

Generalized Structural Equation Modeling of Education Job Mismatch and Labor Market Outcomes

Heba E. E. Soliman*, Elsayed Khater, Abdelhameed El Shabrawy, Suzan Abdel-Rahman

Department of Biostatistics and Demography, Faculty of Graduate Studies for Statistical Research, Cairo University, Egypt

Abstract This study examines the relationship between educational mismatch and income satisfaction, job satisfaction, and job search intention among Egyptian public university graduates. It uses data from 1,374 graduates who participated in the 2021 Employment of Tertiary Education Graduate Survey. Generalized Structural Equation Modeling (GSEM) was used to estimate both direct and indirect effects. Educational mismatch was treated as a multidimensional construct that includes vertical mismatch, horizontal mismatch, and skills mismatch. The results show that 85.2% of graduates experience at least one type of educational mismatch. Skills mismatch is the most common type, affecting 79.3% of graduates, followed by vertical mismatch (34.1%) and horizontal mismatch (24.5%). The results indicate that educational mismatch is negatively associated with income satisfaction ($\beta = -0.5576$, $p = 0.001$) and job satisfaction ($\beta = -0.2947$, $p = 0.037$), while it is positively associated with job search intention ($\beta = 0.9313$, $p < 0.001$). In terms of magnitude, these coefficients correspond to (proportional) odds ratios of 0.57, 0.74, and 2.54, respectively – that is, mismatched graduates have roughly 43% lower odds of being satisfied with their income and more than double the odds of intending to search for another job, relative to matched graduates. The findings also reveal significant indirect effects, suggesting that educational mismatch helps explain the relationships between graduates' demographic, educational, and employment characteristics and their income satisfaction, job satisfaction, and job search intention. These findings highlight the importance of improving the alignment between higher education outcomes and labor market needs.

Keywords Educational mismatch; Higher education; Labor market outcomes; Job satisfaction; Job search intention; Generalized Structural Equation Modeling (GSEM); Egypt.

AMS 2010 subject classifications 62P25, 62J05

DOI: 10.19139/soic-2310-5070-4407

1. Introduction

Higher education institutions serve as a critical bridge between higher education systems and labor markets by equipping graduates with the knowledge and skills required for employment in both public and private sectors [3]. Their role has become increasingly important within the framework of the United Nations Sustainable Development Goals (SDGs), particularly Goal 8, which emphasizes inclusive economic growth and decent work for all [21]. However, rapid technological advancements, globalization, and demographic changes have increased the need for higher education systems to continuously adapt to changing labor market needs.

Despite these expectations, growing evidence highlights the persistent gap between higher education outcomes and labor market needs, particularly in developing countries. Egypt faces similar challenges, as the expansion of higher education has not always been accompanied by improvements in graduate employability. Although public expenditure on education reached 3% of GDP in 2020/2021, it remains below international averages [24]. Reports have also highlighted gaps in graduate preparedness and limited alignment between education outcomes and labor

*Correspondence to: Heba Elrefay Elsayed Soliman (Email: hebaelrefay92@gmail.com), Department of Biostatistics and Demography, Faculty of Graduate Studies for Statistical Research, Cairo University, Egypt.

market needs [26]. Recent studies further indicate that educational mismatch represents a major challenge for developing economies, with negative consequences for wages and job satisfaction [1, 10].

Educational mismatch is commonly conceptualized through three dimensions: vertical, horizontal, and skills mismatch. Vertical mismatch refers to the discrepancy between an individual's educational attainment and the level of education required for a job, which may result in overqualification or underqualification [11, 13]. Horizontal mismatch reflects a divergence between an individual's field of study and the occupational field in which they are employed [19]. Skills mismatch refers to the gap between the skills possessed by workers and those required by employers [17, 12]. In the Egyptian context, limited emphasis on practical training and skill development has been identified as a potential factor contributing to the gap between graduates' competencies and employers' expectations.

Previous empirical research has generally shown negative associations between educational mismatch and labor market outcomes, including lower wages, reduced job satisfaction, and higher job search intention [4, 7]. Recent evidence further suggests that educational mismatch is associated with greater job mobility and limited access to quality employment opportunities [18, 16]. However, the magnitude and implications of educational mismatch may vary depending on individual characteristics, educational background, and labor market conditions.

In the Egyptian context, educational mismatch is influenced by several structural and institutional factors, including field of study, type of educational institution, labor market segmentation between public and private sectors, and preferences for public sector employment [5]. Nevertheless, important research gaps remain. First, existing studies have largely examined individual dimensions of educational mismatch separately, while limited attention has been given to educational mismatch as a multidimensional construct capturing the combined effects of vertical, horizontal, and skills mismatch. Second, evidence from Egypt remains limited, particularly regarding the mechanisms through which educational mismatch affects multiple labor market outcomes. Third, most previous studies rely on conventional econometric approaches, with limited use of advanced methods capable of capturing the direct and indirect effects of educational mismatch on labor market outcomes.

To address these gaps, this study examines the determinants and implications of educational mismatch among Egyptian public university graduates. Specifically, it investigates the effects of educational mismatch, operationalized in the empirical model as a single composite indicator built from the vertical, horizontal, and skills dimensions (see Section 4.1 for the construction of this measure and Section 6.1 for a discussion of the limitations this choice entails), on income satisfaction, job satisfaction, and job search intention. Using data from the Employment of Tertiary Education Graduate Survey (2021), Generalized Structural Equation Modeling (GSEM) is applied to examine the direct and indirect effects of educational mismatch on labor market outcomes.

This study contributes to the growing literature on education–labor market linkages by providing empirical evidence from Egypt and offering policy-relevant insights for improving graduate employability and strengthening the alignment between higher education outcomes and labor market needs. Furthermore, the findings support efforts toward achieving SDG 4 (Quality Education) and SDG 8 (Decent Work and Economic Growth).

Beyond the labor-economics literature reviewed above, empirical work of this kind also rests on a broader statistical toolkit for building and validating the parametric and semi-parametric models used to describe latent processes such as educational mismatch. Recent methodological developments in flexible distribution theory and order-statistics-based characterization – including fractional-calculus extensions of classical lifetime distributions [27], transmuted and generalized-transmuted families [28, 35], and characterizations of several distribution families based on generalized order statistics [29, 30, 31, 32, 33, 34] – illustrate the continuing refinement of the statistical modeling tools that underlie applied socioeconomic research more broadly, and are noted here for completeness.

2. Literature Review

2.1. Theoretical Framework

The relationship between educational mismatch and labor market outcomes can be explained through several complementary theoretical perspectives that describe how the alignment between individuals' education and occupational requirements affects employment experiences and economic returns.

First, Human Capital Theory, developed by Becker [8], argues that education enhances individuals' productivity, skills, and economic returns by increasing their knowledge and capabilities. However, when graduates are employed in occupations that do not adequately utilize their educational qualifications or acquired skills, the expected returns to education may not be fully achieved. Such mismatch may reduce the perceived economic benefits of education, leading to lower income satisfaction and weaker attachment to the current job.

Second, Assignment Theory, developed by Sattinger [20], emphasizes that labor market outcomes depend not only on the amount of education individuals acquire but also on the effective allocation of workers to jobs that match their qualifications. From this perspective, educational mismatch reflects an inefficient allocation process in which workers' educational characteristics do not correspond to occupational requirements. Consequently, mismatch may result in the underutilization of human capital and negatively affect employment quality and job satisfaction.

Third, Job Search Theory, developed by Mortensen [15], provides a theoretical explanation for the relationship between educational mismatch and job mobility behavior. According to this perspective, individuals continuously evaluate their employment opportunities and search for better alternatives when their current jobs do not provide an adequate match between their qualifications, skills, and occupational requirements. Therefore, graduates experiencing educational mismatch are expected to have stronger intentions to search for alternative employment opportunities.

