an important role in NEET youth. level of education, work experience and skills, physical and mental health, marital status, poverty and social inequalities, living situation, and parent income and education, and work status were the most important factors. As a result, numerous efforts are still required to advance the field mentioned here. Theorization, accurate definitions and measurement, novel models, and a need for more precise data on the efficacy of programs and early interventions are among its primary research needs.

However, more must be done to fully meet the expanding needs of the NEET population. Due to limitations in the quantity and quality of available information, the optimal practice for improving the lives and prospects of NEET persons remains uncertain, and substantial future research is necessary. To address the multifaceted needs of NEET youth, integrated, cross-sectoral support systems are needed to align education, employment, health, and social services. Governments and practitioners can use the identified risk factors as a diagnostic framework or checklist to proactively identify vulnerable youth populations. This policy

provides a foundation for designing coordinated, multi-sectoral approaches by addressing the diverse drivers of NEET status. Individual, gender-sensitive approaches are needed by professionals such as educators, social workers, and employment counselors to address young people's intersecting personal, familial, and structural barriers. Based on evidence, interventions should focus on early identification, flexible re-engagement pathways, and targeted support for subgroups most at risk. This systematic mapping provides the basis for Chapter 3, which applies meta-analytic methods to quantify the relative strength of these associations and assess publication bias across the eight risk domains identified.



Chapter 3

Unravelling the NEET phenomenon: a systematic literature review and meta-analysis of risk factors for youth not in education, employment, or training

Rahmani, H., Groot, W., & Rahmani, A. M. (2024). Unravelling the NEET phenomenon: a systematic literature review and meta-analysis of risk factors for youth not in education, employment, or training. **International Journal of Adolescence and Youth**, 29(1), 2331576.
https://doi.org/10.1080/02673843.2024.2331576

Abstract

This systematic review and meta-analysis examines the factors contributing to NEET (Not in Education, Employment, or Training) status among youth. We identified 43 studies that meet our inclusion criteria in Scopus, PsycINFO, ERIC, British Education Index, Social Science Citation Index, Conference Proceedings Index, IEEE Xplore, SpringerLink, and ScienceDirect, covering the period from 2010 to October 2023. We find significant associations between NEET status and various demographic, familial, educational, socio-economic, and health-related factors. Gender-specific disparities and evolving trends within distinct demographic cohorts are revealed. Our findings highlight that NEET is associated with a higher suicide risk (OR=2.8, 1.8-3.8), criminal behaviour (OR=2.06, 1.47-2.65), and unemployment experience (OR=1.98, 0.72-3.25), while higher education levels (OR=0.81, 0.67-0.95) act as a protective factor. These findings underscore the urgent need for comprehensive interventions tailored to the challenges faced by NEET youth. Future research should explore these relationships further to inform policy and practice effectively.

Keywords: NEET Youth, Risk factors, Systematic review, Meta-analysis, Employment, Education, Training.

3.1. Introduction

Chapter 2's scoping review mapped the breadth of risk factors associated with NEET status across 91 international studies, identified eight primary domains, and documented consistent associations with education, family background, health, and labour market conditions. As a result of that narrative synthesis, we were not able to determine whether the findings are robust when pooled across studies with different designs and populations, nor could we assess publication bias. In this chapter, we focus on studies reporting quantifiable effect sizes in order to address those limitations. It is possible to estimate the effect magnitude of each risk factor on NEET status, compare effect magnitudes across domains, and test whether observed associations are sustained after adjusting for the heterogeneity between studies.

Many stakeholders, including policymakers, researchers, and educators, have emphasized the importance of the NEET phenomenon because it poses significant challenges to nations' socio-economic development. Since the COVID-19 pandemic, the number of NEET youth has increased (Aina et al., 2021). According to a recent study by the International Labour Organization (ILO), the global youth NEET rate increased by 1.5 percentage points between 2019 and 2020, reaching its highest level in at least 15 years (ILO, 2021).

Research and policy efforts have mostly focused on understanding the risk factors associated with NEET status among youth (Paabort et al., 2023). The transition of NEET youth into productive, fulfilling life paths is challenging and is impeded by various barriers. Globally, NEET status has emerged as a rising concern, with prevalence rates from 6 to 30% across OECD countries (Kevelson et al., 2020). The majority of NEET youth come from disadvantaged backgrounds and are vulnerable to adversities such as poverty, low academic achievement, health issues, and a lack of social support, even before they leave education (Filia et al., 2023; Matli & Ngoepe, 2021; Pitkänen et al., 2021) .

Diverse individual, family, and societal factors have been associated with an increased risk of NEET status in youth. However, existing evidence on this subject is marked by heterogeneity and uncertainty regarding the comparative strength of different factors or the potential presence of moderating effects (Alfieri et al., 2015; Dickens & Marx, 2020; Quintano et al., 2018). Research on this topic, fragmented across disciplines, populations, and study designs, underscores the need to move beyond an exclusive focus on specific issues, such as improving mental health or reducing school dropout rates. A meta-analysis and systematic review provides a more complete overview of NEET risk factors, synthesizes the literature, reduces

heterogeneity in findings, and facilitate a more comprehensive understanding of the effects of risk factors across multiple contexts (Cragg et al., 2019).

Identifying the factors influencing youth NEET outcomes is crucial to developing effective policy and intervention measures. This systematic review and meta-analysis aims to provide a comprehensive synthesis of studies published from 2010 onwards examining predictors of NEET status among youth. In the meta-analysis, the evidence can be consolidated across studies, allowing more definitive conclusions about the role of key risk factors and identifying remaining gaps that require further investigation (Gholizadeh & Mohammadkazemi, 2022). It is important to effectively address the barriers faced by at-risk youth in education and employment, and to consider comprehensive solutions that account for the complex interactions among risk factors across domains.

The risk factors related to NEET status are examined within a theoretical framework grounded in Human Capital Theory (Becker, 1964) and the Capability Approach (Sen, 1999; Robeyns, 2005). The Human Capital Theory emphasizes that educational attainment and employment experience enhance youth productivity and labour market outcomes, thereby framing factors such as low educational achievement and limited employment history as key barriers. In contrast, the Capability Approach emphasizes the structural and personal constraints that limit young people's access to meaningful education and employment, including health limitations, socioeconomic disadvantage, and gender norms. NEET vulnerability is conceptualized not only as a function of demographic attributes (e.g., age and migration background), family structure (e.g., parental education or income), and health and well-being, but also as an underlying limitation or capability.

Prior research on NEET youth has investigated various risk factors and characteristics. Previous systematic reviews and meta-analyses of risk factors for NEET youth have focused narrowly on a few dimensions, such as psychosocial well-being or mental health, rather than adopting a holistic perspective. For example, Tayfur et al. (2022) conducted a systematic review and meta-analysis examining the relationship between psychosocial factors and education and employment outcomes. The study highlighted associations between adolescent behavioural problems, substance abuse, peer problems, prosocial skills, self-reflection, aspirations, and physical activity with education and employment outcomes in young adulthood, often accompanied by common mental health problems. Gariepy et al. (2021) investigated the association between the mental health status of NEETs and problems like mood, anxiety, behaviour disorders, and substance abuse. They found that young people with

mental health issues are more likely to become NEETs than those without mental health problems.

Similarly, Li and Wong (2015) examined the role of psychosocial factors in shaping young adults' educational and occupational outcomes. Their systematic review provided valuable insights into the significance of adolescents' psychosocial well-being and skill development for a successful transition to adulthood.

Interventions for NEET youth have also been evaluated in various studies. Luthra (2022) found robust evidence on the effects of training interventions, such as career guidance and counseling, vocational education and training, and entrepreneurship education. Conversely, information services and decent work policies had less supporting evidence. Certain demographic groups, such as older youth, ethnic minorities, and individuals with criminal records, were understudied.

While previous systematic reviews, like that of Mawn et al. (2017), have made significant progress, their scope has often remained narrow, focusing exclusively on employment, health, earnings, welfare receipts, and education. This study emphasizes the need for targeted efforts to help jobless individuals secure gainful employment, as well as the crucial role of psychosocial interventions in improving outcomes for NEET youth. Another perspective is offered by Escudero and Lopez (2017), who examined the implementation of Youth Guarantee plans across the European Union. The Youth Guarantee plan is a commitment by all EU member states to ensure that all young people under the age of 30 receive a good-quality offer of employment, continued education, apprenticeship, or traineeship within four months of becoming unemployed or leaving formal education. This initiative aims to reduce youth unemployment and inactivity by keeping young people in touch with the labour market or ensuring further education. They concluded that better outcomes could be achieved by considering key success factors such as clear eligibility criteria, timely response, appropriate resources, and compliance mechanisms.

The risk factors associated with NEET youth are complex and interconnected. Poverty, for instance, can perpetuate the cycle of disadvantage, both as a cause and a consequence of NEET youth (Alcazar et al., 2020; Ruesga-Benito et al., 2018). Social and familial factors can exacerbate the situation, thus highlighting the need for a thorough understanding of the underlying causes and consequences of NEET youth (Apunyo et al., 2022). A multi-sectoral approach is necessary to address both individual and structural factors to address this issue

effectively. Despite the existing evidence, more research is needed to identify and comprehend the root causes of NEET status. In this systematic review and meta-analysis, the primary objective is to analyze the global evidence on risks associated with NEET status among youth aged 15–29, focusing on factors such as demographic characteristics, family background, educational attainment, employment experience, socioeconomic status, health and well-being, gender, and age among youth. To inform future research and youth-oriented policy interventions across diverse regional settings, the study aims to identify consistent patterns and contextual variations in NEET determinants (Eurofound, 2012).

3.2. Data and Methods

This systematic review and meta-analysis conforms to the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Statement (Page et al., 2021). To identify and extract relevant information from primary studies concerning the impact of risk factors on NEET youth, we adopted a systematic approach involving several sequential steps. As a first step, we conduct an extensive literature search in order to identify potential publications. After screening these publications, we shortlist the eligible ones. The relevant information, such as authors, title, source, publication year, country, sample size, odds ratio, effect size, and correlation coefficients, is extracted from the selected publications. A quality assessment is then conducted in the subsequent step. Publication bias (the selective publication of studies with statistically significant positive findings) is assessed for outcomes with ≥10 studies, following PRISMA 2020 guidelines (Page et al., 2021). The assessment included multiple complementary methods to maximise detection sensitivity. Finally, we perform statistical analyses to synthesise the evidence and draw conclusions about the impact of risk factors on NEET youth.

3.2.1. Research strategy and selection criteria

The review was conducted through a systematic search of English-language publications published from 2010 to October 2023. We limited our search to papers published since 2010 to include the most recent and relevant studies, as academic research has become increasingly focused on NEET-related issues due to the effects of the global recession on education and employment. Two researchers independently conducted the search across the following electronic databases: Scopus, PsycINFO, ERIC, British Education Index, Social Science Citation Index, Conference Proceedings Index, IEEE Xplore, SpringerLink, and ScienceDirect. In addition, we searched grey literature collections such as GLADNET and used Google

Scholar as a supplementary source. Each article acquired during the retrieval process was then entered into Litmaps 2023 (litmaps.com) for manual examination of any newly published articles until October 2023, therefore ensuring a thorough and complete review of the existing literature. This approach helped to identify additional studies that met the inclusion criteria for our meta-analysis. To identify relevant studies for our meta-analysis on risk factors of being NEET youth, we used the search terms in Table 3.1:

Table 3.1. Search terms used for this systematic and meta-analysis article.

Population	(youth OR adolescent* OR "young people" OR "young adult*" OR "emerging adult*" OR NEET OR NEETs OR "not in employment, education, or training").TI, AB.
Intervention	(NEET AND (risk factor* OR predictor* OR determinant* OR correlat* OR associat* OR protective factor* OR "labour market" OR "labour market" OR unemployment OR inactivity OR disengagement OR exclusion OR "school-to-work" OR "school dropout" OR "early leaving" OR caregiving OR "family formation" OR "mental health" OR disability)).TI, AB.
Comparison	(odds ratio OR relative risk OR hazard ratio OR effect size OR logistic regression OR "meta-analysis" OR cohort OR cross-sectional OR longitudinal OR panel OR "propensity score" OR multivariate OR adjusted OR controlled OR matched). AF.

The sample for this study comprised individuals aged 15-24 who were categorized as NEET (not engaged in employment, education, or training). The rationale for the age range of 15 to 24 was the International Labour Organization's (ILO, 2017) definition of NEET. However, we acknowledge that there may be a need to increase the upper age limit, such as to 29, due to increased years of education (Boissonneault et al., 2020). Including studies with a wider age range ensured the review was as comprehensive as possible. Consequently, the analysis encompassed studies involving individuals aged 35 and those that provided subgroup analyses specifically for NEET participants within the overall population across different countries.

Our review focused on risk factors and determinants that may contribute to NEET status. The review included any risk factor and other behaviours that could be used to identify someone as

NEET, as well as an assessment of the impact of single and multiple risk factors on NEET status. All studies examining antecedents, predictors, or risk factors for becoming NEET were included. The results of studies that examined the outcome or consequences of NEET status alone (without considering antecedent factors) were excluded. Various study designs were considered, including controlled trials, case-control studies, cohort studies, cross-sectional studies, observational studies and case reports about risk factors affecting NEET.

3.2.2. Screening and eligibility criteria

The bibliographic references in this study were organized and managed using EndNote X9.0 software. Duplicate references were identified and excluded from the references. After removing duplicate records, we conducted a preliminary screening by reviewing the titles and abstracts. We specifically focused on identifying publications that investigated the risk factors and characteristics associated with NEET.

To ensure the reliability of our inclusion/exclusion criteria, we conducted a double screening of all eligible full texts. The open-source artificial intelligence program ASReview was used for priority screening to verify screening results (ASReview version 1.2.1, available at https://asreview.nl/). This additional screening step is a crucial component of our methodology. It ensures that our inclusion/exclusion criteria are applied consistently and accurately, enhancing the validity and reliability of our study findings. There was no independent exclusion of studies, and all decisions were subject to a secondary check, whether it was AI-assisted screening suggestions or human confirmation.

3.2.3. Data extraction and quality assessment

Two reviewers independently extracted the following information from each article: authors, year of publication, study location, sample size, main study objective, study design (including the study population, survey type, and year of data collection), targeted risk factors, methodological approach used in data analysis, and outcomes (including outcome measures). In the present meta-analysis, antecedents and consequences with fewer than three studies were excluded. The accuracy of the extracted or calculated data was confirmed by comparing the collection forms of the two investigators.

Two authors independently assessed the risk of bias in the included cross-sectional studies using a modified version of the Cochrane Risk of Bias Tool 2.0. This tool assesses the quality of studies using criteria similar to the Risk of Bias Assessment Tool for Non-Randomized Studies (RoBANS). The RoBANS tool assesses bias risk across five domains: participant

selection, control of confounding variables, measurement of risk factors or exposures, blinding of outcome assessment, and handling incomplete outcome data. The criteria include: 1) Is there a clear statement of the study objectives and their relevance to the NEET phenomenon? 2) Are the data collection methods explicitly described and designed to minimize bias? 3) Is there a clear description of the methodological approach used in the data analysis, and does it align with the study design and research question? 4) Does the study comprehensively examine and justify the targeted risk factors for NEET youth? 5) Are the outcome measures explicitly defined, validated, reliable, and consistently implemented across all study participants?

We also utilized artificial intelligence (Evidence Prime, Hamilton, ON, Canada) to cross-check screening results. Disagreements were resolved by consensus between the two authors, and any remaining disagreements were resolved by a third author. The total quality score ranged from 0 to 5; studies scoring 4-5 points were considered to have a low risk of bias, those with a score of 2-3 points were regarded as having a moderate risk of bias, and studies assessed with <2 points were considered to have a high risk of bias.

3.2.4. Data synthesis and analysis

We conducted a comprehensive meta-analysis by pooling odds ratios (ORs), depending on data availability from observational studies. We performed random-effects meta-regressions to combine findings from multiple studies. We chose random-effects meta-regression over fixed-effects meta-regression because we expected substantial heterogeneity across studies due to differences in national contexts, welfare systems, NEET definitions, sample compositions, and measurement approaches. The random-effects model assumes that effect sizes vary across studies, allowing us to estimate both the average effect and the degree of variation between studies when synthesizing evidence from diverse populations and settings (Borenstein et al., 2010). The fixed-effects methodology was used to synthesize the findings of studies that presented multiple independent effect sizes. We used robust variance estimation (RVE) in our random-effects models to do this. This allowed us to investigate the relationships between NEET status and our overarching categories.

RVE offers the advantage of aggregating estimates that might be correlated because they come from the same participant groups. Importantly, this method enabled us to incorporate all relevant measures for these categories without explicitly specifying their covariance structures.

Furthermore, our analyses were enhanced with a small-sample correction. This correction is necessary when conducting hypothesis testing using RVE, particularly with smaller sample

sizes. For accurate results when using RVE for hypothesis testing, the degrees of freedom must be at least four. With fewer than four degrees of freedom, the assumptions underlying the t-distribution approximation, upon which the testing is based, no longer hold. This can increase the likelihood of type I² errors beyond what the p-values used for testing indicate.

The I^2 statistic and Cochran's Q test were used to assess statistical heterogeneity. Given that between-study heterogeneity can be misleading when quantified by I² during a meta-analysis of observational studies. Furthermore, we conducted subgroup analyses and used Jamovi version 2.4.11.0 for data analyses.

3.3. Results

In our initial search, we found 2,175 publications. Following de-duplication and screening, 1404 publications were further screened. Then, 1311 articles were excluded by the titles and abstracts, and the remaining 56 articles were removed for different reasons; seven of the studies reported chi-squared statistics, three of them reported beta coefficients from linear regressions, and the rest of them did not report study population or other essential data for odds ratios and Cls. Furthermore, two studies used the same data to obtain identical estimates. When we removed low-quality research, the results remained identical. The meta-analysis includes the final 43 publications. Figure 3.1 shows a PRISMA diagram of the study retrieval procedure.

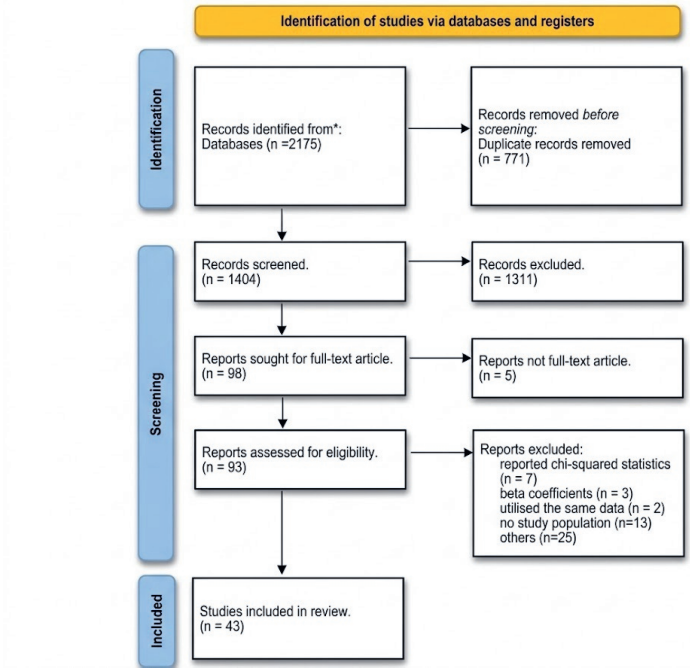


Figure 3.1. PRISMA flow chart of systematic and meta-analysis review.

3.3.1. Study characteristics

The review encompassed 1,001,701 unique individuals from studies conducted in various countries. These countries included Canada (5 studies), England (5 studies), and Finland (4 studies). Other contributions came from Australia (3 studies), Spain (3 studies), and Norway (2 studies). Additionally, there were 2 studies each from Austria and Switzerland, and 1 each from South Africa, Peru, Greece, Mexico, Senegal, France, South Korea, Taiwan, Sweden, Hong Kong, and China. Methodologically, the studies exhibited a diverse range of designs. The majority of studies used a cohort design (24 studies), followed by cross-sectional (18 studies) and case-control (1 study). We distinguished between three validity dimensions: risk of bias (internal validity of individual studies, assessed via RoBANS criteria above), study quality (overall methodological rigor, used for sensitivity analyses), and publication bias (selective reporting across studies, using funnel plots and Egger's test for outcomes with ≥9 studies).

A quality assessment of the study (Table A2 in Appendix) revealed variable methodological rigor. Among 43 studies, 23 (53%) scored high quality (average score 4.0/5.0), 18 (42%) moderate quality (average score 2.0-3.9/5.0), and 2 (5%) low quality (average score <2.0/5.0).

Qualitative strengths included clear study objectives (QAR1: mean = 4.5/5) and appropriate analytical approaches (QAR3: mean = 4.3/5). The primary concerns were data collection methods (QAR2: mean = 3.6/5), the justification of risk factors (QAR4: mean = 3.4/5), and Well-defined outcome measures (QAR5: mean = 4.0/5).

In studies of varying quality, there were no systematic differences in the direction or magnitude of reported risk factors. The robustness of the findings was confirmed through sensitivity analyses that excluded low-quality studies.

The median age of participants across studies was 19 years old, ranging from 15.93 to 23.67 years. Gender distribution was also diverse, with males comprising anywhere from 33% to 67% of the samples. Appendix 3.1 provides an overview of the included studies.

3.3.2. Main analysis

Due to heterogeneity within and across studies, random-effect models were employed to estimate the average effect and its precision. This approach was chosen because it provides a more conservative estimate of the 95% confidence intervals (CIs). The odds ratio and confidence interval for the link between risk factors and becoming NEET were computed to meta-analyze this relationship. Subgroup analysis was conducted using gender and age ranges 15 to 18, 18-24, and youth ≥25 as moderators to explain the variability in the findings. The lack of control-variable information in many studies limited our ability to conduct comprehensive subgroup analyses based on potential confounders.

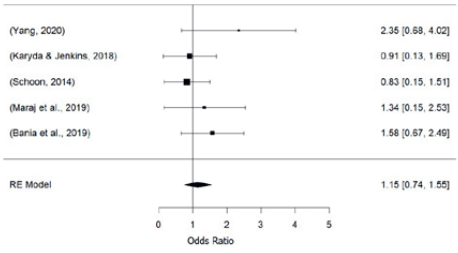
3.3.3. Demographic factors

Twenty studies examined the associations between demographic factors and NEET status. The aforementioned studies were conducted using large cohorts, ensuring that the samples were representative of the entire population. Moreover, the studies exhibited a moderate to high level of quality, as shown in Appendix 3.2. The results of all the research examined in this analysis consistently indicated that the specific outcome was attaining NEET status. A summary of the effect sizes for each study is provided in Appendix 3.3.

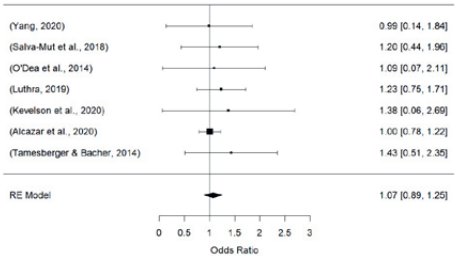
Figure 3.2 shows the relationship between demographic factors and being NEET. Five studies reported odds ratios for ethnicity (Bania et al., 2019; Karyda & Jenkins, 2018; Maraj et al., 2019; Schoon, 2014; Yang, 2020); the pooled odds ratio was 1.15 (CI = 0.74–1.55; I^2 = 3.64%, $p < .001$). The narrow range and consistency across studies suggest that ethnicity alone is not a strong predictor, though this may mask interactions with other factors, such as immigration

status or socioeconomic disadvantage. In these analyses, 'ethnicity' refers to a background other than the main ethnic group in the sample.

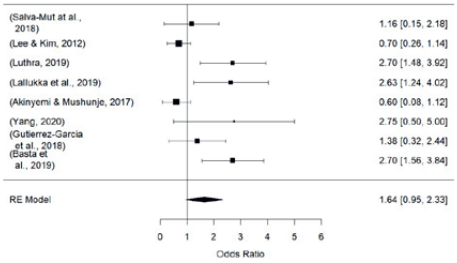
Our analysis included data from seven studies examining the relationship between migrant status and NEET status (Alcazar et al., 2020; Kevelson et al., 2020; Luthra, 2019; O'Dea et al., 2014; Salvà-Mut et al., 2018; Tamesberger & Bacher, 2014; Yang, 2020). The odds ratio for this relationship was 1.07, with a 95% CI ranging from 0.89 to 1.25. A high level of heterogeneity was observed ($I^2 = 60\%$, $p < .001$). This suggests that the impact of migrant status on NEET outcomes varies across populations and regions, including differences in educational and employment opportunities, challenges with social integration, difficulties understanding the language, and discrimination (see Chapter 2). We examined eight studies that investigated the association between marital status and NEET status (Alcazar et al., 2020; Kevelson et al., 2020; Luthra, 2019; O'Dea et al., 2014; Salvà-Mut et al., 2018; Tamesberger & Bacher, 2014; Yang, 2020). The odds ratio for this relationship was 1.64, with a 95% CI spanning from 0.95 to 2.33. The reference group for this variable consists of single or unmarried youth. Once again, substantial heterogeneity was observed ($I^2 = 78.05\%$, $p < .001$), indicating that marital status might not uniformly predict NEET status and may be influenced by various contextual factors. While ethnicity, migrant status, and marital status demonstrate associations with NEET outcomes, the context plays a vital role in shaping these relationships.



Ethnicity



Migrant



Marital status

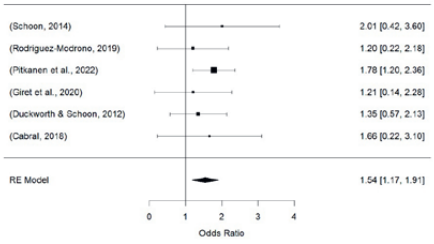
Figure 3.2. Forest plots of demographic factors.

3.3.4. Family factors

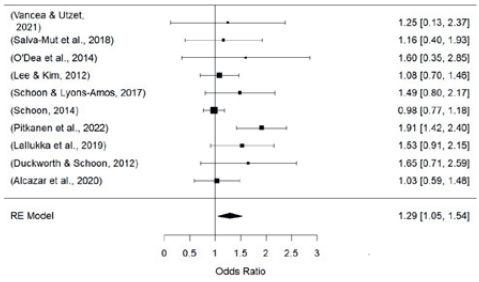
Our investigation of 46 studies examining family-related factors and their association with NEET status underscores their multifaceted impact on youth. Parents being unemployed or out of a job and workplace is a key factor, showing a pooled odds ratio of 1.54 (95% CI: 1.17, 1.91; $I^2 = 45.8\%$)(Cabral, 2018; Duckworth & Schoon, 2012; Giret et al., 2020; Pitkänen et al., 2021; Rodriguez-Modroño, 2019; Schoon, 2014). This highlights that a jobless parent plays a substantial role in predicting NEET status but can be influenced by various contextual factors. Similarly, parents' income emerged as an important determinant, revealing a pooled odds ratio of 1.29 (95% CI: 1.05, 1.54; $I^2 = 49.3\%$) (Alcazar et al., 2020; Lallukka et al., 2019; Lee & Kim, 2012; O'Dea et al., 2014; Pitkänen et al., 2021; Salvà-Mut et al., 2018; Schoon, 2014; Schoon & Lyons-Amos, 2017; Vancea & Utzet, 2018). It is essential to note that, in these analyses, parents' income refers specifically to their economic resources. The reference group for this variable includes youth with high and average parental income. The odds ratio of 1.29 suggests an association between lower parental income and NEET status compared with the reference group of youth with high or average parental income. The parents' education level is an important factor. This was indicated by an odds ratio of 0.87 (95% CI: 0.66, 1.09; $I^2 = 17.8\%$), as found in ten studies (Alfieri et al., 2015; Bania et al., 2019; Karyda, 2020; Karyda & Jenkins, 2018; Kevelson et al., 2020; Lee & Kim, 2012; Rodwell et al., 2018; Schoon, 2014; Su et al., 2022; Yang, 2020). The reference group for this variable includes parents with a high school degree or less. The level of parental education seems to have a significant impact on youth NEET status. It influences their educational aspirations, access to resources, and career opportunities. Consequently, it shapes their trajectories beyond education (see Chapter 2).

Our analysis also considered the impact of living with a single parent on NEET status (Alcazar et al., 2020; Cabral, 2018; Duckworth & Schoon, 2012; Karyda & Jenkins, 2018; Pitkänen et

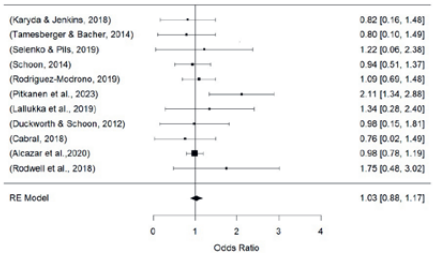
al., 2021; Rodriguez-Modroño, 2019; Rodwell et al., 2018; Schoon, 2014; Selenko & Pils, 2019; Tamesberger & Bacher, 2014). The pooled odds ratio for this association was 1.03 (95% CI: 0.88-1.17). Heterogeneity was once again high (I^2 = 52.9%), indicating that the effect of living with a single parent may not be uniform and could vary by region or social context. Meanwhile, the impact of the number of siblings is 1.11 (95% CI: 0.85, 1.36; I^2 = 36.7%) (Giret et al., 2020; Schoon, 2014; Selenko & Pils, 2019), and care responsibility 1.52 (95% CI: 1.04, 1.99; I^2 = 39.09%) on NEET status (Alcazar et al., 2020; Gutierrez-Garcia et al., 2018; Kevelson et al., 2020; Salvà-Mut et al., 2018; Tamesberger & Bacher, 2014; Vancea & Utzet, 2018) .



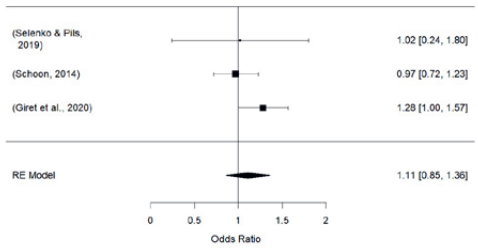
Workless Parent



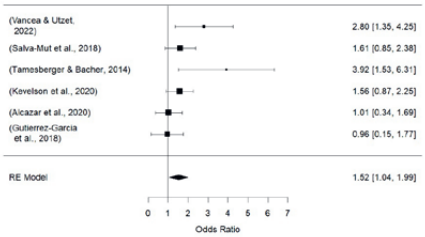
Parent income



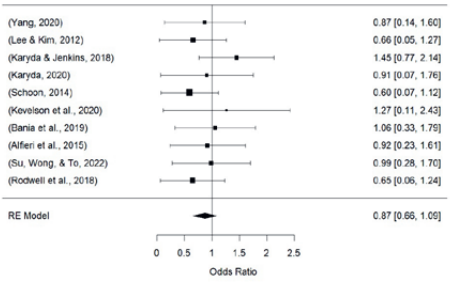
Living with Single parent



Number of siblings



Have care responsibility

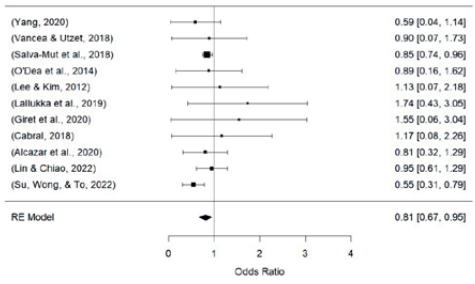


Parental Education Level

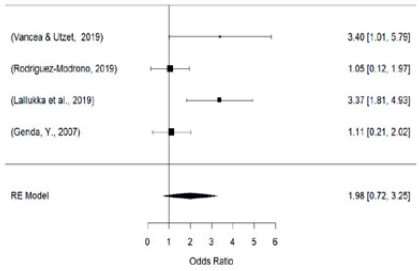
Figure 3.3. Forest plots of family factors.

3.3.5. Education and unemployment experience factors

Our analysis of 15 studies examining education and unemployment experience factors underscores their substantial role in shaping NEET status. Our analysis revealed that educational attainment is a critical determinant of NEET status (Alcazar et al., 2020; Cabral, 2018; Giret et al., 2020; Lallukka et al., 2019; Lee & Kim, 2012; Lin & Chiao, 2022; O'Dea et al., 2014; Salvà-Mut et al., 2018; Su et al., 2022; Vancea & Utzet, 2018; Yang, 2020). The pooled odds ratio for this factor was 0.81 (95% confidence interval: 0.67-0.95). However, substantial heterogeneity was observed in this analysis (I^2 = 51.58%). This suggests that while higher levels of education appear to be associated with a reduced likelihood of NEET status, variations in study contexts may influence the strength of this relationship; the finding is consistent with human capital theory and prior reports. In contrast, prior unemployment experience before becoming NEET presented a more complex picture, with a pooled odds ratio of 1.98 (95% CI: 0.72, 3.25; I^2 = 74.3%). According to these findings, NEET status and prior unemployment experience are strongly related (Genda, 2007; Lallukka et al., 2019; Rodriguez-Modroño, 2019; Vancea & Utzet, 2018).



Level of education

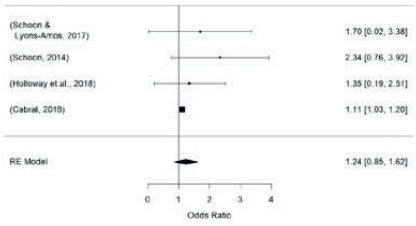


Unemployment experience

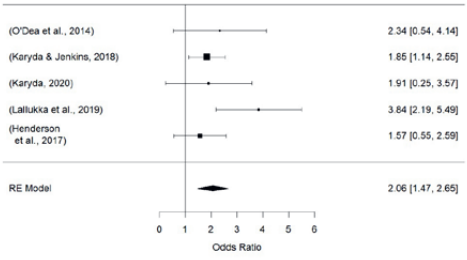
Figure 3.4. Forest plots of education and unemployment experience factors.

3.3.6. Socio-economic factors

The analysis of four studies on deprivation factors revealed a pooled odds ratio of 1.24 (95% confidence interval: 0.85-1.62). This analysis displayed relatively low heterogeneity (I^2 = 15.29%). These findings suggest that residing or experiencing socio-economic deprivation is associated with a moderately increased risk of NEET status among young individuals. Another pivotal factor examined was criminal behaviour, as reported in four studies. The pooled odds ratio for this factor was 2.06 (95% CI: 1.47-2.65). However, this analysis demonstrated substantial heterogeneity (I^2 = 18.82%). These results imply that engagement in criminal behaviour is a substantial risk factor for NEET status, underscoring the need for interventions targeting youth involved in criminal activities.



Living in deprivation



Criminal behaviour

Figure 3.5. Forest plots of socio-economic.

3.3.7. Health and well-being factors

We examined various health-related factors in our analysis of factors contributing to NEET status. Among these factors, anxiety emerged as a contributor to mental health (Basta et al., 2019; Benjet et al., 2012; Gariepy & Iyer, 2019; Goldman-Mellor et al., 2016; Gutiérrez-García

et al., 2018; Holloway et al., 2018; Power et al., 2015). A meta-analysis of seven studies revealed a pooled odds ratio of 1.29 (95% CI: 0.93, 1.65; I^2 = 97.7%). The findings suggest that anxiety plays an important role in contributing to youth's NEET status, although the strength of this association varies across studies.

We also examined the presence of any psychological problems, with an analysis of 14 studies resulting in a pooled odds ratio of 1.28 (95% CI: 0.89, 1.68; I^2 = 81.7%) (Baggio et al., 2015; Bania et al., 2019; Benjet et al., 2012; Gutiérrez-García et al., 2018; Hale & Viner, 2018; Henderson et al., 2017; Holloway et al., 2018; Lallukka et al., 2019; Lin & Chiao, 2022; Maraj et al., 2019; O'Dea et al., 2014; Power et al., 2015; T. H. Stea et al., 2019; Tayfur et al., 2022). This finding emphasizes the substantial impact of psychological well-being on NEET status among young individuals.

The analysis of depressive disorders, encompassing six studies, showed a pooled odds ratio of 1.51 (95% CI: 0.90, 2.12; I^2 = 66.62%), underlining the potential role of depressive disorders in contributing to NEET status (Baggio et al., 2015; Gariepy & Iyer, 2019; Goldman-Mellor et al., 2016; Holloway et al., 2018; Lin & Chiao, 2022; Power et al., 2015).

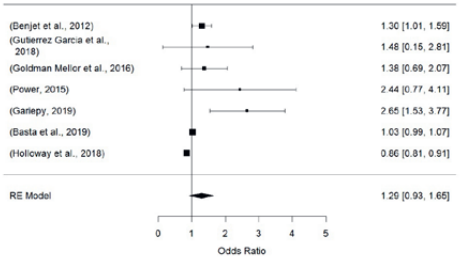
Furthermore, we explored the association of NEET status with suicidal tendencies, analyzing four studies that revealed a significant pooled odds ratio of 2.8 (95% CI: 1.8, 3.8; I^2 = 34.9%). These results underscore the severe implications of suicide risk in relation to NEET status (Benjet et al., 2012; Gariepy & Iyer, 2019; Goldman-Mellor et al., 2016; Power et al., 2015).

Physical health problems were also considered, and the analysis of eight studies indicated a pooled odds ratio of 1.35 (95% CI: 1.02, 1.67; I^2 = 21.8%), emphasizing the importance of physical health in understanding the NEET phenomenon (Bania et al., 2019; Cabral, 2018; Flynn & Tessier, 2011; Lallukka et al., 2019; Salvà-Mut et al., 2018; Schoon, 2014; Su et al., 2022; Tamesberger & Bacher, 2014).

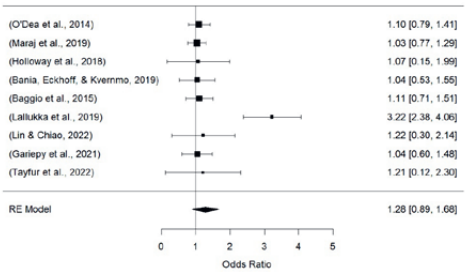
In our study of substance use as an aspect of overall health and well-being, we examined factors related to addiction. The pooled odds ratio for alcohol use, based on nine studies, was 1.09 (95% CI: 0.94, 1.25; I^2 = 10.23%) (Basta et al., 2019; Gariepy & Iyer, 2019; Goldman-Mellor et al., 2016; Gutiérrez-García et al., 2018; Hale & Viner, 2018; Manhica et al., 2019; O'Dea et al., 2014; Rodwell et al., 2018; Tonje H Stea et al., 2019). For cannabis use, based on eight studies, the pooled odds ratio was 1.57 (95% CI: 1.06, 2.07; I^2 = 59.23%) (Baggio et al., 2015; Basta et al., 2019; Gariepy & Iyer, 2019; Goldman-Mellor et al., 2016; Hale & Viner, 2018; O'Dea et al., 2014; Rodwell et al., 2018; Tonje H Stea et al., 2019). Smoking, a specific form

of substance use, revealed a substantial pooled odds ratio of 1.77 (95% CI: 1.26, 2.29; I^2 = 32.95%) across five studies (Basta et al., 2019; Gutiérrez-García et al., 2018; Hale & Viner, 2018; O'Dea et al., 2014; Tonje H Stea et al., 2019). Lastly, our analysis of drug use, based on twelve studies, demonstrated a pooled odds ratio of 1.58 (95% CI: 1.24, 1.93; I^2 = 38.73%) (Benjet et al., 2012; Flynn & Tessier, 2011; Goldman-Mellor et al., 2016; Gutiérrez-García et al., 2018; Henderson et al., 2017; Holloway et al., 2018; Lin & Chiao, 2022; Maraj et al., 2019; O'Dea et al., 2014; Salvà-Mut et al., 2018; Su et al., 2022; Tayfur et al., 2022).

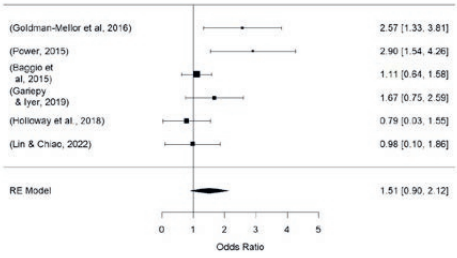
These findings underscore the complex interplay of various health-related factors and their association with NEET status. It is evident that anxiety, along with other factors, contributes significantly to understanding the phenomenon of youth disengagement from education, employment, or training. The high heterogeneity in some of these associations suggests the need for further research to explore the nuances and contextual factors underlying these relationships. Table 3.2 summarizes findings by risk factor type and the pooled OR.



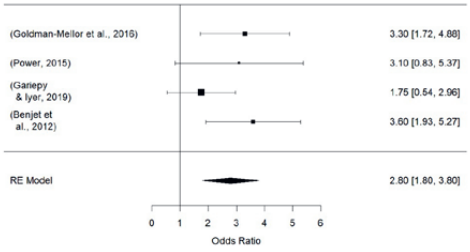
Anxiety



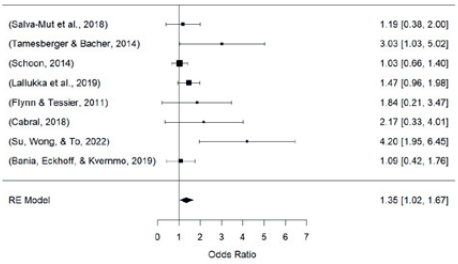
Any psychological problem



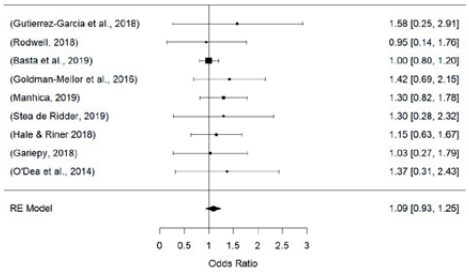
Depressive disorder



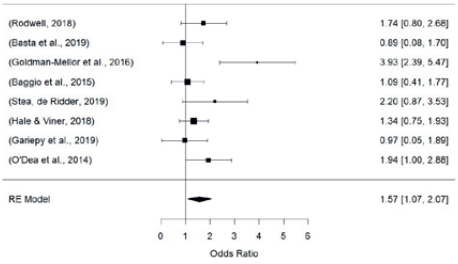
Suicide



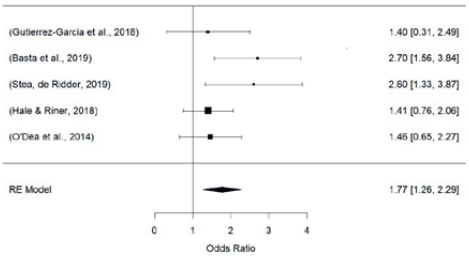
Physical health problems



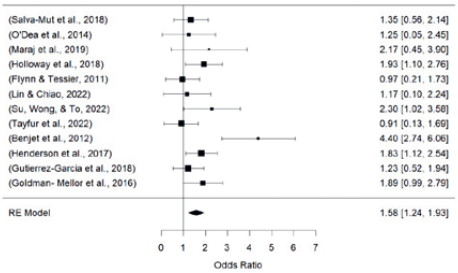
Alcohol use



Cannabis use



Smoking



Substance use disorder

Figure 3.6. Forest plots of health and well-being factors.

Table 3.2. Summary of findings by type of risk factors and the result of the pooled OR.

Type	Number of studies	Pooled OR	95% CI	Std. Error	I^2 (%)	τ^2 (tau-squared)	Q	Z
Demographic Factors								
Ethnicity [a]	5	1.15	(0.74, 1.55)	0.2	3.64	0.01	4.15	5.55
Immigration [a]	7	1.07	(0.89, 1.25)	0.09	60.1	0.09	1.72	11.7
Marital status [b]	8	1.64	(0.95, 2.33)	0.35	78.05	0.67	27.88	4.65
Family Factors								
Workless Parent [a]	6	1.54	(1.17, 1.91)	0.18	45.8	0.05	2.09	8.24
Parental Education level [c]	10	0.87	(0.66, 1.09)	0.11	17.8	0.02	5.68	7.9
Parents' income [d]	10	1.29	(1.05, 1.54)	0.12	49.3	0.06	16.22	10.3
living with a single parent [a]	11	1.03	(0.88, 1.17)	0.07	52.9	0.07	10.97	8.36
Number of siblings [e]	3	1.11	(0.85, 1.36)	0.13	36.7	0.01	2.60	8.5
Have care responsibility [a]	6	1.52	(1.04, 1.99)	0.24	39.09	0.13	10.72	6.24
Education and unemployment experience Factors								
Level of education [c]	11	0.81	(0.67, 0.95)	0.07	51.58	0.01	9.99	11.1
unemployment experience [a]	4	1.98	(0.72, 3.25)	0.64	74.24	1.15	9.59	3.07
Socio-economic Factors								
Living in deprivation [a]	4	1.24	(0.85, 1.62)	0.19	15.2	0.04	2.90	6.25
Criminal behaviour [a]	4	2.06	(1.47, 2.65)	0.30	18.8	0.09	5.78	6.8

Health and Well-being Factors								
Anxiety [a]	7	1.29	(0.93, 1.65)	0.18	97.7	0.13	43.88	7.01
Any psychological problem [a]	9	1.28	(0.89, 1.68)	0.2	81.7	0.25	24.55	6.4
depressive disorder [a]	6	1.51	(0.90, 2.12)	0.31	66.62	0.36	12.85	4.86
Suicide [a]	4	2.80	(1.80, 3.80)	0.51	34.9	0.36	4.15	5.48
physical health problems [a]	8	1.35	(1.02, 1.67)	0.16	21.83	0.04	13.44	8.09
Alcohol use [a]	9	1.09	(0.93, 1.25)	0.08	10.23	0.01	3.46	13.5
Cannabis use [a]	8	1.57	(1.07, 2.07)	0.25	59.23	0.28	16.66	6.2
Smoking [a]	5	1.77	(1.26, 2.29)	0.26	32.95	0.11	6.26	6.74
Drug use [a]	12	1.58	(1.24, 1.93)	0.17	38.73	0.13	21.61	8.94

OR = odds ratio; CI = confidence interval; I^2 = heterogeneity statistic (percent of variation due to true differences rather than chance); Q = Cochran's Q test for heterogeneity; τ^2 = between-study variance; PI = prediction interval (expected range in new setting).
I^2 interpretation: <40% low, 40-60% moderate, 60-90% substantial, >90% considerable heterogeneity

[a] Reference category: No
b Reference category: Single
c Reference category: lower education
d Reference category: high and average income
e Reference category: none

3.3.8. Associations by Gender

Seven studies conducted gender-stratified analyses (Alfieri et al., 2015; Bania et al., 2019; Lallukka et al., 2019; Luthra, 2019; Rodriguez-Modroño, 2019; Schoon, 2014; Vancea & Utzet, 2018). According to a study by Bania et al. (2019), ethnicity significantly increases the likelihood of NEET status among men, with an odds ratio of 1.58 (1.02-2.44, p=0.039). However, ethnicity was not a significant predictor of NEET status among females (OR=0.74, 0.46-1.17, p=0.20). Parental lower education significantly increased the risk of experiencing NEET status for both genders, with the risk being higher for men (OR= 3.22, 1.60 to 6.47, p=0.001) than for women (OR= 2.11, 95% CI = 1.21 to 3.69, p=0.009). Schoon's research highlights that boys growing up with a single parent (OR= 0.96, 95% CI= 0.87,1.22) are slightly more likely to be NEET than females (OR= 0.43, CI 0.27,0.62) in similar circumstances (Schoon, 2014).

Mental health problems were associated with lower odds of becoming NEET in men (OR= 1.02, 0.81 to 0.97, p=0.008), but not in women (OR 1.24, 95% CI= 0.97,1.11, p=0.28). The OR for mental disorders among men was 2.23 (95% CI: 2.10 to 2.36), indicating a substantially increased risk. The OR was also elevated among women but was relatively lower at 1.71 (95% CI = 1.61 to 1.81) (Lallukka et al., 2019).

Luthra (2019) found that having an immigrant history (OR= 1.46, p <0.001, 95%CI = 1.24,1.72) and living with one's parents (OR= 1.34, p <0.001, 95%CI = 1.19,1.52) were characteristics suggesting a greater risk of being NEET for males. However, for women with an immigrant history (OR= 1.01, p < 0.001, 95% CI = 0.83, 1.2) and married women (OR= 3.92, p < 0.001, 95% CI = 2.93, 5.24), these factors elevated the likelihood of becoming NEET considerably.