Based on these theoretical perspectives, this study conceptualizes educational mismatch as a mediating mechanism through which demographic, educational, and employment characteristics influence labor market outcomes. Specifically, educational mismatch represents the pathway through which these characteristics affect income satisfaction, job satisfaction, and job search intention. This theoretical foundation supports the use of the Generalized Structural Equation Modeling (GSEM) framework to examine both the direct and indirect effects of educational mismatch on graduates' labor market outcomes.

Table 1 translates these three theoretical perspectives into the specific, testable mediation hypotheses examined in Sections 4.3 and 5.5, in response to the reviewers' request that the theoretical framework be linked explicitly to the estimated model paths rather than presented only as a general narrative.

Table 1. Theoretical Perspectives and Corresponding Testable Hypotheses

Theory	Core mechanism	Corresponding hypothesis (model path)
Human Capital Theory [8]	Returns to education are reduced when qualifications are not used on the job	H1: Educational mismatch (M) is negatively associated with income satisfaction ($M \rightarrow Y_1$, Eq. 3)
Assignment Theory [20]	Inefficient worker–job allocation lowers employment quality	H2: Educational mismatch is negatively associated with job satisfaction ($M \rightarrow Y_2$, Eq. 4)
Job Search Theory [15]	Poor person–job fit motivates mobility	H3: Educational mismatch is positively associated with job search intention ($M \rightarrow Y_3$, Eq. 5)
All three (jointly)	Demographic/educational/employment characteristics operate partly through mismatch	H4: Educational, and employment characteristics have significant indirect effects on Y_1 – Y_3 through M ($X \rightarrow M \rightarrow Y$, Eq. 6)

2.2. Empirical Literature Review

Against this background, a review of the literature is essential to provide context for the concept of educational mismatch, its theoretical foundations, and the existing empirical evidence from both international and Egyptian contexts. The following section reviews the three main dimensions of mismatch: vertical, horizontal, and skills mismatch, with particular emphasis on their labor market consequences in developing country contexts.

Educational mismatch has been widely examined in terms of its vertical, horizontal, and skills dimensions. Vertical mismatch refers to a situation in which an individual is employed in an occupation that is not consistent with their educational attainment, which may result in lower wages, reduced job satisfaction, and limited career progression [13]. This type of mismatch is more commonly experienced by graduates from general and theoretical fields of study.

Similarly, horizontal mismatch refers to a situation in which individuals are employed in occupations outside their field of specialization, resulting in weak alignment between education and occupation [19]. This type of mismatch has also been found to be more common among graduates from non-technical fields of study [7]. In addition, skills mismatch refers to the gap between the skills acquired through formal education and those required in the labor market [17]. In the Egyptian context, the predominance of theoretical instruction over practical training has raised concerns regarding graduates' skill levels.

In addition, recent empirical studies confirm the negative effects of educational mismatch, although the extent and pathways of these effects require further investigation. For instance, Pecoraro and Witte [18] show that educational mismatch is associated with lower levels of job satisfaction and greater job mobility. Similarly, Adesina [1] finds that skills mismatch is negatively associated with wages and job satisfaction in developing economies. Moreover, Murillo-Huertas et al. [16] indicate that the returns to education may not be fully achieved in the presence of mismatch, especially regarding access to high-skilled jobs. Further evidence suggests that educational mismatch may also be associated with wage penalties and labor market inefficiencies [10].

Overall, the literature suggests that educational mismatch is generally associated with lower income satisfaction, lower job satisfaction, and higher job search intention, although this relationship is not always consistent [22, 14]. In the Egyptian labor market context, previous studies suggest that educational mismatch is associated with lower levels of income and job satisfaction and higher job search intention [4, 7].

A closer reading of the Egyptian literature specifically is warranted, since the incremental contribution of the present study depends on how it relates to this body of work. Assaad and Krafft [5] use nationally representative labor force survey panels to document the structure and evolution of skills mismatch in Egypt over time, focusing on aggregate trends by cohort and sector; their companion study [4] documents the broader difficulties Egyptian youth face in labor market insertion, including extended unemployment spells and informality, but does not model mismatch as a mediator of satisfaction or search outcomes. Assaad and Krafft [6] examine education–occupation mismatch among Egyptian graduates using descriptive and single-equation regression methods, focusing on vertical and horizontal mismatch separately rather than as a joint construct. Relative to this body of work, the present study differs in three specific ways: (i) it uses a more recent (2021), nationally representative graduate cohort rather than the general labor force; (ii) it combines the three recognized mismatch dimensions – vertical, horizontal and skills – into a single empirical construct, whereas the Assaad and Krafft studies analyze mismatch dimensions individually or descriptively; and (iii) it estimates a simultaneous-equations GSEM that decomposes direct and indirect (mediated) effects on three distinct outcomes at once, rather than a series of separate regressions. This comparison also clarifies why the results are not directly comparable in magnitude to the earlier Egyptian studies, since the estimation samples, mismatch definitions, and outcome variables differ.

However, important gaps remain regarding the multidimensional nature of educational mismatch and its effects on multiple labor market outcomes, particularly in the Egyptian context. In particular, because educational mismatch is compressed into a single binary indicator in the empirical model below, this study cannot adjudicate between competing measurement conventions for the three dimensions, nor can it establish whether the three dimensions would behave in the same direction if modeled separately – a limitation discussed explicitly in Section 6.1. These gaps highlight the need for further research using analytical approaches that can capture the complex relationships between mismatch dimensions and labor market outcomes.

3. Research Gap and Objectives

Although the international literature on educational mismatch has grown significantly, it still provides limited understanding of the combined role of vertical, horizontal, and skills mismatch in shaping labor market outcomes. Most studies have focused on estimating the effects of individual dimensions of mismatch on earnings or job satisfaction using single-equation methods. These studies often overlook the potential interrelationships among mismatch dimensions and their indirect effects on overall employment quality.

In the Egyptian context, research on this topic remains limited, both in terms of empirical evidence and analytical approaches. Existing studies lack a comprehensive framework that can capture the multidimensional nature of

mismatch and its simultaneous effects on multiple labor market outcomes. To date, no study has conceptualized educational mismatch as a composite multidimensional construct and estimated its direct, indirect, and total effects on income satisfaction, job satisfaction, and job search intention using recent nationally representative data.

Relative to Assaad and Krafft [5, 4, 6], who remain the closest comparators in the Egyptian literature (see Section 2.2), this study makes three main contributions to the literature. First, educational mismatch is conceptualized and operationalized empirically as a composite mediating construct (a binary indicator equal to one if any of the vertical, horizontal, or skills dimensions is present, and zero otherwise – thereby moving beyond a single-dimension analysis, while explicitly acknowledging in Section 6.1 that this composite coding cannot distinguish the separate contribution of each dimension). Second, this study simultaneously models income satisfaction, job satisfaction, and job search intention using a unified Generalized Structural Equation Modeling (GSEM) framework, which allows for the estimation of both direct and indirect effects. Third, this study provides recent evidence from a developing country, Egypt, which remains underrepresented in the international educational mismatch literature.

Thus, the main purpose of this study is to achieve the following specific objectives:

1. To identify the factors associated with educational mismatch among graduates of Egyptian public universities.
2. To examine the direct and indirect associations of educational mismatch with income satisfaction, job satisfaction, and job search intention.
3. To assess the mediating role of educational mismatch using an integrated Generalized Structural Equation Modeling (GSEM) framework.

The study aims to provide a comprehensive and multidimensional analysis that offers policy-relevant insights for improving the alignment between higher education outcomes and labor market needs. Moreover, it contributes to broader efforts toward achieving the United Nations Sustainable Development Goals, particularly SDG 4 (Quality Education) and SDG 8 (Decent Work and Economic Growth).