Marital status also displayed a gender disparity. The OR for NEET status among unmarried men was 1.49 (95% CI= 1.35 to 1.65), indicating an increased risk. Conversely, unmarried women had a lower OR of 0.91 (95% CI= 0.82 to 1.00), suggesting a reduced risk of NEET status. For divorced individuals, gender differences persist. Divorced men had a considerably higher OR of 2.02 (95% CI= 1.56 to 2.60), while divorced women demonstrated a lower OR of 1.43 (95% CI= 1.17 to 1.75) (Lallukka et al., 2019). The study by Henderson et al.(2017) indicated that substance misuse was associated with being NEET for both men (OR= 1.83, 95% CI= 1.43, 2.34) and women (OR= 2.05, 95% CI= 1.58, 2.66).

Individuals with a higher level of education are less likely to be in the NEET category. This effect is particularly pronounced among women (OR= 0.23, 95% CI= 0.09, 0.59) compared to men (OR= 0.29, 95% CI= 0.11, 0.72). In men, having parents with low income (OR=1.84, 95% CI=1.09, 3.15) increases the likelihood of being a NEET, compared to women (OR=1.15, 95% CI=0.71, 1.86). Having caring responsibilities OR of 2.80 (95% CI= 1.33, 6.01) and unemployment experience OR of 3.19 (95% CI= 1.73, 5.91), considerably enhances the risk of becoming a NEET for women (Vancea & Utzet, 2018).

3.3.9. Associations by Age

Our comprehensive analysis encompassed various studies, each investigating different age groups: 15-18 years (5 studies)(Bania et al., 2019; Benjet et al., 2012; Goldman-Mellor et al., 2016; Henderson et al., 2017; Lallukka et al., 2019), 19-24 years (8 studies) (Baggio et al., 2015; Goldman-Mellor et al., 2016; Gutierrez-Garcia et al., 2018; Hale & Viner, 2018; Power et al., 2015; Rodwell et al., 2018; Vancea & Utzet, 2018; Yang, 2020), and those aged 25 years

and above (3 studies) (Luthra, 2019; Rodwell et al., 2018; Vancea & Utzet, 2018; Yang, 2020). In the youngest age bracket (15-18 years), there were strong correlations between NEET status and mental health issues, behavioural problems, addiction problems, and caring responsibilities. For instance, one study reported a significant association between mental health problems and NEET status 2.70 (95% CI= 1.77, 4.12). The link between behavioural problems and NEET status was also substantial (OR 1.24, 95% CI 1.18, 1.30). The strongest variable in the simple analyses was being a single parent to a child or children under 18 years old, which was associated with a risk almost 6 times higher (OR = 5.55, $p < 0.001$, CI = 4.14, 7.43). Conversely, family factors and health and well-being factors demonstrated weaker associations with NEET status in this age group.

Multiple factors were associated with NEET status among 19-24-year-olds. These included marital status (OR= 1.59, 95% CI= 1.12, 2.26), responsibility (OR= 1.32, 95% CI= 1.12; 1.55), addiction problems (OR= 1.11, 95% CI= 1.05, 1.16), mental illness issues (OR= 1.76, 95% CI= 1.21, 2.54), and criminal behaviour (OR 1.15, 95% CI 1.08, 1.22). Vancea & Utzet (2018) further noted that, for this age group, a higher educational level significantly reduced the likelihood of NEET status, particularly among women (0.29; 95% CI = 0.08, 0.93), and for men (0.47; 95% CI = 0.13, 1.47).

The evidence was mixed in the oldest age group (≥ 25). Marital status, criminal behaviour, and addiction problems showed inconsistent associations across studies. However, some patterns emerged. For instance, there was an association between marital status and NEET status (OR = 1.14, 95% CI = 1.07, 1.21). Higher education level was associated with a lower likelihood of being NEET (0.22; 95% CI = 0.11, 0.42). For women, having caring responsibilities increased the risk of being NEET by 1.96 (95% CI = 1.18, 3.30), while for men, these responsibilities decreased the risk by 0.48 (95% CI = 0.25, 0.91) (Vancea & Utzet, 2018).

The impact of age on NEET status reveals an interesting pattern. Evidence suggests that the likelihood of being NEET increases with age, although some studies have reported higher rates among males. Specifically, NEET status was more likely to occur among males aged between 20 and 25, with an odds ratio of 2.42 (95% CI= 1.64 to 3.57) (O'Dea et al., 2016). Contrarily, Yang (2020) identified a declining risk of NEET status with age beyond the mid-20s. The odds of being NEET were 14.67 times greater for those aged 26 to 29 and 12.41 times greater for those aged 30 to 35, compared with those aged 16 to 21. This finding suggests a shift in the age-related risk of NEET status, with the risk decreasing as individuals transition from youth to adulthood. This trend is echoed in Luthra's findings (2019), which indicated a lower

likelihood of being NEET for both men (OR = 0.60, p < 0.001, CI = 0.53, 0.69) and women (OR = 0.56, p < 0.001, CI = 0.48, 0.65) aged 25 years or older.

Holloway (2018) further explored the relationship between age and NEET status, revealing that age's predictive value varied between adolescents and young adults. For adolescents, increasing age was associated with a near doubling of the risk of NEET status (OR=1.92, 95% CI=1.87, 1.98), while for young adults, the increase was more modest (OR=1.02, 95% CI=0.98, 1.11).

3.3.10. Publication Bias Assessment

A funnel plot was constructed by plotting effect size against standard error (inverted) (Figure 3.7). Three statistical tests were employed: (1) Egger's regression detecting funnel plot asymmetry (significant at p<0.10), (2) Kendall's tauassessing rank correlation between effect size and variance (p<0.10), and (3) Fail-Safe N estimating unpublished null studies needed to nullify findings (robust if exceeding 5x+10 threshold). Visual inspection assessed symmetry; asymmetry suggested selective reporting.

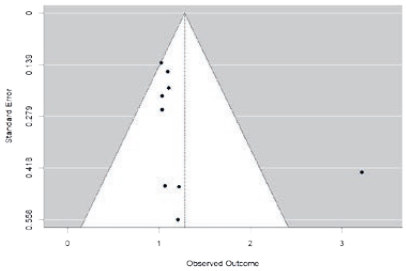
Publication bias was assessed for seven outcomes with ≥9 studies (Table 3.3). Five outcomes showed no evidence of bias: youth education (Egger's p=0.154, fail-safe N=712), parent income (p=0.110, N=818), living with a single parent (p=0.238, N=605), alcohol use (p=0.179, N=465), and psychological problems (Egger's p=0.196, N=685). All fail-safe N values substantially exceeded robustness thresholds (range: 3.5× to 13.6× required values).

Two outcomes showed borderline evidence. Parent education demonstrated a significant Kendall's tau (τ=0.511, p=0.047) despite a non-significant Egger's test (p=0.139), suggesting possible small-study effects, though the fail-safe N remained adequate (229 studies, 3.8× threshold). Psychological problems showed a similar pattern (Kendall's p=0.045, Egger's p=0.196), but very high heterogeneity (I^2=82%) complicates interpretation.

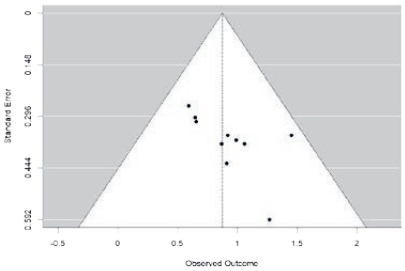
Drug use was the only outcome with definitive bias evidence (Egger's p=0.008), indicating the pooled OR=1.58 may moderately overestimate the true effect. However, the extremely high fail-safe N (599 studies) and significant Kendall's tau suggest a genuine association persists despite potential selective reporting. Seventeen outcomes with <9 studies could not be assessed. Overall, publication bias does not appear to substantially threaten meta-analytic validity, with most key findings demonstrating robustness to selective reporting.

Table 3.3. Publication Bias Assessment Summary

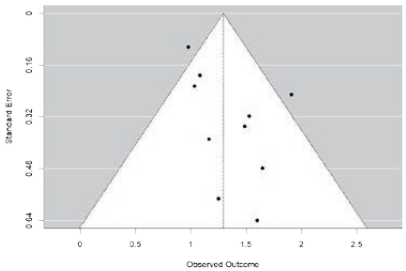
Outcome	K	Egger's p	Kendall's p	Fail-Safe N (×Threshold)	Bias Evidence
Education level	11	0.154	0.121	712 (10.9×)	No
Parent Income	10	0.110	0.381	818 (13.6×)	No
Parent Education	10	0.139	0.047	229 (3.8×)	Borderline
Living with Parent	11	0.238	0.218	605 (9.3×)	No
Psychological Problem	9	0.196	0.045	685 (12.5×)	Borderline
Alcohol Use	9	0.179	0.612	465 (8.5×)	No
Drug Use	12	0.008	0.086	599 (8.6×)	Yes



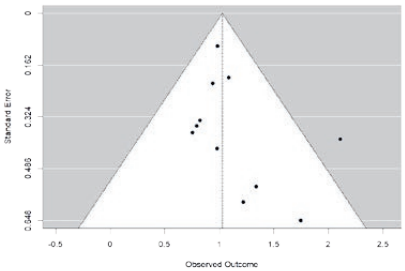
a. Any psychological problem



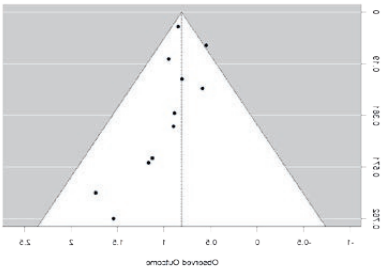
b. Parental education level



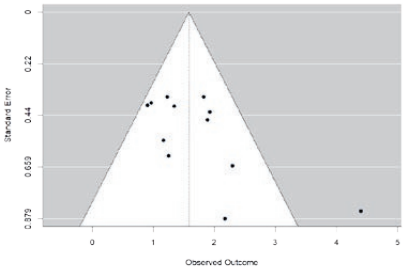
c. Parents' income



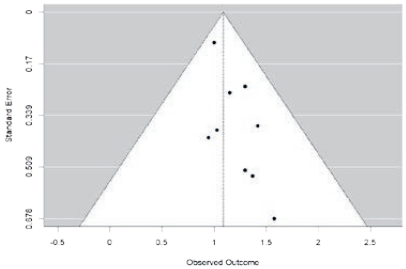
d. Living with a single parent



e. Education level



f. Drug use



g. Alcohol use

Figure 3.7. Funnel plot for factors with more than 9 studies.

3.4. Discussion

This comprehensive systematic review and meta-analysis of 43 published studies has shown that a wide range of variables influence NEET status. We have examined these aspects, including their overall influence and their differentiation by gender and age cohorts. NEET status elements can be better understood using this approach. We enhanced our comprehension by examining the interconnections among demographic factors, family factors, educational and unemployment experience factors, socio-economic factors, and health and well-being factors, shedding light on the complexity of the NEET phenomenon. Our study highlights the substantial correlations between these characteristics and the NEET phenomenon, enhancing our understanding of its multidimensional nature.

3.4.1. Demographic factors

Demographic factors significantly influence the risk of becoming NEET. There is a modest trend suggesting that ethnicity may play a role in becoming a NEET youth. However, the confidence interval range on both sides of the unity line underscores the need for careful, measured interpretation. A review of several studies demonstrates a complex association in which some ethnic groups are more likely to be classified as NEET than others (Bania et al., 2019; Karyda & Jenkins, 2018; Yang, 2020). Nevertheless, it is crucial to underscore that the effect of ethnicity on NEET is context-dependent, as social structures and the varying opportunities available within various groups shape it. Ethnicity can influence NEET status through factors such as discrimination, cultural expectations, and access to resources. Language barriers and socio-economic conditions, typically linked to ethnicity, negatively impact education and employment opportunities (see Chapter 2).

We found a link between migrant status and NEET status. The odds ratio was illuminating but not conclusive. The high level of heterogeneity in the results is an important finding of our

analysis. This marked variation may be due to sociocultural, economic, or legal differences across the studied regions. In other words, while migrant status may be a factor in NEET status in one region, it may not be as influential in another due to local policies, societal acceptance, integration programs, or other contextual factors (Bacher et al., 2020). Considerable attention has been paid to second-generation immigrants stemming from low-skilled migration waves. This cohort often navigates educational and employment pathways that demand lower skill levels, as evidenced by previous research (Laganà et al., 2014).

Marital status emerges as another demographic factor influencing NEET. The analysis underscores the diversity of contexts within which marital status operates. It is crucial to recognize that, although marital status tends to influence NEET, the extent and nature of this impact are subject to complex dynamics. The impact of marital status on NEET scores varies across cultural norms, societal expectations, and economic conditions (Susanli, 2016). This finding emphasizes the importance of recognizing the multifaceted nature of marital status and its potential influence on youth.

3.4.2. Family-related factors

When considering family-related factors, it is clear that jobless parents and low income levels have a major impact on the chance of youth becoming NEET (see Chapter 2). Our research has shown that a jobless parent significantly increases the likelihood of becoming NEET. The statistical significance underscores the important role that a jobless parent plays in shaping individuals' likelihood of becoming NEET. The odds ratio of 1.53 indicates a substantial association between parental joblessness and NEET outcomes. These results highlight the interconnectivity of family relationships and socio-economic situations in defining a young adult’s destiny. Parental unemployment affects the family's financial situation and also serves as a role model for youth regarding work ethic and ambition.

Similarly, parental income influences a young person’s path toward school and work by providing critical resources for education and skill development (see Chapter 2). This demonstrates the clear influence of financial resources on youth disengagement. Higher parental income might reduce the likelihood of NEET status by enabling access to educational opportunities and career prospects. Our analysis included parents’ education, which is pivotal in shaping youth educational and career trajectories. A higher level of parental education frequently translates into greater access to educational resources, a supportive learning environment, and better career opportunities for their children, and consequently, it

significantly influences the aspirations and goals of young individuals (Odoardi, 2020). However, the observed odds ratio indicates a moderate impact, suggesting that while parents' education is influential, it is just one piece of the complex puzzle determining youth's NEET status.

3.4.3. Education and unemployment experience

Education and unemployment experience are other characteristics that contribute to the complexity of NEET status among youth. The correlation between higher levels of education and a lower risk of being classified as NEET typically holds. However, the magnitude of this association varies across specific research settings. As the absence of educational credentials harms all populations (Bonnard, 2020), dropping out of school makes young people more vulnerable, especially during economic crises (Salvà-Mut et al., 2016). Simultaneously, studies emphasize the vulnerability of young people with higher levels of education, as their access to the job market depends on labour market demands, which in turn depend on national education and labour market regulations (Scandurra et al., 2020).

In contrast, experiences of prior unemployment present a more complex dynamic. This calls for a more comprehensive understanding of how prior unemployment experiences may act as risk factors for entering the NEET state. This exploration should consider the duration of unemployment and the contextual factors that may influence this relationship. A complex interaction among variables such as economic conditions, employment availability, and individual motives influences the relationship between unemployment experience and entering the NEET state.

3.4.4. Socio-economic factors

Socio-economic factors, such as living in deprived areas, also play a role in understanding the NEET phenomenon. Residing in deprived areas is associated with a moderately increased risk of NEET among young individuals. This finding underscores the importance of addressing systemic inequalities and providing equal access to education and employment opportunities for youth living in disadvantaged neighborhoods (Szpakowicz, 2022). Notably, the heterogeneity among these studies was relatively low (I^2 = 26.9%), suggesting consistency in this finding. These results imply that residing or experiencing socio-economic deprivation may contribute to a moderately increased risk of NEET status among young individuals. According to Simões (2018), young individuals residing in rural regions face certain constraints. These constraints hinder the provision of effective support and the implementation of institutional

arrangements and practices across multiple domains, such as social affairs, health, education, and employment. Consequently, these inadequacies can lead to disillusionment among young people, potentially resulting in their withdrawal from the labour market (Rikala, 2020).

Another significant factor explored in our analysis was criminal behaviour, as reported in four studies. These findings emphasize the critical role of criminal behaviour as a risk factor for NEET status. Interventions aimed at youth involved in criminal activity are critical for preventing or reducing the chance of becoming NEET. Risk behaviour research can be broadly categorized into two main areas. One area focuses on adopting a proactive approach among NEETs to mitigate the risk of becoming NEET if adequate support is not provided. The other area examines the influence of family background on the subsequent impact of risk behaviour among young individuals. When examining young individuals from privileged families, it is observed that engaging in early risk behaviours such as stimulant use and early sexual initiation does not correlate with the acquisition of NEET status. However, for young individuals from less privileged backgrounds, particularly males, exposure to stimulants at an early age (such as smoking and drug abuse) is found to predict negative outcomes later in life. Additionally, it has been confirmed that women in a NEET state are more likely to experience unplanned pregnancies. These findings are supported by the research conducted by Andrade and Järvinen (2017), Campbell et al. (2020), and Tanton et al. (2021).

3.4.5. Health and well-being

Health and well-being issues add another layer of complication to the NEET phenomenon. We delved into various health-related aspects. Notably, anxiety, a prevalent mental health concern, emerged as a contributor in our investigation. Anxiety significantly influences a young individual's likelihood of being in the NEET category, although the strength of this association varies across studies. Our examination of psychological well-being provided valuable insights. We found that psychological problems have a significant impact on NEET status, highlighting the complex connection between mental well-being and young people disengaging from education or employment.

Additionally, our analysis indicated that depressive disorders might play a role in increasing the likelihood of youth becoming NEET. This underscores the importance of providing mental health support, especially for individuals dealing with depressive disorders, and emphasizes the need to integrate mental health services into educational and employment settings. Furthermore, considering suicide risk as a factor reveals its severe consequences in the context

of NEET status. Our analysis demonstrated a notable link between suicide risk and NEET status. While research suggests a complex and potentially bidirectional relationship between suicide risk and NEET status, with both factors potentially influencing each other, this review focused solely on risk factors for entering NEET status. This decision aligns with the limitations of the included studies, which primarily investigated factors contributing to NEET status, and avoids making causal claims about the influence of NEET status on suicide risk. These findings underscore the urgency of addressing and preventing suicide risk, advocating for mental health and well-being services that cater to young individuals facing the challenges of NEET status. The findings show a significant relationship between mental illness and NEET outcomes, though the strength of this relationship varies across studies. This emphasizes the importance of early detection and support for youth mental health issues, as well as the incorporation of mental health services into educational and employment programs (Gariépy et al., 2021).

Our analysis also examines the role of physical health and illness in influencing the transition to NEET status. The pooled odds ratio underscores the connection between physical health-related challenges and the likelihood of becoming NEET. The moderate level of heterogeneity suggests that, while the overall relationship is present, contextual factors and variations in impact contribute to differences in the effect of physical health issues on NEET status.

Our meta-analysis underscores the significance of addiction as a crucial facet of health and well-being, contributing to NEET status. The pooled odds for alcohol, cannabis, drug use, and smoking emphasize the linkage between addiction and the likelihood of becoming NEET and highlight complex and varied pathways through which addiction influences youth disengagement.

Juberg and Skjefstad (2019) argue that there is limited empirical support for the notion that transitioning into NEET status is directly caused by drug abuse. However, they acknowledge that the alcohol and drug problems experienced by young individuals can significantly impair their long-term employability. Consequently, it is crucial to exercise caution in perpetuating misconceptions regarding NEET youth.

3.4.6. Gender-specific

Our study did not identify a distinct gender-based pattern in the relationship between risk factors and NEET status. However, NEET experiences are gender-differentiated. Our gender-based associations reveal that while factors such as substance misuse and parental education

level influence both genders, their impact is not uniform. For example, mental health issues and immigrant history have disparate implications for men and women. Women are more likely to fall into NEET than men due to factors such as marital status and caring responsibilities that underscore the necessity for interventions tailored to each gender.

3.4.7. Age-specific

The age analysis reveals that while some factors such as mental health issues and addiction problems, affect all age groups, their impact varies. For instance, caring responsibilities have different implications for different age groups. Furthermore, certain factors such as marital status and educational level show age-specific trends. The research findings suggest a gradual increase in the likelihood of individuals becoming NEET as they age, though the relationship is not strictly linear. It is worth noting that individuals aged 25-30 are more likely to be classified as NEET than other age cohorts. Also, findings from NEET-related gender-based studies vary across countries, underscoring the need for age-tailored interventions.

Our findings reinforce a human capital perspective, youth who invest in education (or are supported to do so) have much better odds in the labour market, whereas those who accumulate 'scars' such as health issues or criminal records see their human capital value diminished. At the same time, the capability approach would urge us to ensure that all youth have real opportunities to be in education or work, which means removing barriers indicated by these risk factors. For instance, improving the quality of schooling and addressing socio-economic hardships would enlarge the capabilities of at-risk youth to avoid NEET status.

3.4.8. Strengths, limitations, and future directions

This study has several notable strengths. First, all the studies included in this review demonstrated moderate to high methodological quality, enhancing the reliability of our findings. Second, our review's strengths include the use of comprehensive systematic review procedures, including artificial intelligence-supported dual screening of titles and abstracts, full-text evaluation, risk of bias assessment, and searching for pertinent data up to October 2023. Third, this study marks the first attempt to synthesize the comprehensive evidence on the NEET phenomenon. It differs from prior research by taking a more holistic approach to examining demographic, family, educational, and unemployment experience; socio-economic; and health and well-being factors, rather than relying on a predefined selection of specific terms. As a result of our research, we found that targeted interventions are crucial within frameworks such as the Youth Guarantee (Escudero & López Mourelo, 2017). As part of the

Youth Guarantee offerings, youth with mental health challenges - who are much more likely to become NEET - may receive specialized support (counseling, therapy, flexible training programs). NEET status might also be prevented through integrated rehabilitation and job-training programs for individuals involved in the criminal justice system.

Despite its strengths, this study does exhibit several limitations. Due to the limitations of cross-sectional data and the focus of the included studies, this review cannot establish causal relationships between the identified factors and NEET status. The analysis is limited to exploring associations between factors and the risk of entering the NEET category, not the potential influence of NEET status on other variables. High statistical heterogeneity was observed across meta-analyses, and in one instance, this heterogeneity persisted even after a leave-one-out sensitivity analysis. This may impact the precision and generalizability of the findings. Including a limited number of studies in some meta-analyses may contribute to biased estimates of the overall effect size, a common challenge in meta-analysis research. The research articles were primarily sourced from frequently used databases, potentially omitting relevant studies that were not included. Because control variables were not readily available in many of the included studies, we were unable to conduct comprehensive subgroup analyses that could account for potential confounding factors influencing the relationship between risk factors and NEET status. Publication bias assessment has several limitations. There were only seven studies (29%) that were sufficient to perform a reliable evaluation for seven of the 24 outcomes. The remaining 17 outcomes, including those with large effects like suicide and criminal behaviour, were unable to be assessed. The sensitivity of statistical tests is limited when there are fewer than 15 studies, which may result in subtle biases being missed. High heterogeneity, such as in psychological problems (I^2=82%), complicates interpretation since funnel plot asymmetry might reflect true variation rather than bias. Despite these constraints, multiple tests and high fail-safe N values (229–818 studies) support reasonable confidence in the findings for the assessed outcomes.

Future research may benefit from a broader range of database sources. Additionally, the analysis in this study relied exclusively on quantitative studies, which may have introduced sampling bias and led to the oversight of pertinent qualitative insights. A key limitation of this review is the heterogeneity in age definitions across included studies, as the experiences and risk profiles of NEET youth at age 19 may differ substantially from those at age 29.

While most studies in our review are from Europe/North America (where NEETs often include socially excluded minorities or those with personal disadvantages), in regions like North Africa

or South Asia, high NEET rates are also driven by structural factors such as lack of jobs and gender inequities. Our findings on the importance of education and skill attainment remain highly relevant to those regions' policy agendas, as evidenced by ILO reports linking higher education with lower NEET rates even in North Africa. However, factors like the pronounced female NEET rate in some societies (due to cultural norms) may require additional policy considerations beyond what our mostly Western-centric data captured.

Several potential directions for future research remain unexplored. Firstly, there is a need to broaden the geographical scope of investigations. Research in underrepresented areas is crucial because educational systems differ across countries, and successful transition pathways can vary between developed and developing countries. Considering that most youth worldwide reside in developing countries, where the influence of psychosocial factors may vary by economic and cultural contexts, it is essential to determine whether the existing research applies to youth in these diverse settings. This issue should be a priority in future research.

Future research should prioritize longitudinal studies and randomized controlled trials (RCTs) to establish stronger evidence for causal relationships between potential risk factors and NEET status and to provide insights into the long-term implications of NEET status. Furthermore, future studies could expand the range of databases used for literature retrieval, potentially uncovering research missed in this review, and include under-represented regions (Africa, South Asia, etc.) in NEET research to test whether these risk factors hold globally. Similarly, certain subpopulations might be understudied (rural youth, refugee youth, youth with disabilities). Gathering personal information from NEET youth on mental, emotional, and psychological factors through direct interviews could provide unique insights not typically available in large-scale surveys. Integrating qualitative studies alongside quantitative methods can provide a deeper understanding of the lived experiences and perspectives of NEET youth, offering valuable insights beyond traditional survey data. Future studies could evaluate interventions targeting the identified risk factors (such as mental health programs or educational support) to determine whether they effectively reduce NEET rates. Future research should also prioritize methodologies that enable the exploration of diverse risk factors associated with NEET status while effectively controlling for potential confounding variables.

The NEET phenomenon warrants further exploration, with future research aiming to test the associations of different factors together and their combined effects. Researchers could enrich the diversity of targeted participants by conducting studies across various subgroups, including

those working in high-skilled versus low-skilled jobs and individuals facing different types of vulnerabilities.

3.5. Conclusion

This systematic review and meta-analysis significantly contributes to our understanding of NEET youth. We identify robust predictors, including suicide risk, unemployment experience, and involvement in criminal behaviour, along with the protective factor of higher education. Our analysis highlights demographic disparities and evolving trends, emphasizing the need for tailored interventions. These findings have practical implications, including a call for customized support systems. While our study provides a strong foundation for addressing NEET prevalence, ongoing research is crucial, given the evolving nature of this issue. Unlike previous fragmented studies, this work brings everything together and thus serves as a cornerstone reference on NEET risk factors going forward. This synthesis can guide practitioners in prioritizing interventions: since our review identifies education and mental health as key protective factors, youth policies should ensure access to schooling and psychological support as central elements. By addressing these issues, stakeholders can make progress toward reducing NEET rates and improving youth outcomes in line with international goals. This meta-analysis adds to the scoping review in Chapter 2 by quantifying the effect sizes of 24 risk factors across 43 studies. Education's protective effect (OR=0.81) and family background associations (parental unemployment OR=1.54, income OR=1.29) were key alignments. There is substantial heterogeneity (I^2=45-98%), indicating that effect sizes differ considerably across countries.

The results of this meta-analysis inform future chapters in three ways: First, the variables for Iranian risk-profiling models in Chapter 4 are selected based on factors with the largest effects and the least heterogeneity (education, parental unemployment, mental health). Furthermore, global pooled estimates provide benchmarks; substantial deviations indicate Iran-specific dynamics. In addition, the observed heterogeneity of the labour market justifies the spatial analysis in Chapter 5 that examines the moderate effect of regional labour market structures on individual-level effects.

Chapter 4

Risk Factors of Becoming NEET Youth in Iran: A Machine Learning Approach

This chapter draws upon: Rahmani, Hamed, Wim Groot (2023). World Academy of Science, Engineering and Technology
International Journal of Economics and Management EngineeringVol:17, No:11, 2023.
International Conference on Business, Economics, Financial Sciences and Management ICBEFSM Montreal, Canada

Abstract

This chapter examines the factors that determine NEET (Not in Education, Employment, or Training) status among Iranian youth. The Spring 2021 Quarterly Labour Force Survey (n=192,182 youth aged 15-24) provides nationally representative cross-sectional data, on which Heckman-corrected Probit models are applied to account for selection bias, and classification and regression tree (CART) analysis is used to capture nonlinear interactions. Individual characteristics (education, potential work experience, housework), family characteristics (parental education, number of children under five), and household resources (birthplace, land ownership) are included as explanatory variables.

The findings show that education and work experience reduce the likelihood of being NEET, while housework increases it, with nearly twice as strong effects for women. NEET risks are also lower for urban-born women than rural-born women. Youth who spend over 20 hours per week on housework have an 83% chance of remaining NEET.

These findings indicate that reducing NEET requires improving educational and vocational pathways and addressing structural and cultural barriers, including gendered household labour distributions.

Keywords: NEET youth, Probit model, CART, Heckman correction, classification.

4.1. Introduction

The disengagement and unemployment of young people are pressing challenges worldwide, particularly in middle-income countries. As explained in Chapter 1, Iran's youth unemployment rate is high. In the spring of 2021, 11.8% of Iranians aged 15 and older were unemployed, and 24.4% of Iranian youth aged 15 to 29 were unemployed (World Bank, 2020). Youth unemployment poses a major social and economic challenge to the country, affecting families, communities, and the economy.

Concerns regarding the increase in unemployment, especially among youth with academic degrees, are high as its negative effects on the lives of youth and their families are clearly visible. What is concerning is that those who have dropped out of school and are not working appear to be more vulnerable to, for example, risks of social exclusion, poverty, criminal activity, and drug addiction (Ralston et al., 2022).

NEET is a term first introduced at the political level in England, referring to youth aged 15-24 who have dropped out of school, are not engaged in training, and are not employed (Lőrinc et al., 2020). With weakened educational engagement and precarious work, Fourlong (2006) noted that the notion gained traction as youth transitions became more complex. The consequences of being NEET are diverse, which underscores the need to identify its causes and roots. Youth participation in the economy and society will be enhanced through the development of appropriate strategies.

A variety of factors, including labour market conditions, individual, family and institutional characteristics, can influence the risk of becoming a NEET. Prediction models and evaluation studies have been developed to identify youth at risk. However, policy analyses of interventions often highlight the absence of gender-sensitive or interdisciplinary approaches (Abayasekara et al., 2019).

The Iranian NEET challenge must also be understood in the context of youth exclusion in the Middle East and North Africa (MENA), where gendered labour markets and entrenched sociocultural norms strongly shape youth trajectories. According to the International Labour Organisation (ILO, 2017), female NEET rates in the MENA region exceed 50%, compared with under 20% for males, making it the most gender-unequal region globally. The educational attainment of Iranian women has increased, but their labour force participation remains low due to domestic responsibilities and gender norms. NEET youth comprise a heterogeneous group that includes the unemployed, caregivers, and discouraged workers (Eurofound, 2012). Many international studies of NEET youth emphasise the European context (e.g., Bynner &

Parsons, 2002; Eurofound, 2012; Giret et al., 2020), which have welfare and labour-market institutions that differ from those in developing countries. Despite having one of the highest youth unemployment rates in the world and a highly gendered labour market, the MENA region remains understudied, and Iran is no exception (Hezar Jaribi & Sobhani, 2017; Zavareh et al., 2022).

Despite Iran's exceptionally high youth unemployment rates and a gendered labour market structure, very few studies have examined the determinants of NEET status. This research extends the global NEET literature beyond its European and Asian focus and offers a methodological contribution that enables the identification of nonlinear pathways into NEET status, particularly relevant in settings with complex cultural and institutional dynamics. This study builds on the global knowledge base about NEET risk factors established in Chapters 2 and 3. Chapter 3 illustrates considerable heterogeneity across international contexts, with I^2 values ranging from 45% to 98%. Despite providing useful benchmarks such as the protective effect of education (OR = 0.81), parental unemployment (OR = 1.54), and family income (OR = 1.29), global pooled estimates often conceal context-specific nuances that systematically differ across labour market structures and cultural environments due to this significant variation. The unique socioeconomic configuration of Iran makes it an ideal case study for examining these deviations. It faces exceptionally high youth unemployment (24.4% in 2021) and sanctions-induced economic constraints despite an excellent educational attainment rate of 98.8% and a 64% tertiary enrollment rate. In addition, there is severe gender segregation, with 39.1% of females classified as NEETs compared to 18.2% of males. In this chapter, we examine whether the key predictors identified in the meta-analysis, including education, family background, and mental health proxy measures, are similar in Iran or if some distinct country-specific patterns and mechanisms are different from the pooled international evidence.

We apply both econometric (Heckman-corrected probit) and machine learning (Classification and Regression Tree, CART) methods to a nationally representative dataset. There is no hierarchy between these approaches; they are complementary. It is essential for a comprehensive understanding of the determinants of NEET in Iran's complex institutional context, where non-linear relationships exist between individual characteristics and outcomes, that Probit model provides effect sizes for population-level policy evaluations and that CART enables individual risk stratification for a risk screening framework.

4.2. Literature Review

While other countries have a history of research on NEET (Bynner, J., & Parsons, S., 2002; Giret et al., 2020), there is little evidence available for Iran. Zavareh et al. (2022) demonstrated a strong relationship between household poverty and NEET status in urban settings, whereas poverty primarily served as a trigger for temporary NEET status in rural areas, mitigated by informal agricultural work in Iran. Families with young children and large households were more likely to be in poverty and to have NEETs, while the household head's higher income, age, and education were protective factors (see Chapter 2 for more details). According to Hezar Jaribi and Sobhani (2017), Iran's NEET rate stood at roughly 23% in 2016, with women's rates 2.5 times higher than men's. Certain vulnerabilities were identified, such as being 25-29 years old, having a bachelor's degree, and living in peripheral provinces. A persistent skills mismatch has resulted from the rapid expansion of universities since the early 2000s, driven by uncoordinated development and educational policies.

Salehi-Isfahani and Egel (2007) explored the link between the late 1970s-1980s youth bulge and entrenched social exclusion at the macro level. A high level of competition for university entrance exams restricts access to higher education, making many applicants vulnerable to unemployment and social stigma. Even though women have made significant educational gains, their unemployment rate remains higher than that of men's. Nourani et al. (2024) recommended growth-oriented policies, job creation for educated youth, and strategies to reduce structural unemployment. Consequently, these studies demonstrate that NEET is shaped by a combination of micro-level, structural, and institutional factors, as well as by its economic and social consequences.

According to the human capital theory (Becker, 1964), investing in education and work experience increases productivity and reduces the number of NEETs. Women's cultural and domestic responsibilities disproportionately limit their participation in education and employment (Acker, 1990; Hakim, 2000).

In recent studies, both econometric models and machine learning techniques have been used to analyze NEET dynamics. The WeLaR project on "NEETs in the Digital Age" by Smoter & Szymczak (2024) used a multi-step approach. As a first step, probit regressions were used to compare the likelihood of NEETs with skills and previous work experience with that of their employed peers. An ordinary least squares (OLS) model was used to simulate NEETs' skill levels after this "upskilling" exercise, without observed gaps. Lastly, a Random Forest

classifier was used to determine the relative importance of skill variables and training participation in predicting NEET status. Traditional models can provide interpretable marginal effects using this hybrid approach. At the same time, machine learning techniques can detect complex interaction structures and provide out-of-sample validation. The Middle East and North Africa (MENA) region has few studies, but emerging research demonstrates the relevance of machine learning to the analysis of youth inactivity (Aarthi et al., 2023). A recent study in Morocco used Random Forest and C5.0 classifiers to identify high-risk groups most likely to experience long-term disengagement (El Ferti & coauthors, 2021). A complementary econometric analysis in Turkey has focused on NEET status and mental health outcomes, using bivariate probit models with selection, thereby reinforcing the importance of accounting for selection effects and unobserved heterogeneity (Yüksel & Etiler, 2019).

Our study aims to apply an individual-level analysis to a large, nationally representative dataset. By incorporating variables such as education, potential work experience, housework, family education, and birthplace, we identify risk factors for youth and households. No Iranian study has systematically combined econometric methods with sample selection correction and machine learning to capture individual-level and gendered determinants of NEET status. This study investigates micro-level determinants of NEET in Iran using Heckman-corrected Probit and CART. Most quantitative research has relied on a deductive method, in which hypotheses are derived from theory and then statistically tested to assess the theory's generalizability. This study employs both deductive and inductive approaches. It can provide new insight into the problem under study or confirm what has already been learned about unemployment. An empirically rigorous, data-driven framework is presented for academic understanding and targeted policy interventions.

4.3. Data and methodology

In this study, cross-sectional data from the Iranian Labour Force Survey conducted in Spring 2021 are used. The data was obtained from the Statistical Centre of Iran and the Ministry of Cooperatives, Labour, and Social Welfare (Labour Force Survey 2021). There were 1170 primary sampling units (PSU) included in the Iranian Labour Force Survey. Each PSU or Enumeration Area (EA) was defined as a non-overlapping, contiguous geographical region with discernible borders. The country has five geographical regions: the north, south, east, west, and centre. Each division was further subdivided into urban localities and rural areas. Housing prices categorized households as 'expensive', 'semi-expensive', or 'not expensive'. There were 15 strata in the country as a result.

A total of 120,000 households were included in the sampling frame, with approximately 105 households in each PSU or EA. The PSUs or EAs were set up nationwide to generate a representative sample of Iran's entire population. Multistage cluster random sampling was used for the sampling process. Therefore, the following steps were taken:

To ensure that all three household types are represented, 1170 PSUs and EAs are randomly selected from all districts and 15 regional strata. Second, of the approximately 105 households located within each PSU or EA, 20 households were randomly selected. The formula was used to determine the sample size for subpopulations:

$$n=\left[\frac{(1-p)}{p}\times\left(\frac{z(\alpha/2)}{r}\right)^2\right]\times deff \quad (1)$$

where p is the expected population proportion, z is the standard normal variate corresponding to the desired confidence level, r is the margin of error, and *deff* is the design effect. For this survey, we assumed $\alpha = 0.004$, *deff* = 2, $r = 0.05$, and $p = 0.038$; the minimum required sample size was approximately 167,800 individuals (from Labour Force Survey 2021).

In the original Iranian Labour Force Survey (Spring 2021), 196,250 youth aged 15-24 were included. The final analytical sample contained missing data for several key variables, necessitating careful handling.

In total, 4,068 youths (2.07% of the original sample) had missing values on at least one variable. Missingness was not randomly distributed. Youth with missing employment status data were disproportionately female (62% vs 51% in complete cases) and rural (41% vs 34% in complete cases), suggesting that survey non-response may be associated with social marginalization, the very populations most likely to be NEET.

We employed listwise deletion (complete-case analysis), retaining only observations with valid data on all variables included in the models. This approach yielded a final analytical sample of n = 192,182 youth (97.93% of the original sample).

In the Quarterly Labour Force Survey 2021 dataset, NEET refers to people who meet three requirements: first, they are youth aged 15 to 24; second, they are not employed; third, they have missed education or training in the four weeks preceding the survey. We acknowledge that defining NEET status using a four-week reference period, as per ILO standards, may underestimate long-term disengagement, particularly for women who face structural barriers to labour force participation. We adopt this internationally recognized definition for consistency and comparability. Here, education refers only to formal education; informal

education and short-term educational activities are not included. The term "unemployment" refers to a situation in which there was less than 1 hour of paid work in the previous week. The NEET status was coded as a binary outcome based on our three criteria for selecting NEET individuals from the data: 1 if the individual was NEET, and 0 otherwise. We used three separate NEET variables: one for all youth, one for males, and one for females. As a result, it is easier to conduct the study independently for both males and females and then draw conclusions from the results. Explanatory variables include education, work experience, and time spent doing housework. As these variables were common among youth NEETs and in many previous studies, we could select only NEET youth from the population (Gaspani, 2019; Coles et al., 2010; Buheji, 2019).

The number of years in school was used to determine the education level. Three assumptions were made regarding individuals and their educational qualifications: (i) no individual was assumed to have completed more than one diploma, bachelor's, or master's degree; (ii) individuals who completed a bachelor's or master's degree were assumed not to have completed a diploma beforehand; and (iii) degrees were converted into years of schooling as follows: No schooling = 0 years, Primary completion = 6 years, Lower secondary= 9 years, Upper secondary/Diploma = 12 years, Associate degree = 14 years, Bachelor's degree = 16 years, Master's degree = 18 years and PhD students = 18 years (counted as Master's since incomplete PhD). This coding follows the structure of Iranian higher education and is consistent with UNESCO's ISCED 2011 classification. Although this approach simplifies variation across programs and institutions, such compression is common in large-scale labour force surveys where transcript-level detail is unavailable. We tested alternative coding schemes (e.g., diploma = 13-14 years, bachelor's = 17-18 years, master's = 19-20 years) to address concerns about sensitivity. The results remained robust in terms of sign, magnitude, and statistical significance. In our age group (15-24 years), the highest level of education is a Master's degree (18 years), typically achieved by 24-year-olds who started school at age 6 and progressed without delay. It is extremely rare for PhD students to reach the age of 24, and they are coded as 18 years old (master's level) because they are unable to complete their doctorates. While not perfect, this coding scheme provides a consistent and defensible approximation of educational attainment in Iran. Our dataset did not directly measure work experience. Thus, prospective experience replaced labour market experience. We recognize that the Mincer (1975) measure of potential experience (age – years of education) may overstate actual labour market experience in Iran due to delayed school entry, compulsory military service for men,

and educational interruptions (Nazarzadeh Zare et al., 2024). We considered experience = Age - Years of Education - 6. This standard proxy assumes (a) school entry at age 6, (b) continuous education without gaps, (c) no overlap between work-study and the labour market, and (d) immediate entry into the labour market after education. Since this measure is imperfect, it is likely to underestimate the experience of youth who work while studying (common in Iran) or take gap years. Negative values (which occur when age < education + 6, e.g., 18-year-old with bachelor's degree) are coded as zero, assuming no work experience for early graduates. Despite these limitations, it remains the most widely used proxy in cross-sectional datasets where actual work histories are unavailable. Time spent on household work was the sum of all household activities, production of commodities and services for own use, and total hours worked each week (Krantz-Kent, 2009). The Iranian Quarterly Labour Force Survey is designed to measure employment status, educational attainment, and basic household characteristics; it does not collect information on physical or mental health, substance use, social networks, or neighbourhood characteristics. As a result, the models capture what is measurable in the available data rather than the full set of risk factors found in Chapters 2 and 3.

Social desirability may lead male respondents to over-report and female respondents to under-report in traditional contexts. A face-to-face survey may exacerbate bias.

In addition to these explanatory variables, four exclusion restrictions are incorporated into the Heckman selection equation to account for unobserved family and regional constraints that may bias NEET estimates. These factors reflect the underlying variables that influence a person's educational, work, or training choices. We use these factors to account for unexpected behaviour between variables. These factors include birthplace, the amount of land households hold, the number of children under age 5, and the total years of education for all family members to verify whether family education affects youth NEET status. The type of birthplace is used to determine whether a proxy has early access to schooling and social infrastructure (Çolak & Koç, 2023). Birthplace was coded as a binary indicator distinguishing between youth born in urban versus rural areas, with rural-born as the reference category (1=born in urban area (cities >50,000 population), 0=born in rural area). In this study, household land ownership was considered as a proxy for wealth and family resources. It is expected that the youth NEET status is positively correlated with land ownership (Bisht & Pattanaik, 2023). This is because a wealthier household can afford to engage in more 'conspicuous leisure' than a poor household (Abayasekara & Gunasekara, 2019).

The number of children under five in the household is included because female youth may have to stay at home to care for young children, and male youth may be forced to get a job to help support their families if there are young children in the home (Dicks et al., 2022). While these instruments are common proxies in similar studies, we recognise that they may directly affect NEET status and influence participation decisions. For example, caregiving responsibilities or household wealth may directly constrain labour market engagement (Runcan & Rad 2024). Therefore, we employ the Heckman correction primarily as a robustness exercise rather than as a strict identification strategy.

Family education, measured as the average number of school years completed by all household members divided by household size, serves as an indicator of household aspirations and the educational environment. Educated families create more supportive conditions for human capital development by encouraging schooling. We acknowledge that family education could affect NEET through unmeasured mechanisms (networks, cultural capital), so identification relies partly on the functional form. The variables and their definitions used in this analysis are described in Appendix 4.1.

All statistical analyses were conducted using Stata 17.0 and R version [4.3.1] software packages (rpart version 4.1), ensuring reproducibility of results.

The analysis aims to identify the factors affecting youth NEET status in Iran. Our dependent variable is binary, so our estimations use a Probit model. Two desirable characteristics of Probit led to its selection: (i) the estimated conditional probability is always between zero and one, and (ii) the relationship between the independent and dependent variables is non-linear (Chib & Greenberg, 1998). Consequently, as the estimate of the conditional probability approaches zero or one, the rate of change diminishes as the estimated conditional probability approaches either one or zero (Williams & Jorgensen, 2023).

The Probit models for this analysis are given as follows:

$$\Pr(NEET = 1|X1,X2,X3) = \Phi(\beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \varepsilon i) \quad (2)$$

where, X1 = education , X2 = experience , X3 = housework and Φ = cumulative standard normal distribution function. The determinants of NEET status for all youth, as well as the determinants of NEET status for each gender, are investigated using three independent models.

We run separate models by gender rather than including a gender dummy variable in a single pooled model. A dummy variable in a pooled model constrains all slope coefficients to be equal

across genders, allowing only the intercept to differ, assuming that education, work experience, and housework hours affect male and female NEET risk in the same way. It is unlikely that this assumption holds in the Iranian context, where the mechanisms linking these variables to NEET status are fundamentally gendered. Housework hours, for instance, reflect domestic caregiving obligations that are structurally imposed on women through cultural norms, whereas for men the same variable more often captures voluntary or residual household participation. Similarly, the returns to education in terms of reduced NEET rates may differ by gender because women face additional labour market barriers, employer discrimination, occupational segregation, and mobility restrictions that attenuate the protective effect of schooling.

Separate estimation allows every coefficient, including the selection equation parameters in the Heckman specification, to vary freely across genders. This is equivalent to a fully interacted model (all variables × gender) but more transparent and easier to interpret.

NEET status does not occur randomly; the contexts of families, cultural norms, social networks, and regional conditions heavily influence youth participation in education and employment (see Chapter 2). A simple Probit model for NEET status may produce biased estimates if labour force participation is itself a non-random selection process: youth who choose to participate in the labour force may differ systematically, on unobserved dimensions, from those who do not, and these unobserved factors may also correlate with NEET status. The Heckman-corrected Probit sample selection correction addresses this specific form of selection bias by first modeling the participation decision and then correcting the outcome equation using the inverse Mills ratio derived from that first stage (Heckman, 1979).

In the first stage, a selection equation estimates a youth's likelihood of engaging with the education or employment system. We acknowledge that some exclusion restrictions used in the Heckman correction (e.g., birthplace, land ownership, family education, presence of young children) may directly influence NEET status and participation decisions. Despite concerns about instrument validity, we applied the Heckman-corrected Probit primarily as a robustness test rather than as a strict causal interpretation. Despite these limitations, our results are consistent across both the standard Probit and the Heckman-corrected models, strengthening confidence in the robustness of our findings.

Second, using a Probit outcome equation, the probability of being NEET is estimated (1 = NEET, 0 = not NEET). The first stage's inverse Mills ratio (λ) is included as a regressor, thereby correcting for unobserved heterogeneity. This allows us to obtain unbiased and consistent

estimates of the effects of individual-level variables (education, potential work experience, housework) on NEET status.

The Heckman selection equations use birthplace, land ownership, family education, and number of young children to determine family background and opportunity structure. These variables are assumed to influence participation decisions (education or work) but not directly affect NEET outcomes once individual characteristics are controlled. The Wald test of independent equations is significant, and the estimated rho (ρ) values are non-zero, indicating that selection bias is present and supports the use of the Heckman correction as a robustness check. In principle, these variables could influence NEET status directly, not only through the participation (selection) decision, which raises concerns about instrument validity.

In classical Heckman selection models, valid exclusion restrictions must influence the selection mechanism without directly affecting the outcome. As structural constraints and family resources can directly influence a youth's likelihood of disengagement, we explicitly acknowledge that the instrumental variables used in our first-stage research don't satisfy the exogeneity assumption, including birthplace, land ownership, the presence of young children, and family education. Furthermore, unlike in the classical Heckman setting, where outcomes are observed only for a restricted sample, NEET status is observed for all youths in our dataset. Therefore, our first-stage 'selection' is specifically designed to capture unobserved family and regional constraints that might otherwise bias the coefficients for education, experience, and housework. Because of this, we do not claim pure causal identification. Although our identification relies partially on the functional form and the non-linearity of the inverse Mills ratio (Puhani, 2000), our main results remain highly consistent across both the standard Probit and Heckman-corrected specifications. Considering the consistency of this Heckman specification, as well as the recognition of alternative methods to address such endogeneity, such as bivariate Probit models (Nandakumar, 1984), we are more confident that it is a rigorous sensitivity analysis and robustness test rather than a definitive analysis of causal mechanisms.

To complement the econometric models, we use a Classification and Regression Tree (CART) analysis to capture nonlinear relationships and interactions among predictors of NEET status. Decision trees identify threshold effects and interaction patterns without requiring pre-specification, though they involve subjective choices (tree depth, pruning) and risk of overfitting (Lewis, 2000). Whereas regression models provide average marginal effects, CART identifies conditional associations and empirical clusters through recursive partitioning. Based on shared characteristics, the algorithm groups youth with similar NEET probabilities,

revealing heterogeneity hidden in population averages. The data-driven patterns identify threshold dynamics and high-risk profiles for targeted interventions, not causal mechanisms.

A random subset of 60% of the dataset was used for training, and the remaining 40% was held out entirely for testing. To ensure model robustness and reduce overfitting, we applied a 10-fold cross-validation procedure within the training set only, in which the training data were partitioned into 10 equal folds: 9 for training and 1 for validation in each iteration. The process was repeated until each fold had served as the validation set once. The Gini impurity criterion was used to determine how often an observation would be incorrectly classified if it were labelled according to the distribution of classes within a node. Recursive partitioning proceeded until either the gain in node purity was less than 0.001 or the maximum tree depth, the number of sequential splits from the root node to the terminal node, reached six levels. We required a minimum node size of 20 observations to prevent unstable results from very small samples. Using the "1-SE rule," the simplest model with error within one standard error of the minimum cross-validation error was selected. As a result of these parameter settings, both statistically robust and substantively meaningful results are obtained.

Four standard evaluation measures were used to compare the CART model with the Probit and Heckman-corrected Probit models: accuracy, sensitivity, specificity, and the F1 score. A threshold of 0.5 was used to convert the Probit-based models into binary outcomes, with robustness checks at thresholds of 0.4 and 0.6 also producing consistent results. Using the majority rule at each terminal, predicted class labels were assigned directly within the CART framework. Accuracy reflects the overall proportion of correctly classified cases, sensitivity (true positive rate) captures the share of actual NEETs correctly identified, and specificity (true negative rate) captures the share of non-NEETs correctly identified. The F1 score, defined as the harmonic mean of precision and recall, provides a balanced measure of model performance when the outcome is imbalanced, as is the case for NEET versus non-NEET youth (Pathak et al., 2018). We can provide a more comprehensive comparison of econometric and machine learning approaches by incorporating these complementary indicators.

Our CART analysis prioritizes interpretability; it is exploratory, aiming to identify the most influential predictors and the combinations of conditions that trap youth in NEET status. In this regard, the CART complements the Probit model rather than replacing it, illustrating how education, potential work experience, and housework influence NEET outcomes.

Our modeling approach was validated by assessing model performance and testing for selection bias. In Heckman models, we examined the correlation (rho) between selection and outcome equation errors and the significance of the inverse Mills ratio (lambda). Selection bias requires a two-stage correction when significant values are present.

Multiple metrics were used to assess the performance of the model, including accuracy (proportion correctly classified), F1 score (balancing precision and recall), Diagnostic Odds Ratio (DOR), and Area Under the ROC Curve (AUC). For robustness assessment, we compared Probit, Heckman-Probit, and CART approaches.

4.4. Results

The Quarterly Labour Force Survey Spring 2021 dataset covered 28,112 households and 573,475 individual observations across all age groups. From this dataset, we extracted 196,250 observations for youth aged 15 to 24, excluded 4,068 observations (2.07%) with missing NEET status, and retained a final analytical subsample of 192,182 observations (97.93% of the youth extraction). Within this subsample, 44% (84,560) were male, and 56% (107,622) were female, reflecting the slight overrepresentation of young women in Iran's youth population. Approximately 34% (65,342 individuals) were classified as NEET within this analytic subsample. The prevalence of NEET was notably higher among women: 22% of men (18,603 out of 84,560) were NEET, whereas the corresponding share among women was 43% (46,739 out of 107,622). This gender disparity is consistent with broader labour market patterns in Iran, where young women face greater barriers to education and employment participation. This provides a nationally representative picture of youth participation and disengagement across provinces, stratified by gender, region, and urban–rural residence. The Probit regression coefficients in Table 4.1 indicate that, across all youth, males, and females, education is negatively and statistically significantly associated with the probability of NEET status. However, education has a greater influence on NEET status among males than among females. NEET status is also negatively correlated with potential work experience for all youth. Housework hours are also associated with the likelihood of being a NEET across all models. However, when all other variables are held constant, females are more likely than males to be NEET due to housekeeping. For all models, the Wald chi-square test statistic is significant. The coefficients of the Probit model cannot be interpreted as marginal effects because it is nonlinear (Gujarati, 2013; Stock & Watson, 2011). Wooldridge (2013) recommends calculating the average marginal effects from these models to determine the magnitude of each independent variable's impact on the dependent variable.

Table 4.1. Results of Probit model estimation

Variables	Youth NEET	Male youth NEET	Female youth NEET
Experience	- 0.2072*** (0.0018)	- 0.1899*** (0.0033)	- 0.2107*** (0.0019)
Education	- 0.1292*** (0.0031)	- 0.1485*** (0.0048)	- 0.1312*** (0.0032)
Housework	0.0236*** (0.0003)	0.0091*** (0.0004)	0.0178*** (0.0004)
Wald χ^2	31760.42***	4461.53***	18448.52***
Constant	-4.8986*** (0.0391)	-5.0632*** (0.0819)	-4.2934*** (0.0451)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4.2 presents the average marginal effects from the Probit model and shows that, when all other variables are held constant, each additional year of education decreases the probability of being NEET by 2.5 percentage points (PP) among male youth, while among female youth, the decrease is 2.1 PP. Each year of potential work experience for males is associated with a 3.5 PP lower likelihood of becoming a NEET, while for females it reduces the likelihood by 3.6 PP. Housework duties are almost twice as important in estimating female NEET status as in estimating male NEET status; the likelihood increases by 0.31 PP for females for every additional hour spent on household tasks, but only by 0.18 PP for males. These patterns are consistent with MENA evidence on gender norms and caregiving burdens (Assaad & Roudi-Fahimi, 2007; ILO, 2017).

Table 4.2. Average marginal effects of Probit model estimation

	Youth NEET	Male youth NEET	Female youth NEET
Education	- 0.0263*** (0.0003)	- 0.0252*** (0.0006)	- 0.0211*** (0.0004)
Experience	- 0.0387*** (0.0002)	- 0.0351*** (0.0004)	- 0.0364*** (0.0003)
Housework	0.0044*** (0.0000)	0.0018*** (0.0001)	0.0031*** (0.0000)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4.3 reports the estimates from the Heckman-corrected Probit models for all youth, and separately for male and female subsamples. The Inverse Mills Ratio (λ) is statistically significant in all specifications, indicating selection bias and validating the Heckman

correction. In all three cases, the Wald test of independent equations rejects the null hypothesis, indicating results obtained from estimating simple Probit models without correction would be biased, underscoring the value of the Heckman approach.

The results are broadly consistent with those obtained from the standard Probit model. However, the magnitudes of the coefficients are somewhat smaller, suggesting that earlier models may have overstated the role of certain covariates because they did not account for underlying family- and regional-level constraints. Higher levels of education and work experience reduce the probability of being NEET, with a slightly larger effect for men, whereas time spent on housework increases the risk, particularly for women.

NEET status among female youth is negatively correlated with land ownership, and this effect increases with land ownership, suggesting that young women from wealthier households are less likely to be NEETs. In contrast, land ownership has little impact on men's NEET status. Due to the gendered composition of households, men with young children are at a lower risk of NEET because they are breadwinners, whereas women with young children are at a higher risk because of their increased responsibility for unpaid care. Family education is positively associated with NEET risk for both genders, which may reflect higher reservation standards and unwillingness to accept low-quality employment in more educated households. In addition, the birthplace effect highlights spatial inequalities; female youth born in rural areas are more likely to be NEET than those born in urban areas, highlighting labour-market access inequalities.

Table 4.3. Results of Selection Bias Corrected Probit Model Estimation

Model	Selection equation	Main equation	Selection equation	Main equation	Selection equation	Main equation
Variables	Youth NEET	Youth NEET	Male youth NEET	Male youth NEET	Female youth NEET	Female youth NEET
Experience		- 0.1870***		-0.1820***		-0.1791***
		(0.0022)		(0.0042)		(0.0053)
Education		- 0.1411***		-0.1419***		- 0.1081***
		(0.0025)		(0.0032)		(0.0034)
Housework		0.0311***		0.0072***		0.0184***
		(0.0004)		(0.0001)		(0.003)
Land 2	-0.0758***		0.0117		-0.1241***	
	(0.0058)		(0.0081)		(0.0072)	
Land 3	-0.1475***		0.0417***		-0.1987***	
	(0.0073)		(0.0081)		(0.0064)	
Land 4	-0.1824*		-0.0122		-0.2210***	
	(0.0109)		(0.0146)		(0.0118)	
Land 5	-0.1617***		0.0341		-0.2194***	
	(0.0249)		(0.0327)		(0.0276)	
Number of Children under 5 years old	0.0269***		-0.3311***		0.1707***	
	(0.0032)		(0.0056)		(0.0030)	
Family education	0.0081***		0.0109***		0.0041***	
	(0.0001)		(0.0001)		(0.0001)	
Birthplace	-0.0711***		0.0000		-0.0823***	
	(0.0041)		(0.0063)		(0.0047)	
Constant	-0.9425***	-4.3118***	-1.4040***	-3.9984***	-1.1527***	-3.0531***
	(0.0058)	(0.0029)	(0.0038)	(0.0058)	(0.0043)	(0.0248)
Inverse Mills ratio		-0.2456***		-0.2254***		-0.4328***
		(0.0127)		(0.0144)		(0.0336)
Rho		-0.2643		-0.2512		-0.4462
		(0.0372)		(0.0387)		(0.0372)
LR chi-squared	3476.42***		7223.44***		3897.44***	
Wald chi-squared		7963.44***		5672.61***		1983.42***

After correcting for selection bias, the Heckman average marginal effects in Table 4.4 quantify the impact of key variables on the probability of being NEET. In the Heckman-corrected model, the coefficients for education, experience, and housework are smaller than in the uncorrected probit model. The Heckman-corrected marginal effects are substantially smaller than those from the simple probit (e.g., education: 0.009 vs. 0.026), confirming that the uncorrected model overestimated the influence of these variables by failing to account for unobserved selection factors. The results show that education and work experience consistently decrease this likelihood, while housework increases it, with notable differences between genders. Specifically, each additional year of education decreases the probability of being NEET by 1.24 percentage points (PP) for male youth and 1.05 PP for female youth. The protective effect of work experience is even stronger, reducing the risk by 1.59 PP for males and 1.79 PP for females for every year of potential experience. Conversely, an extra hour of housework increases the chance of being NEET by 0.23 PP for females, an effect substantially larger than the 0.16 PP increase for males.

Table 4.4. Average marginal effects of the Heckman-corrected Probit model

Variables	*Youth NEET*	*Male youth NEET*	*Female youth NEET*
Education	- 0.0093*** (0.0001)	- 0.0124*** (0.0003)	- 0.0105*** (0.0003)
Experience	- 0.0142*** (0.0001)	- 0.0159*** (0.0001)	- 0.0179*** (0.0005)
Housework	0.0017*** (0.0000)	0.0016*** (0.0000)	0.0023*** (0.0000)

In addition to econometric models, classification tree analysis captures conditional interactions among the main correlates of NEET status. The Classification and Regression Trees (CART) model was constructed using the explanatory variables identified in the Probit analysis with education, potential work experience, and housework hours. Unlike regression, which estimates average marginal effects, the classification tree identifies association-based conditional patterns, for example, how housework burden and work experience jointly relate to elevated NEET probability through recursive data partitioning rather than causal estimation. Domestic responsibilities are the single most important classifier of NEET status, with the primary split occurring at the threshold of 20 hours of housework per week. Among youths who spend more than 20 hours on household activities, 83% are NEET, representing 56% of the total. Work history plays a paradoxical role in this high-housework segment; those with less than 3 years of potential experience have a 93% chance of being NEET. This pattern suggests that domestic responsibilities combined with extended absences from education or

employment lead to inactivity. Conversely, a person with less than 20 hours of housework per week has a 78% chance of being in a Not-NEET situation. For this low-housework group, potential work experience is the secondary determinant; those with 5 or more years of experience have a 63% probability of being NEET, though this risk is mitigated by education. Specifically, for those with more than 5 years of experience, having more than 8 years of schooling increases the probability of not being NEET by 58%. Household responsibilities play a significant role in NEET outcomes, though the binary definition of NEET used here does not distinguish between discouraged workers and those in the informal economy.

CART was added to the econometric results to identify critical thresholds that contribute to youth becoming NEETs. However, these thresholds should be considered approximate, as CART models may be subject to overfitting. Considering Iran's sociocultural context, women are primarily responsible for caregiving and domestic work, which is consistent with these results. Internationally, caregiving responsibilities limit women's labour force participation (ILO, 2017; Assaad & Roudi-Fahimi, 2007).

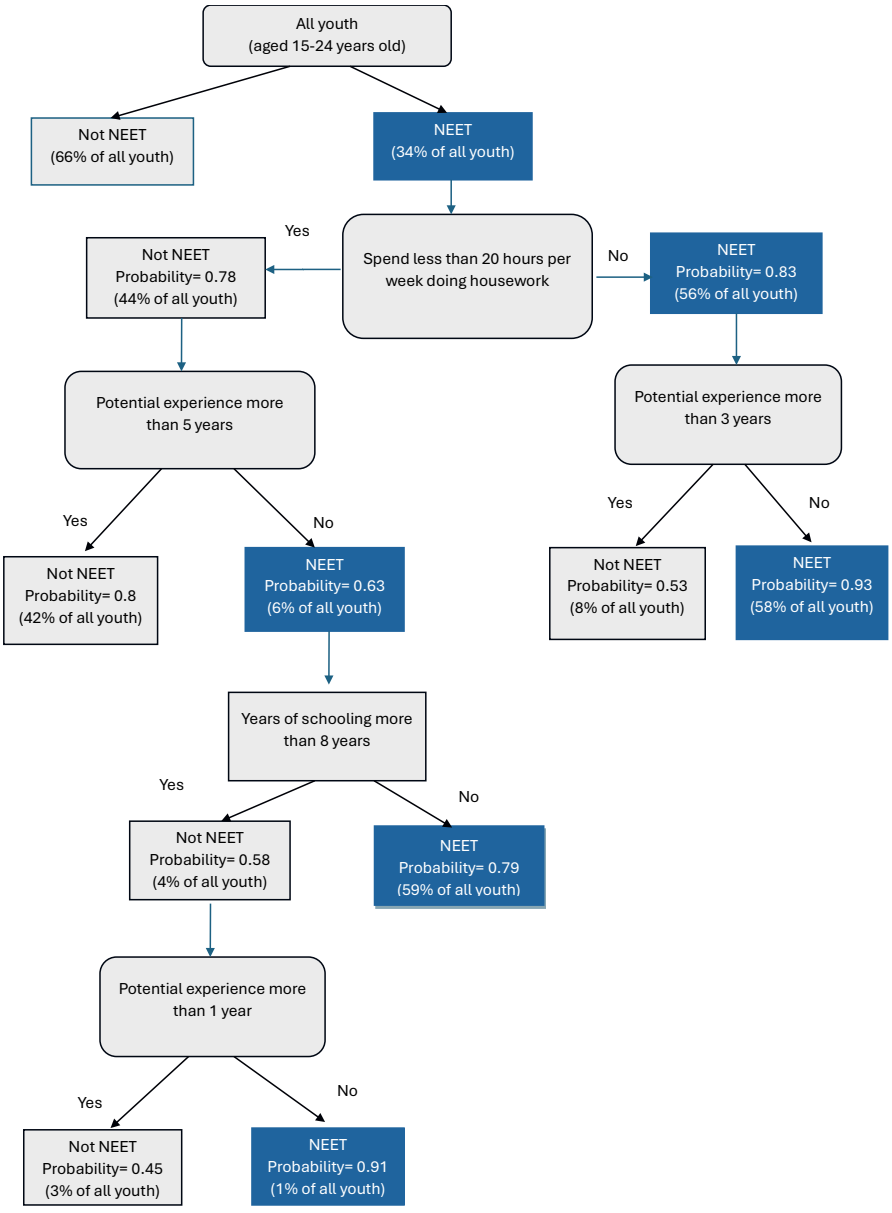


Figure 4.1. A Youth Classification Tree. Classification and Regression Tree estimated using recursive partitioning (60% training sample, 40% testing sample). Splits are based on Gini impurity reduction, and the model is pruned using the 1-SE rule after 10-fold cross-validation.

We use standard classification metrics derived from confusion matrices to evaluate the predictive performance of the Probit, Heckman-corrected Probit, and CART models, including accuracy, sensitivity (TPR), specificity (TNR), precision (PPV), F1-score, and Diagnostic

Odds Ratio (DOR). These indicators assess the models' ability to distinguish between NEET and non-NEET youth. Technical definitions of these measures are provided in Table 4.5.

Table 4.5. A generic confusion matrix and the performance indicators associated.

True condition	Condition positive	Condition negative
Predicted positive	TP (True Positives)	FP (False Positives)
Predicted negative	FN (False Negatives)	TN (True Negatives)

Table 4.6. The performance of the Heckman-corrected Probit model

Metrics	Formula	Description
Prevalence	(TP + FN) / Total	Proportion of actual NEET cases in the dataset.
Accuracy	(TP + TN) / Total	Overall correctness of the model (both NEET and non-NEET).
Sensitivity (Recall, TPR)	TP / (TP + FN)	The model's ability to correctly identify NEET youth.
Specificity (TNR)	TN / (TN + FP)	The model's ability to correctly identify non-NEET youth.
Precision (PPV)	TP / (TP + FP)	Proportion of predicted NEET cases that are truly NEET.
False Discovery Rate (FDR)	FP / (TP + FP)	Proportion of predicted NEET cases that are actually non-NEET.
False Omission Rate (FOR)	FN / (FN + TN)	Proportion of predicted non-NEET cases that are actually NEET.
Negative Predictive Value (NPV)	TN / (TN + FN)	Proportion of predicted non-NEET cases that are truly non-NEET.
F1 Score	2 × (Precision × Recall) / (Precision + Recall)	Balances precision and recall; useful for imbalanced data.
Likelihood Ratio Positive (LR^+)	Sensitivity / (1 – Specificity)	How much more likely are NEET youth to be correctly classified than by chance?
Likelihood Ratio Negative (LR^-)	(1 – Sensitivity) / Specificity	How much more likely are NEET youth to be missed by the model than by chance?

Table 4.7 summarizes performance statistics across all models and subgroups. We have computed all classification metrics in this table on the 40% held-out test set, which was not used during model training or cross-validation, to ensure that they reflect genuine out-of-sample predictive performance. Overall, youth models exhibit high predictive performance, including Heckman-Probit and Probit, both of which achieve accuracy over 83% and AUC

over 0.87. CART has a slightly lower accuracy and AUC (82%), but it has the distinct advantage of identifying conditional pathways that regression models cannot.

The gender-disaggregated results reveal some interesting patterns. While the male models are accurate (approximately 90% for Heckman-Probit), their F1 scores are lower, especially for Heckman (0.48). The F1 scores of female models are higher (0.860-0.90), indicating a more balanced approach to identifying NEETs, while the AUC values are lower (0.72-0.73), indicating weaker discrimination overall. Female NEET outcomes follow more predictable patterns dominated by household responsibilities, while male NEET outcomes are more heterogeneous.

There is also a gender difference in CART's performance. According to CART, women achieve 83.4% accuracy, an F1 score of 0.86, and an AUC of 0.81. It appears that male NEET pathways involve more complex interactions that are difficult to capture through simple decision rules, since CART accuracy drops to 80.3% with weaker discrimination (AUC=0.74).

Table 4.7. Comparative Performance of Probit, Heckman-Probit, and CART Models

Model	Group	Accuracy (%)	F1 Score	Diagnostic Odds Ratio (DOR)	AUC
Probit	Youth	83.40%	0.86	30.7	0.89
	Male	87.80%	0.88	19.4	0.87
	Female	84.40%	0.89	18.1	0.72
Heckman-Probit	Youth	84.90%	0.87	32.5	0.88
	Male	89.70%	0.48	197.3	0.87
	Female	84.70%	0.9	25	0.73
CART	Youth	82.10%	0.83	21.5	0.81

Despite these performance differences, substantive conclusions are consistent across all three approaches: education consistently protects against NEET status, housework burden increases risk (especially for women), and gender differences are significant. By combining these three approaches, we can increase confidence that our findings reflect real patterns rather than

modeling artifacts. The Heckman-Probit method remains the preferred approach for correcting selection bias in statistical inference. Probit provides interpretable risk scores, while CART identifies actionable thresholds and high-risk profiles for a risk-stratification tool for policy targeting.

4.5. Discussion

This study provides new evidence on the determinants of NEET status in Iran by combining econometric models (Probit and Heckman-corrected Probit) with machine learning analysis (CART). The integration of these approaches enables both robust statistical inference and the identification of conditional pathways that push youth into disengagement. The study enriches international debates on youth transitions while addressing a major research gap in Iran.

Consistent with human capital theory (Becker, 1964), both education and potential work experience reduce the probability of being NEET. An additional year of education reduces the risk of disengagement, while more experience strengthens labour market attachment. There is a slightly stronger protective effect for males, but both genders benefit. According to international research from Europe and the OECD, low educational attainment and a lack of labour market experience are consistently among the strongest classifiers of NEET status (Eurofound, 2012; Giret et al., 2020).

Our results reveal significant gender disparities. The risk of women becoming NEET is nearly double that of men, and there are marked differences in the drivers of disengagement between men and women. Domestic responsibilities are seen as a major barrier for women. This is compounded by formal institutional barriers; Iranian public sector recruitment policy gives explicit hiring preference to men over equally qualified women, structurally excluding female youth from formal employment independent of their education or skills. Probit models indicate that each additional hour of housework substantially increases the likelihood of female disengagement, nearly twice as much as for men. CART analysis illustrates this dynamic vividly, young women who work over 20 hours per week in household tasks face an 85% likelihood of remaining NEET. These findings clearly reinforce gender role and social norm theories (Acker, 1990; Hakim, 2000), which emphasize how unpaid care responsibilities constrain women's participation in education and employment.

Heckman-corrected Probit models support these conclusions while also highlighting unobserved family and regional dynamics. After adjusting for selection, education and experience have a smaller impact than in simple Probit models, suggesting that unobserved

family background factors, such as household resources and local opportunities, influence both participation decisions and NEET outcomes. In addition, parental education and family resources affect youth aspirations and capacities beyond individual characteristics (Bourdieu, 1986; Coleman, 1988).

Women face a consistent penalty from housework and childcare responsibilities. Caregiving obligations undermine the value of education, leading to disengagement. The family care responsibilities of women in the MENA region negatively affect their participation in the labour market and education (ILO, 2017; Assaad & Krafft, 2015).

The presence of children under five years old has opposite effects across genders. Having young children increases women's NEET risk, in line with their responsibility to care for them. It is possible to reduce the NEET risk for men by reinforcing breadwinner responsibilities for young children. The persistent division of labour in Iranian households can be seen in the gendered disparity. As a result of the transmission of resources and aspirations from generation to generation, youth who are in educated families are less likely to become NEET. Women are particularly affected, demonstrating how educated families can encourage participation and challenge restrictive gender norms.

Furthermore, the results reveal the intersection between geography and gender. Women are more likely to become NEETs in rural areas because of limited infrastructure, restricted mobility, and conservative gender norms. Women in urban areas have easier access to schools, training, and employment. Place of birth does not significantly affect men's educational attainment or labour-market access. Youth, particularly women, in rural areas are disproportionately disadvantaged (ILO, 2017; El Ferti et al., 2021). It is also important to view NEET status in the context of regional disparities, institutional arrangements, and cultural practices rather than as a solely individual outcome.

The study sheds light primarily on female NEETs, but also on male NEETs. There is a slight difference between men and women in terms of education and experience, but male NEET outcomes are more heterogeneous. Contrary to women, men may withdraw from the labour force after experiencing persistent unemployment or low-quality job offers (Bynner & Parsons, 2002; O'Higgins, 2023). Several young men work in irregular, low-paying informal jobs that are not accounted for in official statistics. The rapid expansion of higher education has created credential inflation and a mismatch between graduates' expectations and labour market demands. To address these issues, specific pathways, labour market mismatches, informal work, and job quality must be addressed (Salehi-Isfahani & Egel, 2007).

The dual-method design enhances both robustness and interpretability. According to the Heckman-corrected Probit model and the Probit model, education, experience, and domestic work influence NEET outcomes. The CART analysis indicates that protective factors (like education) become less effective once domestic responsibilities (e.g., 20+ hours per week) exceed critical thresholds.

Machine learning and econometrics can be integrated to advance youth labour market research. Based on econometric inferences and comparisons with established literature, CART provides transparent, policy-relevant insight into subgroup dynamics (Berigel et al., 2024).

Chapter 1 has outlined an ecological framework that corresponds to these findings. Education, work experience, and hours of housework reflect individual human capital and time allocation at the microsystem level. The Heckman selection variables, including family education, land ownership, and the presence of young children, are representative of mesosystem influences: household resources and family structure that shape the immediate environment in which youth make decisions about schooling and employment. The decrease in the education and experience coefficients after the Heckman correction indicates that these micro-level factors do not operate independently of the meso-level context; family background channels some of their apparent protective effect. The CART results add a further dimension. The 20-hour housework threshold at which education loses its protective effect illustrates what Bronfenbrenner described as cross-level interaction: a mesosystem constraint (domestic role assignment within the family) neutralises a microsystem resource (human capital). The urban-rural birthplace disparity for women similarly reflects exosystem conditions, as provincial infrastructure, labour market density, and transportation access constrain or enable the choices available at lower ecological levels. What the models cannot capture, given the data constraints discussed above, are the macrosystem forces (sanctions, fiscal policy, cultural norms around female employment) and the chronosystem dynamics (how these relationships shift across cohorts or economic cycles). These higher-order influences are addressed in Chapter 5's spatial panel analysis and Chapter 6's synthesis.

4.5.1. Limitations and Future Research

Several limitations of the study should be acknowledged. In the study, the Spring 2021 data are cross-sectional, so establishing causality and tracking persistence would require longitudinal data to distinguish between temporary NEET spells and long-term disengagement. Furthermore, the cross-sectional nature allows for potential reverse causality; for example, high

household work may be a consequence of families assigning domestic duties to already inactive youth rather than housework causing NEET status. Data collection occurred during the COVID-19 pandemic, which may have exacerbated some observed patterns, such as unpaid care work for female NEETs. These pandemic-specific effects may exaggerate short-term gender gaps if they are not accounted for alongside underlying structural trends. In addition, Iran's economic situation has deteriorated from 2021 to 2024, amid increased sanctions and inflation, suggesting that the findings from 2021 may not fully reflect the current, more constrained opportunity structure.

Another limitation is the exclusion restrictions used in the Heckman correction (e.g., land ownership, birthplace, family education, and number of children under five). When individual characteristics are controlled for, these variables are assumed to influence participation in education or employment, but not NEET status directly. There is a possibility that the correction will be biased if these exclusion restrictions are not perfect, meaning identification relies partially on the functional form and the non-linearity of the inverse Mills ratio. Although robustness checks using simple Probit models produced broadly consistent results, future studies should use richer datasets or test alternative identification strategies.

While effect sizes varied, the main conclusions remained consistent in sign and significance, particularly the protective role of education and work experience as well as the disproportionate impact of housework on women. However, our measure of work experience, calculated as Age - Education – 6, is an imperfect proxy that may underestimate experience among youth in the informal economy. Similarly, self-reported hours of housework may be subject to social desirability bias, especially in face-to-face interviews, where men may over-report and women may under-report their participation. The Heckman specification does not appear to be the cause of the findings, suggesting that the findings are robust. However, future research could explore alternative techniques to address potential endogeneity, such as bivariate probit or structural models, which may offer more reliable causal estimates if stronger instruments are available.

Furthermore, the dataset included only structural variables, such as education, potential work experience, and housework. The use of a binary NEET definition also aggregates heterogeneous groups, such as discouraged workers and informal labourers, who may have different policy needs. The study did not include attitudinal or skill-based indicators, nor specific measures of social capital, family-domain variables, health, and mental health (which have shown high Odds Ratios in prior meta-analyses), or community-level factors that have

been shown to influence NEET trajectories in prior international research (e.g., Eurofound, 2012). To better understand youth disengagement in Iran, future surveys should include these dimensions.

The use of advanced machine learning methods should also be considered in future research. Unsupervised approaches, such as clustering, can enhance predictive accuracy, validate the robustness of the dominant predictors identified here, and reveal distinct subgroups of NEET youth with heterogeneous characteristics. However, current CART models may overfit, and the identified thresholds should be viewed as approximate. The extremely large sample (n=192,182) also provides high statistical power, so even trivial effects can reach significance; therefore, readers should pay attention to marginal effects rather than p-values alone. It also relied on listwise deletion for missing data, which could lead to bias if missingness correlates with NEET status, without adjusting standard errors for clustering at the household level. In addition, mixed-methods approaches that combine large-scale survey data with qualitative interviews with NEET youth, employers, and policymakers would shed light on institutional and cultural barriers that are difficult to capture quantitatively. Finally, while the results provide national insights, they mask significant spatial heterogeneity across provinces and are specific to the Iranian institutional context, limiting mechanical generalizability to other MENA or European countries. This analysis is limited to youth aged 15-24. For a more complete understanding of these patterns across the life course, it would be necessary to conduct a broader age analysis, as NEET dynamics can differ among young adolescents (aged 13–19) and older youth (aged 25–29). To assess the durability of these findings and guide more precise policy interventions, longitudinal and post-pandemic data would be particularly valuable.

4.5.2. Policy Implications

The findings can be translated into six specific policy actions, each grounded in the estimated associations rather than general principles. The magnitudes matter: a one percentage point improvement in NEET rates among women corresponds to roughly 16,000 fewer inactive young women nationally, given the 2021 sample composition.

There are several implications for Iranian youth policy and labour market policy arising from the findings. Education has a strong protective effect; thus, reducing early school dropout and expanding access to secondary and tertiary education for disadvantaged groups is urgently needed. It may be possible to reduce NEET rates substantially through re-entry programs for

early school leavers, such as second-chance education or short-cycle vocational courses. Policies that encourage continued education, delay early marriage and childbearing, and create supportive environments for balancing study and family life could help reduce the number of NEETs among young women in particular.

A policy that expands early labour-market participation opportunities is needed to lower NEET rates, given the role of work experience. Employers should be linked with internships, apprenticeships, and vocational training programs to ensure relevance. It is particularly beneficial for disadvantaged youth to have these pathways, as they allow them to bridge the gap between schooling and stable employment.

There is no doubt that structural reforms are needed because young women are disproportionately responsible for domestic duties. Access to affordable childcare and eldercare services as well as incentives to share household responsibilities, can increase women's participation in the labour force. Providing childcare subsidies, flexible work arrangements, and community-based support systems would immediately improve the situation. Public awareness campaigns that challenge restrictive gender norms are necessary to reduce women's household burdens in the long run.

The influence of parental education, household wealth, and birthplace suggests that interventions must also be targeted at disadvantaged families and rural areas. Rural job creation schemes, mentorship programs, and targeted skill-development subsidies could reduce structural inequalities. Improvements in transportation, digital connectivity, and rural development programs would also help reduce the urban–rural divide in female NEET rates by providing rural youth with better access to educational and employment opportunities.

Male NEET pathways also require attention. In contrast to the disproportionate burden of domestic responsibilities placed on women, male youth are often discouraged, dissatisfied with their jobs, or dependent on precarious informal work. It is possible to reduce male disengagement through active labour market policies, such as job-search assistance, wage subsidies for employers hiring young men, and career counseling.

According to the results, Iran needs to adopt a dual strategy to reduce NEET: (i) investing in human capital through education and early work experience; and (ii) addressing institutional and cultural barriers that limit opportunities for youth, particularly gendered labour divisions and rural disadvantages. The Iranian government can reduce the number of NEETs and unlock the untapped potential of the young population by integrating these approaches. In other

contexts, such as the EU's Youth Guarantee, Germany's dual apprenticeship system, and Nordic childcare, training, activation, and family support policies, these policies have been proven to improve youth outcomes. These approaches could be adapted to inform Iranian strategies.

4.6. Conclusion

Data from the 2021 Quarterly Labour Force Survey were used to examine the determinants of NEET status among Iranian youth. A Probit and Heckman-corrected Probit model was used to identify protective factors and structural barriers influencing youth inactivity.

According to the human capital theory, education and work experience significantly reduce the risk of becoming a NEET. For young women, domestic responsibilities are the strongest barrier, with more than 20 hours of housework a week almost ensuring NEET status. Women with young children and those who live in rural areas are most at risk. However, the family's education and the household's wealth mitigate disengagement.

A novel contribution of this study is the application of both econometrics and machine learning to the NEET phenomenon in Iran, one of the few studies in the broader MENA region. A combination of marginal effects from Probit and conditional pathways from CART captures both linear effects and interaction thresholds that traditional models alone cannot reveal.

According to these findings, reducing NEETs requires a dual strategy. Through vocational training and early work experience, policies should expand access to secondary and tertiary education, reduce early school dropout, and create pathways into employment. Interventions must address structural and cultural barriers, particularly unequal divisions of household labour, that limit women's opportunities. The lack of institutional support and gendered labour markets are similar challenges facing young people in middle-income and MENA countries.

This study provides both statistical rigor and intuitive insights into NEETs, although cross-sectional data and a preliminary CART application limit it. A future study using longitudinal datasets and causal identification strategies (e.g., bivariate probit or structural models) could further strengthen inferences. At the same time, qualitative follow-ups with NEET youth will identify persistent subgroups and capture lived experiences, using advanced ensemble methods (e.g., random forests and gradient boosting).

The challenge of reducing NEETs in Iran is not only educational or labour market-related, but also a societal one. Social cohesion and sustainable economic development will require addressing structural inequalities, restrictive gender norms, and investing in youth potential.



Chapter 5

Analysing the Macroeconomic Determinants of NEET Youth in Iran: A Spatial Panel Data Approach

This chapter draws upon Rahmani, H., Groot, W., Arsenijevic, J., & Rahmani, A. M. (2026). Analysing the macroeconomic determinants of NEET youth in Iran: A spatial panel data approach. **Regional Science Policy & Practice**, 100313. https://doi.org/10.1016/j.rspp.2026.100313

Abstract

Youth disengagement is persistently high in Iran due to economic sanctions, rapid demographic growth, and uneven regional development. Macroeconomic factors determine youth not in Education, Employment, or Training (NEET) status, but spatial spillovers, gender, and urban-rural heterogeneity are rarely considered. This study examines the association between NEET rates and provincial-level GDP per capita, unemployment, inflation, government spending, urbanisation, the Gini coefficient, vocational training programs (VET), gross value added in agriculture and services, industrial diversity, and human capital indicators across Iran's 30 provinces. This study differentiates between male, female, urban, and rural youth.

We estimate spatial autoregression (SAR) models. Diagnostic tests (Moran's I, Pesaran's CD test, unit root tests, and cointegration tests) confirm the presence of spatial autocorrelation, cross-sectional dependence, and stationarity.

The results show that a 1% increase in GDP per capita is associated with approximately 0.18% lower NEET rates, with stronger estimated elasticities for females. Human capital and government spending also yield significant negative elasticities, particularly in rural provinces. Contrary to expectations, moderate inflation exhibits a small negative NEET elasticity ($\approx$ -0.047), likely reflecting demand-pull labour opportunities. The SAR spatial lag (ρ = -0.334, $p < 0.05$) reveals significant negative spillovers, where higher NEET in one province corresponds to lower NEET in its neighbours, suggesting labour market migration effects.

To fully comprehend and overcome youth disengagement in Iran requires understanding spatial interdependencies and subgroup heterogeneities. NEET rates could be reduced by combining regionally tailored economic strategies, coordinated cross-provincial training initiatives, and targeted gender and rural-focused interventions.

Keywords: NEET; Spatial Panel Data; Youth Unemployment; Gender Disparities; Urban–Rural Inequalities; Macroeconomic factors

5.1. Introduction

Many countries have developed policies and programs for young people aged 15-24 who are Not in Education, Employment, or Training (NEET). As argued in the previous chapters, NEET has attracted global attention, but it is particularly concerning in Iran due to a mix of political, economic, and demographic developments. Due to economic sanctions, which limit access to global markets and reduce job growth, the country's youth unemployment rate is high. In addition, Iran has a young population, with approximately 60% of its population under 30 (Mehri et al., 2022). Integrating such a large cohort of young entrants into an already constrained labour market is a substantial challenge. Iran's 30 provinces have dramatically different economic structures. Oil-rich and industrial regions function very differently from agriculturally dependent areas, creating distinct and often unequal labour market conditions that national policies struggle to address effectively. There has been very little progress in addressing this issue, suggesting that it is difficult to develop effective programs for job creation, skills development, and education that could help reduce the number of NEET youth (World Bank Data, 2022). This study addresses these regional disparities using spatial panel econometric methods.

Statistical reports from the government indicate that in 2021, there were almost two million unemployed youth in Iran: 941 thousand men and one million and 285 thousand women (Iran, 2022). The Iranian Statistical Centre report shows that NEET rates increased from 27.4% in 2021 to 29.4% in 2022, with men's rates at 18.2% and women's at 39.1%. The unemployment rate for women university graduates is approximately 70% (Ministry of Cooperatives, 2022). As a result of economic hardship and underemployment, NEET youth experience social exclusion and financial challenges, further exacerbating their fears about the future. These barriers highlight the urgent need for targeted interventions (Chapter 3).

Figure 5.1 presents a heat map of the NEET rate in Iran, highlighting significant regional disparities among NEET youth. The NEET rate is lower in more developed provinces because of better infrastructure, higher-quality educational institutions, and a more diverse job market. In contrast, provinces with less developed economies, lower levels of education, and higher poverty rates have higher NEET rates (Salehi-Isfahani & Egel, 2007).

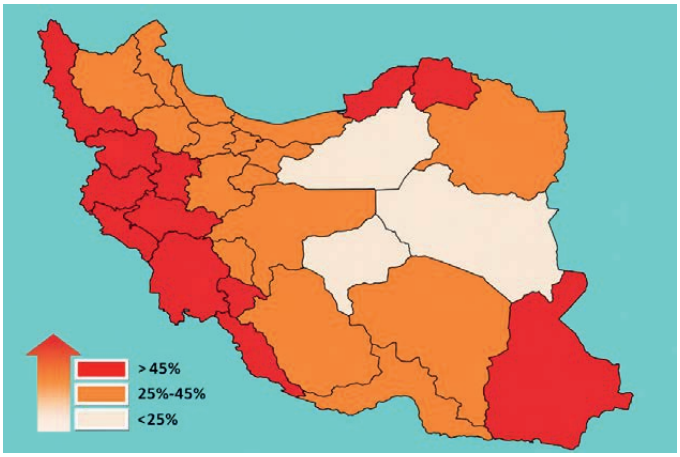


Figure 5.1. Heat map of Iranian NEET rate among youth (15-24 years old). Source: Ministry of Cooperatives, Labour and Social Welfare (2022).

Many policies have been implemented to address the NEET youth problem in Iran, but these initiatives tend to ignore significant differences across provinces and interdependencies between regions. Iran has rolled out a series of targeted interventions since 2016 to engage NEET youth, yet each has struggled to achieve scale or sustained impact. The Vocational Training (VET) Dual System, piloted in 2016 through vocational high schools, sought to bridge classroom learning and on-the-job training for 15- to 24-year-olds. Only around 10% of eligible youth enrolled, and the curriculum lacked the flexibility needed by private employers (Organization, 2016). The National Internship Scheme subsidized internships for university graduates in 2017, offering employers social insurance coverage and modest wage support, but fewer than 30% of interns found permanent jobs, since firms mostly treated them as temporary workers (Ministry of Science, 2017). That same year, eight regional Youth Entrepreneurship Accelerators and the Teen Entrepreneurs Club provided mentoring and seed grants. However, this supported only about 500 startups, far short of the estimated 200,000 graduates seeking work, and grants capped at $ 5,000 proved insufficient to sustain most ventures (Centre, 2018).

In 2018, the government introduced both a Workfare and Wage Subsidy Program and a Rural and Home-Based Work Development initiative (Ministry of Cooperatives, 2018). The subsidy covered up to 100% of the minimum wage for SMEs hiring 18–29 year-olds. A high deadweight loss and complicated application procedures meant many firms would have hired the same youth without a subsidy as well, while smaller enterprises were hindered by bureaucracy (Javadian & Y. Addae, 2013). Similarly, micro-credit and training for home-based crafts and agricultural processing were fragmented across multiple agencies, offering only

limited market linkages and virtually no pathways for scale-up. Across all initiatives, these principal shortcomings, such as outdated curricula, poor job transitions, and limited coverage, are not merely administrative flaws but rather symptoms of a deeper strategic issue: a persistent failure to tailor interventions to the diverse macroeconomic conditions and spatial interdependencies of Iran's provinces. This gap between policy design and local economic reality underscores the critical need for this study's spatial panel data analysis (Ministry of Cooperatives, 2018).

A centralized approach and mismatches in training programs may lead to ineffective outcomes. The significant inter-provincial youth migration and interconnected nature of regional labour markets necessitate a spatial analysis approach to capture spatial spillovers and regional dynamics. By examining how local economic conditions, educational infrastructure, and employment opportunities in one province affect NEET rates in adjacent regions, this study aims to provide insights for targeted policy interventions addressing the spatial dimensions of NEET youth.

Regional disparities affect policy effectiveness, with some provinces experiencing greater difficulty developing effective policies than others. Migration patterns exacerbate these disparities, as NEET youth migrate to urban centres in search of better opportunities, leading to overcrowding and straining urban infrastructure while not necessarily improving their employment prospects (Rafiee et al., 2024). These movements result in spatial interactions that complicate local job markets and school systems (Kelly, 2012). Human capital and organizational demands contribute to a complex interaction between localized NEET populations and broader socioeconomic factors.

A critical gap exists in understanding how regional dynamics shape NEET rates across provinces. A persistently high NEET rate among Iranian youth poses various socioeconomic challenges, including lower labour productivity and intergenerational disadvantages (see Chapter 2 for details).

In order to address this gap, the present study examines the relationship between NEET rates and macroeconomic factors using data from over 19 years for Iran's 30 provinces, focusing on spatial interdependencies. Traditional panel data methods are useful for exploring temporal trends, but they fail to account for spillover effects when changes in one province affect neighbouring provinces. This study uses a spatial panel data approach to understand how local conditions and inter-provincial connections affect NEET outcomes. In addition, it provides

insight into how to tailor regional policy responses. These trends and inequalities are analyzed using spatial panel data models (Güçlü, 2017). Through this spatial methodology, we can analyze the influence of regional economic conditions, policy initiatives, and training programs in neighbouring provinces on NEET rates. Examining spatial clustering patterns across provinces thus reveals broader interdependencies and spillover effects, providing a deeper understanding of how regional macroeconomic factors and conditions collectively shape NEET outcomes. This study addresses three main questions:

1. How do economic factors like GDP, unemployment, inflation, government spending, and urbanization affect NEET rates in Iran's provinces?

2. Do NEET rates in one Iranian province influence neighbouring provinces, showing spatial dependence?

3. How do gender and urban-rural differences in jobs and education affect NEET rates among youth subgroups like women, men, rural, and urban youth?

The study addresses a critical gap in the literature by employing a spatial panel data methodology to investigate regional inequalities and the effectiveness of macroeconomic determinants aimed at NEET challenges in Iran. By integrating spatial dimensions, the study provides a more precise understanding of how local conditions and interprovincial spillovers shape NEET outcomes, thereby offering a stronger basis for devising region-specific policy interventions. The findings aim to inform more precise policy interventions that address local conditions and cross-border spillovers, offering a stronger basis for reducing NEET rates in diverse provincial contexts.

This chapter builds on previous findings by shifting the analytical scale from individuals (Chapter 4) to provinces (Chapter 5). A scoping review in Chapter 2 identified environmental and regional factors as important determinants of NEET, but these factors were not quantified.

The analysis of Iranian microdata in Chapter 4 revealed that education, experience, and housework all affect an individual's probability of being NEET. However, individual characteristics alone cannot explain why NEET rates vary dramatically from 15% in Tehran to 48.2% in Sistan-Baluchistan. If education protects individuals, why do some provinces with similar average levels of education show vastly different NEET rates?

NEET youth in a province with high youth unemployment may be moved to neighbouring provinces in search of employment, thereby affecting NEET rates in those provinces. The

contribution of Chapter 5 is based on these spatial spillovers, which were not discussed in Chapters 3 and 4.

5.2. Literature review

NEET rates are strongly correlated with government policies, macroeconomic conditions, and local factors, especially during recessions, when young people are at greater risk of unemployment (Kelly & McGuinness, 2015). Aina et al. (2025) demonstrated that NEET rates increased during COVID-19 due to the economic crisis, although the effects differed by gender, education level, and socioeconomic status. The heterogeneity of NEET populations requires tailored policy interventions (Mascherini et al., 2017; O'Higgins & Brockie, 2024; Simmons & Thompson, 2011; Suttill, 2017).

A country-specific study can shed light on more specific challenges and solutions. Irwin (2021) highlighted policy deficiencies for those neither in higher education nor in NEET status by describing the 'missing middle' concept in England. According to this study, career pathways and strategies can be utilized to address structural disparities.

Park et al. (2020) examined the Vision Plan Program in South Korea, a pilot program aimed at reducing NEET rates. Participants' job-seeking behaviour and the likelihood of unemployment significantly improved, as indicated by a difference-in-differences analysis of longitudinal data from 2016 to 2018. Valiyev and Babayev (2021) examined Azerbaijan's governmental youth policy and found that, despite detailed goals, implementation inadequacies left NEET youth neglected. Insufficient data collection and vocational training have contributed to feelings of exclusion, emphasizing the need for data-driven policies and integrated interventions.

Amendola (2022) investigated the macro-determinants of NEET rates across 40 countries and found that GDP per capita negatively correlates with NEET rates, suggesting that economic progress reduces NEET rates. On the other hand, social spending positively correlated with NEET rates, indicating inefficiencies in welfare distribution.

Although multiple studies demonstrate ALMPs' effectiveness in reducing NEET rates (Focacci, 2020; Speckesser et al., 2019), others highlight limitations in their efficacy due to misalignment with labour market demands or weak targeting (Wapler et al., 2022). These mixed findings highlight the need for further research, particularly examining ALMP effectiveness across different regional contexts using spatially disaggregated data. Gender disparities significantly influence NEET rates. Rodriguez-Modroño (2022) argues that many policies ignore gender disparities, creating disadvantages for young women in education and

the job market. According to Bacher et al. (2017), gender-sensitive measures helped reduce NEET rates among females through ALMP investments.

Additionally, regional disparities need to be considered. Due to regional interdependence, unemployment in one region can affect nearby regions (Al-Ayouty & Hassaballa, 2020; Rafiee et al., 2024). According to European studies, urban and rural unemployment rates differ because of infrastructure, economic opportunities, and educational access (Agahi et al., 2023; Bal-Domańska & Sobczak, 2018).

The heterogeneity in research methods has contributed to a better understanding of NEETs. A spatial econometric model and dynamic panel data analysis can be applied to better understand the factors associated with NEETs and the policy implications. Liu (2023) examined China's Labour Service Cooperation Policy using spatial analysis. This study emphasized public-private partnerships and regional strategies.