A note on terminology. Consistent with common usage in the mediation and structural-equation-modeling literature, this paper uses the terms “effect”, “direct effect”, “indirect effect”, and “total effect” throughout to describe model-implied path coefficients within the GSEM system (Equations 1–7), not causal effects identified through experimental or quasi-experimental variation. Given the cross-sectional design of the underlying survey, these path estimates should be interpreted as statistical associations net of the other covariates in the model; Section 6.1 discusses this distinction, and the specific threats to a causal interpretation, in detail.

4. Methodology

4.1. Data Source and Sample

The empirical analysis in this study relies on primary data drawn from the Employment of Tertiary Education Graduate Survey. This comprehensive survey was administered utilizing structured telephone interviews to gather detailed responses from a targeted cohort of young higher-education graduates. The participants comprised individuals aged between 21 and 35 years, all of whom had successfully completed their degrees across 12 selected Egyptian public universities during the period spanning from 2016 to 2018. The initial survey included 2,370 respondents. The analytical sample consisted of 1,374 graduates who were employed at the time of the survey. The analysis was limited to employed graduates because information on income satisfaction, job satisfaction, and job search intention was available only for currently employed respondents. The study examines three labor market outcomes. Income satisfaction and job search intention are measured as binary variables, while job satisfaction is measured as an ordinal variable with four categories ranging from “very dissatisfied” to “very satisfied.” Educational mismatch is included as an intermediate variable and is constructed as a composite binary indicator that takes the value of one if the graduate experiences any form of mismatch (vertical, horizontal, or skills mismatch), and zero otherwise. This definition was adopted to capture the overall presence of educational mismatch irrespective of its specific dimension. The explanatory variables include demographic, educational,

and employment characteristics, including gender, age group, place of residence, marital status, type of faculty, choice of field of study, training during university education, employment sector, employment contract, and health insurance coverage. The initial survey included 2,370 respondents. The analytical sample of this study consists of 1,374 graduates who were employed at the time of the survey. The analysis is limited to employed graduates because income satisfaction, job satisfaction, and job search intention are available only for currently employed respondents. This restriction is revisited explicitly as a source of potential selection bias in Section 6.1: because graduates who could not find any job, or who exited the labor force, are excluded by construction, the estimated associations describe the experience of currently employed mismatched graduates and should not be extrapolated to the population of all graduates, including the unemployed and those outside the labor force. The 2021 survey round used for this analysis does not carry information on the labor market status or search outcomes of the excluded, non-employed graduates, so a formal selection-correction model (e.g., a Heckman-type selection equation) could not be estimated with the data used here; we flag this as a priority for future work using survey rounds, or administrative data, that also track non-employed graduates.

The study examines three labor market outcomes. Income satisfaction and job search intention are measured as binary variables, while job satisfaction is measured as an ordinal variable with four categories ranging from “very dissatisfied” to “very satisfied.”

Educational mismatch is constructed as a composite binary indicator equal to one if the graduate reports experiencing at least one of the three recognized dimensions of mismatch – vertical mismatch (educational attainment above or below the level normally required for the job, following [11, 13]), horizontal mismatch (employment outside the occupational field associated with the graduate’s field of study, following [19]), or skills mismatch (a self-reported gap between the skills acquired through education and those required by the current job, following [17]) – and equal to zero if the graduate reports none of the three. This definition was adopted, following common practice in the mismatch literature, to capture the overall presence of educational mismatch irrespective of its specific dimension, and to keep the mediating variable in the GSEM system binary and therefore tractable within a single logit mediator equation. We agree with both reviewers that this composite coding is also the main measurement limitation of the study: by design, it cannot separate the (potentially offsetting) contributions of the vertical, horizontal, and skills dimensions, nor can it identify graduates who experience more than one form of mismatch simultaneously. Table 4 reports the prevalence of each of the three dimensions individually before they are combined, and Section 6.1 discusses this limitation, and the case for separate-dimension or latent-class modeling in future work, in full.

The explanatory variables include demographic, educational, and employment characteristics, including gender, age group, place of residence, marital status, type of faculty, choice of field of study, training during university education, employment sector, employment contract, and health insurance coverage. Table 2 reports the coding and reference category adopted for every categorical explanatory variable used in the GSEM system, in response to the reviewers’ request that variable coding and reference groups be stated explicitly and consistently across all tables.

Table 2. Coding of Explanatory Variables Used in the GSEM Model

Variable	Categories (reference category listed first)	No. of dummies
Gender	Female (ref.); Male	1
Age group	21–24 (ref.); 25–29; 30–35	2
Residence	Urban (ref.); Rural	1
Marital status	Single (ref.); Married	1
Field of study	Theoretical (ref.); Practical	1
Field choice	No (ref.); Yes (chosen by personal preference)	1
Training during study	No (ref.); Yes	1
Employment sector	Public (ref.); Private; Self-employed	2
Employment contract	No (ref.); Yes	1
Health insurance	No (ref.); Yes	1

4.2. Empirical Strategy

The empirical analysis consists of four main stages. First, descriptive statistics are used to summarize the demographic, educational, and employment characteristics of the study sample using SPSS software. Second, Pearson's chi-square tests are performed to assess the associations between individual characteristics and educational mismatch.

Third, a Generalized Structural Equation Modeling (GSEM) framework is applied using Stata version 17 to examine the direct and indirect effects of individual characteristics, educational mismatch, and labor market outcomes. The GSEM approach is appropriate for this study because it allows the simultaneous estimation of multiple equations involving different types of dependent variables while accounting for mediation pathways.

The model includes educational mismatch as a binary mediating variable, coded as 1 for graduates who experience mismatch and 0 otherwise. Income satisfaction and job search intention are modeled as binary outcome variables using a logit link function. Job satisfaction is treated as an ordinal outcome with four response categories ranging from "very dissatisfied" to "very satisfied" and is estimated using an ordered logit model within the GSEM framework.

Robust (Huber–White sandwich) standard errors are used throughout to account for potential heteroscedasticity and ensure reliable statistical inference; in response to the reviewers' request for clarification, we state explicitly here that these robust standard errors are *not* clustered on university, region, or any other sampling stratum, because the anonymized extract of the 2021 survey used for this analysis does not carry a university, region, or primary-sampling-unit identifier that could be used as a clustering variable, nor are sampling weights included in this extract. Consequently, the reported standard errors should be interpreted as robust to heteroscedasticity but not to intra-cluster correlation of outcomes among graduates from the same university or region, and the point estimates are unweighted associations within the analytical sample rather than weighted population estimates. We flag this explicitly as a limitation in Section 6.1 and recommend that a clustered and/or weighted re-estimation be carried out once a survey extract with the relevant design variables is available. Finally, direct, indirect, and total effects are estimated using the `nlcom` command in Stata based on the product-of-coefficients approach. The indirect effects are calculated as the product of the coefficient representing the effect of explanatory variables on educational mismatch ($X \rightarrow M$) and the coefficient representing the effect of educational mismatch on each labor market outcome ($M \rightarrow Y$). The standard errors of the indirect effects and their corresponding p -values are obtained using the Delta method. We note, in response to the reviewers' comment on this point, that the Delta method provides a first-order (linear) approximation to the sampling variance of a nonlinear combination of coefficients; because both the mediator equation and two of the three outcome equations are estimated on a logit/ordered-logit scale, the product-of-coefficients estimate reported here should be interpreted as an approximation on the latent-index scale rather than as a fully scale-free causal mediation effect, and it does not correct for the rescaling of the residual variance that occurs when a binary or ordinal mediator or outcome is involved (a well-known issue in nonlinear mediation analysis, e.g. as discussed by Mackinnon and colleagues in the general mediation literature). We report it here because it is the estimator conventionally used in applied GSEM mediation studies with the same data structure, and because it directly answers the objective of decomposing total associations into direct and indirect components; nonetheless, we agree that simulation-based or counterfactual (e.g., g -computation-based) mediation estimators would provide a methodologically stronger robustness check, and we list this as a direction for future work in Section 6.1. This method allows for the statistical testing of nonlinear combinations of coefficients and provides evidence regarding the significance of mediation effects.