Simanjuntak and Pasaribu (2021) conducted a similar spatial analysis to examine the socioeconomic determinants of NEET rates in Indonesian provinces, emphasizing the need to address regional disparities. Dauth et al. (2016) showed the importance of regional labour-market policies in reducing NEET rates. A study by Maynou et al. (2022) examined the convergence of NEET rates across European regions from 2000 to 2019. It emphasizes regional disparities in NEET rates and the importance of considering subnational data when developing policies.

The international literature provides a solid framework for understanding Iran, but the country's unique circumstances, including severe economic sanctions, a significant demographic bulge, and centralized policies, call for a more specialized approach. Due to these factors, regional disparities differ fundamentally from European or East Asian patterns, suggesting that Active Labour Market Policies (ALMPs) that have been successful elsewhere may not be directly applicable here. Consequently, a localized approach that prioritizes Iran's unique circumstances over the direct application of international findings is necessary to understand the spatial dynamics of the NEET rate. There is no direct research on NEET youth in Iran that employs spatial models. Although a limited number of studies have examined unemployment and regional labour markets using spatial data models, Meidani and Zabihi (2011) examined the dynamic relationship between Iran's unemployment rates and real per capita GDP from 1971 to 2006 using the Auto-Regressive Distributed Lag (ARDL) approach. The study found that

unemployment negatively affects both short- and long-term GDP, underscoring the importance of programs to reduce unemployment and boost efficiency and growth.

Cheratian et al. (Cheratian et al., 2023) analyzed unemployment trends in Iran between 2001 and 2020 using GARCH (Generalized Autoregressive Conditional Heteroskedasticity)-based unit root tests. According to this study, structural issues such as a limited labour market and economic underdevelopment lead to long-term unemployment. They recommended targeted reforms in rural employment diversification, labour market deregulation, and gender-specific job creation initiatives.

Rafiee et al. (2024) analyzed unemployment dynamics in Iranian provinces between 2001 and 2019 using a dynamic Spatial Autoregressive (SAR) model. The study revealed significant temporal and spatial interdependence in unemployment rates, with positive lag effects and negative effects from neighbouring provinces' unemployment rates. The findings suggest that unemployment in one area may affect nearby regions through geographical interconnectedness, and that regional policies aimed at diversifying the economy and expanding human capital are necessary.

A significant gap exists in the literature regarding the spatial dynamics of NEET rates across Iran. Although previous studies have confirmed the significant role of macroeconomic factors in shaping NEET outcomes, very few have explicitly examined how these factors vary across provincial boundaries or how they influence neighbouring regions through spatial spillovers. Comprehensive research on provincial differences in NEET outcomes is limited, underscoring the necessity of spatial econometric approaches. The variations in NEET rates across Iran's provinces have not been extensively examined, underscoring the importance of employing spatial econometric methods to examine regional inequalities. This study contributes to the existing literature by employing spatial panel econometric methods to address limitations in previous research, particularly the lack of investigation into urban-rural and gender-specific dimensions using spatial panel data. This approach clarifies how diverse factors affect NEET rates at the subnational level, thus providing policymakers with evidence to formulate targeted, region-specific interventions.

5.3. Methodological framework

5.3.1. Data

This study utilizes annual panel data covering 30 provinces across Iran for the period 2004 to 2022. Data are collected from several sources, including the Iranian Statistical Center, the Ministry of Cooperatives, Labour, and Social Welfare, the Iranian Economic and Financial Bank Portal, the International Labour Organization (ILO), and World Bank databases. For our study, we use the 30 provinces of Iran as the basis for observation, including Alborz, which became an independent province in 2010. However, due to insufficient data, Alborz is analysed within the province of Tehran. Analyzing this dataset allows us to examine regional disparities in NEET rates and their determinants. NEET rates among 15-24-year-olds in each province are the primary dependent variable in this study.

We transform all variables into natural logarithms to ensure stationarity and facilitate quantitative analysis. Using the natural log can stabilise variance, reduce skewness, and mitigate the effects of outliers. Moreover, when both independent and dependent variables are logarithms, the coefficients can be interpreted as elasticities, providing a more straightforward insight into how percentage changes in one factor affect NEET rates. Table 5.1 presents the data for the total sample and the four subsamples by gender and rural and urban areas.

Various independent variables are used to examine the relationship between NEET rates and macroeconomic trends. For each region, macroeconomic indicators such as provincial GDP per capita, inflation rates, and government spending per capita are included. Understanding how economic growth, fiscal policies, and inflationary pressures affect youth labour market conditions is crucial. The dataset contains unemployment rates for the total population and for youth aged 15-24, segmented by gender and location (urban vs. rural). Employment rate data follows the same categorization, allowing evaluation of disparities in opportunities. The dataset also includes inadequate employment rates, which refer to situations where workers' jobs fail to meet essential criteria such as sufficient income, stability, working conditions, or job security. This comprehensive segmentation by demographic and geographic factors enables a detailed examination of labour market inefficiencies across different population segments.

Table 5.1. Summary statistics and data sources.

Variable	total		male		female		Urban		rural	
	Mean	St. Dv.	Mean	St. Dv.	Mean	St. Dv.	Mean	St. Dv.	Mean	St. Dv.
NEET rate	31.25	1.05	23.75	0.05	48.05	2.05	24.56	2.71	32.2	2.41
Unemployment Rate	11.69	4.42	13.4	5.67	18.7	7.89	10.26	4.49	6.46	3.29
Unemployment Rate (15-24)	25.66	7.97	22.56	7.26	37.48	19.23	30.95	10.29	16.89	9.03
Employment Rate	59.57	4.87	62.36	4.67	12.25	4.43	35.33	3.22	41.5	6.81
Inadequate employment rate	8.33	6.59	9.98	6.07	3.59	3.4	6.59	9.98	6.59	9.98
Higher School participant	42975.17	13267.64	42975.17	13267.64	42975.17	13267.64	42975.17	13267.64	42975.17	13267.64
Dropout Rate	3.38	2.01	3.38	2.01	3.38	2.01	3.38	2.01	3.38	2.01
VET program	41875.63	27031.61	41875.63	27031.61	41875.63	27031.61	41875.63	27031.61	41875.63	27031.61
Illiteracy Rate	15.38	5.08	15.38	7.74	2.29	11.56	15.38	5.08	15.38	5.08
Real GDP per Capita	55.4	41.71	55.4	41.71	55.4	41.71	55.4	41.71	55.4	41.71
Agriculture Share	13.49	13.09	13.49	13.09	13.49	13.09	13.49	13.09	13.49	13.09
Mining Share	1.26	6.56	1.26	6.56	1.26	6.56	1.26	6.56	1.26	6.56
Industry Share	22.89	15.88	22.89	15.88	22.89	15.88	22.89	15.88	22.89	15.88
Services Share	46.71	24.54	46.71	24.54	46.71	24.54	46.71	24.54	46.71	24.54
Inflation Rate	16.05	7.1	16.05	7.1	16.05	7.1	16.05	7.1	16.05	7.1
Urbanization Rate	67.5	12.25	67.5	12.25	67.5	12.25	67.5	12.25	67.5	12.25
Gini Coefficient	0.28	0.02	0.28	0.02	0.28	0.02	0.31	0.03	0.32	0.04
government spending per capita	1.8	2.68	1.8	2.68	1.8	2.68	1.8	2.68	1.8	2.68
human capital	8.16	1.71	8.16	1.71	8.16	1.71	8.16	1.71	8.16	1.71
Population 15-24	1168929	428557.4	5667437	235656.5	5438812	213562.7	825632	53246.2	3135691	12356.4
Industrial diversity	1.5	0.31	1.5	0.31	1.5	0.31	1.5	0.31	1.5	0.31

To account for the sectoral economic structure, we analyze the contributions of agriculture, mining, industry, and services to gross value added (GVA) and to regional economies. Industrial diversity was included as an indicator of regional economic structure, calculated from the variety and distribution of industrial sectors across provinces. This measure examines how regional economic composition impacts NEET rates and labour market outcomes. Using these variables, we can see how regional economies are structured and how they generate diverse jobs.

Enrollment in high schools and universities, illiteracy rates, and dropout rates across provinces all indicate educational attainment. We calculate human capital by combining the cumulative academic years completed by the youth population. Additionally, the dataset accounts for the number of vocational training programs (VET), directly linking education to employment outcomes.

In addition, demographic composition metrics such as the population aged 15-24 and each province's population are considered to determine population dynamics. The Gini coefficient measures inequality between urban and rural areas, which may affect youth employment outcomes. The urbanization rate is calculated by dividing the total population by the urban population. This shows the disparity between the urban and rural populations.

The data preparation process involves several steps to ensure accuracy and completeness. Data from the Iranian Economic and Financial Bank Portal is used to adjust variables for inflation, such as GDP per capita and government budgets. To ensure reliability and accuracy, we managed missing data carefully. We adjusted the model specifications to account for missing values, especially during critical periods when data gaps might affect results. When direct data were unavailable, approximations were derived using the formula (1 – (youth employment rate + youth education enrollment rate)). In each province, missing values were interpolated linearly using two key factors: (a) the underlying series demonstrated smooth year-to-year trends, as confirmed by low second-difference variance, and (b) interpolation preserved the temporal ordering necessary for unit-root and cointegration tests without introducing exogenous assumptions. In this way, a consistent dataset was obtained for analysis.

5.3.2. Methodology

A spatial panel data approach captures the spatial and temporal dimensions of the NEET phenomenon across Iran’s provinces. As part of our analysis of NEET rates, we estimate several spatial econometric models to capture regional interdependencies and spillover effects, as in

Iran factors such as economic activities, education infrastructure, or labour market conditions in one province often spill over to adjacent provinces (Rafiee et al., 2024; Viton, 2010).

A traditional panel model ignores spatial dependence, resulting in bias or inefficiency due to omitted spatially correlated variables (Dauth et al., 2016). Therefore, we use spatial panel models to account for spatial autocorrelation of both the dependent variables and the error terms. Different spatial econometric models are available. The Spatial Durbin Model (SDM) estimates direct effects within a province and indirect spillover effects from neighbouring provinces.

This model is particularly suited for examining how policies or economic conditions in one region are associated with NEET outcomes in adjacent areas. We estimate the following equation:

$$NEET_{it}=\alpha+ \tau NEET_{i,t-1}+\rho W\, NEET_{it}+X_{it}\beta+WX_{it}\delta+\mu_i+\lambda_t+\varepsilon_{it}\ . \quad (1)$$

Where ρ measures the spatial lag of the dependent variable, $X_{it}\delta$ captures spatial lags of the explanatory variables,τ measures the temporal dependence based on the lagged dependent variable ($NEET_{i,t-1}$), W is the spatial weight matrix, and μi and λt represent province-specific and time-specific effects, respectively (Lee & Yu, 2016). Figure 5.2 describes the strategy for selecting the best-fitting model.

A spatial lag model (SAR) examines the spatial dependence of variables, including the relationship between NEET rates within neighbouring provinces (Elhorst, 2017). Furthermore, the Spatial Error Model (SEM) accounts for unobserved spatial autocorrelation in the error term, ensuring robust inferences (Yildirim & Mert Kantar, 2020).

The generalized spatial model, SAC, integrates both the SAR and SEM models. Depending on whether the specification is better suited to accounting for subject-specific, time-specific, or both subject- and time-specific effects, the SAC provides a comprehensive tool for capturing spatial dependencies in both the dependent variable and the error terms, making it particularly robust in addressing complex spatial interrelations. The models may be estimated using either fixed or random effects (Aw & Cabral, 2021). Figure 5.2 summarizes the model selection strategy.

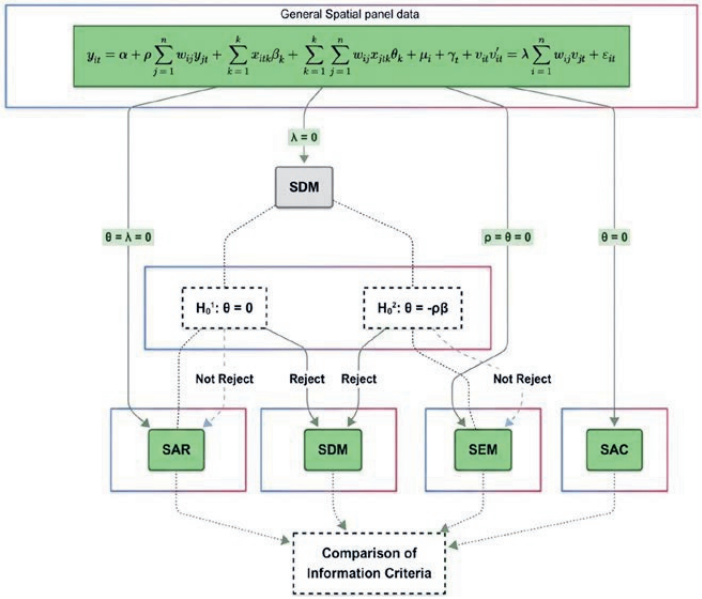


Figure 5.2. Flowchart for the spatial model selection strategy.

Each model uses a contiguity-based spatial weight matrix; provinces sharing a common border are assigned a weight of 1, and non-adjacent provinces are assigned a weight of 0. This results in a binary matrix that is then row-normalized, so that each row sums to 1, and spatial spillover effects can be interpreted as the average impact of neighbouring provinces (Elhorst, 2017).

Different spatial panel models were estimated for male, female, urban, and rural NEET rates. When subgroup-specific variables were available, they were used more effectively to capture each group's socioeconomic and labour-market dynamics. Although education and employment indicators were disaggregated by gender and locality, certain macroeconomic variables, such as GDP per capita and government expenditure, were included in all subgroup models. This approach ensures that both subgroup-specific and common determinants are appropriately considered in our analysis.

Moran's I is a statistical measure developed by Patrick Alfred Pierce Moran to assess spatial autocorrelation, i.e., the tendency for similar values to cluster together. Using Moran's I to assess spatial autocorrelation is crucial in spatial data analysis, as it helps identify underlying spatial patterns and informs the selection of appropriate spatial econometric models. Based on a study area, the variable pattern is evaluated as clustered, dispersed, or random (Calder & Cressie, 2007).

The null hypothesis of this test is that there is no spatial autocorrelation. While the alternative is not exactly specified. When Moran's I is statistically significant, it implies that similar values tend to be geographically concentrated rather than randomly distributed.

The formula for Moran's I is:

$$I=\frac{N}{W}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}wij\,(Xi-x)(Xj-X)}{\sum_{i=1}^{N}(xi-x)2} \quad . \qquad (2)$$

Where N is the number of spatial units(regions), X is the explanatory variable, w_{ij} represents the ith and j^{th} elements of a spatial weights matrix and defines the weight between locations i and j, i and j explain the spatial situations, and W explains the sum of the components of the spatial weight matrix (Lee & Li, 2017).

Aside from Moran's I test, we employed the Pesaran Cross-sectional Dependence (CD) test to assess cross-sectional dependence in our panel data. The CD test evaluates the null hypothesis of weak cross-sectional dependence against the alternative of strong cross-sectional dependence. A significant CD test result indicates strong cross-sectional dependence, indicating a correlation between residuals across entities. To ensure robust and unbiased estimates, econometric methods should account for these interdependencies.

We assessed the stationarity of the explanatory variables using the Hadri-Rao Unit Root Test, which tests the null that the series are stationary around a deterministic trend (Hadri & Rao, 2008).

To ensure the robustness of our econometric models, we apply appropriate transformations when the test indicates non-stationarity. In addition, we use the Pedroni Cointegration Test to determine whether there are long-term relationships between the variables. The Cointegration tests ensure that the observed correlations between non-stationary variables are not spurious and that a long-term equilibrium exists between them (Pedroni, 1999, 2004). The Hausman (1978) test is used to determine whether random or fixed effects should be used to estimate the model, based on panel heterogeneity. We employ a series of model selection and specification tests to ensure the robustness and appropriateness of our spatial econometric models.

Wald Test, Lagrange Multiplier (LM) Test, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) are used to determine the most appropriate spatial econometric model. Using Wald tests, it is possible to simplify the Spatial Durbin Model (SDM) to the Spatial Autoregressive Model (SAR) or Spatial Error Model (SEM). When the Wald Test result

is significant, the SDM should be retained to capture spatial relationships. Models were estimated using maximum likelihood with province- and time-fixed effects. To account for serial correlation within provinces over time, as well as spatial correlation captured by SAR specifications, standard errors were clustered by province. This ensures robust inference that accounts for both spatial and temporal dependence.

The AIC and BIC can also be used to compare alternative spatial models. Models with lower AIC values have a better fit, since they balance goodness-of-fit and model complexity, whereas models with higher BIC values have a stricter penalty for adding more parameters. The Lagrange Multiplier Test confirms that our chosen specification appropriately accounts for any omitted spatial dependence in the dependent variable or error term. The combination of Wald, LM, AIC, and BIC tests ensures the selection of the most appropriate spatial econometric model and yields reliable, valid inferences. We used R (version 4.1.3) for all computations and spatial econometric estimations using relevant spatial econometrics packages.

5.4. Results

Assessing spatial autocorrelation is important before proceeding to empirical estimation, as ignoring geographical interdependencies can lead to biased estimates. Moran's I test is applied as a standard diagnostic for spatial autocorrelation to address this issue. Because Moran's I statistic is designed to detect spatial autocorrelation in cross-sectional data, we compute it separately for each year in our sample.

Table 5.2 confirms the presence of spatial dependence, providing a clear rationale for using spatial econometric models in the subsequent analyses. Statistically significant spatial autocorrelation is indicated by *p*-values below 0.05, showing that provinces with high (or low) NEET rates cluster together.

Table 5.2. Global Moran's I statistics for the spatial autocorrelation of NEET rate.

Year	Moran's I Statistics	*p*-value
2004	0.144**	0.031
2005	0.106**	0.028
2006	0.149**	0.045
2007	0.112**	0.021

Year	Moran's I Statistics	*p*-value
2008	0.125**	0.030
2009	0.158**	0.011
2010	0.107**	0.042
2011	0.113**	0.034
2012	0.155***	0.008
2013	0.111**	0.045
2014	0.104**	0.019
2015	0.117**	0.022
2016	0.141**	0.033
2017	0.108***	0.004
2018	0.136**	0.015
2019	0.109**	0.016
2020	0.125**	0.039
2021	0.114***	0.009
2022	0.113**	0.018

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The use of spatial econometric models is supported by consistently positive, statistically significant Moran's I values (p <0.05) for total NEET rates from 2004 to 2022. Considering that aggregate-level spatial autocorrelation indicates general spatial dependency and suggests similar spatial structures across subgroups, Moran's I was conducted only for the total NEET youth model. This approach provides a robust basis for employing spatial econometric models in all subsequent analyses, including those for various subgroups.

The Pesaran CD test, which accounts for correlations across provinces, was used to test for cross-sectional dependence to evaluate the suitability of the panel data approach. Table 5.3

shows that all variables have p-values below 0.05, which indicates that the null hypothesis of cross-sectional independence is rejected. These findings clearly show that the data exhibit cross-sectional dependence, necessitating econometric methods that account for interdependencies across provinces.

Table 5.3. Pesaran CD test.

Variable	**CD Test Statistic**	***p*-value**
NEET rate	9.786	0.00
Unemployment Rate	26.858	0.00
Agriculture Section Rate	47.754	0.00
Mineral and Natural Resource Rate	3.535	0.004
Industry Resources	18.224	0.00
Service Sector Rate	21.391	0.00
GDP per capita	50.667	0.00
Urbanization	60.014	0.00
Unemployment Rate (15-24)	82.486	0.00
Employment Rate	81.712	0.00
Inadequate Employment Rate	81.823	0.00
Higher School Rate	76.322	0.00
Dropout Rate	76.322	0.00
Vocational Training Programs (VET)	77.209	0.00
Illiteracy Rate	79.537	0.00

Gini Coefficient	80.141	0.00
government spending per capita	55.841	0.00
Inflation	77.574	0.00
Population 15-24	2.665	0.008
Human Capital	31.335	0.00
Population	81.725	0.00
Industrial Diversity	1.989	0.047

Based on Pesaran's cross-sectional dependence tests, virtually all macroeconomic, labour, educational, and demographic variables were highly dependent across Iranian provinces ($p<0.01$). This indicates that national shocks and common factors simultaneously affect all provinces. Hence, our spatial panel model explicitly incorporates year-fixed effects to account for these common influences.

Pesaran's CD test is conducted only on the total NEET youth model because strong national-level shocks affecting total NEET rates inherently imply similar cross-sectional dependence across subgroups. Repeated tests within each subgroup would likely yield similar results, leading to redundancy. Since Tehran and Alborz have large populations and are the capital cities, our models were re-estimated without them to ensure robustness. These provinces did not adversely affect results; therefore, our conclusions remain unaffected.

To avoid spurious regressions, we assessed the time-series properties of our variables before estimating the panel data. The Hadri-Rao panel unit root test is used to test the null hypothesis that a series is stationary around a deterministic trend.

According to Table 5.4, the unit root tests indicate mixed integration orders among the variables. At the 5% significance level ($p > 0.05$), several key variables, such as the NEET rate, provincial GDP per capita, government spending per capita, and the Gini coefficient, were found to be stationary. Conversely, several other crucial predictors were identified as non-stationary, exhibiting unit roots. These include variables central to labour market dynamics and economic structure, such as the youth unemployment rate (15-24), gross value added (GVA) in the industrial and mineral sectors, and demographic variables such as population. It is clear

that this finding of mixed stationarity, with some variables integrated at order zero and others at order one, directly contradicts the assumption and requires a more sophisticated analytical approach.

Non-stationary variables in their levels can produce inaccurate results unless there is a stable, long-run equilibrium relationship among them. Therefore, differencing the non-stationary variables to induce stationarity is one option, but this approach often results in a loss of valuable information about the long-run relationships central to our research questions.

Table 5.4. Hadri and Rao unit root test results

Variable	**Statistics**	***P*-Value**	**Result**
NEET Rate	0.881	0.189	Stationary
Unemployment Rate	1.215	0.112	Stationary
GVA Agriculture	-0.443	0.671	Stationary
GVA Mineral and Natural Resource Rate	-3.952	0.001	Non-Stationary
GVA Industry sector	-6.314	0.000	Non-Stationary
Participation rate	-4.672	0.001	Non-Stationary
government spending per capita	-0.129	0.551	Stationary
Industrial diversity	-3.852	0.000	Non-Stationary
GVA Service Sector Rate	1.554	0.060	Stationary
GDP per capita	0.998	0.159	Stationary
Urbanization	0.152	0.439	Stationary
Unemployment Rate (15-24)	-12.526	0.000	Non-Stationary
Employment Rate	2.370	0.008	Non-Stationary
Inadequate Employment Rate	-1.733	0.014	Non-Stationary
Higher School Rate	1.439	0.075	Stationary
Dropout Rate	2.513	0.135	Stationary
Vocational Training Programs (VET)	2.254	0.009	Non-Stationary
Illiteracy Rate	2.706	0.002	Non-Stationary
Gini Coefficient	0.533	0.297	Stationary

Variable	Statistics	*P*-Value	Result
Inflation	-0.985	0.837	Stationary
Population (15-24)	-4.124	0.000	Non-Stationary
Human Capital	0.312	0.377	Stationary
Population	-3.925	0.000	Non-Stationary
Industrial Diversity	-1.025	0.847	Stationary

Non-stationary panel data can be analyzed more theoretically by testing for cointegration. As a result of cointegration, even though the variables are individually non-stationary, their linear combination is stationary, suggesting a persistent long-term relationship. Consequently, we employed the Pedroni panel cointegration test to determine if such an equilibrium exists between our dependent variable (NEET rate) and the set of non-stationary explanatory variables.

Table 5.5 shows that the Pedroni test results indicate cointegration. All panel-level statistics, including four of the seven test statistics, rejected the null hypothesis of cointegration with high significance levels (p <0.01). It validates our decision to estimate spatial panel models using variables in their level form (after logarithmic transformation). Cointegration ensures that our model captures the long-run elasticities between macroeconomic determinants and NEET rates rather than spurious correlations. While producing robust and reliable econometric estimates, we retain the rich long-term information in the data.

Table 5.5. Pedroni test for Cointegration.

Test Statistic	Value	*p*-value
Panel v-Statistic	1.876	0.030 **
Panel rho-Statistic	-2.458	0.007 ***
Panel PP-Statistic	-3.214	0.001 ***
Panel ADF-Statistic	-2.774	0.003 ***
Group rho-Statistic	-1.354	0.088

Test Statistic	Value	*p*-value
Group PP-Statistic	-2.215	0.013 **
Group ADF-Statistic	-1.420	0.078 *

Note: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

In addition, the Group PP statistic also showed significant cointegration (p=0.013), although other group tests (rho and ADF (Augmented Dickey-Fuller)) provided weaker evidence (p>0.05). Given the stronger, predominant evidence from panel-level statistics and partially significant group-level statistics, we proceed confidently by treating the variables as cointegrated, explicitly noting provincial heterogeneity as a limitation.

Due to the fact that our study period (2004–2022) includes significant national shocks such as the 2008 financial crisis, economic sanctions, and the COVID-19 pandemic events, which are likely to affect all provinces simultaneously, we explicitly include year-fixed effects in our spatial panel model. By using this approach, we control for unobserved common temporal shocks and ensure that the identified spatial spillovers and macroeconomic determinants are not conflated with nationwide events affecting youth NEET rates uniformly across the country. Cointegration tests confirm that our analysis focuses on long-run equilibrium relationships. As a result, short-term fluctuations, dynamic adjustments, or lagged dependent effects are not explicitly modelled.

To ensure the robustness and reliability of the spatial econometric models, we conducted diagnostic tests to detect and address potential multicollinearity. A correlation matrix analysis and a Variance Inflation Factor (VIF) test were used to identify variables with high multicollinearity. Multicollinearity diagnostics using VIF identified GDP per capita, government expenditure, urbanization, industrial diversity, inflation, VET programs, human capital, unemployment rate, Gini, and sectoral GVA variables as sufficiently independent (VIF <8, correlations <0.8). Highly collinear variables were systematically excluded to obtain robust, interpretable spatial model estimates. As a result, multicollinearity concerns are addressed, and coefficients can be interpreted clearly.

Table 5.6 reports the Variance Inflation Factors (VIF) to assess multicollinearity among key predictors. While specific macroeconomic indicators exhibit VIF values exceeding the standard threshold of 10, they were retained in the final model due to their theoretical necessity

in explaining the structural dynamics of the Iranian regional labour market. The complete correlation matrix for all 20 variables is provided in Appendix 5.1.

Table 5.6. Variance Inflation Factors (VIF) for Selected Variables.

Variable	**VIF**	**Status**
Employment Rate	29.60	High Multicollinearity
Inflation	20.27	High Multicollinearity
High School Enrollment	15.17	High Multicollinearity
GVA Industry	13.32	High Multicollinearity
Dropout Rate	13.16	High Multicollinearity
Population	12.55	High Multicollinearity
Unemployment Rate	8.84	Acceptable
GVA Service	8.22	Acceptable
GDP	8.06	Acceptable
Human Capital	7.53	Acceptable

Table 5.7 presents the estimation results for the SEM, SDM, SAC, and SAR spatial panel models, calculated using R. The SAR model is the appropriate one, so we focus our results description on it.

Table 5.7. The results of the spatial models (number of observations (n = 570), provinces (30), and time frame (2004–2022) are indicated).

Variable	SEM	SDM	SAC	SAR	SAR Male	SAR Female	SAR Urban	SAR rural
	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)
LN NEET	-	-	-	0.583*** (0.000)	-	-	-	-
LN GDP	-0.232*** (0.000)	-0.220*** (0.000)	-0.207*** (0.000)	-0.181*** (0.001)	-0.312*** (0.000)	-0.391*** (0.001)	-0.182*** (0.002)	-0.102*** (0.005)
LN budget	-0.064*** (0.000)	-0.062*** (0.000)	-0.058*** (0.000)	-0.047*** (0.000)	-0.062*** (0.000)	-0.053*** (0.000)	-0.036*** (0.001)	-0.042*** (0.002)

LN human cap.	-0.112***	-0.095***	-0.121***	-0.118***	-0.096***	-0.112***	-0.092**	-0.073**
	(0.005)	(0.007)	(0.001)	(0.010)	(0.006)	(0.002)	(0.012)	(0.010)
LN Inflation	-0.050	-0.049*	-0.058***	-0.047***	-0.051	-0.046	-0.041	-0.036
	(0.109)	(0.050)	(0.000)	(0.000)	(0.105)	(0.100)	(0.110)	(0.100)
LN Ind div	-0.076**	-0.070**	-0.065*	-0.086***	-0.078**	-0.081**	-0.083**	-0.062*
	(0.037)	(0.032)	(0.095)	(0.002)	(0.040)	(0.035)	(0.045)	(0.050)
LN AGR	-0.177***	-0.169***	-0.188***	-0.125**	-0.172***	-0.122***	-0.123**	-0.154**
	(0.005)	(0.006)	(0.001)	(0.020)	(0.007)	(0.005)	(0.018)	(0.020)
LN SERVIC	-0.418***	-0.401***	-0.410***	-0.362***	-0.402***	-0.394***	-0.364***	-0.282***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)
LN URB	0.144**	0.172**	0.183**	0.151	0.152**	0.173***	0.134	0.112
	(0.012)	(0.015)	(0.010)	(0.231)	(0.010)	(0.008)	(0.220)	(0.215)
LN unemploy	0.273**	0.255**	0.294***	0.252**	0.254**	0.271**	0.224**	0.242**
	(0.010)	(0.015)	(0.005)	(0.020)	(0.012)	(0.010)	(0.025)	(0.022)
LN Gini	0.121*	0.125*	0.111**	0.092*	0.113*	0.142**	0.074	0.092*
	(0.070)	(0.065)	(0.050)	(0.099)	(0.075)	(0.050)	(0.105)	(0.095)
LN VET	-0.087**	-0.075	-0.104***	-0.081**	-0.072**	-0.091***	-0.056**	-0.067**
	(0.010)	(0.015)	(0.008)	(0.020)	(0.012)	(0.009)	(0.022)	(0.020)
Spatial Lag (ρ)	-	-0.112	-0.091**	-0.334**	-0.118**	-0.098**	-0.325**	-0.316**
		(0.251)	(0.021)	(0.048)	(0.030)	(0.040)	(0.042)	(0.048)
Spatial Error (λ)	0.164***	-	0.438***	-	-	-	-	-
	(0.007)		(0.000)					
R2	0.680	0.720	0.700	0.732	0.721	0.728	0.714	0.702
AIC	-1005.12	-1020.85	-1015.47	-1025.45	-1015.23	-1018.67	-1007.89	-1002.65
BIC	-965.23	-981.2	-975.89	-985.78	-978.54	-980.15	-967.21	-962.4
Hausman Test	13.75**	14.20***	14.50***	14.96***	12.32**	14.67***	12.59***	13.92***
	(0.010)	(0.008)	(0.006)	(0.005)	(0.010)	(0.008)	(0.006)	(0.005)

Wald (Joint Signif.)	25.65*** (0.000)	28.70*** (0.000)	27.45*** (0.000)	29.36*** (0.000)	31.22*** (0.000)	30.45*** (0.000)	27.89*** (0.000)	25.45*** (0.000)
LM Test	14.20*** (0.000)	16.05*** (0.000)	15.67*** (0.000)	16.52*** (0.000)	18.20*** (0.000)	17.78*** (0.000)	15.67*** (0.000)	14.32*** (0.000)

Note: *** p < 0.01, ** p < 0.05, * p < 0.10.

Spatial econometrics provides a solid statistical rationale for selecting the Spatial Autoregressive (SAR) specification to model NEET rates across demographic groups. Following the estimation of the Spatial Durbin Model (SDM), the Wald test for H_0:θ=0 yielded a test statistic of 12.47 (P= 0.188), failing to reach significance at the 5 % level, indicating that spatial lags of the explanatory variables were not jointly impactful, whereas the common-factor restriction H_0: $\theta+\rho\beta=0$ was rejected with a test statistic of 28.94 (P < 0.001), confirming that SAR rather than SEM is the appropriate specification.

Furthermore, both the Lagrange multiplier and Hausman tests consistently supported a fixed-effects approach. SAR model demonstrates robust explanatory power, achieving an R^2 of approximately 0.732, the highest among alternative spatial models (SEM, SDM, SAC), and the lowest Akaike Information Criterion (AIC), indicating a superior fit to the data. SAR captures direct contagion and migration pressures across provincial boundaries while preserving a straightforward interpretation of macroeconomic elasticities by explicitly modeling the spatial lag of the NEET rate.

Nonetheless, simplifying SDM to SAR entails important trade-offs and potential limitations. In choosing SAR, we assume that exogenous spillovers of macroeconomic covariates (i.e., WX) are absent. However, it remains theoretically plausible that changes in one province's GDP per capita or sectoral GVA could exert weaker but meaningful spillover effects on neighbouring NEET rates. Because these spillovers are highly probable, their omission may induce omitted-variable bias, whereby the estimated spatial-lag coefficient ρ and the local elasticity coefficients β inadvertently absorb unmodeled interprovincial influences. Future research might, therefore, consider panel spatial error correction or extended Durbin specifications to jointly accommodate spatial dependence in both the dependent variable and the covariates. The results of the SDM model are presented in Appendix 5.2.

The spatial error coefficient (λ) is positive and highly significant, indicating spatial clustering of residuals. There is a possibility that unobserved factors affecting NEET rates are spatially

correlated, meaning that nearby regions share omitted factors not captured by the included variables.

The lagged dependent variable coefficient (0.583, $p < 0.001$) indicates significant temporal persistence in provincial NEET rates; a one percentage point increase in NEET rates in year t-1 is associated with a 0.58 percentage point higher rate in year t, while controlling for other variables. This persistence underscores the importance of early intervention, as high NEET rates tend to persist over time. Provinces that experience NEET shocks may face long-lasting effects, so policymakers should act quickly.

In our log-log framework, all coefficients represent elasticities; a 1% change in an explanatory variable translates into roughly a β% change in the NEET rate. The SAR spatial lag coefficient ($\rho = -0.334$, $p < 0.05$) is statistically significant at the 5% level, indicating a strong negative spatial correlation. It implies a form of spatial competition or displacement, in which provinces with higher NEET rates tend to be surrounded by neighbours with lower rates, and vice versa. An alternative or complementary explanation involves economic competition among provinces. Wealthy provinces can attract investment and jobs from neighbouring poorer provinces, leading to regional divergence rather than convergence. NEET dynamics are also characterized by a negative spatial lag, suggesting that traditional spatial econometric models that assume positive spillovers (e.g., knowledge diffusion, trade linkages) may not be applicable. Through migration and resource competition, NEET reduction appears zero-sum or competitive, unlike technological or economic growth that diffuses to neighbours. When NEET youth emigrate, they reduce the province's youth population, mechanically lowering the NEET rate (fewer NEET youth in the numerator). However, because NEET youth are least likely to migrate successfully (due to limited resources and networks), out-migration only partially reduces origin NEET rates.

In all subgroups, the log (GDP per capita) variable is negative and highly significant ($p < 0.01$). Specifically, according to the SAR model, a 1% rise in GDP per capita corresponds to a 0.31% lower male NEET rate, a 0.39% lower female NEET rate, a 0.10% lower rural NEET rate, and a 0.18% lower urban NEET rate. The elasticity is slightly weaker for the total sample at -0.18, with slightly lower estimates across subgroups.

The logarithm of the government spending per capita is also negative and significant at the 1% level, with a 1% higher budget being associated with 0.06% lower NEET rates for males, 0.05% for females, 0.036% for urban youth, and 0.042% for rural youth in the SAR model. At the

aggregate level, the SAR model estimates a slightly smaller impact of 0.047%, suggesting that government spending is beneficial but its effects are less pronounced across different spatial contexts.

According to all models, human capital has a negative but less significant effect. A 1% increase in human capital among males reduces NEET rates by 0.09%, while among females the effect is slightly stronger at 0.11%. A rural area's effect is -0.073%, while an urban area's is -0.092%. Human capital is statistically significant, though its impact is somewhat weaker, underscoring that skill mismatches remain challenging across settings.

Although macroeconomic theory often predicts that high inflation can reduce real incomes and exacerbate unemployment, our SAR estimates reveal a statistically significant negative elasticity between inflation and NEET rates, suggesting that higher inflation may reflect stronger economic activity, thereby decreasing youth disengagement. A 1% higher inflation is associated with a 0.051% lower male NEET rate, a 0.046% lower female NEET rate, a 0.036% lower rural NEET rate, and a 0.041% lower urban NEET rate. According to the SAR model, inflation-driven economic activity mitigates youth disengagement.

Industrial diversity has a negative and significant effect across all models, with stronger effects for females and urban youth. A 1% increase in industrial diversity reduces male NEET rates by 0.078%, female NEET rates by 0.081%, rural NEET rates by 0.062%, and urban NEET rates by 0.083%. A diverse economy is more likely to offer youth better job prospects than one with fewer opportunities.

The agricultural sector plays a crucial role in rural employment, with increased agricultural GVA reducing rural NEET rates by 0.15%. However, it has a smaller impact on urban NEET rates (-0.12%) and is less significant. Agriculture is also identified as a strong determinant of rural NEET reduction in the model, though with somewhat lower significance. The service sector has a moderately weak impact on urban NEET rates; a 1% expansion reduces urban NEET rates by 0.36% and rural NEET rates by 0.28%.

As urbanization correlates positively with NEET rates, especially among females and males, it is evident that urban growth does not guarantee adequate employment opportunities. As urbanization increases by 1%, male NEET rates rise by 0.15 %, female NEET rates rise by 0.17%, rural NEET rates rise by 0.11%, and urban NEET rates rise by 0.13%.

All youth groups are affected by the unemployment rate, with females most affected (0.27%), while rural youth are least affected (0.24%). The SAR model suggests that while unemployment is a crucial factor, its regional impact varies.

Vocational training programs also have a notable impact. A 1% increase in vocational training participation reduces NEET rates by 0.07% for males, 0.09% for females, 0.06% for rural youth, and 0.05% for urban youth.

Youth disengagement is generally exacerbated by higher income inequality, as measured by the Gini coefficient, which measures income inequality. Females are most affected by 0.14%, and rural youth are least affected by 0.09%. In addition, the model identifies a positive relationship but with slightly lower coefficients, suggesting that income inequality remains a significant barrier to youth employment and education.

5.5. Discussion

This study uses a spatial panel analysis to better understand the dynamics of NEET youth in Iranian provinces. This study highlights the complexity of youth disengagement, which is influenced not only by economic factors but also by spatial interdependence and structural inequalities. We analyze how macroeconomic factors, including educational attainment indicators and demographic composition, shape the NEET phenomenon in Iran by focusing on previously overlooked geographical variations and spillover effects. The results of our study offer insights into this pressing issue, contributing to both academic literature and policy discourse.

This study uses spatial econometric models to reveal significant inter-provincial dependencies in NEET rates across Iran. According to the SAR model's spatial lag coefficient (= -0.334), there is an inverse correlation between NEET rates within a province and their neighbours. So, the high NEET rates in one area often coincide with lower NEET rates in neighbouring areas.

As a result of these negative spatial autocorrelations, spatial economic models depart from conventional theoretical approaches. According to standard spatial theory, based on knowledge spillovers and agglomeration economies, prosperity diffuses to neighbors through cooperative mechanisms (Anselin, 2003; Elhorst, 2014). In contrast, we find that Iranian youth labour markets function through competitive spatial sorting rather than cooperative diffusion. Figure 5.1 illustrates this visually: high-NEET provinces (red: >45%) systematically border low-NEET provinces (beige: <25%), a spatial pattern inconsistent with diffusion theory. This distinction between cooperative spillovers (knowledge transfer, linked prosperity) and

competitive spillovers (migration-driven displacement) suggests that spatial labour market models developed for stable Western economies may not generalize to developing contexts with high internal migration and spatially concentrated opportunities.

Regional labour market dynamics can explain the negative spillover effect of the NEET rate in neighbouring provinces. Due to high NEET rates in one province, youth may seek employment or education in neighbouring provinces. As a result of this movement, neighbouring areas may see a decrease in NEET rates. In addition, provinces with higher NEET rates may implement targeted policies or programs to address youth disengagement, such as vocational training and employment programs. This approach may attract youth from neighbouring regions, reducing the NEET rate in their own provinces as well. There are also economic asymmetries between provinces. It is possible that provinces with a robust economy and better infrastructure may attract youth from neighbouring areas with fewer opportunities, thereby redistributing NEET populations and contributing to the observed negative spillover effect. Negative spatial spillovers shape NEET outcomes in Iran through local circumstances, regional mobility, and economic asymmetries (Rafiee et al., 2023). It is more important to anticipate and manage labour flows regionally than to make isolated efforts at the provincial level, given their interdependencies.

We found a negative correlation between NEET rates and GDP per capita, conditional on province- and year-fixed effects, consistent with the existing literature (Bingöl, 2020). This pattern is consistent with the view that economic expansion creates conditions that help young people avoid inactivity (Caroleo et al., 2020), though we note that the relationship may also operate in reverse provinces with lower NEET rates may attract investment and generate higher GDP. Different demographic groups in Iran show different estimated elasticities, with men and women showing stronger associations than urban youth. Iran's provincial-level data show that regions with higher per capita GDP have fewer NEET youth, a pattern consistent with, though not sufficient to establish, the idea that higher provincial incomes generate employment and training opportunities. International sanctions restricted foreign investment and technology transfer during the study period (2004-2022), which is associated with lower youth employment growth (Early & Peksen, 2019). The findings suggest that economic growth is an important correlate of lower NEET rates in Iran, and that policies fostering more diversified, sanctions-resistant development are likely to support youth engagement, given the consistency of this pattern across model specifications and subgroups. Moreover, provinces with robust GDP growth appear to generate indirect positive spillovers to neighbouring areas, most likely

by creating more jobs and increasing investment. Although Iran's economic growth is benefiting the country overall, its heavy reliance on volatile oil revenues and the uneven geographic distribution of gains may reduce those benefits (Farzanegan & Krieger, 2019). According to gender-specific models, the aggregate GDP elasticity is a misleading average that fails to capture the true association for men or women. Simpson's Paradox (Sarmukaddam, 2017) illustrates how combining data from different groups can obscure or distort underlying trends. Because of unobserved heterogeneity between the male and female populations, the aggregate model obscures the true magnitude of the estimated relationship. This shows that the primary source of heterogeneity in the response of NEET youth to economic growth is gender, rather than geography. This highlights the importance of considering gender-specific elasticities when analyzing economic associations with NEET rates.

Government spending also plays a crucial role. It is possible to reduce youth disengagement by increasing provincial budgets for infrastructure, education, and employment programs, especially among males and youth in rural areas. Iran's historically centralized fiscal framework may contribute to this low impact due to inefficiencies and misaligned spending priorities. The Iranian government seems to prioritize short-term subsidies over long-term investments in human capital, according to Cheratian et al. (2023). A strategic infrastructure investment can be effective, but it must meet local needs, such as supporting local businesses and building schools. Government spending cannot reduce NEET prevalence without addressing these structural inefficiencies. In some cross-national studies, social spending is associated with higher NEET rates, indicating welfare dependency or mistargeting (Amendola, 2022).

According to the analysis, unemployment is strongly associated with higher NEET prevalence among young males in Iran (Cheratian et al., 2023). Given Iran's informal employment rate of nearly 30% and the lack of formal job creation keeping pace with demographic growth, Iranian youth face systemic barriers to employment. Spatial analysis reveals considerable regional heterogeneity due to migration pressures and economic downturns. Regions with a robust educational system or a thriving informal economy may be more resilient than others.

The inflation rate and the NEET rate have a modest negative correlation, which is paradoxical. The inflation rate in Iran was often driven by demand-pull factors or loose monetary policies associated with oil revenue windfalls, which could have stimulated job creation in the short run (Rafiee et al., 2024). As a result, periods of moderate inflation alongside economic expansion may have temporarily reduced youth disengagement. Inflation is likely to have a nonlinear

relationship with poverty; it may drive youth into informal employment, which is not reflected in NEET metrics, thereby masking deeper vulnerabilities. A higher price may also have incentivised youth to seek formal or informal work to maintain purchasing power, thereby reducing NEET status (Bayrak & Tatli, 2018).

Furthermore, inflationary periods may push youth into informal employment, a sector that expanded significantly under sanctions pressure (Esfahani & Pesaran, 2009; Farzanegan & Markwardt, 2009). Since informal work is not captured in official NEET statistics, inflation may reduce measured NEET rates by driving youth into unregistered economic activity rather than formal employment. Taghizadeh-Hesary et al. (2021) also found similar results, documenting the growth of Iran's informal sector as a coping mechanism under economic sanctions, along with the literature suggesting that moderate inflation can coexist with employment growth in developing economies (Loayza & Rigolini, 2011).

Across Iranian provinces, human capital and vocational training are key correlates of NEET rates. School, university, and VET enrollment consistently correlate with lower youth inactivity, especially among women and rural youth. In contrast, the modest effect sizes observed in this analysis suggest that education alone will not suffice without concurrent improvements in labour market integration. The high percentage of women who graduate from university without employment indicates that their skills are not in demand on the labour market (Rezai-Rashti & Moghadam, 2011). The education system, VET programs, and employment must be linked more closely to close this gap. Investments in education infrastructure, addressing gender disparities, and integrating curricula with regional economic priorities are necessary to achieve this goal.

Industrial diversity, urbanization, and sector-specific economic performance (GVA in agriculture and services) are important correlates of regional NEET dynamics. In provinces with more diversified industrial bases, NEET rates are consistently lower, since diversification is associated with lower vulnerability to sector-specific shocks and broader employment opportunities for women and rural youth (Pallares & Adkisson, 2017). Our results suggest that supporting industrial diversity is not only a social policy needed to involve young people but also a goal for economic development. Moreover, expanding the agricultural sector significantly lower rural NEET rates, underscoring agriculture's central role in rural economies. However, the service sector primarily associations for educated young people and young urban women, because it offers entry-level jobs that are especially accessible to them (Rendall, 2014).

According to studies from other countries and the broader literature, the NEET landscape in Iran is complicated by urbanization. NEET rates are positively correlated with urbanization, meaning that provinces experiencing rapid growth are experiencing an increase in disengaged youth. Insufficient job creation, overcrowding, and skill mismatches are likely contributing to this paradox in urban centres that cannot absorb rural migrants. According to Rafiee et al. (2024), rural-to-urban migration often intensifies competition for low-quality or informal jobs, leaving many young people in long periods of "waithood" rather than entering the job market. NEET rates, however, are not directly affected by urbanization; rather, they are influenced by spatial interactions between regions.

The Gini coefficient shows that income inequality is also a significant factor contributing to youth disengagement. Among female youth, NEET rates are higher in provinces with higher inequality levels. There is a need for redistribution policies and targeted investments in marginalized communities, including progressive budgeting, enhanced social protection, and inclusive community services. Youth employment and career prospects are enhanced through these interventions, which address inequality and reduce youth disengagement.

Iran's NEET population has significant gender and urban-rural disparities. Female NEET rates are consistently higher than male rates, indicating that educational-employment pathways and labour-market access are gendered. Women's NEET rates are significantly lowered by human capital determinants, particularly school attendance and VET participation, emphasizing the need for women-specific educational and training initiatives. Similarly, rural adolescents face significant disadvantages, including lower educational attainment, limited access to vocational infrastructure, and a low-productivity agricultural economy. Despite metropolitan regions providing more diverse prospects, NEET rates among urban youth, particularly females, have increased. Subgroup models reveal substantial heterogeneity that was masked by aggregate analyses. NEET rates among women are more sensitive to GDP per capita (-0.391 vs. -0.312) and to vocational training (-0.091 vs. -0.072), indicating that women are more likely to benefit from economic growth and vocational training investments. Rural youth respond more strongly to agricultural GVA (-1.154 vs. -0.123 for urban), whereas urban youth are more sensitive to service sector growth (-0.364 vs. -0.282). These differential elasticities underscore that one-size-fits-all policies will fail; interventions must be tailored by gender and geography.

Interactions such as these highlight the need for context-sensitive interventions to overcome systemic gender barriers. A tailored approach should leverage agriculture in rural areas and

expand service-sector employment in urban areas, while guaranteeing equitable access to institutional resources regardless of gender or location.

A provincial context moderates effects at the individual level rather than merely enhancing them. When labour demand is high in high-GDP provinces like Tehran, education has a powerful protective effect, but it is weaker in low-GDP provinces like Sistan-Baluchistan, where graduates have limited employment options. Whether individual education leads to employment depends on provincial GDP. The adverse effects of housework burden on women are exacerbated in provinces with high unemployment rates, in which women are assigned to domestic roles due to a shortage of jobs. A woman in a high-unemployment province with heavy housework faces compounded disadvantages due to both provincial constraints and household expectations. For effective policy implementation, both levels must be addressed simultaneously.

The spatial panel results extend the ecological framework from Chapter 1 to the exosystem and macrosystem levels that Chapter 4's individual-level models could not directly address. It is the provincial GDP per capita, government spending, and sectoral composition that represent exosystem conditions: the economic and institutional environment outside of the individual's immediate control, but shapes the opportunity structure within which micro- and meso-level factors operate. The negative spatial lag coefficient captures a dynamic interaction between exosystems, as Bronfenbrenner's framework anticipates, but few NEET studies have empirically demonstrated: conditions in one province's labour market alter the opportunity structure in neighbouring provinces through youth migration and competitive sorting. Gender-specific elasticities demonstrate how macrosystem forces, such as cultural norms assigned to women in domestic roles, affect the translation of exosystem resources into individual outcomes. Despite their inherently higher participation rates, women are subject to macrosystem constraints that suppress their baseline participation. By removing modest exosystem barriers, women are able to participate more fully. In low-GDP provinces, education's protective effect weakens, supporting the ecological model's prediction: micro-level resources (human capital) require supportive exosystem conditions (a functioning labour market) to produce outcomes. Without that alignment, individual investment in education produces credential accumulation but not employment, the pattern identified as "waithood" in the MENA youth literature (Dhillon & Yousef, 2009).

5.5.1. Policy Implications

These recommendations converge on a single strategic principle: Iran's NEET crisis cannot be resolved by any single ministry acting alone. The individual-level findings in Chapter 4 require action from the Ministry of Education and Ministry of Social Welfare. The spatial findings in Chapter 5 require simultaneous action from the National Planning and Budget Organization and provincial governments. Furthermore, the gender elasticity gap (-0.391 for women versus -0.312 for men in the GDP model) indicates that, even if all macroeconomic targets are met, the female NEET rate will converge only to the male rate if the structural domestic labour constraint identified in Chapter 4 is addressed in parallel. The policy framework must therefore be cross-ministerial by design, not by aspiration.

This study's findings demonstrate that reducing Iran's persistently high NEET rates requires moving beyond broad national policies to an integrated, spatially informed, and evidence-driven approach. Our quantitative results offer specific guidance for sharpening policy interventions.

The most critical finding is the significant adverse spatial spillover effect ($\rho = -0.334$), which indicates that high NEET rates in one province are associated with suppressed rates in its neighbours. This suggests that youth migrate from provinces with fewer opportunities to adjacent ones, displacing the problem rather than solving it. A purely province-focused policy is, therefore, insufficient. The magnitude of this coefficient, implying that a neighbour's NEET rate has a one-third-level impact, necessitates the creation of a National Framework for Regional Labour Market Coordination. This should involve interprovincial task forces to manage youth labour flows, share data on skill gaps and vacancies, and coordinate investments to foster balanced regional growth, preventing a counterproductive "beggar-thy-neighbour" dynamic.

Our results provide a clear mandate for regionally customized economic strategies. The distinct sectoral effects documented above, agriculture for rural areas, services for urban centers confirm that a one-size-fits-all approach to job creation will fail. The policy should therefore directly link vocational training (VET) to these regional economic profiles. Agricultural technology training focused on value-added processing and agribusiness development is among the interventions for rural provinces, as are mobile VET units that provide skills training to remote communities. Young agricultural entrepreneurs can also be supported in forming cooperatives. In urban centres, there is a need to prioritize digital literacy programs, IT training,

and employment opportunities in retail, hospitality, and financial services to attract and retain young people.

As our subgroup analysis demonstrated, economic growth disproportionately benefits women's labour market integration. This justifies targeted interventions to improve female labour force participation. This justifies targeted interventions to improve female labour force participation. Some specific steps that should be taken include: (i) subsidized childcare centers located next to vocational training centers so that young mothers can learn new skills; (ii) flexible work schedules and part-time apprenticeship programs that allow young women to take care of their families; (iii) gender-sensitive VET curricula that prepare women for growing service-sector jobs in healthcare, education, and digital services; (iv) mentorship programs that connect female graduates with women entrepreneurs; and (v) transportation subsidies or safe transit options to make it easier for young women to get around.

The modest elasticity of government spending (-0.047) suggests that increasing budget allocations alone is not enough; spending must become more efficient and targeted. This implies shifting from generalized subsidies to performance-based funding tied to employment outcomes, investment in job placement services that actively match youth with vacancies, and public-private partnerships to co-fund training programs aligned with employer needs. Furthermore, to counter the urbanization paradox discussed above, policies must promote balanced regional development, thereby enhancing the economies of mid-sized cities and rural areas, making migration a choice rather than a necessity.

5.5.2. Limitations of the study

Several limitations must be acknowledged when interpreting the results of this study. First, while provincial-level NEET data can provide valuable spatial analysis, they may obscure important differences at micro- and intra-provincial levels, such as the distinction between unemployed youth and youth who are inactive for cultural or personal reasons. NEET young women may be involved in unpaid domestic work or constrained by social norms, which may influence their responses to macroeconomic shifts differently than those of their male counterparts. Furthermore, provincial data on variables like vocational training and employment quality may not be reliable or complete, potentially introducing measurement errors. A linear interpolation for missing NEET data assumes smooth year-to-year trends, which may not hold during times of economic shocks, such as sanctions intensification or COVID-19 pandemics, potentially introducing measurement error. Due to a lack of pre-2010

data, Alborz and Tehran are being merged, potentially masking distinct labour market dynamics in this rapidly growing peri-urban area, which has seen substantial industrial growth and demographic changes since gaining provincial status in 2010.

The robustness checks excluded outlier provinces such as Tehran and Alborz. However, caution should be exercised when interpreting specific elasticities, as unobserved factors such as informal economic size, migration flows, or local policy initiatives could also influence NEET outcomes.

It is important to consider the trade-offs when choosing between the SAR and SDM specifications. While statistics favor the simpler SAR model, it ignores direct effects from neighbouring economic factors and focuses solely on the NEET rate. Furthermore, our estimates may be biased by absorbing unobserved effects resulting from neighbouring economic conditions on local youth disengagement. In comparison with more complex models, these indirect impacts are minimal, suggesting that our findings remain valid. Future research should explore SDM specifications to quantify how changes in one province's VET or GDP spill over into adjacent areas.

The model does not explicitly isolate the impact of the COVID-19 pandemic, which caused unprecedented disruptions in 2020–2021. As a result, part of the late-period variation in NEET rates may be related to the pandemic and not fully captured by the macro variables.

Our approach is not a structural causal model; it establishes correlations consistent with theory, but we cannot definitively claim causality for each determinant. We identified mixed integration orders in our panel data as a key methodological consideration in our analysis. While the NEET rate and GDP per capita were stationary, other variables, such as youth unemployment rates and sectoral GVA, were non-stationary, raising concerns about spurious regression. Pedroni panel cointegration was used to mitigate this risk and confirmed a long-run equilibrium relationship among our variables, thereby justifying level modelling. The validation ensures that our spatial framework captures substantive long-term connections rather than artifacts. Although the interaction between non-stationarity and spatial dependence adds complexity, future studies could explore panel spatial error-correction models to jointly address these dynamics.

5.5.3. Recommendations for Future Research

This research could be expanded in various significant directions in the future. Methodologically, examining alternative geographical weight matrices, such as those based on

economic connections, migratory patterns, or trade networks, may reveal spatial dynamics beyond physical proximity. Advanced spatial econometric techniques, such as Spatial Durbin Models or dynamic spatial panels, can illuminate direct and indirect spillovers. Furthermore, including finer data, such as district-level or individual longitudinal tracking, would enable us to investigate NEET duration, reintegration pathways, and province-specific strategies. In the future, spatial difference-in-differences methods could be used to assess targeted youth programs and phased policy interventions. We contextualized spatial data and identified behavioural and cultural factors that promote young disengagement by combining quantitative analysis with qualitative methods, including interviews and case studies, in selected regions. Furthermore, broadening the research to include comparative analyses with other Middle Eastern economies or to assess the impact of major shocks, such as COVID-19 or changes in sanctions regimes, would provide useful insights into the resilience and responsiveness of youth labour markets to changing macroeconomic conditions.

We opted for the SAR model over the SDM, even though the SDM could have estimated spatial lags of both the dependent and explanatory variables. While SDM offers richer inferences on the indirect effects of covariates, its complexity can obscure clear policy levers. A SAR-based elasticity directly links changes in a given province's GDP or government spending to NEET outcomes both locally and in neighbouring provinces. However, future research should explore SDM specifications to quantify precisely how, for example, a 1 % increase in one province's VET participation spills over into adjacent areas, which our current SAR framework cannot fully capture. Despite SAR's parsimony and good fit, future research could benefit from alternatives such as structural modelling to better capture these dynamics.

5.6. Conclusion

This study presents a geographical analysis of the macroeconomic determinants driving NEET rates in Iran. This study fills a gap by incorporating spatial and subgroup analyses; it uncovers dynamics that national-level analyses would overlook. No prior research has simultaneously examined urban-rural and gender-specific NEET dynamics with spatial methods. Through applying spatial panel econometric models, we discovered considerable inter-provincial linkages and structural inequities that standard approaches generally ignore. The results emphasize that economic growth, industrial diversification, and investment in human capital, particularly through vocational training and improved access to higher education, are crucial in reducing youth disengagement. While agriculture continues to play a vital role in sustaining

rural employment, the service sector is especially crucial for integrating urban youth. Notably, urbanization alone does not guarantee lower NEET rates; rather, rapid urban growth may worsen youth idleness without adequate job creation and infrastructure. The data also underscores the gendered and geographic dimensions of the NEET dilemma, with female and rural youth showing heightened responsiveness to educational and economic opportunities. Overall, tackling young disengagement in Iran demands more than broad national reform. It requires coordinated, regionally tailored plans that integrate economic development with social fairness and labour market inclusion, ensuring that growth is robust and accessible to all parts of the population.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Chapter 6

General Discussion and Conclusion

6.1. Synthesis of Key Findings

This dissertation set out to answer a relatively simple question: why do so many young Iranians end up outside education, employment, and training, and what can be done about it? The answer, as the preceding chapters have shown, is not simple at all. It involves individual risk factors, family circumstances, gender dynamics, regional economic structures, and macroeconomic forces, all operating simultaneously and reinforcing one another. To capture this complexity, the dissertation combined four approaches: a scoping review of global evidence (Chapter 2), a meta-analysis quantifying effect sizes across 43 studies (Chapter 3), a machine learning model using Iranian household data (Chapter 4), and spatial panel analysis of provincial NEET dynamics over time (Chapter 5). What follows is a synthesis of what each approach revealed.

Risk Factor Identification (Research Question 1)

Chapter 2, a scoping review of 91 international studies covering the period 2000-2022, discusses the factors linked to youth becoming NEET. As a result of this review, eight primary domains of risk were identified, including individual attributes, education, employment history, health (including mental health and addiction), social environment, family circumstances, and broader economic context. There is evidence that inadequate educational attainment is a major driver of NEET status worldwide, as youth without qualifications struggle to find employment. Additionally, young people with histories of unemployment or precarious work are more likely to fall into NEET, suggesting that early joblessness can lead to future disengagement. The influence of family background, low socioeconomic status, and parental unemployment was also identified as a critical factor, all of which may diminish young people's opportunities and support, leading them to become NEETs. Young people who face mental health disorders and substance abuse often disengage from school or work due to personal challenges or social stigma. Chapter 2 underscored that NEET youth are a heterogeneous group. Among this group, there are subgroups such as those who have caregiving responsibilities, those who have illnesses or disabilities, and even some who are unemployed by choice for a period. Treating NEET youth as a homogeneous group can be misleading. Some risk factors (e.g., low education, poor health) are universally important, but their characteristics differ across countries. In many societies, young women's NEET status is often influenced by household care responsibilities or early marriage, while labour market conditions and personal motivation may influence young men's NEET status. The purpose of this chapter is to lay a foundation for

a better understanding of NEET's multidimensional and interconnected causes. In the following chapters, we have explored these factors more deeply through a multimethod approach.

Quantified Effect Sizes and Demographic Variations (Research Question 2)

Chapter 3 synthesises risk factors quantitatively based on a meta-analysis of 43 studies. A number of key drivers identified in Chapter 2 were statistically confirmed. There was an inverse relationship between NEET status and educational attainment; youth with higher education were significantly less likely to be NEETs (consistent with Human Capital Theory; Becker, 1994). NEET rates were also associated with fewer local job opportunities and low family income. Gender and age subgroup differences emerged clearly. NEET rates were significantly elevated among women with caregiving duties and early family establishment, whereas for men, ethnicity and parental education were influential factors. Unmarried or divorced men exhibited a greater propensity to be NEET compared to women. Mental health and behavioral factors predominated in the 15–18 age bracket, whereas criminal behavior and marital status were prevalent in the 19–24 age range. The chapter illustrated that structural disadvantages, poverty, and gender inequality perpetuate elevated NEET rates, even when individual risk factors are considered, through the application of random-effects models with robust variance estimates.

The two synthesis chapters contribute more than a mapping of existing knowledge. Chapter 2 is the first scoping review to organise NEET risk factors across eight domains simultaneously and to document the comparative neglect of developing-country contexts: only 10% of the 91 studies examined conditions outside high-income OECD economies. This gap directly motivates the Iranian chapters. Chapter 3 adds three findings that were not visible in any individual study. The pooled suicide risk odds ratio of 2.8 (95% CI: 1.8–3.8) across four studies reaches statistical stability only through meta-analytic pooling; no single study had sufficient power to establish this association reliably. Also, the subgroup analysis by gender and age reveals heterogeneity patterns that individual studies could not detect: the protective effect of education is significantly stronger for women than for men when pooled across OECD contexts, a pattern that Chapter 4's Iranian data then inverts, in Iran, education is slightly more protective for men, suggesting that cultural and institutional constraints on female labour market entry suppress the education return in ways that the international literature does not capture. Finally, the high heterogeneity estimates ($I^2 = 45–98\%$) are themselves a finding: they demonstrate that NEET risk factors are not universal constants but highly context-dependent, providing the methodological justification for an Iran-specific primary analysis rather than

simply applying international estimates. These two chapters therefore function not merely as context-setting but as evidence-generating components whose outputs directly constrain and motivate the empirical choices in Chapters 4 and 5.

Risk Profiling Models for the Iranian Context (Research Question 3)

In contrast to the first two chapters, Chapter 4 focused on the Iranian context, asking: What are the key risk factors associated with Iranian youth becoming NEET, and how do these factors differ by gender? We identify the determinants of NEET status among Iranian youth aged 15–24 using econometric modelling (Probit and Heckman-corrected Probit) and machine learning (Classification and Regression Tree, or CART), focusing primarily on variables such as education, work experience, household chores, family characteristics, and geographical factors.

The results confirmed the risk factors identified in Chapters 2-3 while revealing Iran-specific patterns. NEET status in Iran is significantly influenced by educational attainment. The Probit models demonstrate that schooling plays a protective role by reducing the likelihood of becoming NEET for male youth by 2.5 percentage points (pp) and for female youth by 2.1 pp for each year of education. Youth with fewer years of education had higher NEET rates than those with higher educational attainment. A lack of potential work experience also significantly increased the likelihood of being a NEET. For males and females, the study calculated potential work experience (age minus years of education) to calculate the NEET probability. It concluded that for every additional year of potential work experience, the probability of being a NEET youth decreased by 3.5 pp and 3.6 pp, respectively. Failure to find employment or gain experience during the school-to-work transition can result in prolonged unemployment. Other factors that influenced the NEET risk included household characteristics. The selection bias-adjusted Probit model indicated that female youth from wealthier households were less likely to be NEET, reflecting the ability of affluent families to support education and employment. Having children under 5 increases the likelihood of NEET status among females (due to caregiving), but reduces it among males (who may seek employment to support their families). Furthermore, youth from families with more cumulative years of education were less likely to be NEETs.

The Classification and Regression Tree (CART) analysis identified interaction effects contributing to NEET risk. According to the CART model, youth who spend more than 20 hours a week on housework have an 83% higher probability of being NEET, and this risk

increases to 90% if they have 3 or more years of work experience. Housework has a significant impact on females, in line with cultural norms that prioritize domestic roles. The CART model demonstrated reasonable predictive accuracy, with the selection-bias-adjusted Probit model achieving an overall accuracy of 84.91% (89.69% for males, 84.69% for females) and an area under the Receiver Operating Characteristic (ROC) curve ranging from 0.72 (males) to 0.89 (all youth). These data-driven models successfully classified youth as NEETs or non-NEETs when developing a risk screening framework to identify at-risk individuals. The study highlights Iran's unique context and regional variations alongside global NEET risk factors, such as education and work experience. According to the statistical models, female youth are significantly more likely to become NEETs due to housework and rural birthplaces. According to Iranian data, the majority of NEET youth are female.

Macroeconomic and Spatial Determinants (Research Question 4)

Chapter 5 examines the macroeconomic factors influencing NEET status among young people in Iran using a spatial panel data methodology. This chapter aimed to investigate the existence of spatial interdependencies among Iranian provinces due to overarching macroeconomic forces. This study analyzed the influence of variables including Gross Domestic Product (GDP), unemployment rates, inflation, government spending, and urbanization on the prevalence of NEET using spatial econometric models, including spatial lag, Durbin, and geographic error models.

A central finding from Chapter 5 was the significant spatial dependence across provinces, indicating that NEET rates in one province substantially affect those in neighbouring provinces. As a result of this spatial spillover, provincial policies and economic conditions may have broader regional implications, highlighting the importance of coordinated, regional interventions rather than isolated provincial strategies.

Additionally, distinct macroeconomic factors were identified as driving NEET rates. A higher provincial GDP was associated with lower NEET rates, net of province- and year-fixed effects, suggesting that economic development may play a role in reducing youth inactivity. However, reverse causality cannot be ruled out, as provinces with lower NEET concentrations may simultaneously generate higher economic output. Conversely, elevated unemployment rates significantly increased NEET prevalence, highlighting how economic instability and labour-market conditions directly affect youth disengagement. Government spending exhibited multifaceted effects. Targeted spending in education and employment programs could lower

NEET rates, whereas inefficient or misaligned expenditure might contribute to youth inactivity by failing to address specific regional labour market needs.

The study's findings show that underdeveloped provinces in Iran have NEET rates that are disproportionately higher than those in developed provinces. Particularly vulnerable were provinces with limited educational infrastructure, limited economic diversity, and fewer job opportunities. Urbanization and migration patterns, often driven by young people seeking better opportunities, have exacerbated spatial disparities, stressing urban infrastructures and labour markets while lagging behind rural provinces.

The spatial analysis also revealed significant differences in NEET rates between urban and rural areas. Rural areas lack employment opportunities and educational opportunities, while urban areas face competition for jobs and mismatches between skills and market demand. Women's NEET rates were significantly higher than men's, exacerbated by sociocultural barriers and limited employment opportunities.

Chapter 5 provided insight into how macroeconomic factors and regional spatial dynamics interact to shape NEET outcomes in Iran. Economic and social interventions must consider regional interdependencies, economic contexts, and demographic disparities. In addition, this spatially informed analysis offers valuable evidence for developing comprehensive, region-specific strategies to mitigate the NEET phenomenon.

All of these chapters provide a comprehensive picture of the NEET phenomenon. The study reveals several overarching themes. Chapters 2, 3, and 4 repeatedly identified the lack of education as a risk factor. Conversely, improving education/vocational training is an important solution (Chapters 3, 4, and 5). In addition, socio-economic (poverty, rural underdevelopment) and demographic (gender norms, caregiving burdens) inequalities also influence who becomes a NEET. Young Iranian women, especially those in traditional roles or with weak family support, and those living in economically disadvantaged regions, are particularly vulnerable.

The research indicates that a multilevel approach is essential; not only are individual characteristics important, but family influences and macroeconomic factors are as well. According to Bronfenbrenner's Ecological Systems theory (Paquette & Ryan, 2001), factors spanning micro (individual health), meso (family), exo (community), and macro (national economy) levels interact to influence NEET outcomes. An individual's motivation may falter due to a depressed job market, or a poor community infrastructure may prevent them from benefiting from a well-intentioned policy. There is a dynamic component to NEET status; many

young people move in and out of it rather than being permanently enrolled (OECD, 2016 & 2021). This was noted in the dissertation, which identified subgroups (e.g., short-term NEET vs. chronic NEET) and emphasized the importance of early intervention to prevent temporary disengagement from becoming a chronic problem. Finally, all chapters emphasize the importance of targeted interventions. The evidence suggests that targeted strategies should be used rather than treating NEET youth as a monolithic problem, including keeping adolescents in school (to prevent NEET), offering tailored assistance to unemployed graduates, and supporting young mothers to return to school. It illustrates how a developing and culturally specific context fits into (and sometimes challenges) patterns observed elsewhere.

6.2. Discussion of Implications

The study's results have important implications for theory, practice, and understanding youth issues in Iran and similar settings. We discuss how the findings advance academic theories of youth and development, what practical steps they suggest for different stakeholders, and their contextual relevance to Iran's socio-economic landscape.

6.2.1. Theoretical Implications

The dissertation's findings contribute to existing theoretical frameworks dealing with youth employment, social exclusion, and human development. Capability Approach (Sen, 1999 & 2014) is one lens to consider, as it emphasizes the opportunities (capabilities) individuals have to achieve the life outcomes they value. This approach can be used to reinterpret the Iranian NEET phenomenon. According to our results, many young Iranian people remain NEET because they choose to do so or fail to do so, rather than because they lack the necessary skills. Youth are limited by inadequate education and training because they lack the necessary skills and qualifications to turn their aspirations into employment (a key function). Women constrained by caregiving roles or cultural expectations often have fewer opportunities to participate in the workforce or pursue further education.

There is evidence that structural factors (such as regional economic disparities or gender norms) limit the freedoms and options available to youth. By identifying these specific factors, the study practically refines the Capability Approach, pinpointing the capabilities that NEET youth in Iran lack (e.g., access to education, employment, women's mobility, and health support), enabling targeted interventions. The study finds that Iranian youth's capability deprivation varies geographically, which is empirically consistent with the Capability Approach. A concept called "geographies of opportunity" is proposed, emphasizing the spatial

dimension of capability deprivation (William, 2008). Evidence supports the theory that enhancing human capabilities (through education, health, and social inclusion) reduces NEET rates. Sen argues that poverty and exclusion result from a lack of capabilities rather than a lack of income (Sen, 2014).

This study's scoping review and meta-analysis highlight the complex interplay between individual, familial, and socio-economic factors. The interdisciplinary approach combines sociology, economics, and psychology, rather than focusing on a single theoretical lens. Findings indicate that individual characteristics, family circumstances, and broader socio-economic conditions affect NEET outcomes when viewed from a multi-dimensional perspective.

Furthermore, the findings engage with Human Capital Theory and related labour market theories. Human Capital Theory posits that individuals' education and skills are investments that yield returns in the labour market (Schultz, 1961; Becker, 1964). Studies consistently show that education acts as a protective factor against NEET status, demonstrating that investments in human capital (e.g., schooling, training) keep youth productively engaged. According to the results, the quality and relevance of education are just as important as quantity. Chapter 5 found that generic training programs do not always work, implying that human capital development can fail without alignment to market demands.

While the dissertation reinforces Human Capital Theory by confirming the protective role of education, it also identifies its limitations, particularly for women. Findings from the study indicate that gendered institutional constraints limit the returns on educational investments made by young women, suggesting the need to integrate human capital perspectives with female perspectives and to conduct an institutional analysis of labour market segregation. According to labour market mismatch theories, even educated youth can become NEET if their skills do not match available jobs (Quintini, 2011). A good example of this is the Iranian context, where university-educated young people (especially women) faced unemployment rates as high as 70%. Human capital theory must be accompanied by an understanding of the labour market structure based on market segmentation and insider-outsider theories (Lindbeck & Snower, 1988).

These theories align with our findings on gender disparities and the challenges faced by rural youth. It is often the case that women and rural youths in Iran are excluded from the primary labour market, not because of individual shortcomings, but because of structural barriers (e.g.,

specific jobs are effectively off-limits to them or networks and norms exclude them). Based on Chapter 5, the persistence of NEET status among these groups reinforces the idea that labour markets are segmented based on gender and region. Hence, improving human capital alone is insufficient unless accompanied by structural reforms that enable these newly skilled youth actually to gain employment, thereby integrating micro-level and macro-level theories.

Spatial panel data analysis highlights the importance of context-specific theoretical frameworks. The results indicate that NEET dynamics in Iran are uniquely shaped by regional economic disparities, centralized governance, and cultural norms, underscoring the need for context-sensitive theories rather than applying Western-centric youth transition models in isolation. As a result of regional spillover effects in NEET rates, spatial economic theory is strengthened by the evidence that labour markets are interdependent across provincial boundaries (LeSage & Pace, 2009). The results of this study challenge methodological individualism in youth transition research and advocate for regionally based theoretical models.

In Chapter 4, machine learning methods are utilized to introduce a new, data-driven perspective on youth disengagement. To better understand NEET risk, classification modelling challenges traditional linear assumptions and suggests more dynamic, interactive models. It reveals the complex, non-linear relationships between classifiers and NEET outcomes that conventional statistical methods may overlook.

The dissertation also considered Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979), which examines how individuals are affected by interactions within layered environments (family, community, society). Multidimensional findings support this perspective. A mesosystem factor (such as parental employment or support) can impact a youth's NEET risk, and broader exosystem and macrosystem factors (such as regional economies, cultural norms, and national policies) heavily influence outcomes. The interplay between economic recessions (macro) and family well-being (exo/meso), and ultimately, a youth's trajectory (micro), is a practical validation of Bronfenbrenner's theory.

Despite the preceding discussion demonstrating how established theories illuminate Iranian NEET dynamics, three empirical findings represent theoretical extensions rather than just using applications.

The negative spatial lag coefficient ($\rho = -0.334$, Chapter 5) contradicts the positive spillover assumption in standard spatial economic theory. Iranian youth labour markets demonstrate competitive spatial sorting through out-migration, contrary to existing models which predict

cooperative diffusion (Anselin, 2003). There is a systematic association between high-NEET provinces and low-NEET provinces, indicating that migration displaces rather than diffuses NEET status. Through this distinction between cooperative and competitive spatial processes, spatial labour market theory can be extended beyond stable-economy assumptions and help identify which mechanism operates in a given situation.

The CART analysis in Chapter 4 challenges the linear returns assumption of Human Capital Theory. Among all youth exceeding the twenty-hour housework threshold, 83% are classified as NEET regardless of educational level, and the CART analysis confirms that this pattern is driven predominantly by women, for whom housework is the primary splitting variable. The protective effect of education disappears completely once she reaches this threshold. For youth with limited housework burden, education's protective effect becomes meaningful only above 8 years of schooling, suggesting non-linear rather than continuous returns to human capital investment. Marginal policy improvements may not be sufficient to generate impact; interventions must cross thresholds. A threshold-based model of Human Capital Theory replaces the continuous investment model with the capability-based model. A human capital framework integrating Becker's human capital factors with Sen's conversion factors is required for conversion.

The magnitude of selection effects ($\rho = -0.446$ for women vs. $\rho = -0.251$ for men, Chapter 4) operationalizes Sen's Capability Approach by quantifying the intensity of constraints. While the Capability Approach conceptually emphasizes how structural barriers limit freedom to convert resources into functioning (Sen, 1999), it has been criticized for lacking empirical measurement (Robeyns, 2005). The selection coefficient provides a measurable indicator: larger $|\rho|$ indicates stronger unobserved constraints on participation decisions independent of observed qualifications. This enables cross-context comparison, and future research can test whether constraint intensity ($|\rho|$) varies systematically with gender equality indices or legal frameworks, thereby bridging Sen's conceptual framework with empirical labour economics.

These contributions demonstrate that NEET dynamics in contexts with high spatial inequality, gendered labour markets, and cultural constraints operate fundamentally differently than implied by theories developed in Western settings. Future NEET research should incorporate spatial competition, threshold non-linearities, and measurable structural constraints as core theoretical elements rather than contextual complications.

6.2.2. Practical Implications

The findings of this study have significant implications for stakeholders, including government policymakers, educators, community leaders, and families.

Both machine learning and regression models identify determinants of NEET risk, and each has distinct practical applications. Regression quantifies average population-level effects, whereas CART translates associations into interpretable decision rules, such as flagging students with limited education who work more than 20 hours a week, which is directly applicable to early warning systems in schools (Berigel et al., 2023; Park et al., 2020). Actionability is the added value, not methodological complexity. A combination of counseling, mentoring, and targeted support can significantly reduce disengagement due to poor academic performance, absenteeism, and mental health issues (Simmons & Thompson, 2011).

A curriculum must align with the skills employers require (Irwin, 2021; Vooren et al., 2018). Providing career services, internship opportunities, and employer partnerships are essential to ensuring students gain valuable work experience and make a smooth transition once they graduate (Bacher et al., 2017; Speckesser et al., 2019). Continuing education can be accessed through flexible pathways, such as night classes, online courses, and short digital literacy and entrepreneurship courses. Students can develop resilience and job-seeking skills through life skills and career guidance (Noh & Lee, 2017).

Women's NEET rates must be addressed by addressing gender-specific barriers. As educational institutions, young women should be encouraged to pursue diverse career paths and challenge restrictive cultural norms through community engagement and advocacy (Valiyev & Babayev, 2021). Caregiver-friendly education and training, childcare support, and safe transportation are some of the practical solutions. To maximize the return on women's educational investments, interventions must address both skill development and structural barriers to education (Rafiee et al., 2023).

Communities and NGOs can support NEET youth by connecting them with resources (Focacci, 2020; Liu, 2023). Mentoring programs can offer guidance and expand young people's professional networks. Several job fairs, skill workshops, and training centres can be held at community centres in disadvantaged areas. The influence of religious leaders and community leaders can help change the norms that prevent young women from enrolling in school. The civil society sector should offer support groups, apprenticeship programs, and microfinance initiatives to vulnerable subgroups of young entrepreneurs (Ebaidalla, 2016).

Families play a crucial role in preventing NEET status by supporting educational and career aspirations (Sutill, 2017). Providing unemployed youth with employment opportunities is essential to helping parents discourage early marriage. Targeted campaigns can raise public awareness of the long-term risks of youth disengagement. Youth should use available resources, such as free courses, internships, and employment services, to avoid transitioning from voluntary to involuntary NEET status (Mina, 2023).

6.2.3. Policy Implications

The four empirical chapters generate a consistent set of findings that point toward specific, sequenced policy interventions rather than general principles. This section organises those implications by responsible actor and policy domain, drawing directly on the estimated associations to indicate where effort is most likely to yield measurable reductions in NEET prevalence.

Education is the strongest protective factor across all four methods and all demographic subgroups. The meta-analysis (Chapter 3) estimates an odds ratio of 0.81, a 19% lower odds of NEET status for higher-educated youth internationally. In Iran's individual-level models (Chapter 4), each additional year of schooling reduces the probability of being NEET by 2.5 percentage points for males and 2.1 for females. Heckman correction reduces those figures to 1.24 pp and 1.05 pp, confirming that family background explains part but not all of education's protective role.

The Ministry of Education should take three actions. First, introduce a national secondary school re-entry programme offering flexible, modular qualifications for early school leavers, prioritising the five provinces with NEET rates above 40%: Sistan-Baluchestan, Golestan, Hormozgan, Kermanshah, and Lorestan. Second, expand vocational education and training enrolment in provinces where Chapter 5's spatial analysis shows the strongest negative elasticity (0.091 for women and 0.072 for men) where each enrolment unit produces the largest NEET reduction. Third, redirect university places toward fields with stronger labour market absorption, since Chapter 2 documents substantially higher NEET risks among humanities and arts graduates than among health and social science graduates, with the effect most acute in provinces where graduate unemployment exceeds 50%.

Chapter 4's CART analysis identifies a threshold of 20 hours of weekly housework: above that, education no longer protects against NEET status, and the NEET probability reaches 83%. The housework coefficient is twice as large for women as for men (0.31 pp per hour versus 0.18

pp), confirming that domestic role assignment drives the gender NEET gap. Education and employment policies alone will not close the female NEET gap while the domestic burden remains unaddressed.

The Ministry of Social Welfare should introduce subsidised childcare facilities co-located with vocational training centres, in line with the ILO's 2019 guidelines on decent jobs for youth. Governors in high-NEET rural provinces should pilot community-based eldercare schemes that reduce the caregiving load on young women with elderly dependants. The Ministry of Cooperatives should create a part-time apprenticeship pathway that counts as full VET completion, allowing young women with caregiving responsibilities to accumulate qualifications over an extended period.

Chapter 5's spatial lag coefficient ($\rho = -0.334$) has not been documented in any prior study of Iranian youth labour markets. High NEET rates in one province are associated with lower rates in adjacent provinces. Youth migrate from high-NEET provinces into neighbouring ones; the receiving provinces absorb the labour supply without reducing aggregate national inactivity. Province-specific programmes, the current design of most Iranian youth policy, address the symptom rather than the pattern.

The National Planning and Budget Organisation should establish a National Framework for Regional Labour Market Policy with three functions: a shared real-time database of provincial skill gaps and vacancies so that outflow youth reach vacancies in receiving provinces instead of concentrating in Tehran; joint VET investment planning across contiguous province pairs (Sistan-Baluchestan and Kerman, Golestan and Mazandaran) to eliminate duplicate provision; and transport and housing subsidies that give rural youth genuine mobility rather than forcing migration as the only exit.

Agricultural GVA growth reduces NEET rates far more sharply in rural provinces (elasticity: -1.154) than in urban ones (-0.123); for services, the relationship reverses. Single-sector national investment produces uneven results across provinces with different economic bases. The Ministry of Economic Affairs and Finance should direct agribusiness investment (value-added food processing, cold chain infrastructure, cooperative formation) toward provinces where agriculture dominates employment, and digital services and healthcare investment toward urbanising provinces where services are the primary growth sector.

Provincial government spending carries a negative elasticity of -0.047, a weak association reflecting expenditure composition rather than budget size. Provincial budgets focus on public-

sector wage bills and consumer subsidies; little reaches job creation or vocational training. Increasing the budget alone will not close the NEET gap. The Ministry of Economic Affairs and Finance should condition provincial youth employment transfers on employment outcome data from the quarterly Labour Force Survey, replacing input-based funding. Provinces that document measurable NEET reductions receive higher per-capita allocations the following year.

The Chapter 4 CART model generates a workable screening instrument, with 82% out-of-sample accuracy and an AUC of 0.81. Education level, work experience, and hours of housework classify youth into high- and low-risk NEET profiles, and all three variables are already available in the quarterly Labour Force Survey. The Ministry of Cooperatives should operationalise this as a routine Labour Force Survey (LFS) flag: women aged 20–24 who do more than 20 weekly hours of housework and have fewer than 12 years of schooling receive outreach from provincial employment offices. Running the tool requires no new data collection.

6.3. Contextual Relevance for Iran and Similar Settings

Due to Iran's unique socio-political context, the findings of this dissertation have particular significance for the country's NEET crisis among youth. Demographically and economically, Iran is at a crossroads. Despite large youth populations (a potential "demographic dividend"), many of these young people do not contribute to the economy or their own advancement, turning the dividend into a liability (Salehi-Isfahani, 2010; Dhillon and Yousef, 2009). The findings of this study shed light on why this is happening and what can be done to prevent it, making it highly relevant to Iranian policymakers and society in general.

The results show that Iran's NEET problem is multifaceted. Iran has high NEET rates (approximately 30% among youth) due to entrenched issues (Chapter 1). As a result, any solution must address Iran's macro-level problems, such as economic instability, sanctions, and slow job creation, which not only affect the youth but also directly impact them (Rafiee et al., 2023; Sobhani, 2018). As a result of inflation and business stagnation, fewer new jobs are available for graduates, which explains why even well-educated youth are joining the ranks of the NEETs. Our policy evaluation found that the NEET crisis cannot be fully resolved without broader economic growth and diversification (away from over-reliance on oil and a few sectors). Thus, the importance of contextual relevance is clear; recommendations like boosting vocational training will only be effective if the economy can absorb new workers, which

requires macroeconomic reforms and stability in Iran. In similar developing contexts, this interplay between macro conditions and youth outcomes is equally relevant; countries in the Middle East and North Africa (MENA) and South Asia, for example, share some of these structural issues (youth bulges, unemployment, and sometimes gender norms restricting women) (Mina, 2023). Our findings about the need for holistic improvement (economic plus social) could also inform those contexts.

Secondly, the social and cultural context of Iran, especially in terms of gender roles and family expectations, makes the NEET issue somewhat unique. Institutional factors compound cultural pressures; formal public sector hiring policies explicitly favouring male applicants, occupational restrictions on women, and inadequate childcare provision structurally exclude women from formal employment regardless of qualifications. Cultural and institutional barriers, therefore, require parallel reform; neither alone is sufficient. The dissertation revealed that most of Iran's NEET youth are female, often because young women are expected to prioritize domestic duties or face labour market limitations. The fact that Iran needs to empower young women through policy (e.g., enforcing antidiscrimination laws, providing childcare, and encouraging female entrepreneurship) is a critical insight. Iran cannot afford to have such a large portion of its young workforce sidelined. Given the context of a relatively traditional society, any intervention should be sensitive and gradual. Women might gain more support if home-based work is promoted or community-approved enterprises are encouraged. It is important to consider the cultural context when planning interventions (for instance, neighbouring countries such as Pakistan and Arabic states face similar problems with female NEETs) (Zanfrini & Giuliani, 2023). The findings stress that context-aware solutions (like the mentorship for women or transport safety measures mentioned earlier) can make a difference in places where women's mobility and work are culturally regulated.

Thirdly, Iran's regional diversity (economically and socially) is an important context highlighted by the research. The differences between Tehran (and other developed cities) and remote provinces in terms of NEET rates and opportunities are vast. Regional disparities mean that national averages can be misleading; a province like Sistan and Baluchestan might have NEET rates nearly double those of a province like Yazd. Our spatial analysis (Chapter 5) found that provincial factors (such as infrastructure, industrial base, and educational facilities) heavily influence youth outcomes. This suggests that policies must be nationally coordinated and locally adapted, a principle that likely holds in other large or regionally varied countries (such as Turkey, India, or Indonesia) (Karaalp-Orhan, 2020). It is possible that youth in oil-rich

Khuzestan might need different support (perhaps to address conflict and displacement) than youth in more industrialised provinces like Markazi or in tourist-based economies like Isfahan and Shiraz. Iran should develop region-specific action plans as part of a comprehensive national strategy to ensure that no region is left behind. Similarly, international organizations or comparative organizations can benefit from Iran's experience by analyzing regional data within their own countries.

Iran's political and institutional framework is another aspect of context. Iran may face challenges in implementing policies due to bureaucratic obstacles, government changes, and interactions between the central and local administrations. Chapter 5 found that, despite strategies existing on paper, execution was often weak (a not uncommon scenario in many developing contexts). Therefore, improving institutional capacity and coordination between agencies is part of the solution. Specifically, Iran needs better coordination between the Ministry of Cooperatives, Labour, and Social Welfare (which handles employment programs) and the Ministry of Education (which can help with dropouts and training). To contextualize our recommendations, we propose mechanisms such as a cross-ministerial task force on youth or a public-private partnership platform. Such collaborative models may also be beneficial to countries with complex governance systems (e.g., those that balance central and provincial authorities) (Andersson, 2020).

The relevance of these findings extends beyond Iran, given global shocks and trends. The study period coincided with the tail end of the 2010s and the early 2020s, a period that included the COVID-19 pandemic, which significantly impacted youth employment worldwide. While our research focuses on Iran, the identified risk factors and necessary responses (such as boosting digital skills or establishing safety nets) emerged dramatically during COVID. For instance, youth with digital access to higher education could pivot to online learning or remote work when the pandemic hit, whereas those without such capabilities fell further behind. Although resilience to shocks is not the focus of our chapters, it is an important consideration. Sanctions and the COVID-19 pandemic likely exacerbated Iran's NEET rates (World Bank, 2022). The context-specific lesson is that Iran (and similar economies) should build resilience into youth policies, such as digital infrastructure to maintain education continuity, and emergency public works to employ inactive youth. As a result of our findings, NEET issues cannot be decoupled from their context; instead, they should inspire a contextualized approach that adapts global knowledge to local conditions.

In conclusion, the contextual relevance of this dissertation lies in its ability to tailor and situate the understanding of NEET youth within Iran's cultural, economic, and institutional framework. This provides a blueprint for Iran and insights that can be applied to other countries facing similar youth disengagement under analogous conditions (such as high youth unemployment, gender norms, or regional disparities). It is particularly significant for Iran that it addresses NEET youth, as this is critical to the country's future development, social cohesion, and even political stability (as large numbers of disaffected youth can cause unrest and undermine public trust). As a result, we should acknowledge and act on these findings within the context of their findings.

6.4. Limitations

Although this study has provided insights into Iranian NEETs, its limitations should also be acknowledged. Interpretation of the findings is important, since both methodological choices and contextual constraints influence them.

Given the scope of available literature and data constraints, some limitations exist. According to Chapter 2, the scoping review was broad but primarily focused on English-language studies up to June 2022. Studies or reports published in local languages may not have been included or may have been published recently. There is a possibility that certain risk factors or characteristics are not considered in under-researched regions. The meta-analysis in Chapter 3 included 43 studies, a large number, but NEET research is still in its early stages, and many studies did not meet the inclusion criteria. The meta-analysis simplified diverse contexts to combine results (using odds ratios), which might overlook complex interactions. In Chapter 4's machine learning analysis, the labour force survey data were cross-sectional, providing a snapshot of the labour force at a given point in time. This means our machine learnin and probit models indicate an association rather than confirmed causation; for example, we found that low education is associated with NEET status. However, we cannot be certain from that data alone if improving education causes a youth to leave NEET (though theory and other evidence strongly suggest it). The cross-sectional nature also limits our ability to see dynamic transitions (youth moving in and out of NEET) over time. In Chapter 5, the spatial panel analysis integrates key macroeconomic indicators with illustrative case studies and the patchwork of available data compilations. A primary limitation is the lack of full-scale, standardized evaluations of how macroeconomic shifts affect Iranian youth. Instead, we were compelled to draw on disparate government statistical releases and a limited number of outcome summaries.

Consequently, the estimated relationships between economic fluctuations, especially those toward the very end of our 2004–2022 study period, and NEET prevalence may be underestimated or unobserved due to reporting lags and data gaps. A large portion of the quantitative data (used in both meta-analysis and machine learning) is collected through surveys and studies in which people (youth, households) report their status (workforce participation, school attendance, etc.). Inaccuracies can occur in self-reported data. For example, some youth might not declare the informal work they do (resulting in them appearing NEET when they are actually doing odd jobs).

The definition of NEET can vary slightly depending on the source. We always use the standard definition (not in formal employment, education, or training), but some surveys may categorise borderline cases differently (for example, a short training course may or may not be included). We attempted to harmonize these definitions in our analyses, but slight inconsistencies in the source data limit precision. Likewise, the labour force survey might under-sample certain hard-to-reach populations (like very remote rural youth or those not registered as job seekers), potentially underestimating or misrepresenting some subgroups. Chapter 5's spatial models also face potential endogeneity: provincial GDP and NEET may be simultaneously determined (low NEET results in more workers and higher GDP). While province-fixed effects partially address this, instrumental-variable approaches (e.g., using oil-price shocks that affect provincial revenues) would strengthen causal claims. The inability to isolate sanctions-specific effects from general macroeconomic dynamics represents a further limitation inherent to the observational design. Although year fixed effects control for common temporal shocks, they cannot distinguish between the sanctions channel, global oil-price movements, and domestic policy responses, all of which vary simultaneously. The theoretical mechanisms through which sanctions affect youth employment, but formal identification of these channels would require either sanctions-specific instrumental variables or a comparative design with non-sanctioned economies sharing similar structural characteristics. Additionally, our choice of a contiguity-based spatial weight matrix (provinces sharing borders) could be complemented with distance-based or economic-similarity matrices to test the robustness of spatial lag findings.

Regarding contextual and structural constraints, the study focuses on Iran, resulting in context-specific findings. While we have drawn comparisons to global trends, one should be cautious about generalizing the numerical results to contexts beyond those similar to them. For instance, the exact importance of a given risk factor (the weight of parental unemployment on youth NEET odds) might differ across countries with different welfare systems or cultural settings.

Moreover, within Iran, our analysis had to operate at aggregate levels, particularly in Chapter 5's spatial analysis, which looked at provincial averages. This can obscure intra-provincial disparities; a province might have both affluent cities and very poor villages, and youth experiences can differ widely within the same province. Not capturing these micro-differences is a limitation imposed by the level of available data. Another contextual limitation is that our study period and data mostly predate the full effects of the COVID-19 pandemic (which hit Iran hard) and any major policy shifts in its aftermath. Thus, our analysis might not reflect very recent changes (such as the expansion of online education or new policies post-2022). Additionally, certain structural factors, such as the role of the informal economy, where many Iranians work without formal contracts, were not deeply explored; some NEET youth may actually be engaged in informal activities not counted as employment, which our study could not fully quantify.

For the chosen methodology, each approach we used comes with trade-offs. The scoping review (Chapter 2) prioritized breadth over depth within each study, meaning we summarized broad patterns but did not conduct a fine-grained critical appraisal of each study's quality beyond inclusion criteria. The meta-analysis (Chapter 3) provided a rigorous statistical synthesis but faced heterogeneity; different studies used different measures or age ranges for NEET, so while we applied random-effects models to account for this, the average effects have wide confidence intervals in some cases. The machine learning methodology employed in Chapter 4 provided an innovative capability for exploring complex interactions; however, this sophisticated predictive power often came at the expense of interpretability. We mitigated this by using CART, which is more interpretable, but more complex ensemble methods (not used here) might have yielded even more accurate predictions at the cost of interpretability. Also, while decent, the classification model's performance was not perfect, meaning some at-risk youth would not be identified, and some identified youth may not actually become NEET (false negatives and false positives are inherent limitations of predictive analytics). In Chapter 5's assessment of macroeconomic determinants, a principal limitation stems from potential model-specification bias. Although we began with the intention of rigorously testing how regional GDP growth, unemployment, and inflation shape NEET dynamics, the selection and operationalization of these indicators involve some subjectivity. To mitigate this, we conducted multiple robustness checks, examining alternative measures (e.g., real versus nominal GDP, youth versus overall unemployment rates) and disaggregating results by gender and urban–rural status but, in the absence of quasi-experimental or instrumental-variable strategies,

establishing a definitive causal link (for instance, that a 1 percent rise in unemployment directly increases NEET prevalence by Z percent) remains challenging.

We deliberately focus on broad patterns and significant correlations; there will always be individual exceptions and outliers that a nationwide study cannot explain fully. As we discuss next, future research can address many of these limitations by extending and deepening the analysis (for instance, using longitudinal data or more fine-grained qualitative work to complement our findings). Overall, despite the noted limitations, such as data constraints, potential biases, and context specificity, the strengths of the research design (large combined sample of studies, multiple methods, and consistency with theoretical expectations) provide a solid degree of confidence in the results. The limitations highlight areas where interpretation should be careful, but do not detract from the validity of the key messages about NEET youth in Iran.

6.4.1. Ethical Considerations and Data Protocols

Youth populations are subject to specific ethical obligations that require explicit consideration, even when data are drawn from national statistical surveys rather than primary fieldwork. The empirical chapters of this dissertation use two types of data with distinct ethical profiles.

Chapter 4 examines individual microdata from the Iranian Quarterly Labour Force Survey (Spring 2021). Iran's national statistics legislation mandates respondent confidentiality and prohibits the release of records that are individually identifiable. The microdata made available to researchers are anonymised: personal identifiers (names, national ID numbers, precise addresses) are removed prior to release, and geographic information is limited to the provincial level. These protections are broadly consistent with the ILO's Guidelines Concerning Statistics of Employment and Unemployment (2013) and the United Nations Fundamental Principles of Official Statistics (2014), both of which require that individual data collected for statistical purposes be kept strictly confidential and used exclusively for statistical purposes. We did not have access to any information that could identify individual respondents, and no attempt was made to re-identify observations.