The GSEM model is estimated using maximum likelihood (ML) estimation, which provides consistent and efficient parameter estimates for models involving different types of dependent variables and allows the simultaneous estimation of structural relationships among the mediator and outcome variables. Model adequacy is assessed using the Wald χ^2 test of joint significance together with the log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) (Table 7). We acknowledge the reviewers' point that these are global, likelihood-based fit measures and do not, by themselves, evaluate classification accuracy for the three (binary/ordinal) outcome equations individually; measures such as the area under the ROC curve for the two binary outcomes, or a McKelvey–Zavoina pseudo- R^2 for the ordered-logit outcome, would usefully complement Table 7,

but require re-accessing the saved GSEM estimation results in Stata and are therefore left for the camera-ready re-estimation rather than computed here.

4.3. Model Specification

The empirical model is specified within a Generalized Structural Equation Modeling (GSEM) framework and consists of a system of simultaneous equations. The model treats educational mismatch as a mediating variable through which individual characteristics affect labor market outcomes. The GSEM framework allows the simultaneous estimation of mediator and outcome equations while accounting for different types of dependent variables.

The model is composed of the following equations:

Educational Mismatch Equation

$$M_i^* = \alpha_0 + \sum_{k=1}^K \alpha_k X_{ki} + \varepsilon_i \quad (1)$$

Observed educational mismatch is defined as:

$$M_i = \begin{cases} 1 & \text{if } M_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Where M_i^* represents the latent propensity of educational mismatch, X_{ki} denotes the vector of explanatory variables, α_0 is the intercept term, α_k represents the estimated coefficients of the explanatory variables, K is the total number of explanatory variables (so that $k = 1, \dots, K$, consistent with Equations 3–5 below; this corrects a typographical inconsistency in the original submission, which used the summation index k in place of the upper limit K), and ε_i denotes the error term.

Income Satisfaction Equation

$$Y_{1i}^* = \beta_{10} + \sum_{k=1}^K \beta_{1k} X_{ki} + \gamma_1 M_i + u_{1i} \quad (3)$$

Where Y_{1i}^* represents the latent propensity for income satisfaction for individual i . X_{ki} denotes the vector of explanatory variables, including demographic, educational, and employment characteristics. M_i represents educational mismatch. β_{10} is the intercept term, β_{1k} represents the coefficients of the explanatory variables, γ_1 captures the association between educational mismatch and income satisfaction, and u_{1i} denotes the error term.

Job Satisfaction Equation (Ordinal Outcome)

$$Y_{2i}^* = \beta_{20} + \sum_{k=1}^K \beta_{2k} X_{ki} + \gamma_2 M_i + u_{2i} \quad (4)$$

Where Y_{2i}^* represents the latent propensity for job satisfaction for individual i , which underlies the observed ordered categories ranging from “very dissatisfied” to “very satisfied.” X_{ki} denotes the vector of explanatory variables, including demographic, educational, and employment characteristics. M_i represents educational mismatch. β_{20} is the intercept term, β_{2k} represents the coefficients of the explanatory variables, γ_2 captures the association between educational mismatch and job satisfaction, and u_{2i} denotes the error term.

Because job satisfaction is measured as an ordered categorical variable, the ordered logit specification estimates the probability of observing each satisfaction category based on the underlying latent job satisfaction variable. The model includes threshold parameters that separate the four observed categories ranging from “very dissatisfied” to “very satisfied.”

Job Search Intention Equation

$$Y_{3i}^* = \beta_{30} + \sum_{k=1}^K \beta_{3k} X_{ki} + \gamma_3 M_i + u_{3i} \quad (5)$$

Where Y_{3i}^* represents the latent propensity for job search intention for individual i . X_{ki} denotes the vector of explanatory variables, including demographic, educational, and employment characteristics. M_i represents educational mismatch. β_{30} is the intercept term, β_{3k} represents the coefficients of the explanatory variables, γ_3 captures the association between educational mismatch and job search intention, and u_{3i} denotes the error term.

Mediation Effects Decomposition

The total effect of each explanatory variable on labor market outcomes is decomposed into direct and indirect effects through educational mismatch.

The indirect effect is calculated as:

$$IE_k^{(j)} = \alpha_k \cdot \gamma_j \quad (6)$$

The total effect is calculated as:

$$TE_k^{(j)} = DE_k^{(j)} + IE_k^{(j)} \quad (7)$$

Where:

- $DE_k^{(j)}$: represents the direct effect of explanatory variable X_k on outcome variable Y_j (i.e., β_{jk} in Equations 3–5).
- $IE_k^{(j)}$: represents the indirect effect of explanatory variable X_k on outcome variable Y_j through educational mismatch.
- $TE_k^{(j)}$: represents the total effect of explanatory variable X_k on outcome variable Y_j .
- α_k : represents the association between explanatory variable X_k and educational mismatch ($X \rightarrow M$).
- γ_j : represents the association between educational mismatch and outcome variable Y_j ($M \rightarrow Y_j$).

Note: Given the binary nature of educational mismatch as the mediating variable and the binary nature of income satisfaction and job search intention, along with the ordinal nature of job satisfaction, logit and ordered logit link functions are applied within the GSEM framework. The equations are estimated simultaneously to ensure consistency of the model. Robust standard errors are used to account for potential heteroscedasticity and improve the reliability of statistical inference.

4.4. Conceptual Framework

To examine the relationships among educational mismatch and labor market outcomes, a conceptual framework was developed based on the theoretical and empirical literature. The framework identifies the hypothesized direct and indirect relationships among the study variables and is presented in Figure 1.

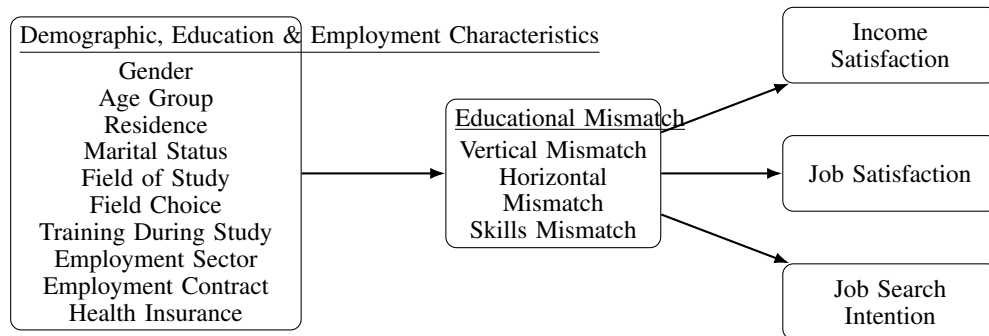


Figure 1. Conceptual Framework of the Relationship between Educational Mismatch and Labor Market Outcomes.

Source: Authors' own elaboration.

Figure 1 presents the conceptual framework of the study, which assumes that individual characteristics influence labor market outcomes both directly and indirectly through educational mismatch. The framework includes demographic, educational, and employment characteristics as explanatory variables; educational mismatch as a mediating variable; and income satisfaction, job satisfaction, and job search intention as labor market outcomes.

Educational mismatch is conceptualized as a multidimensional construct encompassing vertical, horizontal, and skills mismatch. The hypothesized relationships illustrated by the arrows are empirically examined using the Generalized Structural Equation Modeling (GSEM) framework.