Several ethical considerations specific to youth survey research nonetheless warrant acknowledgment. First, the Labour Force Survey includes respondents aged 15 and older, meaning that a portion of our sample (those aged 15–17) are minors. Although the survey is household-based and administered to or through adult household members, the ILO's Guidelines on Measuring Decent Jobs for Youth (2019) emphasise that research involving

young respondents should be attentive to power dynamics within the interview setting, particularly when sensitive topics such as employment status and domestic responsibilities are discussed in the presence of family members. Self-reported housework hours, a variable central to our Chapter 4 analysis, may be especially susceptible to social desirability effects in face-to-face household interviews where parental expectations shape what young women feel able to disclose. We flag this as both a measurement limitation and an ethical concern: the interview setting may constrain young respondents, particularly women in conservative households, from accurately reporting their circumstances.

In addition, the classification of youth as NEET may carry a stigma attached. Young people may perceive the NEET label negatively, especially when it conflates voluntary inactivity (such as caregiving by choice) with involuntary exclusion (ILO, 2015). While we use the NEET classification as an analytical category throughout this dissertation, we have been careful to emphasise its heterogeneity (Section 1.3, Chapter 4 discussion) and to avoid framing NEET status as an individual failing. The Bronfenbrenner's ecological framework adopted in Chapter 1 explicitly positions NEET outcomes as products of structural constraints rather than personal deficiencies.

Chapter 5 uses province-level aggregate data compiled from published statistical yearbooks and publicly available government databases. Because these data are already aggregated to the provincial level, individual privacy concerns do not apply. Data quality and transparency are the ethical considerations here. It is not always possible to verify provincial-level figures independently since Iranian statistical agencies operate under institutional constraints. Section 5.5.2 acknowledges interpolation and measurement concerns, but we acknowledge that government-compiled statistics should be trusted in any country.

The scoping review and meta-analysis (Chapters 2 and 3) synthesise published studies, each of which would have been subject to its own institutional ethics approval process. We did not assess the ethical protocols of the included studies, a common practice in systematic reviews but a limitation, as ethical standards for youth research vary across the 43 countries represented in our sample.

No primary data collection involving human subjects was undertaken for this dissertation. All analyses rely on either anonymised secondary microdata or published aggregate statistics. The research was conducted in accordance with Maastricht University's research ethics guidelines. In the future, research extending this work into qualitative interviews or longitudinal tracking of NEET youth would require a formal ethical review, which would pay particular attention to

informed consent procedures for minors, confidentiality protections in contexts where NEET status may carry social stigma, and the duty of care researchers have when engaging directly with vulnerable youth whose experiences are likely to include exclusion, hardship, and distress.

6.5. Suggestions for Future Research

This dissertation sheds light on youth NEET in Iran, opening up several opportunities for further study. Future research can address the gaps and limitations identified in this study based on these findings. Observing how and when Iranian young people enter and exit NEET status over time is a clear next step. When individuals are tracked from late secondary school to mid-20s, key turning points or triggers are identified (e.g., does military service or marriage predict transition to NEET status? How long do typical NEET spells last? What helps some youth exit NEET status?).

Longitudinal data would enable more causal inference, for example, confirming that losing a first job without finding a new one within X months significantly increases the risk of long-term NEET, or that early motherhood without support leads to persistent withdrawal from work/education. It would also enable analysis of the long-term consequences of being NEET (such as impacts on income, health, and further employment up to the 30s), which are currently inferred but not directly measured. Such studies could be panel surveys or use administrative data linkage (such as linking education records to later employment records). By addressing the limitations of cross-sectional data, this approach would offer a dynamic perspective on the NEET phenomenon.

Evaluating intervention programs (experimental or quasi-experimental studies) is crucial as interventions are implemented. Experimental designs (randomized controlled trials) or quasi-experimental methods (e.g. difference-in-differences, regression discontinuity) could be used to test specific programs. Researchers could compare NEET outcomes before and after implementing a vocational training program in one province to measure its impact. Randomized assignment could also be used to evaluate pilot programs that provide stipends to help young mothers return to school. The effectiveness and cost-efficiency of different strategies (skills training, apprenticeships, entrepreneurship grants, counselling, etc.) in Iran could be evaluated. As a result, policies could be fine-tuned with a better understanding of which components are most beneficial (e.g., does adding mentorship significantly improve program success?) and whether certain subgroups benefit more (e.g., women respond better to

online training than men to in-person training, etc.). Through this type of applied research, policymakers can learn from each initiative and scale up only those that truly reduce NEETs.

A promising research direction focuses on how digital skills development and online employment can help NEET youth integrate into the workforce as Iran and the world move further into the digital age. Studies could examine the role of ICT in alleviating NEET status in the future, for example, would training NEET youth in coding, digital marketing, or online freelancing open up remote employment opportunities for those in remote or restrictive environments (like rural youth or young women who cannot easily work outside the home)? Assessing the uptake and outcomes of pilot projects teaching such skills would be possible. Furthermore, research into internet access and smartphone usage among NEET youth could reveal untapped engagement channels (such as e-learning). Considering the Iranian context, where brain drain and the emigration of skilled youth are common, one might also examine whether digital jobs (which allow one to earn in global markets while residing in Iran) could incentivize youth to stay and remain productive. In the future, Iran's educated NEET population may benefit from global digital opportunities, a topic not well covered in our current research.

A comparative analysis of Iran's NEET situation could be conducted both regionally and internationally in the future to better understand the problem and learn from other countries. A qualitative analysis of regional differences within Iran could complement our quantitative provincial analysis. Ethnographic or case studies in high-NEET provinces could shed light on cultural, educational, or policy differences that explain these regional disparities. A comparison of Iran with other Middle Eastern countries or with economies that are at a similar level of development (such as those in North Africa or South Asia) may reveal common challenges. It may be possible to gain insights into cultural and structural factors related to the treatment of women who are not in the labour force by analyzing the approaches taken by Iran, Turkey, and Egypt. Another option is to examine a country that has significantly reduced its NEET rate and compare it with Iran. To understand why some contexts perform better than others, comparative research can use metrics such as NEET rates by gender and region, as well as policy analysis frameworks. Moreover, given Iran’s unique factors (such as sanctions), comparing scenarios pre- and post-major events (e.g., before sanctions tightened vs. after) within country data or with a control country could isolate those effects. These broader-lens studies could both validate and challenge our findings: validating that many risk factors are universal and challenging the notion that some Iran-specific findings might differ when the context changes, thereby refining our understanding of what is truly context-specific.

Future research should also focus on specific subpopulations of NEET youth. A qualitative study could be conducted with young women NEETs across different regions to hear, in their own words, the barriers they face and what would help them most, adding a human dimension to the statistical patterns. Researchers can also ensure that policies are inclusive of NEET youth who also belong to other vulnerable groups (such as those with disabilities or from minority ethnic communities in Iran). In addition, since mental health and attitude were mentioned as factors, a study on the aspirations, motivation, and identity of NEET youth could be insightful. Are they discouraged or hopeful and just waiting for the right opportunity? It is possible to tailor interventions (for example, addressing learned helplessness or igniting entrepreneurship) based on their mindset. Research could fill in the micro-level details behind our macro findings, ensuring the voices and experiences of NEET youth are heard and incorporated into solution-building efforts.

Furthermore, researchers could simulate or forecast how different macroeconomic or policy scenarios might affect NEET rates. For example, under current trends, what will Iran's NEET situation look like in 10 years, based on economic modelling or systems dynamics? Can a sustained 5% GDP growth or a major education reform affect the number of NEETs? Alternatively, what is the impact of continued high NEET rates on Iran's future (lost GDP, social costs)? Long-term planning can be informed by answering these questions. In addition, assessing the impact of global changes such as automation (will increased automation of jobs worsen NEET by reducing low-skilled jobs, or will it create new tech opportunities?) would provide a forward-looking research perspective.

6.6. Concluding Remarks

In this final chapter, the research strands are combined to provide an overview of NEET youth in Iran. We have summarized and synthesized the key findings of each chapter, illustrating how these elements (from understanding risk factors to evaluating policies) contribute to the understanding of why many young Iranians are neither enrolled in school nor employed nor in training. During this discussion, theory and practice were brought together, and targeted, context-sensitive approaches were emphasized. To qualify our conclusions, we provided concrete recommendations for policymakers and society to reduce NEET rates. This pressing issue has prompted several suggestions for future research. Considering the methodological strength and consistency of the evidence, as well as the possible impact this research may have on academia, policy, and society in general, we are confident in the robustness of our findings.

Reducing Iran's NEET rates requires immediate action alongside long-term reforms. The Ministry of Cooperatives should double its vocational training budget and pilot dropout tracking in high-NEET provinces. Governors of provinces must diversify their local economies over the next 10 years. This research has shown that it is a challenge that can be overcome. It is clear from the insights and evidence presented here that inaction will have a greater cost than action: disengaging a large share of the youth population is a waste of human capital, undermines social cohesion, and ultimately harms the country's future economic prosperity. Educating, training, and implementing inclusive policies can really help young Iranians. NEETs can be reduced through education and training, as well as active community engagement. Taking action on the NEET issue is essentially about securing Iran's future. Youth is a nation's greatest asset and will drive innovation and growth for years to come. Our final point is to emphasize that guiding young people from the margins into mainstream education and employment is not just an individual success story, but also a contribution to Iran's economic and social development. In our view, the findings and recommendations of this thesis should inform policy and practice, ultimately transforming the NEET phenomenon into an opportunity to empower Iran's youth.

6.6.1. Declaration on the Use of Generative AI and AI-assisted Technologies

During the preparation of this dissertation, the authors used ChatGPT to assist with grammar checking and enhance the academic quality of the manuscript. In Chapter 3, AI-assisted tools were employed to support the initial sorting and categorization of articles during the literature screening process. Furthermore, generative AI was used as a technical aid in writing and debugging R code for the data analysis presented in the empirical sections of this work.

All AI-generated suggestions, code, and organized data were meticulously reviewed, edited, and verified by the author. The author exercised full human oversight throughout the process and takes full responsibility for the accuracy, originality, and final content of the dissertation.

Impact Statement

The dissertation makes several noteworthy contributions to academic knowledge and policy regarding youth Not in Education, Employment, or Training, with implications for society and the economy. Specifically, we emphasize the societal impact of the research, highlighting how it advances understanding and why it is relevant to stakeholders beyond academia.

Prior to this study, the NEET phenomenon in Iran was under-researched. The study fills a significant research gap by systematically investigating the issue. The primary academic contribution is the multi-method analysis, including a scoping and meta-analysis that synthesizes findings from around the world and provides a reference on the risk factors associated with youth NEETs. In this dissertation, a solid foundation is laid for scholars studying youth unemployment, social exclusion, and development. Additionally, the dissertation discusses the methodological utility of mixed-methods research in social science. By combining literature reviews, meta-analytic techniques, predictive analytics, and spatial panel data, this approach enables the simultaneous analysis of individual, household, and provincial determinants, providing a multi-scale framework applicable to similar social phenomena in comparable contexts.

This study extends theories such as the Capability Approach and Human Capital Theory to a new context (Iran). The Capability Approach is extended to Iranian institutions, where structural barriers, including regional economic disparities, gender norms, and discriminatory labour-market policies, limit youth capabilities and prevent them from converting their human capital into productive employment outcomes (Sen, 1999). In addition, the research emphasizes the interplay among various factors (education, gender, region, etc.), suggesting that future theories of youth NEET should incorporate multidimensional rather than single factors. Youth marginalization can be addressed by identifying specific high-risk groups (e.g., rural women caregivers). While machine learning methods have been applied to youth employment research in high-income contexts (Smoter & Szymczak, 2024), this dissertation applied CART-based risk profiling modelling to NEET determinants in a developing country context with structurally segmented gender and regional labour markets, showing that data-driven approaches can generate actionable insights outside of Western welfare state settings. This method provides a framework for analysis, encourages interdisciplinary approaches, and advances academic knowledge about Iranian youth employment.

The implications of this research are potentially far-reaching. This research provides policymakers in Iran with evidence-based insights and recommendations. This dissertation translates academic findings into concrete policy recommendations. By identifying the most influential risk factors, policymakers and practitioners can now focus their resources on them. For example, improving educational outcomes and promoting female inclusion are top priorities for those who wish to reduce NEETs. As part of this dissertation, we highlight the shortcomings of current policies and suggest ways to improve them (such as tailoring programs to women and regions). Government ministries and youth organizations can also use it to justify and design new initiatives. For example, if the Ministry of Labour proposes expanding apprenticeship programs, it can cite this research to support the claim that inexperience is a significant risk factor, thereby adding urgency and weight to its case.

International agencies and NGOs that focus on youth employment and development may also find it relevant. Organizations such as the United Nations (e.g., UNICEF, UNDP) or the World Bank often support youth employment projects in countries like Iran; the detailed context and evidence provided here can guide those interventions to be more context-specific. Based on these findings, international frameworks for gender equality and rural development could be shaped, demonstrating how these issues intersect with youth employment and advocating integrated approaches (e.g., combining job training and women's empowerment programs).

One of the most significant impacts of addressing the NEET issue is the enhancement of social inclusion and economic productivity. As a result of the research findings and recommendations, more young people in Iran would be able to transition into education or employment. A reduction in NEET contributes to a more productive workforce, a higher GDP, and better utilization of the country's human capital. In a country like Iran, it could mean the difference between a demographic dividend and a demographic burden. Socially, engaging youth in constructive activities (school, work, training) reduces the risks of the negative outcomes associated with idle youth, such as crime, drug use, or social unrest (Chapter 2). There is a consistent link between youth disengagement and increased risks of social instability, with high NEET rates being associated with increased crime, substance abuse, and political disaffection (ILO, 2021; World Bank, 2022). NEET reduction serves both individual welfare and broader social cohesion objectives. By highlighting the challenges young women face, the research implicitly advocates policies that could transform gender relations, including increasing female participation in the workforce and higher education, shifting perceptions, and empowering a new generation of women. By documenting both cultural constraints (domestic expectations,

caregiving burdens) and formal institutional barriers (public-sector hiring preferences for men, occupational restrictions, inadequate childcare infrastructure), this research provides evidence for targeted policy reform that addresses structural exclusion rather than merely cultural advocacy. Modernization and equity are broader societal goals that require institutional reform alongside cultural change.

The implementation of the insights from this research could potentially change the lives of both the youth themselves and their communities. For example, the CART model found that female youth who spend more than 20 hours per week on housework have an 85% probability of becoming NEET, regardless of education level. Integrating this threshold into school dropout monitoring systems would allow provincial authorities to flag at-risk individuals before disengagement becomes entrenched. These individual changes multiply into community uplifting; when youth are productively engaged, they can contribute to their families (financially and otherwise), breaking cycles of poverty and dependency.

The policy discourse has also been affected more broadly in Iran. This dissertation can contribute to shifting the narrative from viewing NEET youth as a marginal statistic or a social problem to recognizing them as a crucial segment that requires investment and empowerment. A data-driven study adds credibility to youth advocacy in public forums or media. Therefore, the research can indirectly contribute to public debate. These findings could be used by newspapers or civil society to call for action, armed with statistics such as "nearly one in three young Iranians is NEET" and explanations for why this is the case. In an era when evidence-based policymaking is increasingly valued, having a solid evidence base, as provided here, can change the way decisions are made.

The NEET problem has long-term implications for sustainable development. Engaging youth in education and decent work aligns with the United Nations' Sustainable Development Goals (notably Goal 8: Decent Work and Economic Growth, Goal 4: Quality Education, and Goal 5: Gender Equality) (United Nations, 2015). As a result, the dissertation's practical importance is tied to these global goals, potentially helping Iran (and similar countries) meet their commitments. In research, youth are tapped for their energy and talents by investing in human capital and inclusive growth. In line with demographic dividend theory, reducing Iran's NEET rate from 30% to 25% would expand the productive workforce, increase tax revenues, reduce welfare expenditures, and strengthen human capital accumulation, creating compounded economic returns.

In summary, this dissertation has a multifaceted impact: academically, it pioneers research on NEET youth in Iran; practically, it provides a roadmap for policies and programs to reduce youth disengagement; and societally, it promotes a more productive and inclusive world. Readers and decision-makers should take away from this study that addressing the NEET issue is more than just about social welfare. Based on the insights provided, Iran could enhance its social well-being and economic vitality by fully leveraging the potential of its young generation.

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Appendices

Appendix 1.1. Theory to measurement mapping for NEET risk in Iran

Theory	Mechanism	Observable indicators in this dissertation	Expected association with NEET risk or NEET rate	Main chapter link
Human capital theory	Lower education and weaker skill accumulation reduce employability and raise inactivity risk	Micro: education, potential work experience. Macro: human capital indicator, illiteracy rate, higher school rate, dropout rate, vocational education and training (VET) programs	Higher education and higher experience link to lower NEET risk. Higher human capital links to lower NEET rates. Higher illiteracy and higher dropout link to higher NEET rates	Chapters 2 and 3, 4, and Chapter 5
Matching and mismatch theory	Skills and credentials mismatch with available jobs raises unemployment and discouragement	Micro: education by subgroup (gender, rural, urban) as a proxy for unequal returns. Macro: youth unemployment rate, industrial diversity, sectoral gross value added (GVA) structure	Higher youth unemployment links to higher NEET rates. Lower industrial diversity and adverse sector structure link to higher NEET rates. Stronger mismatch patterns expected among young women and rural youth	Chapters 2 and 3, Chapter 5
Labour market segmentation theory	Dual labour markets restrict youth entry into stable jobs, with gender and place shaping access	Micro: subgroup models by gender, rural and urban residence. Macro: sectoral GVA, industrial diversity, urbanization, regional inequality indicators	Higher segmentation links to higher NEET risk among women and rural youth. Higher urbanization and stronger economic capacity link to lower NEET rates, with subgroup differences	Chapter 3, 4, and Chapter 5
Insider-outsider theory	Incumbents hold advantages, entrants face barriers to stable jobs	Micro: potential work experience, labour-market entry selection correction. Macro: unemployment rate, GDP per capita, government spending	Higher experience links to lower NEET risk. Higher unemployment links to higher NEET rates. Higher GDP per capita and effective spending link to lower NEET rates	Chapter 4, Chapter 5
Social stratification theory	Family background and institutional sorting reproduce unequal transitions	Micro: family education, household wealth proxies, land ownership, birthplace, presence of young children, caregiving constraints. Review domains: family and environment risks	Higher household resources and higher family education link to lower NEET risk. Care responsibilities and weak resources link to higher NEET risk, with stronger associations for young women	Chapters 2 and 3, Chapter 4

Theory	Mechanism	Observable indicators in this dissertation	Expected association with NEET risk or NEET rate	Main chapter link
Ecological systems theory (Bronfenbrenner)	NEET emerges from interacting individual, family, community, policy, and historical forces	Micro: education, experience, housework. Meso: family background indicators, caregiving, household resources. Macro: GDP per capita, inflation, government spending, Gini, urbanization, spatial dependence (neighbouring provinces)	Higher housework is associated with higher NEET risk, particularly among young women. Macro disadvantage and inequality link to higher NEET rates. Spatial dependence implies provincial clustering	Chapter 2, 4, and Chapter 5
Capability approach (optional interpretive frame)	Capability deprivation limits feasible education and work choices, shaped by norms and opportunity gaps	Micro and meso: gendered caregiving, household constraints. Macro: regional opportunity disparities	Lower capabilities are linked to higher NEET risk, and stronger constraints for young women and youth in disadvantaged provinces.	Chapters 4 and 5

Appendix 2.1. Overview of NEET Youth Determinants Included in the Review

Author(s) and Year	Country	Methodology/ number of sample	Study Focus	Year of Data/ Sample characters	Determinants
(Zuccotti & O'Reilly, 2019)	England	Quantitative, survey, intersectional analysis. , logistic regression (*N*=50,000).	the differential effects of ethnicity, gender and parental households' employment status	2009 to 2015/ 16–29 years	Ethnicity, Gender, Household
(Zhang et al., 2020)	emerging countries	Quantitative, fuzzy DEMATEL, logistic regression.	Effects of family, Individual, and environment. attrition	2020/ -	Uneducated parent, low-income family, poor family support, divorced or separate living of parents, lack of education, drug addiction,….
(Vasile & Anghel, 2015)	Romania	Quantitative, school documents, questionnaire, discrete-time logistic regression.	Assessing factors Education	2014/ aged 20-29	level of education
(Yang, 2020)	China	Quantitative, multilevel logistic regression. (*N*=4,978)	Demographic characteristics, marital status. region of birth , father's education respondent's Party membership, and family income	2012-2020/ 4,978 individuals are aged 16 to 35	age, gender, ethnicity (Han versus non-Han), education level ,and marital status. region of birth , father's education , migration, respondent's Party membership, and family income
(Veldman et al., 2015)	Netherlands	Quantitative, questionnaire, (*N*=1711)	mental health problems	2007, 2009/ 1711 (76.8% of the initial cohort) TRAILS participants,	Age, gender, Parental educational, Family composition, Physical health, Externalising problems, Internalising problems
(Varshavskaia, 2017)	Russia	Quantitative, ILO methodology .	Socio-Demographic Characteristics	2014/ aged 15 to 24	Age, gender, education level ,resident place ,and marital status
(Vancea & Utzet, 2018)	Spain	Quantitative, cross-sectional survey, multivariate logistic regression models (n = 1.826).	To compare them with their non-NEET counterparts regarding social capital and family background.	2016/ ages 18–35 years	Age, gender , education level, Marital status, Caring responsibilities, Having children, parent education family income, Parental immigration background, Work experience, Social capital(friends)
(Tamesberger & Bacher, 2014)	Austria	Quantitative, survey, Latent cluster analyses (*n = 59.844*)	o examine the socio-structural attributes that characterise NEET youth in Austria, the main reasons for the NEET situation, whether there are different subgroups of NEET, whether the NEET situation is permanent or temporary and the extent to which those with NEET status have contact with the Public Employment Service.	2008–2010/ 16 and 24 years	Gender, Migration, Population, Living circumstances, , education level, parent education, Care responsibilities, Illness
(Sveinsdottir et al., 2018)	Norway	Quantitative, a randomized controlled trial, questionnaire (N= 96)	social and health-related problems	2014-2016/ aged 18–29	Gender, education level, Marital status, Having children ,Family composition, Physical health, immigration background, Work experience, drug and alcohol addiction, Bullying, victim, coping, and social support ,disability level, mental health

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Author(s) and Year	Country	Methodology/ number of sample	Study Focus	Year of Data/ Sample characters	Determinants
(Shinozaki, 2012)	Japan	Quantitative, questionnaire, Multinomial logit models. (*N*=3168)	local job markets and varying family characteristics	2000 to 2006/ aged 20–34	Gender, Age, education level, Regional unemployment rate, Regional minimum wage, birth year-based, parent employment, family income, parent education,
(Selenko & Pils, 2019)	Austria,	Quantitative, questionnaires, descriptive statistics. (*N*= 300).	aggravating factors (young age, low socioeconomic status) and alleviating factors (relationship with parents)	2007 and 2011 / average 16.67 years of age	Gender, Age, Nationality, number of sibling, family composition , parent employment, Cognitive abilities, Relationship quality, dropout
(Schoon & Lyons-Amos, 2017)	England	Mix methodology(qualitative, quantitative), questionnaire, interviews, Longitudinal Study, and descriptive statistics. (*N*= 9791).	the role of structural and agentic resources in shaping school-to-work transitions	2004 and 2010 / young people 13/14-19/20	Academic expectations, Goal certainty (forethought), Academic self-concepts (self-efficacy), School engagement (self-directedness), Parental education, parent income, family composition, living area, gender ethnicity. Life satisfaction, Transition patterns
(Schoon, 2014)	England	Mix methodology, questionnaire, interviews, Longitudinal Study, descriptive statistics. (*N*=9879)	parental worklessness and the experiences of their offspring making the transition from school to work	2004 and 2006, 2007 and 2010 / ages 16 to 20 years	Parental worklessness , family structure, housing conditions, and health, as well as area deprivation Academic expectations, Goal certainty (forethought), Parental education, Long standing illness or disability in the family, ethnicity, parent income, gender
(Sánchez-Soto & Bautista León, 2020)	Mexico	Mix methodology, questionnaire, interviews, quantitative, multinomial logistic regression model. (*N*=8965)	determinants of being NEEt relative to other activities	2015 and 2016/ ages 18 to 25	Age, education level, household headship, education of household head, relationship to the household head, household economic characteristics
(Salvà-Mut et al., 2018)	Spain	Mix methodology, questionnaire, statistical and regression analysis, biographical interview. (*N*=622)	common characteristics of the NEET	2010 to 2012 / aged 25–29 years	Gender, dropout, education level, immigrants status, family immigrants status, parent education, parent work, Personal situation, economic situation, health, time usage, educational background, Work history
(Salvà-Mut et al., 2016)	Spain	Mix methodology, questionnaire, (*N*=905).	the effect of dropout on the school-to-work transitions of young people without qualifications in times of crisis	2000–2001, 2010–2012 / aged 26–28	Gender, Birthplace, Cohabitation model Education level, School biography, Job characteristics (employed), Income, Employment, Physical/psychological well-being, Have children
(Sadler et al., 2015)	UK	Quantitative, longitudinal study, survey, (*N*= 14713)	To examine the factors that may contribute to a young person becoming NEET and applies these to the demographics of a rural area in England	2010 / aged 16–24	Gender, Ethnic origin, Parental occupation, Parental qualifications, Free school meals, General Certificate of Secondary Education (GCSE qualifications), Truancy, Population ,Working age population, Income ,Health, deprivation and disability,
(Ruesga-Benito et al., 2018)	European Union	Quantitative, structural equation modelling (SEM).	analyse the influence of the socioeconomic environment and the risk of vulnerability as explanatory variables	2016, / 15-29 years old	Economic Environment, Poverty and Social Exclusion, age

Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(Rodriguez-Modroño, 2019)	Spain	Mix methodology, probit model	the impact of structural factors on the risk of being a NEET	2013 and 2016/15-29 years old	gender, age, household income, education, nationality or country of origin and Work experience
Quintano, C. Mazzocchi,P. Rocca,A.(2018)	Italy	Quantitative, probit model. (*N*=12774)	determinants of the NEET condition in Italy through a step-by-step procedure beginning with the identification of their main characteristics and then proceeding with a focus on specific homogeneous clusters	2005 and 2015/ Age 15-34	Age, education, parent education, Civil status, Nationality, Field of study, Gender
(Pitkänen et al., 2021)	Finland	Quantitative, questionnaires, logistic regression models. on a 20% random sample (*N*= 99,137)	Effect of family socioeconomic resources, parental psychiatric disorders and substance abuse, parental death, living in a single-parent household and out-of-home placement	1987–2012/	Parental unemployment, education of parents, Household income quintiles, Parental psychiatric disorder, Parental substance abuse, Parental death, Living with single parent, Placed outside home
(Pemberton, 2008)	England	Qualitative, semistructured interviews ,(*N*=21)	A focus is placed on the degree to which intergenerational factors influence NEET status, as opposed to peer influence, (low) educational attainment/disaffection, poor labour-market experience, or a lack of (place-specific) employment/education or training opportunities	2005/ age 16-18	peer influences, educational attainment/experience, poor labour-market experience,
(Ose & Jensen, 2017)	Norway	Qualitative, semistructured interviews,(*N*=586)	investigate the NLFET population and to identify barriers to education or employment	2014/ aged 18–29 years	health problems, low education, work experience, exhausted, low self-esteem, depressed, sleeping problems
(Odoardi, 2020)	Italy	Quantitative, different regression models,	The effect of parents' education	15–29 years	Household, employment condition, level of education, parents education, poverty, martial status,
(B. O'Dea et al., 2014)	Australia	Mix methodology, longitudinal cohort (N=696)	explore the prevalence of NEET status in a cross-section of young adults seeking help at a primary mental healthcare service.	2011-2012/ aged 15 - 25 years	age, gender, immigration background, postsecondary education, Indigenous background, Economic hardship, Criminal charges, Government benefits, Substance misuse, Childhood onset disorder, Depressive symptoms, Anxiety, Clinical stage, Disability, Social and occupational functioning
(Noh & Lee, 2017)	South Korea	Quantitative, longitudinal cohort (N= 2,300)	individual and family characteristics at ages 16–17 affect the probability of being in NEET during 20–25 years old period	2007–2014 / 15–29-year	household income, school satisfaction, grades and career planning
(Nestić & Tomić, 2018)	Croatia	Quantitative, probit regression models	assessment of employment prospects of the NEET population depending on their individual and household characteristics.	2008 and 2011/ age 20–64	Gender, Level of education, household size, urban settlement region,

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Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(Mizintseva et al., 2017)	World	Quantitative, multivariate analysis, examination, sociological survey (in particular questionnaire survey)	the pervasive problems in the modern labour market of young people in the world	2017/ aged 15-24	Work experience, Lack of proper education, Shortage of jobs, Inaccessibility of information on vacancies, Low salary level, Difficulties in employment because of the large number of senior citizens who occupy jobs, Problems with employment, self-dependence, government interest,
(Mendolia & Walker, 2015)	England	Mix methodology, semi-structured interviews, matching methods, (*N*=9200)	the relationship between personality traits in adolescence and education and labour market choices.	2004/ age 17–21	Health, ethnic background,, gender, marital status, age of the mother at birth, maternal education ,employment status, single parent family, grandparents' education, family income, older siblings
(McMurray, 2019)	Scotland.	Quantitative	impact of funding cuts to the Further Education colleges in Scotland.	2007and 2016/16 and 25	Colleges Funding cuts
(Mawn et al., 2017)		Quantitative, Randomised and quasi-randomized trials, systematic review and meta-analysis, (*N*=54923)	the effectiveness of interventions targeting young people, not in employment, education, or training (NEET)	1990-2017/ 16-24 years	employment; health, earnings, welfare receipt, and education
(Maraj et al., 2019)	Canada	Quantitative, Multivariate Cox proportional hazards regression (*N*=394)	how being vocationally inactive (NEET) affects engagement in early intervention services.	2018/ 14 to 35 years old	age, sex, visible minority status, social and material deprivation indices, and family involvement, duration of untreated psychosis, substance use disorder, medication nonadherence, and baseline positive and negative symptoms
(Mansuy & Werquin, 2018)	Morocco	Quantitative, survey, empirical test (N= 1,062)	identification of the determinants of young women's inactivity; and the labour force status for all the economically active young people	2013, /aged 15–34 years	Labour force status, Father self-employed, Parents' education, Dwelling, Family income, Rank among siblings, Number of siblings, living area, gender
(Maguire, 2018)	England	Qualititative,Survey, interview (N= 57 young women)	lives of young women who carry NEET and economically inactive (EI)	2016-2017/ 16–25 years	Motherhood, Having caring responsibilities, Poor health, Being in transition between education and employment, Family networks, Isolation, Mental health issues, Income constraints, The welfare system, Careers and work,
(Luthra, 2019)	Sweden	Quantitative,logistic regression analyses (N = 12,269)	analyse the family situation for those who are in Employment, Education or Daily activity (NEED)	1981–2010/ 18 years and older	gender, age, immigrant background, married, common law, single parent, living parents
(Lorinc et al., 2020)	England	Qualitative , semi-structured interviews , focus group (N = 53)	examining the structural context of young people's negative school experiences and difficult transition to work, and the impact of macrosystemic forces on their opportunities and choices	2013–2018/ 16 to 24 years of age	school experiences, funding cuts in education and support services, transformations in the labour market and socioeconomic deprivation.
(Lindemann & Gangl, 2019)	Germany	Quantitative, non-parametric propensity score matching (PSM) ,longitudinal survey (N = 2295)	parental unemployment on students' post-secondary transitions.	1984-2015/ age 12–19	Parent education, parent Age group, parent work experience, Economic sector, Household situation, Child's characteristics, Child's transition outcomes
(Lee & Kim, 2012)	South Korea	Quantitative, multinomial logistic regression analysis (N = 2557)	macro- and micro-level factors that produce the growing trends of inactive youth and the problem of youth joblessness.	1998/aged 15 and above	Gender, age, Married, education level, job training, Father's education, Residing area, Father's occupational

Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(Lallukka et al., 2019)	Finland	Quantitative, survey, logistic regression (N=46521)	determinants of longterm unemployment in early adulthood, using a birth cohort with nearly a 30-year follow-up from birth to early adulthood.	1987–2015 /25–28 years	Health-related, School performance, Marital status, unemployment rate, Parental health, Parental education,
(Ladhani et al., 2019)	Canada, United States, United Kingdom European nations; Australia NewZealand	Qualitative , Systematic review,	transitions to adulthood for young people with mental health and/or substance use problems who are engaged or disengaged with the education system	2000 to 2018/ 15 to 24 years	mental health, substance use
(Kevelson et al., 2020)	OECD Countries	Mix methodology, Logistic Regression interview. (N=37,721)	explored the extent to which disconnection influences civic participation and well-being among NEETs with and without college degrees.	2012 and 2015/ aged 20–29	Education, Community engagement, health and disability, parent education, immigrant, age , gender, Field of study,
(Karyda & Jenkins, 2018)	England	Mix methodology, binary logistic regression mode,interview (N= 8,480)	the effects of neighbourhood context on young people who experience NEET status	2004-2010/ages 18 to 19	Crime, area deprivation, parent education, ethnicity, Family background,
(Karyda, 2020)	England	Quantitative , logistic regression, propensity score matching	influence of neighbourhood context and in particular the effect of living in a high crime area on young people's trajectories after compulsory education	2004-2010/ ages 16–19	Neighbourhood deprivation, Gender, Ethnic group, Prior educational attainment, Mother's and father's highest educational qualifications, Socio-economic classification (SEC), Entitlement to low income benefits, Involvement of the police, Experience of aggressive behaviour in school, Engagement in risky behaviour.
(Holloway et al., 2018)	Australia	Quantitative , Multinomial logistic regression, (N= 57,644)	t investigates the extent of non-participation of young people presenting to mental health care, and reports the demographic and clinical correlates of non-participation	2013-2015/ 15–25 years	Age, Gender, Sexuality, Living Situation, Rurality of headspace Centre, culturally and linguistically diverse, Diagnosis
(Egan et al., 2015)	England	Quantitative , Probit model (N=19,217)	measures of psychological distress taken in childhood are associated with unemployment	2006-2010/ ages 16 and 21	psychological distress
(Hegelund et al., 2018)	Denmark	Quantitative, Binary logistic regression, negative binomial regression and median regression (N=1,098,742)	investigated the role of IQ in predicting a wide range of indicators of unsuccessful educational and occupational achievement among young men	1968–2016/ aged 18-30	Ethnicity, Birth region, Parental education, , health, IQ
(Hakkarainen et al., 2016)	Finland	Quantitative ,Structural equation modelling, (N = 597)	how these difficulties would affect the participants' educational transitions into further studies or work	2004/ aged 16-21	arithmetic algebra, Geometry, Error-finding ,Word-chain reading comprehension Externalising problems, father's education Mother's education , low prosocial skills High antisocial behaviour delayed graduation Short educational track NEET

Appendices

Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(Gutman & Schoon, 2018)	England	Quantitative , Regression Models, (N = 9966)	provide descriptive information on the career aspirations, sociodemographic variables and outcomes of adolescents with SEN in comparison to those without SEN	2004/ ages 14–20	prior academic ability, parental expectations, academic self-concept, school motivation , sociodemographic characteristics, career aspirations,
(Giret et al., 2020)	France	Quantitative, survey, multinomial logistic regression mode,(N = 30,049)	analyse the school-to-work transition of young people. in order to understand their risk of becoming and remaining NEET.	2009-2013/aged 15 to 26	gender, migrant origin, late entering secondary school, highest qualification reached, type of training, field of study, reason for leaving studies, parents' education level, parents' status and situation, place of residence upon leaving education, the rate of unemployment in the respondents' residential area upon leaving education
(E. Ghignoni et al., 2019)	Italy	Quantitative , survey ,probit models (N =26,000)	university dropouts to high school graduates with no university experience, rather than to university graduates	2011/ aged post-14	Dropout, Bad job, Monthly earnings, Type of high school, Family educational level, Parents' occupational,
(Genda, 2007)	Japan	Quantitative , survey ,Multinomial logistic regression (N= 13,389)	there are substantial differences in the reasons for jobless between the unemployed and NEETs	1992, 1997 and 2002 / aged 15–34	Age, gender, Level of education, work experience, household income, Household type
(Flynn & Tessier, 2011)	Canada	Quantitative , Cross-sectional hierarchical regression , sequential logistic regression (N= 406)	risk factors would be related to less favorable educational outcomes among ECM youth.	2006-2009/18–20 years	Health-related disability, Cognitive impairments, Soft-drug use, Self-care skills, Developmental assets ,Age, Gender
(Duckworth & Schoon, 2012)	England	Quantitative , multiple imputation by chained equations (N= 12,744)	assesses the effect of multiple independent socioeconomic risk factors in shaping the transition from school to work	2004 and 2010/ 16 and 18	Low parent education, Low parent social class, Lone parent family. Teen parent, Social housing, Workless family, Gender.Income.Ethnicity, Reading/English., Mathematics, YP wants to stay on post-16, Parent wants YP to stay on post-16, School motivation, YP has a part-time job, YP does not truant., Proportion of pupils at school from low SES families/ eligible for free school meals
(Dorsett & Lucchino, 2014)	England	Mix methodology, interview, multinomial logit model model (N= 1352)	the school to work transition in the UK with the aim of achieving a richer understanding of individuals' trajectories in the five years after reaching school leaving age	1991 to 2008/ ages 16 and 21	Sex , Ethnicity, School attainment, Receipt of grants for education , Month of birth, Health , Smoker, Parental qualifications, Employment of household head, Sibling labour force status, Housing tenure, Household income quartile,Labour market context
(de Almeida & Simões, 2020)	Portugal	Quantitative ,linear regression analysis(N= 188)	how self-efficacy perceptions are associated with Perceived Barriers, meaning beliefs about constraints on current/future vocational development, and Professional Expectations among rural	2019/ aged 18–29 years	Gender, Age, Educational level, parent employed, parent education, Household, Income, Self-efficacy, perceived barriers, professional expectations
(Contini et al., 2019)	Italy	Mix methodology, interview, multinomial logit model (N= 1352)	the condition over time of young adults whose age at the first interview ranges between 19 – when regular students complete upper secondary education – and 29	2008-2011/ 19–29 years	Gender, living area, education level, Family composition, Individual careers status

Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(Chen, 2018)	Vietnam, Cambodia and Nepal	Quantitative , non-parametric survival models , Cox model multinomial logit model (N= 5,597)	the association between education and the timing and quality of transition to work	aged 15 to 29	gender, Residence, Education attainment, Age
(Chen et al., 2016)	England	Quantitative ,Hierarchical variable clustering, k-means clustering, and correlation analysis	highlight factors that are correlated with NEET, the negative consequences and causes of NEET, and potential solutions to NEET	2009 to 2013/ aged 16 -18	population, crime offences, benefits claimants, median property price, active businesses, immigrants, and conception under 18
(Caroleo et al., 2020)	European countries	Quantitative , simple logit models (N= 839,681)	explain the propensity of an individual to be NEET, accounting for his/her personal characteristics and for factors related to the institutional and education characteristics of his/her country of residence	2016/ aged 19 and 30 years	Gender,Marital status, Family background (at least one parent with university degree), Education level, Immigrant status,Institutional factors Union Density, Tax wedge, Minimum salary
(Cabral, 2018)	Senegal	Quantitative, binomial model,	assess the extent of the phenomenon of NEET by measuring its rate and identify the key factors of the status of NEET	2011/ 15 and 34 years old	existence of a physical and mental disability, age and gender of the young person, gender and education status of the head of household, occupational and matrimonial status of the head of household, and household income
(Bradley & Crouchley, 2020)	England and Wales	Quantitative, trivariate model (N= 70,000)	the relationships between test scores, truancy and labour market outcomes for youths	1989–90 to 2000–2001 /aged 15/16–18/19	Ethnic background, Fathers occupation , Household status, School characteristics , Region,
(Blajeski, 2020)	USA	Qualitative ,Semi-structured interviews(N=10)	the structural barriers that challenge those from marginalized families, reevaluate traditional disability ideology in mental health treatment, and better support new pathways to secure employment and education for all young adults	aged 15 to 25 years	Family support, forming careers, and breaking the disability mindset, poverty, Social causation, University disability support
(Berloffa et al., 2017)	European country	Quantitative, multinomial logit model,	the influence of parental employment status during adolescence on adult children's labour outcomes across European country groups, according to the gender of both parents and children	2011 /aged 25-34	Employment status, education, Cohabiting with parents, Household occupational structure
(Bania et al., 2019)	Norway	Quantitative ,Logistic regression model(n= 4881)	explore the prevalence of young adults NEET defined by no educational engagement, long-term recipient of sickness benefit, medical and non-medical benefit receipt or long-term unemployment in an unselected population of young people	2003–2005/ aged 15–16 years	gender, ethnicity, residency, parental education, mental health problems and musculoskeletal pain
(Baggio et al., 2015)	Swiss	Quantitative ,Linear Models , cross-sectional comparisons , logistic Regression, cross-lagged panel models (n= 4,758)	examine if NEET youths differ from other contemporaries in terms of personality, mental health and substance use, and to provide longitudinal examination of NEET	2010 -2013/ 20 years old	Personality, Mental health., Alcohol use, Tobacco use., Cannabis use, Demographic covariates.

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Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(Bacher et al., 2017)	Austria	Quantitative , multilevel model(N = 32,728)	deepen knowledge concerning the causes of regional differences in NEET rates within Austria and to specify individual and contextual effects	2006 to 2012/ 15–19 and 20–24 years	gender, age, place of residence, country of birth, citizenship, motherhood, economic growth and minimum wage regulations
(Andrade & Jarvinen, 2017)	Denmark	Quantitative ,latent class analysis, Bayesian Information Criterion (N=1439)	how early risk behaviours are related to subsequent negative life events among young men and women from different socioeconomic backgrounds	2005 /age 16 and 24	Early alcohol debut, Binge drinking, cannabis use, cigarette smoking, sexual debut, Crime, Hospitalisation
(Alvarado et al., 2020b)	Brazil, Chile, Colombia, El Salvador, Haiti, Mexico Paraguay	Mix methodology, interview, questioner, survey(N= 12,450)	the role of cognitive skills, socioemotional skills, aspirations and expectations on the likelihood of being NEET	2017 and 2018 /15 to 24 year	Age, gender, Education level, teenage parenthood dummy, Household income, Number of household members, aspirations, big five, Activities
(Alfieri et al., 2015)	Italy	Quantitative ,probit regression model (N= 9,087)	investigates the relationship between family variables (parents' educational level, relationship quality, intrusiveness, support, and autonomy) and young Italians' status as NEETs	2011 /18 and 29 years	parents' educational level, relationship quality, intrusiveness, support
(Alcazar et al., 2020)	Peru	Mix methodology, interview, non-linear logit	development of a contextually nuanced definition of precarious young workers, and provides an estimation of their numbers with those of NEETs.	2015/aged 15–29	Age, Education, Poverty, Presence of children under 5, Migrant, Household level of vulnerability, Number of household members Dropped out of school, health
(Akinyemi & Mushunje, 2017)	South Africa	Mix methodology, interview, probit regression (N= 167)	To determine the prevalence of 'not in education, employment or training' (NEET) status among rural youth in Eastern Cape Province	aged 16 to 25	Receiving grant Govt. funding Parent farming, Gender Age Marital status Baby, Baby number
(Abayasekara & Gunasekara, 2019)	Sri Lanka	Quantitative ,binomial and multinomial logistic regression models(N= 3,067)	identify the risk factors of falling into NEET, and of belonging to a specific NEET subgroup, relative to a reference group.	2016/ 20 to 24 age	demographic characteristics, household ,locational characteristics, ethnicity , religion, marital status, level of education, experience, household income , gender, age, Employed parent in household, Dependent kids, Dependent elders, resident place
(Lin & Chiao, 2022)	Taiwan	Quantitative, Regression and mediation analyses, (N= 2903)	examine the relationship between adverse childhood experiences (ACEs) in early adolescence and heavy smoking in emerging adulthood	2000/ age of 14 years until the age of 22 years	Adverse childhood experiences, Abuse, parental divorce or separation, parental addiction , parental mental illness , and criminal in the household, Emotional neglect, Heavy smoking, Parent's education, educational aspiration, substance abuse, self-esteem, and depression
(Plenty et al., 2021)	Sweden	Quantitative, multivariate regression models (N= 4452)	the longitudinal associations that internalising and externalising problems during adolescence share with the risk of being NEET in young adulthood, with a focus on the mediating role of school performance.	Age 15- 22 years	Mental health, school performance,

Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(LIEW et al., 2021)	SINGAPORE	Quantitative, Lasso regressions and cross-validations, survey (N= 127)	establish the validity of the culture marginalisation theory in explaining NEET/Hikikomori risk in the Singaporean context	Mean age = 21.3	Personality, self-esteem, depression, cultural self-construal, anxiety
(Simões et al., 2022)	International	Qualitative, a bibliometric analysis and Cluster Thematic Analysis	characterize the knowledge about rural NEETs aged 15 to 24 in the context of the international scientific literature	2009 and 2019/ aged 15 to 24	Living situation
(Bojadjieva et al., 2022)	Bosnia and Herzegovina; Croatia; Montenegro; North Macedonia; Serbia; and, Slovenia	Quantitative, multiple linear, regression models ordinary least square method	to evaluate the impact of the flows in different levels of education upon youth employability and changes in the NEET youth population	2009 to 2019/ aged 15–24	level of education
(Avagianou et al., 2022)	Italy, Spain, Greece and Cyprus	Quantitative (descriptive statistics and ANOVA statistical tests) and qualitative (semi-structured interviews)	examination of the geographically and temporally uneven distribution of young NEETs	2008 and 2018/ aged 15–29	tertiary education attainment, early school leavers (ESL), gross domestic product (GDP) and household income , demographic characteristics
(Román et al., 2022)	Chile	Quantitative, descriptive statistics and ANOVA statistical tests (N= 236,424)	analyse the profiles of NEETs in Chile based on their self-identified reasons for not studying and working as well as their previous work and educational experience	2017/18 to 29 years	Age, Schooling, household income, Number of people in the household, Sex , Marital status
(Apunyo et al., 2022)	international	Qualitative, Systematic review	catalogue impact evaluations and systematic reviews on youth employment interventions to improve discoverability of evidence by decision makers, development patterners and researchers	2000 and 2019, 15–35 years	education and skills; entrepreneurship; employment; welfare and economic outcomes
(Su et al., 2022)	Hong Kong	Quantitative, multivariate logistic regression analyses, (N = 4,726)	examine the overall sociodemographic and career-related profiles of NEETs in Hong Kong and compare the different profiles of longer-term versus transitional NEETs by taking into consideration their strengths and weaknesses, and risk and protective factors	2015-2020/aged 15–21	Gender, Age, Educational attainment , the role of carer, Seclusion at home , Involvement in deviant activities, Having addiction, health problems, Lack of clear goals for work, study & life, Limitation of abilities
(Gariépy et al., 2021)	international	Mix methodology, systematic review and meta-analysis (N = 548,862)	the association between NEET status and youth mental health and substance use problems.	1999–2020/ 15–25 years old	anxiety, behaviour , alcohol use, cannabis use, and drug use disorders, general psychological distress, suicidal behaviours, and any psychiatric disorder

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Author(s) and Year	Country	Methodology	Study Focus	Year of Data/ Sample	Determinants
(Dayioglu et al., 2022)	Turkey.	Quantitative, regression discontinuity design (N= 28,823)	understanding the effect of youth minimum wages on the labour market and education outcomes of 15-year-olds.	2012-2015 and 2014-2017 panel/ aged 15 years and above	Minimum wage
(Ringbom et al., 2022)	Finland	Quantitative, Logistic regression , Sensitivity analyses (N= 1438)	To carry out a comprehensive overview of the associations between different psychiatric illnesses and long-term NEET status	2008–2015 / 20–26 years	Psychiatric disorder, Substance misuse, Depressive disorders, Anxiety disorders, Personality disorders, Learning disabilities, Autism spectrum disorder, hyperactivity disorder, Bipolar disorder, Eating disorders,
(Zudina, 2021)	Russia	Quantitative, multinomial logit analyses and dynamic,multinomial logit panel regressions (N= 134,000)	the impact of education on NEET status, which would contribute to the existing discussion on the human capital of NEETs using Russian data	1995- 2017 / 15 - 24 years old	Education level
(Tayfur et al., 2022)	England	Quantitative, Survey, binary and multivariable logistic regression analyses (N=2224)	identify longitudinal associations between adolescent psychosocial factors and subsequent NEET status among this population in a nationally representative sample of secondary school students	2005 and 2015/ 15-26 years old	Self-esteem, Locus of control, Substance use, Bullying, Behavioural problems, Educational aspirations, Attitudes to school, Job aspirations, Physical activity, Sex, Ethnicity, Socioeconomic status, Family composition, Caring responsibility
(Lindhardt et al., 2022)	international	Qualitative, Systematic review	to identify the occurrence of psychosis among the NEET population outside mental healthcare services and to identify if the presence of symptoms of psychosis could be quantified among the NEET status youth.	1999-2020/ range from 16 to 34 years old	mental disorders, psychosis
(Anyanwu, 2013)	African countries	Quantitative, cross-sectional data	present the characteristics of youth employment in Africa as well as investigate its macroeconomic determinants, with a view to proffering some solutions	1991–2009/ aged 15–24	GDP , Inflation, Education, Youth population, Democracy, Time trend,
(Pennoni & Bal-Domańska, 2022)	EU countries	Quantitative, hidden Markov model	maximum likelihood estimation of the model parameters, and provides a dynamic classification of the countries into clusters representing different levels of the phenomena.	2004 to 2019/ aged 15 to 29,	GDP, Part-time employment, Temporary contracts, Persons employed in science and technology, Participation rate in education or training, Early leavers from education and training, *Labour cost index*
(Fakih et al., 2020)	MENA countries	Quantitative, probit model (N= 10,000)	meticulously examinesnthe microeconomic determinants of youth unemployment in the MENA region using a unique and novel data on young people	2016/ aged 15–29	Gender issues, socio-economic factors, education, skills mismatch, institutional issues, household characteristics, political engagement, cultural values, parents'education, institutional factors, and political engagement, martial status, Area of residence
(Pattinasarany, 2019)	Indonesia	Quantitative, logistic regression analysis	analyze factors affecting Indonesian youth to be NEET beyond those related to employment matters.	2015/ aged 15-24	marital status, engagement in social activities, access to information, and capability to read and write in Latin, Arabic, or other alphabets, gender of the head of household, composition of household members, house ownership status

Appendix 2.2. Figure A1, A2 and Table A2& A3

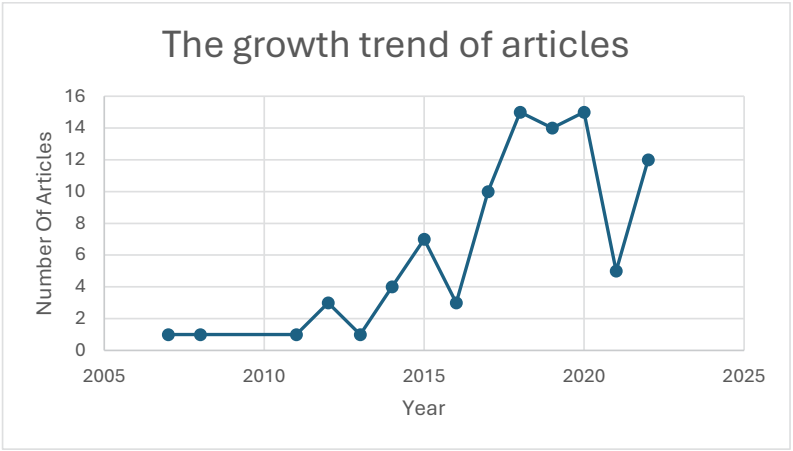

Fig A1. The growth trend of articles.

Table A2. Frequency of methodology used in articles.

Methodology	Year of publishing			Percentage	Total
	2005-2010	2011-2015	2016-2022		
Qualitative method	15	19	24	64%	78
Quantitative method	3	6	8	25%	17
Mixed method	1	3	6	11%	10

Table A3. Study general characteristics.

Characteristic	Number	Percentage
Geographical location		
Asia (Bangladesh, China, Indonesia, Singapore, Korea, Turkey,Japon, …)	13	14.29
Americas	10	10.99
Italy	7	7.69
Spain	7	7.69
Finland	6	6.59
United Kingdom and Ireland	16	17.58
Norway	4	4.40
Multiple countries	18	19.78
Not Applicable (N/AP)	10	10.99
Method		
Case study	11	12.09
Correlational	7	7.69
Delphi study	1	1.10
Experimental or quasi-experimental	12	13.19
Literature review	6	6.59
Others	12	13.19
Phenomenological	9	9.89
Statistical analyses	16	17.58
Survey	14	15.38
N/AP	3	3.30

Data collection		
Academic/institutional databases	21	23.08
Focus groups	4	4.40
Interviews	14	15.38
Publications (literature)	7	7.69
Scales	5	5.49
Survey/questionnaire	22	24.18
Others	8	8.79
N/AP	6	6.59
N/P	4	4.40
Journals		
Journal of Youth Studies	7	7.69
Social Indicators Research	3	3.30
Journal of Education and Work	3	3.30
Children and Youth Services Review	3	3.30
International Journal of Lifelong Education	3	3.30
International Journal of Manpower	3	3.30
Social Science Japan Journal	2	2.20
Longitudinal and Life Course Studies	2	2.20
Advances in Mental Health	2	2.20
Annals of the American Academy of Political and Social Science	2	2.20
Journal of Adolescent Health	2	2.20
BMJ Open	2	2.20
Youth & Society	2	2.20
Rest journal with one time	55	60.44



Fig A4. Radar graph of the number of risk factors.

Appendix 2.3. Influence of each risk factor on being NEET.

Factor	Influence	Study
Individual Characteristics		
Aspirations and expectations	Negative	(Alvarado et al., 2020b; de Almeida & Simões, 2020; Gutman & Schoon, 2018; Maguire, 2018; Noh & Lee, 2017; Schoon, 2014; Schoon & Lyons-Amos, 2017) (Su et al., 2022) (Tayfur et al., 2022)
Autonomy	Negative	(Alfieri et al., 2015)
Isolating	Positive	(Maguire, 2018)
IQ	Negative	(Hegelund et al., 2018)
Life satisfaction	Negative	(Schoon & Lyons-Amos, 2017)
Self-esteem	Negative	(Ose & Jensen, 2017) (LIEW et al., 2021) (Tayfur et al., 2022)
Personality	Neutral	(Baggio et al., 2015; LIEW et al., 2021) (Ringbom et al., 2022)
Risky behaviours	Positive	(Karyda, 2020)
Self-efficacy	Negative	(de Almeida & Simões, 2020)
Self-confidence	Negative	(Mizintseva et al., 2017)
Skill	Negative	(Kevelson et al., 2020) (Apunyo et al., 2022) (Fakih et al., 2020)
Time usage	Positive	(Salvà-Mut et al., 2018)
Age	Positive	(Román et al., 2022) (Su et al., 2022) (Tayfur et al., 2022) (Fakih et al., 2020) (Yang, 2020) (Veldman et al., 2015) (Varshavskaia, 2017) (Vancea & Utzet, 2018) (Ruesga-Benito et al., 2018) (C. Quintano et al., 2018) (B. O'Dea et al., 2014) (Luthra, 2019) (Lee & Kim, 2012) (Kevelson et al., 2020) (Holloway et al., 2018) (Genda, 2007) (Flynn & Tessier, 2011) (de Almeida & Simões, 2020) (Chen, 2018) (Cabral, 2018) (Bacher et al., 2017) (Alvarado et al., 2020b) (Akinyemi & Mushunje, 2017) (Abayasekara & Gunasekara, 2019)
Gender	Positive	(Román et al., 2022) (Su et al., 2022) (Fakih et al., 2020) (Zuccotti & O'Reilly, 2019) (Yang, 2020) (Varshavskaia, 2017) (Vancea & Utzet, 2018) (Tamesberger & Bacher, 2014) (Schoon, 2014) (Salvà-Mut et al., 2018) (Salvà-Mut et al., 2016))Rodriguez-Modroño, 2019((C. Quintano et al., 2018) (B. O'Dea et al., 2014) (Mansuy & Werquin, 2018) (Luthra, 2019) (Kevelson et al., 2020) (Karyda, 2020) (Giret et al., 2020) (Flynn & Tessier, 2011) (de Almeida & Simões, 2020) (Contini et al., 2019) (Caroleo et al., 2020) (Bania et al., 2019) (Bacher et al., 2017) (Akinyemi & Mushunje, 2017) (Abayasekara & Gunasekara, 2019)

Work Characteristics		
Work history	Negative	(Mizintseva et al., 2017; Ose & Jensen, 2017; Pemberton, 2008; Rodriguez-Modroño, 2019; Salvà-Mut et al., 2018; Vancea & Utzet, 2018) (Apunyo et al., 2022)
Income	Negative	(Salvà-Mut et al., 2016),(Sadler et al., 2015), (Maguire, 2018), (Duckworth & Schoon, 2012; Mawn et al., 2017)
Low salary	Positive	(Mizintseva et al., 2017) (Pennoni & Bal-Domańska, 2022)
Minimum wage	Positive	(Shinozaki, 2012),(Bacher et al., 2017) (Dayioglu et al., 2022)
Unemployment history	Positive	(Rodriguez-Modroño, 2019; Salvà-Mut et al., 2018; Vancea & Utzet, 2018)
Job training	Negative	(Lee & Kim, 2012)
Education Characteristic		
Field of study	Positive& Negative	(C. Quintano et al., 2018),(Kevelson et al., 2020),(Giret et al., 2020)
Dropout	Positive	(Selenko & Pils, 2019),(Salvà-Mut et al., 2018),(E. Ghignoni et al., 2019), (Alcazar et al., 2020) (Avagianou et al., 2022) (Pennoni & Bal-Domańska, 2022)
Problem learning	Positive	(Hakkarainen et al., 2016) (Ringbom et al., 2022)
School performance	Negative	(Lallukka et al., 2019; Plenty et al., 2021) (Tayfur et al., 2022)
Truancy	Positive	(Sadler et al., 2015)
Education level	Positive	(Odoardi, 2020) (Kevelson et al., 2020) (Lee & Kim, 2012)
Education level	Neutral	(Abayasekara & Gunasekara, 2019)
Education level	Negative	(Giret et al., 2020),(Lee & Kim, 2012),(B. O'Dea et al., 2014),(Mawn et al., 2017),(Caroleo et al., 2020),(Odoardi, 2020), (Yang, 2020),(Kevelson et al., 2020), (Abayasekara & Gunasekara, 2019), (Chen, 2018), (Alcazar et al., 2020), (Nestić & Tomić, 2018), (Genda, 2007), (Cabral, 2018), (Tamesberger & Bacher, 2014), (Salvà-Mut et al., 2018),(Shinozaki, 2012), (Contini et al., 2019),(Mizintseva et al., 2017), (de Almeida & Simões, 2020), (Varshavskaia, 2017), (Vancea & Utzet, 2018),(Salvà-Mut et al., 2016),(Zhang et al., 2020), (Pemberton, 2008), (C. Quintano et al., 2018), (Vasile & Anghel, 2015),(Karyda, 2020), (Berloffa et al., 2017), (Sveinsdottir et al., 2018), (Ose & Jensen, 2017), (Rodriguez-Modroño, 2019), (Sánchez-Soto & Bautista León, 2020),(Alvarado et al., 2020b) (Bojadjieva et al., 2022) (Avagianou et al., 2022) (Román et al., 2022) (Apunyo et al., 2022) (Su et al., 2022) (Zudina, 2021) (Anyanwu, 2013) (Fakih et al., 2020)
School conditions	Negative	(Schoon & Lyons-Amos, 2017), (Salvà-Mut et al., 2016), (L. Rodwell et al., 2018), (Noh & Lee, 2017; L. Rodwell et al., 2018), (Lallukka et al., 2019), (Duckworth & Schoon, 2012), (Dorsett & Lucchino, 2014)
Health Characteristics		

Health condition	Positive	(Alcazar et al., 2020; Dorsett & Lucchino, 2014; Flynn & Tessier, 2011; Hegelund et al., 2018; Kevelson et al., 2020; Lallukka et al., 2019; Maguire, 2018; Mawn et al., 2017; Mendolia & Walker, 2015; Bridianne O'Dea et al., 2014; Ose & Jensen, 2017; Sadler et al., 2015; Salvà-Mut et al., 2018; Sveinsdottir et al., 2018; Veldman et al., 2015) (Su et al., 2022)
Disability	Positive	(Cabral, 2018; Flynn & Tessier, 2011; Bridianne O'Dea et al., 2014; Sadler et al., 2015; Sveinsdottir et al., 2018) (Su et al., 2022)
Psychiatric disorder	Positive	(Egan et al., 2015; Bridianne O'Dea et al., 2014) (Gariépy et al., 2021) (Lindhardt et al., 2022)
Mental Health	Positive	(Baggio et al., 2015; Bania et al., 2019; Blajeski, 2020; Cabral, 2018; Ladhani et al., 2019; Maguire, 2018; Maraj et al., 2019; Bridianne O'Dea et al., 2014; Sveinsdottir et al., 2018; Veldman et al., 2015) (Gariépy et al., 2021) (Ringbom et al., 2022) (Lindhardt et al., 2022)
Sexual debut	Positive	(Andrade & Jarvinen, 2017; Dorsett & Lucchino, 2014; Holloway et al., 2018; Maraj et al., 2019)
Musculoskeletal pain	Positive	(Bania et al., 2019)
Depression	Positive	(Bridianne O'Dea et al., 2014; Ose & Jensen, 2017; Sadler et al., 2015) (LIEW et al., 2021) (Gariépy et al., 2021) (Ringbom et al., 2022)
Anxiety	positive	(LIEW et al., 2021) (Gariépy et al., 2021) (Ringbom et al., 2022)
Bullying	Positive	(Sveinsdottir et al., 2018) (Tayfur et al., 2022)
Disability mindset	Positive	(Bridianne O'Dea et al., 2014)
Addiction		
Smoker	Neutral	(Andrade & Jarvinen, 2017; Dorsett & Lucchino, 2014)
Tobacco use	Positive	(Baggio et al., 2015)
Alcohol debut	Positive	(Andrade & Jarvinen, 2017)
Binge drinking / drinking behaviour	Positive	(Andrade & Jarvinen, 2017; Baggio et al., 2015; L. Rodwell et al., 2018; Sveinsdottir et al., 2018) (Gariépy et al., 2021)
Cannabis use	Positive	(Andrade & Jarvinen, 2017; Baggio et al., 2015; L. Rodwell et al., 2018) (Gariépy et al., 2021)
Drag addiction	Positive	(Sveinsdottir et al., 2018; Zhang et al., 2020) (Su et al., 2022) (Gariépy et al., 2021) (Tayfur et al., 2022)
Misuse	Positive	(Ladhani et al., 2019; Lin & Chiao, 2022; Maraj et al., 2019; Bridianne O'Dea et al., 2014)
Soft drug	Positive	(Flynn & Tessier, 2011)
Social characteristics		

Birth place/Nationality	Neutral	(Bacher et al., 2017; Salvà-Mut et al., 2016; Selenko & Pils, 2019) (Rodriguez-Modroño, 2019) (C. Quintano et al., 2018) (Giret et al., 2020)
Citizenship	Negative	(Bacher et al., 2017)
Generation effect Birth year- based	Negative / Positive	(Shinozaki, 2012)
Immigrant background	Positive	(Salvà-Mut et al., 2018) (Luthra, 2019) (Kevelson et al., 2020) (Giret et al., 2020) (Caroleo et al., 2020; Chen et al., 2016) (Alcazar et al., 2020) (Yang, 2020) (Tamesberger & Bacher, 2014)
Sociodemographic characteristics	Negative	(Abayasekara & Gunasekara, 2019; Avagianou et al., 2022; Baggio et al., 2015; Gutman & Schoon, 2018) (Tayfur et al., 2022) (Fakih et al., 2020)
Ethnicity and Indigenous Background / Minority	Negative	(Schoon, 2014; Yang, 2020; Zuccotti & O'Reilly, 2019) (Schoon & Lyons-Amos, 2017) (Mendolia & Walker, 2015; Sadler et al., 2015; Yang, 2020) (Karyda & Jenkins, 2018) (Karyda, 2020) (Abayasekara & Gunasekara, 2019; Bania et al., 2019; Dorsett & Lucchino, 2014; Duckworth & Schoon, 2012; Hegelund et al., 2018) (Tayfur et al., 2022)
Religion	Positive	(Abayasekara & Gunasekara, 2019)
Community engagement	Negative	(Kevelson et al., 2020)
Indigenous Background	Negative	(Bridianne O'Dea et al., 2014)
Crime offences/charges	Positive	(Andrade & Jarvinen, 2017; Chen et al., 2016; Karyda & Jenkins, 2018; B. O'Dea et al., 2014)
Deprivation	Positive	(Karyda & Jenkins, 2018; Sadler et al., 2015; Schoon, 2014) (Karyda, 2020)
Party membership and engagement	Negative	(Maraj et al., 2019; Pemberton, 2008; Vancea & Utzet, 2018; Yang, 2020)
Living situation	positive	(Andrade & Jarvinen, 2017; Mansuy & Werquin, 2018) (Abayasekara & Gunasekara, 2019) (Tamesberger & Bacher, 2014) (Schoon & Lyons-Amos, 2017) (Mansuy & Werquin, 2018) (Contini et al., 2019; Duckworth & Schoon, 2012; Holloway et al., 2018; Nestić & Tomić, 2018; Pitkänen et al., 2021) (Simões et al., 2022) (Fakih et al., 2020)
House type and price	Neutral	(Nestić & Tomić, 2018) (Bradley & Crouchley, 2020; Genda, 2007) (Dorsett & Lucchino, 2014; Lindemann & Gangl, 2019)
Family Characteristics		
Parent divorced/death	Positive	(Zhang et al., 2020) (Pitkänen et al., 2021) (Zhang et al., 2020)
Living with single parent	Positive	(Pitkänen et al., 2021) (Mendolia & Walker, 2015) (Luthra, 2019)

Marital status	Positive (women)/ Negative (men)	(Román et al., 2022) (Fakih et al., 2020) (Yang, 2020) (Varshavskaia, 2017) (Vancea & Utzet, 2018) (Sveinsdottir et al., 2018) (Odoardi, 2020) (Mendolia & Walker, 2015) (Luthra, 2019) (Lee & Kim, 2012) (Lallukka et al., 2019) (Caroleo et al., 2020) (Akinyemi & Mushunje, 2017) (Abayasekara & Gunasekara, 2019)
Care Responsibility	Positive	(Maguire, 2018; Tamesberger & Bacher, 2014; Vancea & Utzet, 2018) (Su et al., 2022) (Tayfur et al., 2022) (Alcazar et al., 2020)
Have children	Negative (men) / Positive (women)	(Vancea & Utzet, 2018) (Sveinsdottir et al., 2018) (Salvà-Mut et al., 2016) (Maguire, 2018)
Poor family background	Positive	(Caroleo et al., 2020; Karyda & Jenkins, 2018)
Cohabitation alone	Negative	(Berloffa et al., 2017; Salvà-Mut et al., 2016)
Family composition	Positive	(Contini et al., 2019; Schoon & Lyons-Amos, 2017; Selenko & Pils, 2019; Sveinsdottir et al., 2018; Veldman et al., 2015) (Román et al., 2022) (Tayfur et al., 2022) (Maguire, 2018)
Member of sibling	Positive	Biddlecom et al. (2008); Flisher et al. (2010); Korinek & Punpuing (2012); No et al. (2012); Smits & Huisman 2013); Huisman & Smits (2015);
Rank among siblings/ number of sibling	Neutral	(Mansuy & Werquin, 2018; Mendolia & Walker, 2015; Selenko & Pils, 2019)
Family/ household income	Negative	(Mansuy & Werquin, 2018; Shinozaki, 2012; Vancea & Utzet, 2018; Yang, 2020) (Avagianou et al., 2022) (Román et al., 2022) (Zhang et al., 2020) (Yang, 2020) (Vancea & Utzet, 2018) (Shinozaki, 2012) (Schoon & Lyons-Amos, 2017) (Rodriguez-Modroño, 2019) (Pitkänen et al., 2021) (Noh & Lee, 2017) (Mendolia & Walker, 2015) (Mansuy & Werquin, 2018) (Genda, 2007) (Dorsett & Lucchino, 2014) (Alvarado et al., 2020b) (Alvarado et al., 2020b)
Number of children	Positive	(Akinyemi & Mushunje, 2017)
Family health status	Positive	(Pitkänen et al., 2021) (Lallukka et al., 2019)
Parent occupation	Negative	(Abayasekara & Gunasekara, 2019; Dorsett & Lucchino, 2014) (Shinozaki, 2012) (Selenko & Pils, 2019) (Schoon, 2014) (Pitkänen et al., 2021) (Mansuy & Werquin, 2018) (Lee & Kim, 2012) (E. Ghignoni et al., 2019) (Dorsett & Lucchino, 2014) (Dorsett & Lucchino, 2014) (de Almeida & Simões, 2020) (Bradley & Crouchley, 2020) (Salvà-Mut et al., 2018) (Lindemann & Gangl, 2019) (Lindemann & Gangl, 2019) (Sadler et al., 2015) (Cabral, 2018) (Berloffa et al., 2017) (Schoon, 2014)
Teenage parent hood	Positive	(Mendolia & Walker, 2015) (Duckworth & Schoon, 2012) (Alvarado et al., 2020b) (Maguire, 2018) (Bacher et al., 2017)
Parent education level	Negative	(Pitkänen et al., 2021; Sánchez-Soto & Bautista León, 2020) (Zhang et al., 2020) (Veldman et al., 2015; Yang, 2020))Veldman et al., 2015((Vancea & Utzet, 2018) (Schoon & Lyons-Amos, 2017; Tamesberger & Bacher, 2014)

		)Tamesberger & Bacher, 2014((Shinozaki, 2012) (Schoon, 2014) (Sánchez-Soto & Bautista León, 2020) (Salvà-Mut et al., 2018) (L. Rodwell et al., 2018) (C. Quintano et al., 2018) (Pitkänen et al., 2021) (Odoardi, 2020) (Mendolia & Walker, 2015) (Mansuy & Werquin, 2018) (Maguire, 2018) (Lindemann & Gangl, 2019) (Lee & Kim, 2012) (Lallukka et al., 2019) (Kevelson et al., 2020) (Karyda & Jenkins, 2018) (Hegelund et al., 2018) (Hakkarainen et al., 2016) (Giret et al., 2020) (E. Ghignoni et al., 2019) (Duckworth & Schoon, 2012) (Duckworth & Schoon, 2012) (de Almeida & Simões, 2020) (Cabral, 2018) (Bania et al., 2019) (Alfieri et al., 2015)
Relationship quality	Negative	(Zhang et al., 2020) (Blajeski, 2020) (Sánchez-Soto & Bautista León, 2020) (Alfieri et al., 2015) (Selenko & Pils, 2019)
Sibling work status	Negative	(Dorsett & Lucchino, 2014)
Parental workless	Positive	(Schoon, 2014) (Duckworth & Schoon, 2012) (Pitkänen et al., 2021)
Family support	Negative	(Zhang et al., 2020) (Blajeski, 2020) (Alfieri et al., 2015)
Environment characteristic		
College funding cuts	Positive	(McMurray, 2019)
Employment conditions	Negative	(Mansuy & Werquin, 2018; B. O'Dea et al., 2014) (Pennoni & Bal-Domańska, 2022)
Economic and social inequalities	Positive	(Karyda, 2020; Maguire, 2021; B. O'Dea et al., 2014; Zuccotti & O'Reilly, 2019) (Apunyo et al., 2022)
Economic crisis	Positive	(Bacher et al., 2017; Caroleo et al., 2020; B. O'Dea et al., 2014; Salvà-Mut et al., 2018) (Pennoni & Bal-Domańska, 2022)
Received grants	Negative	(Akinyemi & Mushunje, 2017) (Dorsett & Lucchino, 2014)
Inaccessibility information	Positive	(Mizintseva et al., 2017)
Inadequacy infrastructure	Positive	(Anyanwu, 2013; Karyda, 2020)
Population	Negative	(Chen et al., 2016; Sadler et al., 2015; Tamesberger & Bacher, 2014) (Anyanwu, 2013)
Regional unemployment rate	Negative	(Giret et al., 2020) (Pennoni & Bal-Domańska, 2022)
welfare receipt	Positive	(Maguire, 2018; Mawn et al., 2017) (Apunyo et al., 2022)
Working age population	Positive	(Mizintseva et al., 2017)
Social support	Negative	(Mizintseva et al., 2017; B. O'Dea et al., 2014; Sveinsdottir et al., 2018)
Poverty	Positive	(Odoardi, 2020) (Alcazar et al., 2020; Blajeski, 2020)
Shortage of job	Positive	(Mansuy & Werquin, 2018; Mizintseva et al., 2017)
COVID-19 pandemic	Positive	(Crismon et al., 2021)

Appendix 2.4. The studies of each characteristic group.

Individual characteristics	(Abayasekara & Gunasekara, 2019; Akinyemi & Mushunje, 2017; Alfieri et al., 2015; Alvarado et al., 2020b; Apunyo et al., 2022; Ashby & Schoon, 2010; Bacher et al., 2017; Baggio et al., 2015; Bania et al., 2019; Caroleo et al., 2020; Chen, 2018; de Almeida & Simões, 2020; Fakih et al., 2020; Flynn & Tessier, 2011; Genda, 2007; Giret et al., 2020; Gutman & Schoon, 2018; Hegelund et al., 2018; Holloway et al., 2018; Jongbloed & Giret, 2021; Karyda, 2020; Kevelson et al., 2020; Lee & Kim, 2012; LIEW et al., 2021; Luthra, 2019; Maguire, 2018; Mansuy & Werquin, 2018; Mizintseva et al., 2017; B. O'Dea et al., 2014; Ose & Jensen, 2017; C. Quintano et al., 2018; Rodriguez-Modroño, 2019; Román et al., 2022; Ruesga-Benito et al., 2018; Salvà-Mut et al., 2016; Salvà-Mut et al., 2018; Schoon, 2014; Schoon & Lyons-Amos, 2017; Selenko & Pils, 2019; Su et al., 2022; Tayfur et al., 2022; Vancea & Utzet, 2018; Varshavskaia, 2017; Veldman et al., 2015; Yang, 2020)
School and education characteristics	(Abayasekara & Gunasekara, 2019; Akinyemi & Mushunje, 2017; Alcazar et al., 2020; Anyanwu, 2013; Apunyo et al., 2022; Avagianou et al., 2022; Bacher et al., 2017; Bania et al., 2019; Caroleo et al., 2020; Chen, 2018; de Almeida & Simões, 2020; Dorsett & Lucchino, 2014; Duckworth & Schoon, 2012; Fakih et al., 2020; Flynn & Tessier, 2011; Genda, 2007; E. Ghignoni et al., 2019; Emanuela Ghignoni et al., 2019; Giret et al., 2020; Hakkarainen et al., 2016; Holloway et al., 2018; Karyda, 2020; Kevelson et al., 2020; Lallukka et al., 2019; Lee & Kim, 2012; Luthra, 2019; Mansuy & Werquin, 2018; Noh & Lee, 2017; B. O'Dea et al., 2014; Pennoni & Bal-Domańska, 2022; Plenty et al., 2021; C. Quintano et al., 2018; Claudio Quintano et al., 2018; Ringbom et al., 2022; Rodriguez-Modroño, 2019; L. Rodwell et al., 2018; Román et al., 2022; Ruesga-Benito et al., 2018; Sadler et al., 2015; Salvà-Mut et al., 2016; Salvà-Mut et al., 2018; Schoon, 2014; Schoon & Lyons-Amos, 2017; Selenko & Pils, 2019; Tayfur et al., 2022; Vancea & Utzet, 2018; Varshavskaia, 2017; Veldman et al., 2015; Yang, 2020)
Work characteristics	(Abayasekara & Gunasekara, 2019; Apunyo et al., 2022; Bacher et al., 2017; Berloffa et al., 2017; Contini et al., 2019; Dayioglu et al., 2022; de Almeida & Simões, 2020; Genda, 2007; E. Ghignoni et al., 2019; Lee & Kim, 2012; Lindemann & Gangl, 2019; Maguire, 2018; Mawn et al., 2017; Mendolia & Walker, 2015; Mizintseva et al., 2017; Odoardi, 2020; Ose & Jensen, 2017; Pemberton, 2008; Pennoni & Bal-Domańska, 2022; Rodriguez-Modroño, 2019; Sadler et al., 2015; Salvà-Mut et al., 2016; Salvà-Mut et al., 2018; Shinozaki, 2012; Su et al., 2022; Sveinsdottir et al., 2018; Vancea & Utzet, 2018)
Health characteristics	(Andrade & Jarvinen, 2017; Baggio et al., 2015; Bania et al., 2019; Blajeski, 2020; Cabral, 2018; Dorsett & Lucchino, 2014; Egan et al., 2015; Flynn & Tessier, 2011; Gariépy et al., 2021; Hegelund et al., 2018; Holloway et al., 2018; Kevelson et al., 2020; Ladhani et al., 2019; Lallukka et al., 2019; LIEW et al., 2021; Lindhardt et al., 2022; Maguire, 2018; Maraj et al., 2019; Mawn et al., 2017; Mendolia & Walker, 2015; Bridianne O'Dea et al., 2014; B. O'Dea et al., 2014; Ose & Jensen, 2017; Plenty et al., 2021; Ringbom et al., 2022; Sadler et al., 2015; Salvà-Mut et al., 2018; Selenko & Pils,

	2019; Su et al., 2022; Sveinsdottir et al., 2018; Tamesberger & Bacher, 2014; Tayfur et al., 2022; Veldman et al., 2015)
Addiction characteristics	(Andrade & Jarvinen, 2017; Baggio et al., 2015; Dorsett & Lucchino, 2014; Flynn & Tessier, 2011; Gariépy et al., 2021; Ladhani et al., 2019; Lin & Chiao, 2022; Maraj et al., 2019; Bridianne O'Dea et al., 2014; Ringbom et al., 2022; L. Rodwell et al., 2018; Su et al., 2022; Sveinsdottir et al., 2018; Tayfur et al., 2022; Zhang et al., 2020)
Environment characteristics	(Akinyemi & Mushunje, 2017; Alcazar et al., 2020; Anyanwu, 2013; Apunyo et al., 2022; Bacher et al., 2017; Blajeski, 2020; Caroleo et al., 2020; Chen et al., 2016; Dayioglu et al., 2022; de Almeida & Simões, 2020; Dorsett & Lucchino, 2014; Fakih et al., 2020; Giret et al., 2020; Gutman & Schoon, 2018; Karyda, 2020; Luthra, 2019; Maguire, 2018; Maguire, 2021; Mansuy & Werquin, 2018; Mawn et al., 2017; McMurray, 2019; Mizintseva et al., 2017; B. O'Dea et al., 2014; Odoardi, 2020; Pennoni & Bal-Domańska, 2022; L. Rodwell et al., 2018; Ruesga-Benito et al., 2018; Sadler et al., 2015; Salvà-Mut et al., 2018; Schoon, 2014; Shinozaki, 2012; Sveinsdottir et al., 2018; Tamesberger & Bacher, 2014; Zuccotti & O'Reilly, 2019)
Social characteristics	(Abayasekara & Gunasekara, 2019; Alcazar et al., 2020; Andrade & Jarvinen, 2017; Avagianou et al., 2022; Bacher et al., 2017; Baggio et al., 2015; Bania et al., 2019; Bradley & Crouchley, 2020; Caroleo et al., 2020; Chen et al., 2016; Contini et al., 2019; Dorsett & Lucchino, 2014; Duckworth & Schoon, 2012; Genda, 2007; Giret et al., 2020; Gutman & Schoon, 2018; Hakkarainen et al., 2016; Hegelund et al., 2018; Holloway et al., 2018; Karyda, 2020; Karyda & Jenkins, 2018; Kevelson et al., 2020; Lee & Kim, 2012; Lindemann & Gangl, 2019; Luthra, 2019; Mansuy & Werquin, 2018; Maraj et al., 2019; Mendolia & Walker, 2015; Nestić & Tomić, 2018; Bridianne O'Dea et al., 2014; B. O'Dea et al., 2014; Pemberton, 2008; Pitkänen et al., 2021; C. Quintano et al., 2018; Rodriguez-Modroño, 2019; Ruesga-Benito et al., 2018; Sadler et al., 2015; Salvà-Mut et al., 2016; Salvà-Mut et al., 2018; Schoon, 2014; Schoon & Lyons-Amos, 2017; Selenko & Pils, 2019; Shinozaki, 2012; Simões et al., 2022; Tamesberger & Bacher, 2014; Tayfur et al., 2022; Vancea & Utzet, 2018; Varshavskaia, 2017; Veldman et al., 2015; Yang, 2020; Zuccotti & O'Reilly, 2019)
Family Characteristics	(Abayasekara & Gunasekara, 2019; Akinyemi & Mushunje, 2017; Alfieri et al., 2015; Alvarado et al., 2020b; Avagianou et al., 2022; Bania et al., 2019; Berloffa et al., 2017; Blajeski, 2020; Bradley & Crouchley, 2020; Cabral, 2018; Caroleo et al., 2020; Contini et al., 2019; de Almeida & Simões, 2020; Dorsett & Lucchino, 2014; Duckworth & Schoon, 2012; Fakih et al., 2020; Genda, 2007; E. Ghignoni et al., 2019; Giret et al., 2020; Hakkarainen et al., 2016; Hegelund et al., 2018; Karyda, 2020; Karyda & Jenkins, 2018; Kevelson et al., 2020; Lallukka et al., 2019; Lee & Kim, 2012; Lindemann & Gangl, 2019; Luthra, 2019; Maguire, 2018; Mansuy & Werquin, 2018; Mendolia & Walker, 2015; Noh & Lee, 2017; Odoardi, 2020; Pitkänen et al., 2021; C. Quintano et al., 2018; Rodriguez-Modroño, 2019; L. Rodwell et al., 2018; Román et al., 2022; Salvà-Mut et al., 2016; Salvà-Mut et al., 2018; Sánchez-Soto & Bautista León, 2020;

	Schoon, 2014; Schoon & Lyons-Amos, 2017; Selenko & Pils, 2019; Shinozaki, 2012; Su et al., 2022; Sveinsdottir et al., 2018; Tamesberger & Bacher, 2014; Tayfur et al., 2022; Vancea & Utzet, 2018; Varshavskaia, 2017; Veldman et al., 2015; Yang, 2020; Zhang et al., 2020)

Appendix 3.1. Characteristics of the selected studies

References	country	year	design	N	Sample	methods	study focus	covariates
(Akinyemi & Mushunje, 2017)	South Africa	2016	Cross-sectional	167	youth aged 16 to 25	Logistic regression	To determine the prevalence of 'not in education, employment or training' (NEET) status among rural youth in Eastern Cape Province	Gender, Age Marital status Baby, Baby number
(Alcazar, Balarin, Glave, & Rodriguez, 2020)	Peru	2015	Cross-sectional	6125	youth aged 15–29	mixed methods	development of a contextually nuanced definition of precarious young workers, and provides an estimation of their numbers with those of NEETs	Female, children, Age, Level of education, Migrant, lives with parents, family member
(Alfieri, Sironi, Marta, Rosina, & Marzana, 2015)	Italy	2011	Cross-sectional	9087	18 and 29 years	Logistic regression	investigates the relationship between family variables (parents' educational level, relationship quality, intrusiveness, support, and autonomy) and young Italians' status as NEETs	parents' educational level, relationship qualit
(Baggio et al., 2015)	Switzerland	2010–2012	Cohort	4758	Young men in their early 20's at baseline	Logistic regression	examine if NEET youths differ from other contemporaries in terms of personality, mental health and substance use, and to provide longitudinal examination of NEET status	Depressive symptoms, Binge drinking, Cannabis use disorder, General mental health
(Bania, Eckhoff, & Kvernmo, 2019)	Norway	2003–2012	Cohort	3987	Youth 15–16 years old at baseline	Logistic regression	explore the prevalence of young adults NEET defined by no educational engagement, long-term recipient of sickness benefit, medical and non-medical benefit receipt or long-term unemployment in an unselected population	Ethnicity, Parent education, Depression
(Basta, 2019)	Greece	2016	Cross-sectional	2771	Youth 15–24 years old	Logistic regression	the associations of anxiety and depressive symptoms, and substance use with NEET status in a large, randomized population-based sample in Greece.	Age, Living with parents, Being married Financial support, Smoking, Use of cannabis or other drugs, Alcohol drinks
(Benjet, 2012)	Mexico,	2005	Cross-sectional	3005	Youth 12–17 years old	Logistic regression	to estimate the prevalence of psychiatric disorders, substance use and suicidal behaviour in youth classified as NEET and to compare with those who study only, work only or do both.	Anxiety disorder, Substance use disorder Behavioural disorder, Suicidal attempt, Alcohol, Tobacco, Drugs, Any substance Any substance,
(Cabral, 2018)	Senegal	2011	Cross-sectional	53494	15 and 34 years old	Logistic regression	assess the extent of the phenomenon of NEET by measuring its rate and identify the key factors of the status of NEET	Disability, deprivation, parent education, Age, Gender, parent employment, family resources
(Duckworth & Schoon, 2012)	England	2004-2010	Cohort	12,744	16 and 18	Logistic regression	assesses the effect of multiple independent socioeconomic risk factors in shaping the transition from school to work	Low parent education, Workless family, Low social class, lives in a lone parent family

(Flynn & Tessier, 2011)	Canada	2006-2009	Cross-sectional	406	Youth 18–20 years	Logistic regression	risk factors would be related to less favorable educational outcomes among extended care and maintenance youth.	Gender, Age, Health-related , disability, Soft-drug use
(Gariepy, 2019)	Canada,	2014	Cross-sectional	5622	Youth 15–29 years old	Logistic regression	describe the associations between a broad range of mental and substance disorders and being NEET	Depressive disorder, Generalized anxiety disorder, Alcohol use disorder, Cannabis disorder, Drug use disorder, Suicidal ideation
(Giret, Guégnard, & Joseph, 2020)	France	2009-2013	Cohort	30049	aged 15 to 26	Logistic regression	analyse the school-to-work transition of young people. in order to understand their risk of becoming and remaining NEET.	gender, migrant origin, highest qualification reached, type of training, field of study, reason for leaving studies, parents' education level, parents' status and situation, place of residence upon leaving education
(Goldman−Mellor et al., 2016)	United Kingdom	2012–2013	Cohort	2232	Twins 17–18 years old at baseline	Modified Poisson and logistic regression	compare four types of work-related self-perceptions, as well as vulnerability to mental health and substance abuse problems, among youths not in education, employment or training (NEET) and among their peers	Depressive disorder, Generalized anxiety disorder, Alcohol dependence, Cannabis dependence, Conduct disorder Depressive disorder, Anxiety disorder, Harmful substance use Suicidal behaviou
(Gutierrez−Garcia et al., 2018)	Mexico,	2005	Cross-sectional	1071	Youth 19–26 years old	Logistic regression	to examine the socio-demographic, education, employment and incident mental health outcomes in early adulthood of education and employment status in adolescence, particularly of NEET adolescents compared to their peers who study, work or both.	Mood disorder, Anxiety disorder, Behavioural disorder , Alcohol use disorder, Drug use disorder, Suicidal ideation, Suicidal plan , Suicidal attempt
(Hale & Viner, 2018)	United Kingdom	2004	Cohort	8682	Youth 13 years old at baseline	Logistic regression	to examine the impact of health in early adolescence on educational attainment and NEET status at the end of secondary education	Psychological distress, Alcohol use, Smoking, Cannabis use
(Henderson, 2017)	Canada,	2009–2013	Cross-sectional	2576	Youth 12–24 years old seeking services	Chi-square tests	explore the characteristics of NEET youth compared to their non-NEET peers in a large, crosssectoral sample ofservice-seeking youth in Canada.	Internalizing disorders ,Externalizing disorders, Substance use disorder
(Holloway et al., 2018)	Australia	2013-2015	cohort	57644	15–25 years	Chi-square tests	investigate participation in employment, education, or training among a national cohort of young people presenting to youth-specific mental health services across Australia	Age, Gender, Sexuality, Living Situation Rurality,Substance use disorder, Depressive disorder, Anxiety disorder , Psychological distress

(Karyda & Jenkins, 2018)	England	2004-2010	cohort	8480	ages 18 to 19	Logistic regression	investigates the effects of neighbourhood context on young people who experience NEET status at the ages 18 to 19 in one cohort born in 1989/90	Crime, area deprivation, parent educatio ethnicity, Family background
(Karyda, 2020)	England	2004-2010	cohort	8480	ages 16–19	Logistic regression	examines the extent to which social disorganisation, understood as the level of crime experienced in the neighbourhood, can influence young people's educational and employment outcomes.	Neighbourhood deprivation, Gender, Ethnic group, Prior educational attainme Mother's and father's highest educationa qualifications, Socio-economic classification (SEC), Engagement in risk behaviour
(Kevelson, Marconi, Millett, & Zhelyazkova, 2020)	OECD Countries	2012 and 2015	cohort	37721	aged 20–29	Logistic regression	explored the extent to which disconnection influences civic participation and well-being among NEETs with and without college degrees.	Education, Community engagement, hea and disability, parent education, immigrant, age , gender, Field of study
(Lallukka et al., 2019)	Finland	1987–2015	cohort	46521	25–28 years	Logistic regression	determinants of longterm unemployment in early adulthood, using a birth cohort with nearly a 30-year follow-up from birth to early adulthood.	Health-related, School performance, Marital status, unemployment rate, Parental health, Parental education,
(Lee & Kim, 2012)	South Korea	1998	cohort	2557	aged 15 and above	Logistic regression	macro- and micro-level factors that produce the growing trends of inactive youth and the problem of youth joblessness.	Gender, age, Married, education level, jo training, Father's education, Residing ar Father's occupational
(Lin & Chiao, 2022)	Taiwan	2000	cohort	2903	age of 14 years until the age of 22 years	Regression and mediation analyses	examine the relationship between adverse childhood experiences (ACEs) in early adolescence and heavy smoking in emerging adulthood, focusing on the mediating role of individuals' not in education, employment, or training (NEET) status.	Adverse childhood experiences, Abuse, parental divorce or separation, parental addiction , parental mental illness , and criminal in the household, Emotional neglect, Heavy smoking, Parent's education, educational aspiration, substance abuse, self-esteem, and depression
(Luthra, 2019)	Sweden	1981–2010	Cross-sectional	12269	18 years and older	Logistic regression	describe and analyse the family situation for those who are NEED.	gender, age, immigrant background, married, common law, single parent, livi parents
(Manhica 2019)	Sweden	2005–2009	Cohort	485,839	Youth 19–24 years old with secondary education	Cox regression	To investigate to what extent being outside education, employment or training after completed secondary education in Sweden might affect the risk of subsequent alcohol use disorders	Alcohol use disorder

(Maraj et al., 2019)	Canada	2018	Cohort	394	14 to 35 years old	Cox regression	examine how being vocationally inactive (NEET) affects engagement in early intervention services.	age, sex, visible minority status, social a material deprivation indices, and family involvement, duration of untreated psychosis, substance use disorder, medication nonadherence, and baseline positive and negative symptoms
(O'Dea et al., 2014)	Australia,	2011–2012	Cohort	448	Youth seeking services 15–25 years old at baseline	Multinomial logistic regression and chisquare tests	to examine NEET status and its correlates in a sample of such youth.	Age, Immigrant background, Criminal charges, Postsecondary education, Economic hardship, Alcohol risk, Tobac risk , Cannabis risk, Anxiety score, Depression score,
(Pitkänen, Remes, Moustgaard, & Martikainen, 2023)	Finland	1987–2012	Cohort	99137	age 13-18 years old	Logistic regression	assess a broad range of concurrent childhood determinants of NEET status in the context of a universal welfare state, where education is free and transitions to secondary education are strongly encouraged.	Parental unemployment, education of parents, Household income quintiles, Parental psychiatric disorder, Parental substance abuse, Parental death, Living with single parent, Placed outside home
(Power et al., 2015)	Ireland,	2000–2002	Cohort	168	Youth 15–25 years old	Logistic regression	the associations between economic inactivity and mental disorder (including suicidal behaviour) in a community sample of young people in Ireland.	depressive disorder, anxiety disorder, suicidal attempt
(Ringbom et al., 2022)	Finland	1998 and 2007, 2008 and 2015	cohort	55,273	Youth 15–25 years old	Logistic regression	To carry out a comprehensive overview of the associations between different psychiatric illnesses and long-term NEET status.	Psychiatric disorder, Substance misuse, Depressive disorders, Anxiety disorders, Personality disorders, Learning disabiliti Autism spectrum disorder, hyperactivity disorder, Bipolar disorder, Eating disord
(Rodriguez-Modroño, 2019)	Spain	2013 and 2016	cohort	1,612	15-29 years old	Logistic regression	The purpose of this paper is to apply an intersectional analysis to assess the impact of structural factors on the risk of being a NEET for youth in Spain.	gender, age, household income, educatio nationality or country of origin and Wor experience
(Rodwell, 2018)	Australia,	1992–1993	Cohort	1938	Youth 14–15 years old at baseline	Logistic regression	to examine independent associations between common mental disorders, substance use (i.e. alcohol and cannabis), and disruptive behaviours in adolescence and being NEET in young adulthood.	Cannabis use, Any heavy binge drinking , parental education, Parental divorce or separation
(Salvà-Mut, Tugores-Ques, & Quintana-Murci, 2018)	Spain	2010 to 2012	Cross-sectional	622	aged 25–29 years	Logistic regression	finding common characteristics of the NEET	Gender, dropout, education level, immigrants status, family immigrants status, parent education, parent work, Personal situation, economic situation,

								health, time usage, educational background, Work history
(Schoon & Lyons-Amos, 2017)	England	2004 and 2010	cohort	9791	young people 13/14-19/20	Logistic regression	introduce a socio-ecological model of agency to address the issue of personenvironment interactions.	Academic expectations, Goal certainty (forethought), Academic self-concepts (self-efficacy), School engagement (self-directedness), Parental education, parent income, family composition, living area, gender ethnicity. Life satisfaction, Transition patterns
(Schoon, 2014)	England	2004 and 2006, 2007 and 2010	cohort	9879	ages 16 to 20 years	Logistic regression	examine the inter-generational link between parental worklessness and a young person's likelihood of being NEET during a time that included a major economic downturn	Parental worklessness , family structure, housing conditions, and health, as well as are deprivation Academic expectations, Goal certainty (forethought), Parental education, Long standing illness or disability in the family, ethnicity, parent income, gender
(Selenko & Pils, 2019)	Austria	2007 and 2011	Cross-sectional	300	average 16.67 years of age	Logistic regression	predict adolescents' chances of succeeding on an apprenticeship programme after having gone through a period of being NEET	Gender, Age, Nationality, number of sibling, family composition , parent employment, Cognitive abilities, Relationship quality, dropout
(T. H. Stea et al., 2019)	Norway	2016	Cross-sectional	480	NEET youth from vocational services and non-NEET youth attending high school, 16–21 years old	Logistic regression	investigate differences in health-related behaviours between young people who are not in education, employment or training (NEET) and high school students in Norway.	Psychological distress, Alcohol use, Smoking Cannabis use
(T. H. Stea et al., 2019)	Norway	2016	Cross-sectional	480	NEET youth, 16–21 years old	Logistic regression	the differences in self-perceived health, mental health, and prevalence of pain between Norwegian adolescents	health, mental health

(Su, Wong, & To, 2022)	Hong Kong	2015-2020	Cross-sectional	4,726	aged 15–21	Logistic regression	to examine factor structure of the CAAS-China Form in youth with a longer spell of NEET status	Gender, Age, Educational attainment , the ro of carer, Seclusion at home , Involvement in deviant activities, Having addiction, health problems, Lack of clear goals for work, study life, Limitation of abilities
(Tamesberger & Bacher, 2014)	Austria	2008–2010	Cross-sectional	*59.844*	16 and 24 years	Logistic regression	examine the socio-structural attributes that characterise NEET youth in Austria, the main reasons for the NEET situation	Gender, Migration, Population, Living circumstances, , education level, parent education, Care responsibilities, Illness
(Tayfur et al., 2022)	England	2005 and 2015	cohort	2224	15-26 years old	Logistic regression	identify longitudinal associations between adolescent psychosocial factors and subsequent NEET status among this population in a nationally representative sample of secondary school students.	Self-esteem, Locus of control, Substance use Bullying, Behavioural problems, Educational aspirations, Attitudes to school, Job aspiratio Physical activity, Sex, Ethnicity, Socioeconomic status, Family composition, Caring responsibility
(Vancea & Utzet, 2018)	Spain	2016	Cross-sectional	1.826	ages 18–35 years	Logistic regression	investigates the main sociodemographic characteristics of Spanish young people not in education, employment or training (NEETs).	Age, gender , education level, Marital status, Caring responsibilities, Having children, pare education family income, Parental immigration background, Work experience, Social capital(friends)
(Yang, 2020)	China	2012-2020	Cross-sectional	4,978	individuals are aged 16 to 35	Logistic regression	understand the prevalence and characteristics of individuals aged 16 to 35	age, gender, ethnicity (Han versus non-Han), education level ,and marital status. region of birth , father's education , migration, respondent's Party membership, and family income

Appendix 3.2. Quality assessment of the selected studies

Quality Assessment:
QAR1: Is there a clear statement of the study objectives and their relevance to the NEET phenomenon?
QAR2: Are the data collection methods explicitly described and designed to minimize bias?
QAR3: Is there a clear description of the methodological approach used in data analysis, and does it align with the study design and research question?