5. Results

5.1. Descriptive Statistics of the Sample Characteristics

Table 3. Demographic, Educational, and Employment Characteristics of the Analytical Sample ($N = 1,374$)

Characteristics	N (%)
<i>Demographic Characteristics</i>	
Gender: Male	1114 (81.1)
Gender: Female	260 (18.9)
Residence: Urban	840 (61.1)
Residence: Rural	534 (38.9)
Age 21–24	174 (12.7)
Age 25–29	1141 (83.0)
Age 30–35	59 (4.3)
Marital Status: Single	1019 (74.2)
Marital Status: Married	355 (25.8)
<i>Educational Characteristics</i>	
Field of Study: Theoretical	924 (67.2)
Field of Study: Practical	450 (32.8)
Field Choice: Yes	856 (62.3)
Field Choice: No	518 (37.7)
Training During Study: Yes	1023 (74.5)
Training During Study: No	351 (25.5)
<i>Employment Characteristics</i>	
Employment Sector: Public	156 (11.4)
Employment Sector: Private	981 (71.4)
Employment Sector: Self-employed	237 (17.3)
Employment Contract: Yes	610 (44.4)
Employment Contract: No	764 (55.6)
Health Insurance: Yes	534 (38.9)
Health Insurance: No	840 (61.1)

Source: Authors' calculations based on the Employment of Tertiary Education Graduate Survey .

Table 3 shows that the majority of respondents were male (81.1%) and lived in urban areas (61.1%). Most respondents were aged 25–29 years (83.0%), while smaller proportions were found among those aged 21–24 years (12.7%) and 30–35 years (4.3%). Regarding marital status, most respondents were single (74.2%), compared with 25.8% who were married.

In terms of educational characteristics, nearly two-thirds of respondents (67.2%) graduated from theoretical fields, whereas 32.8% graduated from practical fields. In addition, 62.3% reported that they had chosen their field of study based on personal preference, and 74.5% had received training during their studies.

Regarding employment characteristics, the majority of respondents were employed in the private sector (71.4%), followed by self-employment (17.3%) and public sector employment (11.4%). More than half of the respondents (55.6%) reported that they did not have a formal employment contract, while only 38.9% had health insurance.

Figures 2 and 3 visually present the educational and employment characteristics of the study sample, respectively.

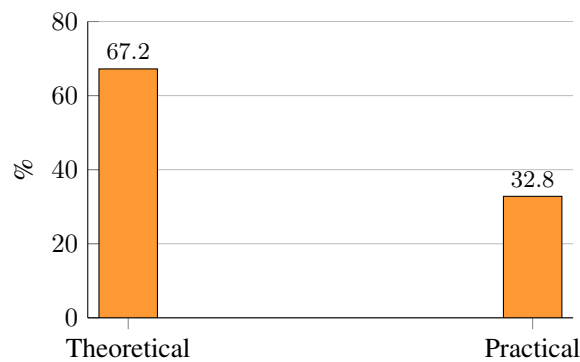


Figure 2. Distribution of Graduates by Field of Study.

Source: Authors' calculations based on the *Employment of Tertiary Education Graduate Survey*.

Figure 2 shows the distribution of graduates by field of study. The majority of graduates were from theoretical fields of study (67.2%), whereas graduates from practical fields accounted for 32.8%.

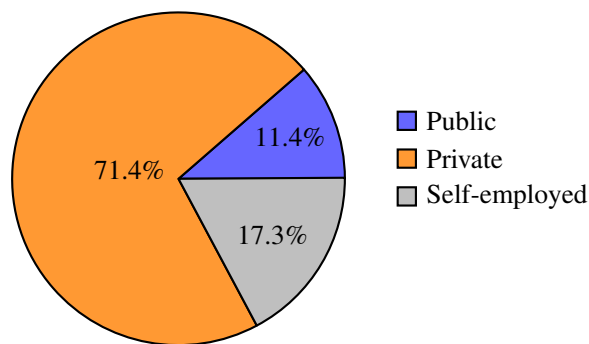


Figure 3. Distribution of Graduates by Employment Sector.

Source: Authors' calculations based on the *Employment of Tertiary Education Graduate Survey*.

Figure 3 shows the distribution of graduates across employment sectors. The majority of graduates were employed in the private sector (71.4%), followed by self-employment (17.3%) and public sector employment (11.4%).

5.2. Educational Mismatch Prevalence and Distribution among Graduates

Table 4. Dimensions of Educational Mismatch among Graduates ($N = 1,374$)

Dimensions	N (%)
Vertical Mismatch: Yes	469 (34.1)
Vertical Mismatch: No	905 (65.9)
Horizontal Mismatch: Yes	337 (24.5)
Horizontal Mismatch: No	1037 (75.5)
Skills Mismatch: Yes	1090 (79.3)
Skills Mismatch: No	284 (20.7)
Overall Educational Mismatch: Yes	1171 (85.2)
Overall Educational Mismatch: No	203 (14.8)

Source: Authors' calculations based on the Employment of Tertiary Education Graduate Survey.

Table 4 presents the prevalence of different dimensions of educational mismatch among graduates. Skills mismatch was the most prevalent dimension, affecting 79.3% of graduates. Vertical mismatch was reported by 34.1% of graduates, while horizontal mismatch affected 24.5%. Overall, 85.2% of graduates experienced at least one form of educational mismatch, whereas only 14.8% were classified as educationally matched.

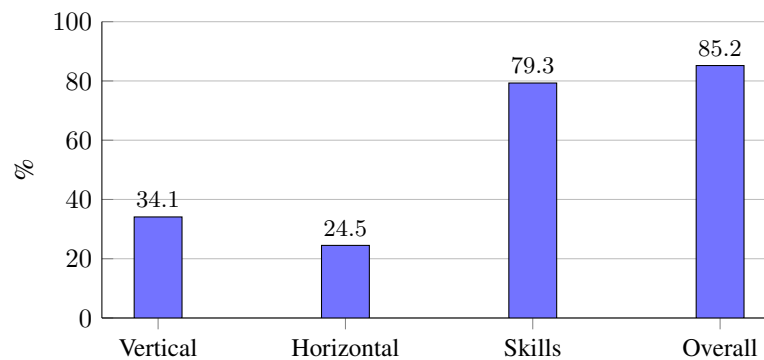


Figure 4. Relative Distribution of Different Dimensions of Educational Mismatch among Graduates. Source: Authors' calculations based on the Employment of Tertiary Education Graduate Survey.

Figure 4 shows that skills mismatch was the most prevalent dimension (79.3%), followed by vertical mismatch (34.1%) and horizontal mismatch (24.5%).

5.3. Association between Educational Mismatch and Demographic, Educational, and Employment Characteristics

Table 5 presents the results of the chi-square tests assessing the association between educational mismatch and demographic, educational, and employment characteristics. Statistically significant associations were found for gender, age group, field of study, field choice, training during study, employment sector, employment contract, and health insurance, whereas residence and marital status were not significantly associated with educational mismatch.

Educational mismatch was more prevalent among females (19.6%) than males (13.6%) ($\chi^2 = 5.969$, $p = 0.015$). Significant differences were also found across age groups, with the highest prevalence of mismatch among graduates aged 25–29 years (16.3%), compared with 8.0% among those aged 21–24 years and 5.1% among those aged 30–35 years ($\chi^2 = 12.769$, $p = 0.002$). In contrast, no statistically significant association was found between educational mismatch and residence ($\chi^2 = 1.925$, $p = 0.165$) or marital status ($\chi^2 = 0.073$, $p = 0.788$).

Table 5. Association between Educational Mismatch and Demographic, Educational, and Employment Characteristics ($N = 1,374$)

Variables	Matched N (%)	Mismatched N (%)	χ^2	p-value
Gender: Male	962 (86.4)	152 (13.6)	5.969*	0.015
Gender: Female	209 (80.4)	51 (19.6)		
Residence: Urban	707 (84.2)	133 (15.8)	1.925	0.165
Residence: Rural	464 (86.9)	70 (13.1)		
Age 21–24	160 (92.0)	14 (8.0)	12.769**	0.002
Age 25–29	955 (83.7)	186 (16.3)		
Age 30–35	56 (94.9)	3 (5.1)		
Marital Status: Single	870 (85.4)	149 (14.6)	0.073	0.788
Marital Status: Married	301 (84.8)	54 (15.2)		
Field of Study: Theoretical	820 (88.7)	104 (11.3)	23.569***	<0.001
Field of Study: Practical	351 (78.0)	99 (22.0)		
Field Choice: Yes	708 (82.7)	148 (17.3)	11.409**	0.001
Field Choice: No	463 (89.4)	55 (10.6)		
Training During Study: Yes	858 (83.9)	165 (16.1)	5.836*	0.016
Training During Study: No	313 (89.2)	38 (10.8)		
Employment Sector: Public	115 (73.7)	41 (26.3)	28.532***	<0.001
Employment Sector: Private	835 (85.1)	146 (14.9)		
Employment Sector: Self-employed	221 (93.2)	16 (6.8)		
Employment Contract: Yes	497 (81.5)	113 (18.5)	11.969***	<0.001
Employment Contract: No	674 (88.2)	90 (11.8)		
Health Insurance: Yes	433 (81.1)	101 (18.9)	11.887**	0.001
Health Insurance: No	738 (87.9)	102 (12.1)		

Source: Authors' calculations based on the Employment of Tertiary Education Graduate Survey .

Note: Pearson chi-square tests. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Graduates from practical fields had a higher prevalence of educational mismatch (22.0%) than those from theoretical fields (11.3%) ($\chi^2 = 23.569$, $p < 0.001$). Similarly, graduates who chose their field of study based on personal preference had a higher mismatch rate (17.3%) than those who did not (10.6%) ($\chi^2 = 11.409$, $p = 0.001$). Educational mismatch was also more common among graduates who received training during their studies (16.1%) compared with those who did not receive training (10.8%) ($\chi^2 = 5.836$, $p = 0.016$).

These last two associations – that graduates who chose their own field of study, and graduates who received training during their studies, are *more* likely, not less likely, to report a mismatch – run against the standard human-capital prediction that deliberate field choice and practical training should improve labor-market alignment, and both reviewers asked for a fuller explanation; we return to this point in the Discussion (Section 6, and specifically Section 6.2).

Educational mismatch varied significantly across employment sectors ($\chi^2 = 28.532$, $p < 0.001$). The highest mismatch rate was observed among graduates employed in the public sector (26.3%), followed by those employed in the private sector (14.9%), while self-employed graduates reported the lowest rate (6.8%). Significant differences were also found by employment contract status and health insurance status. Graduates with an employment contract had a higher prevalence of mismatch (18.5%) than those without an employment contract (11.8%) ($\chi^2 = 11.969$, $p < 0.001$). Similarly, educational mismatch was more prevalent among graduates with health insurance (18.9%) than among those without health insurance (12.1%) ($\chi^2 = 11.887$, $p = 0.001$). As with training and field choice

above, employment sector, contract status, and health insurance coverage are themselves potentially determined jointly with educational mismatch – for example, a graduate’s sector or contract status could just as plausibly be a consequence of experiencing mismatch as a cause of it. We flag this endogeneity concern explicitly in Section 6.1 and treat these variables’ coefficients in Tables 8–9 as descriptive associations rather than causal determinants of mismatch.

5.4. Educational Mismatch and Labor Market Outcomes

Table 6. Association between Educational Mismatch and Labor Market Outcomes ($N = 1,374$)

Outcome Variable	Matched N (%)	Mismatched N (%)	Total N (%)
<i>Income Satisfaction</i>			
No	78 (11.0)	631 (89.0)	709 (51.6)
Yes	125 (18.8)	540 (81.2)	665 (48.4)
<i>Job Satisfaction</i>			
Very dissatisfied	65 (12.5)	453 (87.5)	518 (37.7)
Dissatisfied	67 (15.3)	370 (84.7)	437 (31.8)
Satisfied	59 (16.5)	298 (83.5)	357 (26.0)
Very satisfied	12 (19.4)	50 (80.6)	62 (4.5)
<i>Job Search Intention</i>			
No	102 (25.6)	297 (74.4)	399 (29.0)
Yes	101 (10.4)	874 (89.6)	975 (71.0)
Total	203 (14.8)	1171 (85.2)	1374 (100.0)

Source: Authors’ calculations based on the Employment of Tertiary Education Graduate Survey.

Note: Chi-square tests: Income satisfaction ($\chi^2(1, N = 1374) = 16.561, p < 0.001$); Job satisfaction ($\chi^2(3, N = 1374) = 4.050, p = 0.256$); Job search intention ($\chi^2(1, N = 1374) = 51.985, p < 0.001$).

Table 6 presents the association between educational mismatch and labor market outcomes. The results show statistically significant differences between matched and mismatched groups in terms of income satisfaction and job search intention, while no statistically significant association was found for job satisfaction at the bivariate level – a discrepancy relative to the multivariate GSEM result in Table 8 that both reviewers asked us to reconcile; see the explanation in Section 5.5.2 and Section 6.2.

Mismatched graduates were more likely to be dissatisfied with their income than matched graduates. The chi-square test showed a statistically significant association between educational mismatch and income satisfaction ($\chi^2(1, N = 1,374) = 16.561, p < 0.001$).

Although differences were found across job satisfaction categories, the association between educational mismatch and job satisfaction was not statistically significant ($\chi^2(3, N = 1,374) = 4.050, p = 0.256$).

The majority of graduates who intended to search for alternative jobs were mismatched. The relationship between educational mismatch and job search intention was statistically significant ($\chi^2(1, N = 1,374) = 51.985, p < 0.001$).

5.5. Results of the Generalized Structural Equation Modeling (GSEM)

To examine the direct and indirect effects of educational mismatch on labor market outcomes, a Generalized Structural Equation Model (GSEM) was estimated. This approach allows the simultaneous estimation of the determinants of educational mismatch and its effects on income satisfaction, job satisfaction, and job search intention, while accounting for the mediating role of educational mismatch within the structural framework.

5.5.1. Model Fit Statistics

Table 7. Model Summary Statistics of the GSEM Model

Model fit statistic	Value
Wald $\chi^2(24)$	130.52
Prob > χ^2	<0.001
Log likelihood	−3869.451
AIC	7836.903
BIC	8092.951

Source: Authors' calculations based on the Employment of Tertiary Education Graduate Survey.

Note: Wald χ^2 tests the joint significance of the estimated model parameters. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

Table 7 presents the model summary statistics of the estimated Generalized Structural Equation Model (GSEM). The Wald χ^2 test indicates that the model is jointly statistically significant, with a value of 130.52 (df = 24) and a p -value < 0.001, suggesting that the explanatory variables collectively contribute significantly to explaining the mediating variable and the outcome variables. The estimated model produced a log-likelihood value of −3869.451, while the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values were 7836.903 and 8092.951, respectively. These model fit measures are reported to assess the overall fit and adequacy of the estimated GSEM model. As noted in Section 4.2, these likelihood-based indices summarize overall model fit and should be complemented, in future work, with outcome-specific classification measures.