QAR4: Does the study comprehensively examine and justify the targeted risk factors for NEET youth?
QAR5: 5) Are the outcome measures explicitly defined, validated, reliable, and consistently implemented across all study participants?

Each question is worth 5 points, and we assigned points based on the question's aim and the quality of the information in the article. At the end, we added a column for the average point to indicate the article's quality.
We used the Likert scale to assign points from high quality (5 points) to low quality (1 point).

Authors, year	QAR1(5)	QAR2(5)	QAR3(5)	QAR4(5)	QAR5(5)	Average point (5)
(Akinyemi & Mushunje, 2017)	4	3	3	2	4	3.2
(Alcazar, Balarin, Glave, & Rodriguez, 2020)	5	4	4	4	4	4.2
(Alfieri, Sironi, Marta, Rosina, & Marzana, 2015)	5	4	5	4	3.5	4.3
(Baggio et al., 2015)	4	3	5	4	4	4
(Bania, Eckhoff, & Kvernmo, 2019)	5	4	5	4	5	4.6
(Basta, 2019)	5	4	5	4	3	4.2
(Benjet, 2012)	5	4	5	4	5	4.6
(Cabral, 2018)	4	4	5	4	4	4.2
(Duckworth & Schoon, 2012)	5	5	5	4	5	4.8
(Flynn & Tessier, 2011)	4	4	5	4	5	4.4
(Gariepy, 2019)	4	3	3	2	4	3.2
(Giret, Guégnard, & Joseph, 2020)	5	5	5	1	3	3.8
(Goldman−Mellor et al., 2016)	5	4	4	1	4	3.6
(Gutierrez−Garcia et al., 2018)	3	3	2	3	2	2.6
(Hale & Viner, 2018)	4	2	3	3	4	3.2
(Henderson, 2017)	5	4	5	4	5	4.6
(Holloway et al., 2018)	4	2	1	1	2	2
(Karyda & Jenkins, 2018)	5	4	5	4	4	4.4
(Karyda, 2020)	5	5	5	4	4.5	4.7
(Kevelson, Marconi, Millett, & Zhelyazkova, 2020)	5	4	4	1	4	3.6
(Lallukka et al., 2019)	4	4	5	4	4	4.2
(Lee & Kim, 2012)	5	4	5	4	5	4.6
(Lin & Chiao, 2022)	4	5	5	4.5	5	4.7
(Luthra, 2019)	4	4	5	4	5	4.4
(Manhica 2019)	4	2	4	2	3	3
(Maraj et al., 2019)	5	4	5	3	5	4.4
(O'Dea et al., 2014)	5	4	5	4.5	5	4.7

(Pitkänen Moustgaard, & Martikainen, 2023)	4	3	3	3	2	3
(Power et al., 2015)	5	2	3	1	4	3
(Ringbom et al., 2022)	2	2	1	2	2	1.8
(Rodriguez-Modroño, 2019)	2	4	4	2	3	3
(Rodwell, 2018)	4	5	5	4.5	5	4.7
(Salvà-Mut & Quintana-Murci, 2018)	5	4	5	4	5	4.6
(Schoon & Lyons-Amos, 2017)	3	2	2	2	3	2.4
(Schoon, 2014)	5	4	5	4	5	4.6
(Selenko & Pils, 2019)	5	4	5	4	5	4.6
(Stea, De Ridder 2019)	4	4	5	2	5	4
(Stea, Abildsnes et al 2019)	4	5	5	2	5	4.2
(Su, Wong, & To, 2022)	5	4.5	5	4.5	5	4.8
(Tamesberger & Bacher, 2014)	5	4.5	5	4.5	5	4.8
(Tayfur et al., 2022)	4	3	4.5	3	4	3.7
(Vancea & Utzet, 2018)	4	4	5	4	5	4.4
(Yang, 2020)	5	4	5	4	5	4.6

Appendix 3.3. Detailed summary of findings by study.

Study	Measure	Risk Factors	Results	Group
(Akinyemi & Mushunje, 2017)	Coefficients	Age	0.3483	
	Std. Error	gender	-0.9997	
		married	-1.6468	
		children	-1.197	
(Alcazar, Balarin, Glave, & Rodriguez, 2020)	Marginal effects	Female	0.0450***	
	Std. Error	children	0.0126	
		Age	0.00654***	
		Level of education	-0.213	
		Migrant	0.00347	
		lives with parents	-0.0161	
		family member	-0.00643	
(Alfieri, Sironi, Marta, Rosina, & Marzana, 2015)	Marginal Effects	Education of the mother	-0.0874***	Men
	Z	Education of the father	-0.0853***	Men
		relation with family	0.0161	Men
		Education of the mother	-0.0786**	Women
		Education of the father	-0.0690**	Women
		relation with family	-0.0002	Women
(Baggio et al., 2015)	Odds Ratio	Depressive symptoms	1.11	
		Binge drinking	NA	
		Cannabis use disorder	1.09	
		General mental health	1.11	
(Bania, Eckhoff, & Kvernmo, 2019)	Odds Ratio	ethnicity	1.58	Men
	95% CI	Parent education	1.75	Men
		Depression	0.88	Men
		ethnicity	0.74	Women
		Parent education	1.06	Women
		Depression	1.04	Women
(Basta, 2019)	Odds Ratio	Age	1.28	Men
	95% CI	Living with parents	2.68	Men
		Being married	2.07	Men
		Financial support	1.56	Men
		Smoking	1.84	Men
		Use of cannabis or other drugs	0.99	Men
		Alcohol drinks	1.01	Men
		Age	1.57	Women
		Living with parents	2.2	Women
		Being married	2.41	Women
		Financial support	3.4	Women

Study	Measure	Risk Factors	Results	Group
		Smoking	1.16	Women
		Use of cannabis or other drugs	0.518	Women
		Alcohol drinks	0.96	Women
(Benjet, 2012)	Odds Ratio	Anxiety disorder	1.3	
	95% CI	Substance use disorder	4.4	
		Behavioural disorder	2.1	
		Suicidal attempt	1.7	
		Alcohol	3	
		Tobacco	3.9	
		Drugs	3.5	
		Any substance	3.4	
(Cabral, 2018)	Coefficients	Disability	0.774***	total
		deprivation	0.108	total
		parent education	0.157***	total
		Age	-0.0122***	total
		Gender	1.444***	total
		parent employment	0.505***	total
		family resources	-0.165***	total
		Disability	1.105***	Men
		deprivation	0.413***	Men
		parent education	0.0142	Men
		Age	0.0551***	Men
		parent employment	0.680***	Men
		family resources	-0.175***	Men
		Disability	0.505***	women
		deprivation	0.157***	women
		parent education	0.384***	women
		Age	0.00575*	women
		parent employment	0.377***	women
		family resources	-0.156***	women
(Duckworth & Schoon, 2012)	Odds ratio	Low parent education	1.31*	
	Effect size	Workless family	1.32*	
		Low social class	1.65***	
		YP lives in a lone parent family	1.20*	
(Flynn & Tessier, 2011)	Odds Ratio	Gender	1.08	
		Age	0.82	
		Health-related disability	1.84	
		Soft-drug use	0.97	
(Gariepy, 2019)	Odds Ratio	Depressive disorder	1.7	
	95% CI	Generalized anxiety disorder	2.6	
		Alcohol use disorder	1	
		Cannabis disorder	1	
		Drug use disorder	3.2	

Study	Measure	Risk Factors	Results	Group
		Suicidal ideation	1.8	
(Giret, Guégnard, & Joseph, 2020)	Odds Ratio	gender	1.165**	
		Level of education	1.513***	
		Field of study	0.942	
		family member	1.282**	
		Father not in employment	1.207**	
		Mother not in employment	1.135**	
(Goldman−Mellor et al., 2016)	Odds Ratio	Depressive disorder	1.68	
	95% CI	Generalized anxiety disorder	1.84	
		Alcohol dependence	1.42	
		Cannabis dependence	3.93	
		Conduct disorder	1.46	
		Depressive disorder	2.57	
		Anxiety disorder	1.38	
		Harmful substance use	1.89	
		Suicidal behaviours	3.3	
(Gutierrez−Garcia et al., 2018)	Odds Ratio	Mood disorder	1.67	
	95% CI	Anxiety disorder	0.4	
		Behavioural disorder	0.83	
		Alcohol use disorder	1.19	
		Drug use disorder	1.03	
		Suicidal ideation	1.94	
		Suicidal plan	1.18	
		Suicidal attempt	2.4	
(Hale & Viner, 2018)	Odds Ratio	Psychological distress	1.72	Men
	95% CI	Psychological distress	1.49	Women
		Alcohol use	1.15	Men
		Alcohol use	2.04	Women
		Smoking	1.41	Men
		Smoking	2.07	Women
		Cannabis use	1.34	Men
		Cannabis use	2.19	Women
(Henderson, 2017)	Odds Ratio	Internalizing disorders	1.15	Total
	95% CI	Internalizing disorders	0.95	Age 18
		Internalizing disorders	1.33	Age 18
		Internalizing disorders	1.39	Men
		Internalizing disorders	1.08	Women
		Externalizing disorders	0.9	Total
		Externalizing disorders	1.18	Age 18
		Externalizing disorders	1.13	Age 18
		Externalizing disorders	0.93	Men
		Externalizing disorders	0.87	Women

Study	Measure	Risk Factors	Results	Group
		Substance use disorder	1.94	Total
		Substance use disorder	1.44	Age ≤18
		Substance use disorder	2.19	Age≥18
		Substance use disorder	1.83	Men
		Substance use disorder	2.05	Women
(Holloway et al., 2018)	Odds Ratio	Age	1.92	
	95% CI	Sex	1.78	
		Rurality	1.09	
		Substance use disorder	1.93	
		Depressive disorder	0.79	
		Anxiety disorder	0.86	
		Psychological distress	0.97	
(Karyda & Jenkins, 2018)	Coeff.	Highest qualification of main parent	1.453	
	std. err.	Single-parent family	0.823	
		Ethnic group	0.891	
		person's behaviour	1.66	
(Karyda, 2020)	Odds Ratio	sex	0.774	
		Ethnicity	0.844	
		highest educational qualification of mother	0.928	
		highest educational qualification of father	0.711	
		experienced aggressive behaviour	1.288	
(Kevelson, Marconi, Millett, & Zhelyazkova, 2020)	Odds Ratio	Parent education	1.173	
		Migrant	1.377	
		Female	2.118	
		Age	1.223	
		Caring responsibility	0.609	
		Field of study	1.234	
(Lallukka et al., 2019)	Odds Ratio	Any mental disorder	3.22	Men
	95% CI	Any mental disorder	2.74	Women
		Marital status	1.7	Men
		Marital status	1.08	Women
		Long-term unemployed	4.04	Men
		Long-term unemployed	3.37	Women
		Parental education	1.26	Men
		Parental education	1.54	Women
		level of education	1.45	Men
		level of education	1.75	Women
		living with single parent	1.58	Men
		living with single parent	1.34	Women

Appendices

Study	Measure	Risk Factors	Results	Group
(Lee & Kim, 2012)	Odds Ratio	Age	0.27	
	B	Married	0.674	
		Education	0.754	
		Father's education	0.656	
		Father's occupation	1.018	
(Lin & Chiao, 2022)	OR	Male	1.99	
	ES	Education level	0.96	
		Substance use	1.07	
		Depressive symptoms	1.26	
(Luthra, 2019)	Odds Ratio	Gender	1.21***	
	95% CI	Age	0.60***	Men
		Age	0.56***	Women
		Immigrant	1.46***	Men
		Immigrant	1	Women
		Married	1.47	Men
		Married	3.92***	Women
		Single parent	1.94	Men
		Single parent	7.44***	Women
(Manhica, 2019)	HR	Alcohol use disorder	1.30	
	95% CI			
(Maraj et al., 2019)	Odds Ratio	Age	0.94	
	95% CI	Male	2.98	
		Visible minority	1.34	
		Substance use disorder	0.54	
		Material deprivation	1.03	
(O'Dea et al., 2014)	Odds Ratio	Age	2.42	
	95% CI	gender	2.24	
		Immigrant background	1.09	
		Criminal charges	2.85	
		Postsecondary education	0.84	
		Economic hardship	2.15	
		Alcohol risk	1.37	
		Tobacco risk	1.46	
		Cannabis risk	1.94	
		Anxiety score	1.54	
		Depression score	2.72	
(Pitkänen, Remes, Moustgaard, & Martikainen, 2023)	Odds Ratio	Parental education	1.61	
	95% CI	Parental unemployment	1.61	
		Household income	1.12	
		Living with a single parent	1.35	
(Power et al., 2015)	Odds Ratio	depressive disorder	2.81	
	95% CI	anxiety disorder	2.9	
		suicidal attempt	3.21	

Study	Measure	Risk Factors	Results	Group
(Ringbom et al., 2022)	Odds Ratio	Gender	1.8	
	95% CI	Parental education	1.4	
		Any psychiatric	3.7	
		Substance misuse	3.1	
		Depressive disorders	2.8	
		Anxiety disorders	3.1	
(Rodriguez-Modroño, 2019)	marginal effects	Age	0.00858***	men
	std. err.	Age	0.00187	women
		household income	-0.00000236***	men
		household income	-0.00000375***	women
		household Work	-0.0380**	men
		household Work	-0.0476**	women
		Unemployed W 6 months	0.0449	men
		Unemployed W 6 months	0.0852***	women
(Rodwell, 2018)	Odds Ratio	Cannabis use	1.74	
	95% CI	Any heavy binge drinking	0.80	
		parental education	0.59	
		Parental divorce or separation	1.75	
(Salvà-Mut, Tugores-Ques, & Quintana-Murci, 2018)	Marginal effects	educational level	-0.1606	
		female	0.0023	
		Immigrant	0.3312**	
		Poorly educated father	0.2297*	
		Poorly educated mother	0.005	
		Married	0.152	
		With children	0.4798***	
		economic hardship	0.1515***	
		relevant illnesses	0.1707	
		relevant addictions	0.2990**	
(Schoon & Lyons-Amos, 2017)	Coefficient	Family resources	-0.015	
	Std. Err	Urban	-0.022	
		Unemployed after some education	-.627***	
		Female	.094**	
		Non-white	-0.069	
(Schoon, 2014)	Coefficient	Parental worklessness	0.655	
	Std. Error	Parental education	-0.65	
		Single parent household	-0.04	
		Number of siblings	0.192	
		household income	0.021	
		Urban/rural	0.458	
		ethnicity minority	-0.683	

Study	Measure	Risk Factors	Results	Group
(Selenko & Pils, 2019)	Odds Ratio	Gender	1.03	
	95% CI	Nationality	2.25	
		Nr of siblings	1.02	
		Single parent household	0.55	
		Age	0.6	
(Stea De Ridder et al., 2019)	Odds Ratio	Psychological distress	1.13	
	95% CI	Alcohol use	1.15	
		Smoking	1.41	
		Cannabis use	1.34	
(Tamesberger & Bacher, 2014)	Coefficient	Female	1.327*	
		Migration background	1.432*	
		Living with parents	0.535**	
		Have child(ren)	3.919***	
		Care responsibilities	5.172**	
(Tayfur et al., 2022)	Odds Ratio	Substance use	1.02	
	95% CI	Behavioural problems	0.92	
(Vancea & Utzet, 2018)	Odds Ratio	Education	0.88	
	95% CI	Education	0.43	
		Caring responsibilities	0.68	
		Caring responsibilities	2.8	
		Parents' economic self-sufficiency	0.97	
		Parents' economic self-sufficiency	0.53	
		Unemployment experience	3.4	
		Unemployment experience	4.84	
(Yang, 2020)	Odds Ratio	Age group	15.26	
	Std. Error	Female	7.47	
		Ethnicity	1.9	
		Education	0.16	
		Married	3.63	
		Father's education	0.93	

Appendix 4.1. Definitions of variables and code

Variable	Definition / Measurement	Coding Scheme	Type
Youth NEET (Overall)	Binary indicator of NEET status for all youth aged 15–24	0= Not NEET 1= NEET	Binary
Male NEET	Binary indicator of NEET status for males aged 15–24	0= Male, Not NEET 1= Male, NEET	Binary
Female NEET	Binary indicator of NEET status for females aged 15–24	0= Female, Not NEET 1= Female, NEET	Binary

Variable	Definition / Measurement	Coding Scheme	Type
Education	Highest level of education completed, measured by years of schooling	No schooling = 0 years, Primary completion = 6 years, Lower secondary= 9 years, Upper secondary/Diploma = 12 years, Associate degree = 14 years, Bachelor's degree = 16 years, Master's degree = 18 years, and PhD students = 18 years	Ordinal (years)
Potential Work Experience	Years of potential labour market exposure, calculated as: Age-Years of Education-6	Continuous (years); Assuming school entry at age 6	Continuous
Housework	Total hours per week spent on unpaid domestic labour (cooking, cleaning, childcare, etc.)	Continuous (hours/week)	Continuous
Family Education	Total cumulative years of formal education for all household members	Continuous (sum of years)	Continuous
Birthplace	Type of location where youth was born	0= Rural birthplace, 1 = Urban birthplace	Binary
Children Under 6	Number of children aged 0–5 years in the household	Count (0, 1, 2, ...)	Count
Land/House Ownership	Household property ownership categorized by size (m^2) as a proxy for wealth	**Land 1:** 0 m^2 **Land 2:** 20–50m^2 **Land 3:** 50–100 m^2 **Land 4:** 100–199 m^2 **Land 5:** 200+ m^2 • Not expensive (Land 1-2) • Semi-expensive(Land 3) • Expensive (Land 4-5)	Categorical (dummy variables)

Appendix 5.1. Correlation Matrix and VIF

	Unemp. Rate	GVA Agri.	GVA Ind.	GVA Serv.	GVA Min.	Pop.	Ind. Div.	Emp. Rate	Unemp. 15-24	Higher School	Dropout Rate	VET	Illit. Rate	Budget	Part. Rate	Infl.	Gini	Human Cap.	GDP	Urb.	VIF
Unemp. Rate	1																				8.84
GVA Agri.	0.01	1																			7.32
GVA Ind.	0.054	-0.026	1																		13.32
GVA Serv.	-0.015	0.001	0.005	1																	8.22
GVA Min.	0.004	-0.028	0.103	0	1																6.51
Population	-0.004	0.025	0.047	-0.048	-0.057	1															12.55
Ind. Div.	-0.051	-0.028	-0.014	0.008	0.001	-0.002	1														7.21
Emp. Rate	0.008	-0.009	0.021	0.001	0.013	-0.026	0.069	1													29.6
Unemp.youth	0.08	0.09	0.071	0.025	0.03	-0.008	-0.014	0.012	1												9.81
High School	-0.028	-0.01	0.035	-0.004	0.107	-0.045	0.021	-0.073	0.056	1											15.17
Dropout Rate	-0.017	0.069	0.028	-0.035	-0.016	0.005	0.042	-0.061	-0.043	0.038	1										13.16
VET	0.005	-0.103	0.004	0.032	0.023	-0.024	-0.07	0.038	-0.03	-0.069	0.006	1									6.25

Illit. Rate	0.014	0.078	0.016	0.084	0.013	-0.04	-0.006	0.011	0.035	-0.039	0.003	0.042	1								8.02
Budget	-0.034	0.04	0.01	0.069	-0.006	-0.067	0.054	-0.028	-0.022	0.007	-0.002	0.013	0.045	1							9.08
Part. Rate	-0.041	-0.047	0.085	0.018	-0.109	-0.015	0.013	0.051	-0.031	-0.014	0.041	-0.024	0.002	-0.052	1						7.42
Inflation	0.072	-0.011	0.053	0.014	-0.016	0.012	-0.08	-0.057	-0.04	0.012	-0.081	-0.015	0.069	0.073	-0.013	1					20.27
Gini	-0.047	-0.103	-0.064	0.029	-0.052	0.044	0.024	0.002	0.01	-0.019	-0.032	0.033	-0.026	0.01	-0.025	0.048	1				7.26
Human Cap.	0.008	-0.034	-0.044	0.076	-0.001	0.042	-0.042	0.027	0.022	0.047	0.046	-0.032	0.001	0.029	0.02	-0.074	0.015	1			7.53
GDP	0.015	-0.07	-0.024	-0.052	0.038	-0.021	0.002	0.023	-0.007	-0.01	0.03	0.021	0.033	0.011	0.015	0.061	0.011	0.002	1		8.06
Urbanization	0.027	0.106	0.007	-0.11	-0.059	-0.01	0.071	0.006	0.054	0.018	-0.01	-0.034	-0.046	-0.006	-0.029	-0.032	0.114	0.024	0.04	1	9.28

Appendix 5.2. SDM Estimation Results for Total NEET Sample

Variable	Direct Effect	Indirect Effect	Total Effect
	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
LN GDP per capita	-0.220*** (0.041)	0.039 (0.052)	-0.181*** (0.058)
LN Budget	-0.062*** (0.012)	0.015 (0.021)	-0.047*** (0.025)
LN Human capital	-0.095*** (0.031)	-0.023 (0.045)	-0.118** (0.051)
LN Inflation	-0.049 (0.030)	0.002 (0.038)	-0.047 (0.044)
LN Industrial diversity	-0.070** (0.029)	-0.016 (0.040)	-0.086** (0.045)
LN Agriculture GVA	-0.169*** (0.055)	0.044 (0.072)	-0.125 (0.085)
LN Services GVA	-0.401*** (0.065)	0.039 (0.088)	-0.362*** (0.095)
LN Urbanization	0.172** (0.071)	-0.021 (0.095)	0.151 (0.112)
LN Unemployment	0.255** (0.105)	-0.003 (0.132)	0.252* (0.145)
LN Gini	0.125* (0.065)	-0.033 (0.085)	0.092 (0.101)
LN VET	-0.075 (0.051)	-0.006 (0.068)	-0.081 (0.081)
Spatial lag (ρ)	-0.112 (0.251)		
R^2	0.720		
AIC	-1020.85		
Wald test ($\theta = 0$)	$\chi^2 = 12.47$		$p = 0.188$

from neighbouring provinces (WX). Total effects are the sum of direct and indirect effects.
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

Summary

There are a number of serious social and personal consequences associated with youth who are not in education, employment, or training (NEET). One in five young people is NEET, and two-thirds of them are women (Kaya, 2023). Young people face socioeconomic marginalization, persistent poverty, social isolation, and a tendency to commit crimes and become addicted (Chapter 2). Youth disengagement represents a personal crisis for affected youth and a threat to societal goals, including economic growth and social cohesion.

The urgency of this problem is particularly observed in Iran, where the NEET rate reached an alarming 38% of the youth population (aged 15-24) in 2020. The NEET rate in Iran contrasts sharply with the global average of 22.1% and with rates in many neighbouring and low-income countries, such as Turkey, Iraq and Pakistan (Aziz, 2021). NEET is more than a trend; it is a pressing national crisis that requires specific attention. The high rate of NEET youth in Iran further compounds the gender disparity. Iranian women are more than twice as likely to be in NEET status (39%) as Iranian men (18%). Of Iran's young population (60 percent of the population is under 30), a significant portion is inactive, indicating that this demographic dividend has not yet translated into active engagement (Chapter 5). There are several factors contributing to Iran's high NEET rate: persistent macroeconomic instability, driven in part by U.S. and EU trade and financial sanctions; high inflation; currency devaluation; and poor job growth, as well as structural issues like institutional gender inequality, which have exacerbated the problem (Toprak, 2020). This dissertation focuses on the NEET phenomenon in this Iranian context and on designing holistic, context-sensitive strategies to transform youth disengagement into an opportunity for inclusive growth.

In this dissertation, we identify and analyze the key risk factors for NEET status among Iranian youth. In this study, determinants of NEET status, predictive tools, and policy implications were examined.

To achieve this goal, the research focused on four core questions :

1. What are the key individual, familial, socio-economic, and psychological risk factors contributing to youth becoming NEET? (Addressed in Chapter 2)

2. What are the primary risk factors contributing to NEET status among youth, how do these factors vary across different demographic groups, and which factors demonstrate the strongest associations with NEET status to inform targeted, evidence-based interventions? (Addressed in Chapter 3)

3. What predictive models can be created using machine learning to assess and forecast the likelihood of youth becoming NEET? (Addressed in Chapter 4)

4. How can macroeconomic conditions and structural disparities explain regional and demographic variations in NEET outcomes across Iran, and how can these insights lead to more regionally tailored and gender-sensitive policy responses? (Addressed in Chapter 5)

Different methodological strategies are used to address these multifaceted research questions. A funneled research design enabled a comprehensive, contextually grounded analysis of the NEET phenomenon, beginning with broad international evidence and progressively narrowing to the specific socioeconomic, cultural, and spatial determinants shaping youth disengagement in Iran.

To capture the complexity of NEET determinants, a Mixed-methods design was deployed. Based on a scoping review of international literature, the study identified and mapped the broad range of risk factors associated with NEET status (Chapter 2). In Chapter 3, a systematic review and meta-analysis are used to synthesize key risk factors and their effects across diverse studies. To identify micro-level determinants of NEET status in Iran and to develop predictive models for NEET status, economic modeling, specifically Probit models and machine learning techniques, including Classification and Regression Trees (CART), were applied to Iranian national labour force survey data (Chapter 4). In Chapter 5, spatial panel data econometrics are employed to analyze the macroeconomic factors that determine NEET rates and regional interdependencies.

By combining the qualitative synthesis of scoping review findings with advanced quantitative analysis, we gained a comprehensive understanding of NEET challenges from both global and local perspectives.

In the first phase of the study, NEET youth were systematically examined. The scoping review in Chapter 2 (93 studies, 2000-2022) identified eight primary risk domains: individual characteristics, education/school, work, health, addiction, social factors, family, and environment. Among 43 studies included in Chapter 3, higher education attainment significantly reduces the likelihood of becoming a NEET (Odds Ratio = 0.81). The odds of being a NEET were significantly increased by unemployment (OR = 1.98), criminal behavior (OR = 2.06), and suicide risk (OR = 2.8). Since NEETs have different needs, policies should be tailored accordingly. Across contexts, these findings demonstrate consistent patterns of vulnerability among youth, emphasizing education, family background, and health-related barriers as recurrent determinants of NEET status.

Data from Iran's 2021 labour force survey showed that years of education significantly reduced the probability of being a NEET (e.g., 2.4% for males and 2.1% for females). The likelihood of becoming a NEET is significantly increased by excessive housework (CART: >20 hours/week = 83% higher likelihood). The likelihood of female NEETs increased with household wealth (land ownership), while the likelihood of male NEETs decreased with young children in the household. NEET risk was lower among female youth born in urban areas. Following the adjustment for selection bias, the Probit model achieved an overall accuracy of 84.91% (Area Under the ROC Curve = 0.89), indicating potential for early warning systems. Based on these insights at the individual and household level, the next phase expands the analysis to include macroeconomic and spatial dynamics that contribute to regional disparities in NEET rates.

Based on spatial panel data analysis (using macro data for 30 provinces for the period 2004-2022), NEET rates were significantly reduced by higher provincial GDP per capita (1% GDP increase, about -0.18% total NEET rate). Government spending and human capital are also associated with lower NEET rates. An increase in unemployment and income inequality led to an increase in NEETs. Inflation rates and NEET rates were negatively correlated, with an elasticity of -0.047. In some models, urbanization is positively correlated with NEET rates, suggesting that inclusive job creation lags behind urban migration. A crucial finding was the significant negative spatial lag coefficient ($\rho \approx -0.33$), indicating that provinces with higher NEET rates tend to be surrounded by provinces with lower NEET rates, likely due to labour migration or displacement.

The majority of Iranian NEETs are women, due to structural and cultural factors such as housework and caregiving, as well as significant regional and urban-rural inequalities. There are higher NEET rates in underdeveloped provinces because of limited opportunities. The heterogeneity of the NEET population necessitates tailored, targeted interventions (Chapter 5).

A consistent pattern emerges across methodologies: NEET outcomes in Iran are determined by intertwined micro-, meso-, and macro-level factors. To guide the selection and interpretation of risk factors in the Iranian case, different theories (Human Capital Theory, Capability Approach, and Bronfenbrenner's Ecological Systems Theory) were employed. While formal hypothesis tests of these theories are beyond the scope of this article, empirical results were used to assess how well each framework explains observed patterns. NEET rates among educated Iranian women challenge simple Human Capital Theory predictions, emphasizing structural barriers. In addition to advancing the understanding of NEET heterogeneity, the

study demonstrated significant negative spatial spillovers in NEET rates. The dissertation provided a multi-level framework that bridged micro- and macro-level theories of disengagement.

Using a mixed-methods design that combines a scoping review, systematic review, and meta-analysis, as well as Probit models, machine-learning classification (CART), and spatial panel data analysis, we conducted a robust, triangulated analysis. The use of machine learning (CART and Probit models) to predict NEETs in Iran represents a significant step forward in providing policymakers with data-driven tools. In a pioneering spatial panel data analysis, NEET rates across Iranian provinces were assessed in relation to regional interdependencies.

This study addresses a previous research gap by examining the multifaceted determinants of NEETs in Iran. There is strong, quantifiable evidence that NEETs are more likely to be females and that they are more prevalent in some regions than others (e.g., 48.2% in Sistan-Baluchistan province). Specifically, it identified policy levers for Iran, including improving female education and labor market access, supporting rural youth, and promoting regional collaboration.

By integrating ecological, human capital, capability, gender, and spatial frameworks, this dissertation illustrates the heterogeneity of disengaged youth. The study is the first empirical investigation in Iran to link micro-level household labour force data with macro-level spatial dynamics across provinces and to quantify the elasticities of key economic variables with respect to NEET rates. In combining these multi-scale perspectives, the research introduces a data-driven framework that demonstrates how individual, structural, and regional factors influence youth disengagement. This integrative perspective extends existing NEET scholarship by bridging micro- and macro-theoretical explanations and provides a basis for designing context-sensitive, gender-responsive, and spatially informed youth policies in Iran and comparable developing-country settings.

Five interdependent strategies are derived from the systems-based synthesis in this dissertation. Firstly, investing in preventive education and training should include integrating digital and soft-skills curricula. Also, to harness spatial dynamics, spatially targeted programming requires training units, e-learning platforms, and cross-provincial internship programs. To improve labour market predictability, inclusive macroeconomic reforms should direct youth-focused public spending to underprivileged regions. Predictive targeting and early intervention systems should integrate CART-based early warning tools into labour surveys and school dropout monitoring, complemented by multi-stakeholder youth hubs that combine training, counseling, and labour market information.

A spatial insight and early-warning tool provide actionable guidance to national stakeholders, including Ministries of Education, Labour, and Cooperatives. Regional development plans can incorporate gender-focused measures and spatial spillover patterns into ongoing vocational reforms. Researchers from international agencies may use this study's findings to adapt policies across the MENA region. Experiments and quasi-experiments should be used to evaluate the effectiveness of integrated education, gender, and regional interventions. To improve forecasting and policy targeting, data integration across administrative sources and qualitative research into hard-to-reach NEET subgroups are necessary.

The causes of NEETs in Iran are rooted in inequalities related to education, gender, and region. Solving this problem is urgent and possible. Youth disengagement is described in the dissertation as well as a pathway to an integrated, evidence-based policy for youth engagement. Iran can turn its demographic challenge into a demographic dividend by investing in education, gender equity, spatial awareness, and early warning systems.

Samenvatting

Jongeren die niet werken, geen onderwijs volgen en geen opleiding doen (NEET: not in education, employment, or training*)* worden geconfronteerd met ernstige sociale en persoonlijke gevolgen. Eén op de vijf jongeren is NEET, en twee derde van hen is vrouw (Kaya, 2023). Deze jongeren hebben te maken met sociaaleconomische marginalisering, hardnekkige armoede en sociaal isolement, en lopen een grotere kans om in de criminaliteit terecht te komen of verslaafd te raken (hoofdstuk 2). Uitval van jongeren is niet alleen een persoonlijke crisis voor de betrokkenen, maar ook een bedreiging voor maatschappelijke doelen, zoals economische groei en sociale cohesie.

De urgentie van dit probleem is vooral zichtbaar in Iran, waar het NEET-percentage in 2020 opliep tot zorgwekkende 38% van de jongeren (15-24 jaar). Dit percentage steekt scherp af tegen het wereldwijde gemiddelde van 22,1% en tegen de cijfers van veel buurlanden en lageinkomenslanden, zoals Turkije, Irak en Pakistan (Aziz, 2021). NEET is meer dan een trend: het is een acute nationale crisis die specifieke aandacht vereist. Het hoge NEET-percentage in Iran gaat bovendien gepaard met een sterke genderongelijkheid. Iraanse vrouwen hebben meer dan twee keer zo vaak de NEET-status (39%) als Iraanse mannen (18%). Van de Iraanse bevolking is 60 procent jonger dan 30 jaar, maar een aanzienlijk deel van deze jongeren is inactief, wat erop wijst dat dit demografische dividend nog niet is omgezet in actieve participatie (hoofdstuk 5). Het hoge NEET-percentage in Iran heeft meerdere oorzaken: aanhoudende macro-economische instabiliteit, mede veroorzaakt door handels- en financiële sancties van de VS en de EU, hoge inflatie, valutadevaluatie en een zwakke banengroei, maar ook structurele problemen zoals institutionele genderongelijkheid, die het probleem hebben verergerd (Toprak, 2020). Dit proefschrift richt zich op het NEET-fenomeen in deze Iraanse context en op het ontwikkelen van integrale, contextgevoelige strategieën om de uitval van jongeren om te zetten in een kans voor inclusieve groei.

In dit proefschrift worden de belangrijkste risicofactoren voor de NEET-status onder Iraanse jongeren geïdentificeerd en geanalyseerd. Daarbij zijn de determinanten van de NEET-status, voorspellende instrumenten en beleidsimplicaties onderzocht.

Om dit doel te bereiken, richtte het onderzoek zich op vier kernvragen:

1. Wat zijn de belangrijkste individuele, gezinsgerelateerde, sociaaleconomische en psychologische risicofactoren die bijdragen aan het NEET worden van jongeren? (Behandeld in hoofdstuk 2)

2. Wat zijn de belangrijkste risicofactoren voor de NEET-status onder jongeren, hoe verschillen deze factoren tussen demografische groepen, en welke factoren hebben het sterkste verband met de NEET-status, als basis voor gerichte, evidence-based interventies? (Behandeld in hoofdstuk 3)
3. Welke voorspellende modellen kunnen met behulp van machine learning worden ontwikkeld om de kans dat jongeren NEET worden te beoordelen en te voorspellen? (Behandeld in hoofdstuk 4)
4. Hoe kunnen macro-economische omstandigheden en structurele ongelijkheden de regionale en demografische verschillen in NEET-uitkomsten in Iran verklaren, en hoe kunnen deze inzichten leiden tot meer regionaal toegesneden en gendersensitieve beleidsreacties? (Behandeld in hoofdstuk 5)

Voor de beantwoording van deze meerlagige onderzoeksvragen zijn verschillende methodologische strategieën gebruikt. Een trechtervormig onderzoeksontwerp maakte een omvattende, contextueel verankerde analyse van het NEET-fenomeen mogelijk. Het begon met breed internationaal bewijs en vernauwde zich geleidelijk tot de specifieke sociaaleconomische, culturele en ruimtelijke determinanten van uitval onder jongeren in Iran.

Om de complexiteit van de determinanten van NEET te vatten, is een mixed-methods-ontwerp toegepast. Op basis van een scoping review van de internationale literatuur zijn de risicofactoren die samenhangen met de NEET-status in kaart gebracht (hoofdstuk 2). In hoofdstuk 3 zijn een systematische review en meta-analyse gebruikt om de belangrijkste risicofactoren en hun effecten over verschillende studies heen samen te vatten. Om determinanten van de NEET-status op microniveau in Iran te identificeren en voorspellende modellen te ontwikkelen, zijn economische modellen, met name Probit-modellen, en machine-learningtechnieken, waaronder classificatie- en regressiebomen (CART), toegepast op de Iraanse nationale arbeidskrachtenenquête (hoofdstuk 4). In hoofdstuk 5 is ruimtelijke paneldata-econometrie gebruikt om de macro-economische factoren te analyseren die de NEET-percentages en regionale onderlinge afhankelijkheden bepalen.

Door de kwalitatieve synthese van de bevindingen uit de scoping review te combineren met geavanceerde kwantitatieve analyse, is een breed inzicht verkregen in de NEET-problematiek vanuit zowel een mondiaal als een lokaal perspectief.

In de eerste fase van het onderzoek zijn NEET-jongeren systematisch onderzocht. De scoping review in hoofdstuk 2 (93 studies, 2000-2022) identificeerde acht primaire risicodomeinen:

individuele kenmerken, onderwijs/school, werk, gezondheid, verslaving, sociale factoren, gezin en omgeving. In de 43 studies die in hoofdstuk 3 zijn opgenomen, verlaagt een hoger opleidingsniveau de kans om NEET te worden significant (odds ratio = 0,81). De kans om NEET te zijn nam significant toe door werkloosheid (OR = 1,98), crimineel gedrag (OR = 2,06) en suïciderisico (OR = 2,8). Aangezien NEET-jongeren uiteenlopende behoeften hebben, moet het beleid dienovereenkomstig worden toegesneden. Over verschillende contexten heen tonen deze bevindingen consistente patronen van kwetsbaarheid onder jongeren, waarbij onderwijs, gezinsachtergrond en gezondheidsgerelateerde belemmeringen steeds terugkerende determinanten van de NEET-status blijken.

Gegevens uit de Iraanse arbeidskrachtenenquête van 2021 toonden aan dat het aantal jaren onderwijs de kans om NEET te zijn significant verlaagde (bijvoorbeeld met 2,4% voor mannen en 2,1% voor vrouwen). De kans om NEET te worden neemt significant toe bij overmatig huishoudelijk werk (CART: >20 uur per week = 83% hogere kans). De kans op NEET-status bij vrouwen nam toe met de welvaart van het huishouden (grondbezit), terwijl de kans op NEET-status bij mannen afnam bij aanwezigheid van jonge kinderen in het huishouden. Het NEET-risico was lager bij jonge vrouwen die in een stedelijk gebied zijn geboren. Na correctie voor selectiebias bereikte het Probit-model een algehele nauwkeurigheid van 84,91% (oppervlakte onder de ROC-curve = 0,89), wat wijst op het potentieel voor vroegsignaleringssystemen. Voortbouwend op deze inzichten op individueel en huishoudniveau wordt de analyse in de volgende fase uitgebreid met macro-economische en ruimtelijke dynamiek die bijdraagt aan regionale verschillen in NEET-percentages.

Uit de ruimtelijke paneldata-analyse (met macrogegevens voor 30 provincies over de periode 2004-2022) bleek dat de NEET-percentages significant afnamen bij een hoger bbp per hoofd van de bevolking op provinciaal niveau (een stijging van het bbp met 1% leidt tot een daling van het totale NEET-percentage met ongeveer 0,18%). Ook overheidsuitgaven en menselijk kapitaal hangen samen met lagere NEET-percentages. Een toename van werkloosheid en inkomensongelijkheid leidde tot een toename van het aantal NEET-jongeren. Inflatie en NEET-percentages waren negatief gecorreleerd, met een elasticiteit van -0,047. In sommige modellen is verstedelijking positief gecorreleerd met NEET-percentages, wat erop wijst dat inclusieve banencreatie achterblijft bij de migratie naar de stad. Een belangrijke bevinding was de significant negatieve ruimtelijke lagcoëfficiënt ($\rho \approx -0{,}33$). Deze geeft aan dat provincies met hogere NEET-percentages doorgaans omringd worden door provincies met lagere NEET-percentages, waarschijnlijk als gevolg van arbeidsmigratie of verplaatsing.

De meerderheid van de Iraanse NEET-jongeren is vrouw, als gevolg van structurele en culturele factoren zoals huishoudelijk werk en zorgtaken, alsook van aanzienlijke regionale en stad-plattelandsongelijkheden. In minder ontwikkelde provincies liggen de NEET-percentages hoger vanwege beperkte kansen. De heterogeniteit van de NEET-populatie vraagt om op maat gemaakte, gerichte interventies (hoofdstuk 5).

Over alle methoden heen komt een consistent patroon naar voren: NEET-uitkomsten in Iran worden bepaald door onderling verweven factoren op micro-, meso- en macroniveau. Om de selectie en interpretatie van risicofactoren in de Iraanse casus te sturen, zijn verschillende theorieën gebruikt (de humankapitaaltheorie, de capability-benadering en de ecologischesysteemtheorie van Bronfenbrenner). Hoewel formele hypothesetoetsing van deze theorieën buiten het bestek van dit artikel valt, zijn de empirische resultaten gebruikt om te beoordelen in hoeverre elk kader de waargenomen patronen verklaart. De NEET-percentages onder hoogopgeleide Iraanse vrouwen stellen de eenvoudige voorspellingen van de humankapitaaltheorie ter discussie en wijzen op structurele belemmeringen. Naast een beter begrip van de heterogeniteit van NEET toonde het onderzoek significante negatieve ruimtelijke spillovers in NEET-percentages aan. Het proefschrift levert een meerlagig kader dat micro- en macrotheorieën over uitval met elkaar verbindt.

Met een mixed-methods-ontwerp dat een scoping review, een systematische review en meta-analyse combineert met Probit-modellen, machine-learningclassificatie (CART) en ruimtelijke paneldata-analyse is een robuuste, getrianguleerde analyse uitgevoerd. Het gebruik van machine learning (CART en Probit-modellen) om NEET-jongeren in Iran te voorspellen is een belangrijke stap voorwaarts in het voorzien van beleidsmakers van datagestuurde instrumenten. In een baanbrekende ruimtelijke paneldata-analyse zijn de NEET-percentages in de Iraanse provincies beoordeeld in relatie tot regionale onderlinge afhankelijkheden.

Deze studie vult een eerdere leemte in het onderzoek op door de meervoudige determinanten van NEET in Iran te onderzoeken. Er is sterk, kwantificeerbaar bewijs dat NEET-jongeren vaker vrouw zijn en dat zij in sommige regio's vaker voorkomen dan in andere (bijvoorbeeld 48,2% in de provincie Sistan en Belutsjistan). Concreet zijn beleidsmaatregelen voor Iran geïdentificeerd, waaronder het verbeteren van onderwijs en toegang tot de arbeidsmarkt voor vrouwen, het ondersteunen van jongeren op het platteland en het bevorderen van regionale samenwerking.

Door ecologische, humankapitaal-, capability-, gender- en ruimtelijke kaders te integreren, laat dit proefschrift de heterogeniteit van uitgevallen jongeren zien. Het is het eerste empirische onderzoek in Iran dat huishoudgegevens uit de arbeidskrachtenenquête op microniveau koppelt aan macro-niveau ruimtelijke dynamiek over provincies heen, en de elasticiteiten van belangrijke economische variabelen ten opzichte van NEET-percentages kwantificeert. Door deze perspectieven op meerdere schaalniveaus te combineren, introduceert het onderzoek een datagestuurd kader dat laat zien hoe individuele, structurele en regionale factoren uitval onder jongeren beïnvloeden. Dit integratieve perspectief verrijkt de bestaande NEET-literatuur door micro- en macrotheoretische verklaringen te verbinden en biedt een basis voor het ontwerpen van contextgevoelig, gendergericht en ruimtelijk geïnformeerd jeugdbeleid in Iran en vergelijkbare ontwikkelingslanden.

Uit de systeemgerichte synthese in dit proefschrift worden vijf onderling afhankelijke strategieën afgeleid. Ten eerste moet de investering in preventief onderwijs en preventieve opleiding de integratie van digitale en soft-skillscurricula omvatten. Om ruimtelijke dynamiek te benutten, vereist ruimtelijk gericht beleid bovendien opleidingseenheden, e-learningplatforms en interprovinciale stageprogramma's. Om de voorspelbaarheid van de arbeidsmarkt te verbeteren, moeten inclusieve macro-economische hervormingen de op jongeren gerichte overheidsuitgaven naar achtergestelde regio's sturen. Voorspellende targeting en systemen voor vroege interventie moeten op CART gebaseerde vroegsignaleringsinstrumenten integreren in arbeidsenquêtes en de monitoring van schooluitval, aangevuld met multistakeholder-jeugdcentra die opleiding, begeleiding en arbeidsmarktinformatie combineren.

Een instrument voor ruimtelijk inzicht en vroegsignalering biedt bruikbare handvatten voor nationale belanghebbenden, waaronder de ministeries van Onderwijs, Arbeid en Coöperaties. Regionale ontwikkelingsplannen kunnen gendergerichte maatregelen en ruimtelijke spillover-patronen opnemen in lopende hervormingen van het beroepsonderwijs. Onderzoekers van internationale organisaties kunnen de bevindingen van deze studie gebruiken om beleid in de MENA-regio aan te passen. Experimenten en quasi-experimenten moeten worden ingezet om de effectiviteit van geïntegreerde interventies op het gebied van onderwijs, gender en regio's te evalueren. Om voorspelling en beleidsgerichtheid te verbeteren, zijn de integratie van gegevens uit verschillende administratieve bronnen en kwalitatief onderzoek naar moeilijk bereikbare NEET-subgroepen noodzakelijk.

De oorzaken van NEET in Iran liggen in ongelijkheden op het gebied van onderwijs, gender en regio. Het oplossen van dit probleem is urgent en haalbaar. In het proefschrift wordt uitval onder jongeren beschreven als een weg naar een geïntegreerd, evidence-based beleid voor jongerenparticipatie. Iran kan zijn demografische uitdaging omzetten in een demografisch dividend door te investeren in onderwijs, gendergelijkheid, ruimtelijk bewustzijn en vroegsignaleringssystemen.

Acknowledgements

I would like to express my most sincere appreciation to all the people who have supported me during my PhD journey. I would never have completed this thesis without you!

I would like to thank my supervisors, Professor Wim Groot, and Dr. Jelena Arsenijevic, for their help and guidance during these years. Thank you for believing in me since the very beginning and pushing me outside my comfort zone and thank you for always listening to my words and for your insightful comments that aided in the completion of this thesis. My gratitude to you is infinite and endless.

I would like to say thanks a million to all my friends and colleagues, for their valuable guidance during this journey. I thank all of the passionate people who are always thinking, seeking to understand, and turning the unknown into the known, and those who have dedicated their lives to science and humanity.

Finally, there's no bond stronger than family. My mother and my father, thank you for always supporting me, even when it is not easy to do. Without you, I could not get through the hard times. My dear brother, thank you for always being there for me and for giving me, so much love and support and being with me every step of the way during these hard times. I'm looking forward to seeing your great success.

About the author

Hamed Rahmani is a researcher and PhD candidate at Maastricht University/ UNU-MERIT. He holds a Bachelor's degree in Engineering and an M.Sc. in Operations Research, providing him with a strong foundation in systems thinking and data-driven policy analysis.

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