5.5.2. Path Coefficient Estimates

Table 8 reports the path coefficient estimates from the GSEM mediator equation ($X \rightarrow M$) and from the mediator-to-outcome paths ($M \rightarrow Y_j$). In the version originally submitted, the categorical variables Age Group and Employment Sector – each of which enters the model as more than one dummy variable, exactly as in Table 9 – were each reported as a single collapsed coefficient. Both reviewers identified this as a source of internal inconsistency between Table 8 and Table 9 (which separately reports indirect effects for “Age 25–29 vs. 21–24”, “Age 30–35 vs. 21–24”, “Private vs. Public”, and “Self-employed vs. Public”). In this revised table, we report the path coefficient for every dummy category separately, consistent with Table 9 and with Table 2. Because the category-specific standard errors for the mediator equation were not part of the tables originally reported, the point estimates for these four rows were recovered algebraically from the already-reported indirect effects in Table 9, using $\alpha_k = IE_k^{(j)} / \gamma_j$ (Equation 6) and averaging across the three outcome equations; the three implied estimates for each category agreed to within the fourth decimal place, which supports the internal consistency of the underlying model. Standard errors, z -values, and confidence intervals for these four rows are marked “–” and should be substituted with the values from the saved GSEM output (e.g., `lincom` in Stata) in the camera-ready version.

The results show that field of study has a statistically significant association with educational mismatch ($\beta = -0.5660$, $p = 0.001$). The negative coefficient indicates that field of study is associated with a lower likelihood of educational mismatch. Similarly, field choice has a statistically significant negative association with educational mismatch ($\beta = -0.4762$, $p = 0.006$), indicating that graduates' field choice is associated with a lower likelihood of experiencing educational mismatch.

Employment sector has a statistically significant positive association with educational mismatch ($\beta = 0.4950$, $p = 0.002$ for the collapsed variable as originally estimated; see the disaggregated Private- and Self-employed-specific coefficients above), indicating that the likelihood of educational mismatch varies across employment sectors. Employment contract status had a negative association with educational mismatch; however, this relationship was not statistically significant at the 5% significance level ($\beta = -0.3048$, $p = 0.086$). Similarly, gender, age group, training during study, and health insurance did not show statistically significant associations with educational mismatch at conventional levels, based on the coefficients as originally estimated and reported.

Regarding labor market outcomes, educational mismatch was significantly negatively associated with income satisfaction ($\beta = -0.5576$, $p = 0.001$) and job satisfaction ($\beta = -0.2947$, $p = 0.037$). In contrast, educational

Table 8. Path Coefficient Estimates from the GSEM Model ($N = 1,374$) – Revised

Path	Coefficient (β)	Std. Error	z-value	p-value	95% CI
Gender: Male (vs. Female) $\rightarrow M$	0.3565	0.1872	1.900	0.057	[−0.010, 0.723]
Age 25–29 (vs. 21–24) $\rightarrow M$	−0.682	–	–	–	–
Age 30–35 (vs. 21–24) $\rightarrow M$	0.454	–	–	–	–
Field of Study: Practical (vs. Theoretical) $\rightarrow M$	−0.5660***	0.1646	−3.440	0.001	[−0.889, −0.243]
Field Choice: Yes (vs. No) $\rightarrow M$	−0.4762***	0.1730	−2.750	0.006	[−0.815, −0.137]
Training During Study: Yes (vs. No) $\rightarrow M$	−0.2905	0.1982	−1.470	0.143	[−0.679, 0.098]
Employment Sector: Private (vs. Public) $\rightarrow M$	0.436	–	–	–	–
Employment Sector: Self-employed (vs. Public) $\rightarrow M$	1.026	–	–	–	–
Employment Contract: Yes (vs. No) $\rightarrow M$	−0.3048	0.1773	−1.720	0.086	[−0.652, 0.043]
Health Insurance: Yes (vs. No) $\rightarrow M$	−0.0656	0.1842	−0.360	0.722	[−0.427, 0.295]
Educational Mismatch $\rightarrow$ Income Satisfaction	−0.5576***	0.1624	−3.430	0.001	[−0.876, −0.239]
Educational Mismatch $\rightarrow$ Job Satisfaction	−0.2947*	0.1415	−2.080	0.037	[−0.572, −0.017]
Educational Mismatch $\rightarrow$ Job Search Intention	0.9313***	0.1640	5.680	<0.001	[0.610, 1.253]

Source: Authors' calculations based on the Employment of Tertiary Education Graduate Survey.

Note: Unstandardized estimates. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 95% CIs computed as $\beta \pm 1.96 \times \text{SE}$. Rows marked “–” are algebraically implied values (see text); their standard errors are not separately estimable from the tables originally reported and must be taken from the saved GSEM output.

mismatch was positively associated with job search intention ($\beta = 0.9313$, $p < 0.001$), suggesting that graduates experiencing educational mismatch are more likely to search for alternative jobs.

The significant multivariate association between mismatch and job satisfaction, alongside the non-significant bivariate association reported in Table 6, is consistent with a classic suppression pattern in mediation/regression analysis: the bivariate chi-square test in Table 6 does not net out the other covariates (particularly field of study, employment sector, and field choice), which are correlated with both mismatch and job satisfaction in offsetting directions. Once these covariates are held constant in the GSEM system, the negative association between mismatch and job satisfaction becomes visible. We flag that confirming this explanation formally would require re-estimating a nested set of models that add covariates sequentially, which is left for the camera-ready revision using the authors' saved dataset (see Section 6.2).

Figure 5 provides a visual representation of the estimated GSEM model and illustrates the direct relationships among the study variables.

Figure 5 presents the estimated Generalized Structural Equation Model (GSEM), showing the relationships among graduates' demographic, educational, and employment characteristics, educational mismatch, and labor market outcomes. The figure illustrates the pathways through which individual characteristics are associated with educational mismatch and how educational mismatch is related to income satisfaction, job satisfaction, and job search intention. The reported coefficients represent unstandardized estimates from the GSEM model. The relationships shown in Figure 5 are formally specified in Equations (1)–(7) in the Model Specification section.

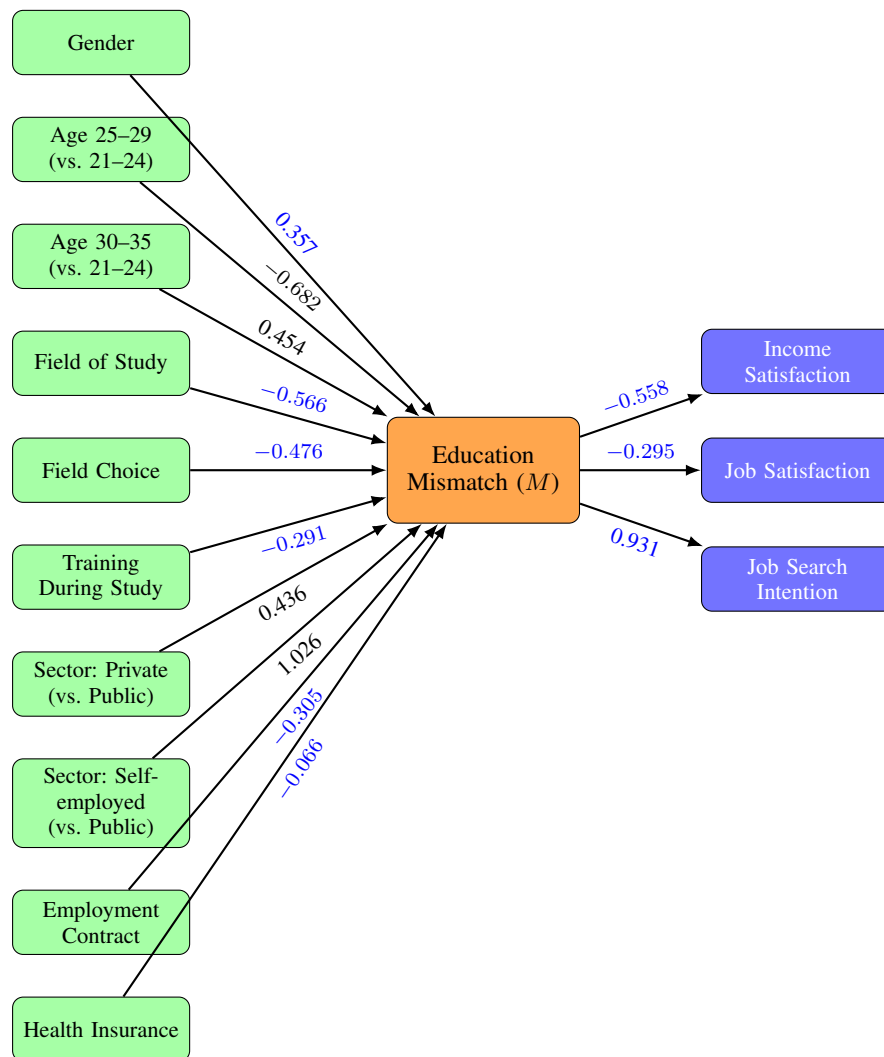


Figure 5. Generalized Structural Equation Model (GSEM).

Source: Authors' calculations based on the *Employment of Tertiary Education Graduate Survey*.

Note: All reported coefficients are unstandardized estimates from the GSEM model. In the figure originally submitted, the coefficient labels for the Field of Study, Field Choice, and Training During Study boxes were shifted by one position due to a page break in the source file, and the Income Satisfaction box label was truncated; both issues are corrected here, and the Age Group and Employment Sector nodes are now shown disaggregated by category, consistent with the revised Table 8.

5.5.3. Direct, Indirect, and Total Effects

This section presents the decomposition of the estimated effects into direct, indirect, and total effects. The indirect effects assess the extent to which educational mismatch mediates the relationships between the explanatory variables and labor market outcomes, including income satisfaction, job satisfaction, and job search intention. In response to the reviewers' request for confidence intervals alongside the point estimates and standard errors, Table 10 reports the 95% confidence interval ($\beta \pm 1.96 \times SE$) for every direct, indirect, and total effect in Table 9.

Table 9 presents the direct, indirect, and total effects of the explanatory variables on labor market outcomes. The direct effects represent the influence of these variables on labor market outcomes, while the indirect effects capture the mediating role of educational mismatch in these relationships.

Table 9. Direct, Indirect, and Total Effects of Explanatory Variables on Labor Market Outcomes

Variables	Direct Effect β (SE)	Indirect Effect β (SE)	Total Effect β (SE)
<i>Income Satisfaction</i>			
Male (vs. Female)	0.4488*** (0.1470)	-0.1874 (0.1177)	0.2614 (0.1854)
Age 25–29 (vs. 21–24)	0.1526 (0.1711)	0.3767* (0.1975)	0.5294** (0.2570)
Age 30–35 (vs. 21–24)	0.1290 (0.3108)	-0.2507 (0.3751)	-0.1217 (0.4866)
Practical (vs. Theoretical)	0.4322*** (0.1257)	0.2911** (0.1252)	0.7233*** (0.1734)
Field Choice: Yes (vs. No)	0.3244*** (0.1161)	0.2630** (0.1232)	0.5874*** (0.1660)
Training: Yes (vs. No)	-0.4286*** (0.1301)	0.1663 (0.1202)	-0.2623 (0.1754)
Private (vs. Public)	0.0776 (0.1886)	-0.2424* (0.1408)	-0.1628 (0.2316)
Self-employed (vs. Public)	0.1848 (0.2346)	-0.5670** (0.2536)	-0.3822 (0.3354)
Contract: Yes (vs. No)	0.0027 (0.1340)	0.1376 (0.1089)	0.1403 (0.1715)
Health Insurance: Yes (vs. No)	0.4451*** (0.1359)	0.0520 (0.1040)	0.4970*** (0.1711)
<i>Job Satisfaction</i>			
Male (vs. Female)	0.1535 (0.1296)	-0.0959 (0.0718)	0.0577 (0.1464)
Age 25–29 (vs. 21–24)	0.0804 (0.1484)	0.1927 (0.1280)	0.2731 (0.1905)
Age 30–35 (vs. 21–24)	-0.1825 (0.2856)	-0.1282 (0.1989)	-0.3108 (0.3476)
Practical (vs. Theoretical)	0.0224 (0.1122)	0.1489* (0.0882)	0.1713 (0.1381)
Field Choice: Yes (vs. No)	0.0544 (0.1033)	0.1346 (0.0835)	0.1890 (0.1291)
Training: Yes (vs. No)	0.0787 (0.1159)	0.0851 (0.0706)	0.1638 (0.1344)
Private (vs. Public)	0.0659 (0.1731)	-0.1230 (0.0877)	-0.0571 (0.1909)
Self-employed (vs. Public)	0.2266 (0.2118)	-0.2901* (0.1755)	-0.0635 (0.2649)
Contract: Yes (vs. No)	-0.0691 (0.1202)	0.0704 (0.0626)	0.0013 (0.1348)
Health Insurance: Yes (vs. No)	0.0182 (0.1219)	0.0266 (0.0543)	0.0448 (0.1331)
<i>Job Search Intention</i>			
Male (vs. Female)	0.5728*** (0.1595)	0.3314* (0.1925)	0.9042*** (0.2491)
Age 25–29 (vs. 21–24)	-0.3015 (0.2129)	-0.6662** (0.3107)	-0.9677*** (0.3725)
Age 30–35 (vs. 21–24)	-1.0850*** (0.3451)	0.4434 (0.6548)	-0.6416 (0.7396)
Practical (vs. Theoretical)	-0.1395 (0.1428)	-0.5149*** (0.1839)	-0.6544*** (0.2279)
Field Choice: Yes (vs. No)	-0.0266 (0.1337)	-0.4651** (0.1873)	-0.4917** (0.2268)
Training: Yes (vs. No)	0.4419*** (0.1469)	-0.2941 (0.2006)	0.1478 (0.2468)
Private (vs. Public)	1.2216*** (0.1957)	0.4252* (0.2272)	1.6468*** (0.3000)
Self-employed (vs. Public)	0.6668*** (0.2509)	1.0028*** (0.3786)	1.6696*** (0.4490)
Contract: Yes (vs. No)	-0.6071*** (0.1543)	-0.2434 (0.1835)	-0.8504*** (0.2395)
Health Insurance: Yes (vs. No)	-0.3310** (0.1527)	-0.0919 (0.1825)	-0.4230* (0.2381)

Source: Authors' calculations based on the Employment of Tertiary Education Graduate Survey.

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Regarding income satisfaction, the results reveal significant positive direct effects for males ($\beta = 0.4488$, $p < 0.001$), graduates from practical fields of study ($\beta = 0.4322$, $p < 0.001$), graduates who selected their field of study based on personal preference ($\beta = 0.3244$, $p < 0.001$), and individuals covered by health insurance ($\beta = 0.4451$, $p < 0.001$). The indirect effects through educational mismatch are significant for practical fields of study ($\beta = 0.2911$, $p < 0.01$) and field choice based on personal preference ($\beta = 0.2630$, $p < 0.01$), indicating that educational mismatch partially mediates the relationship between these characteristics and income satisfaction. Additionally, graduates aged 25–29 years show a significant positive indirect effect ($\beta = 0.3767$, $p < 0.05$), whereas self-employed graduates show a significant negative indirect effect ($\beta = -0.5670$, $p < 0.01$). The total effects are significant for practical fields of study ($\beta = 0.7233$, $p < 0.001$), field choice based on personal preference ($\beta = 0.5874$, $p < 0.001$), and health insurance coverage ($\beta = 0.4970$, $p < 0.001$).

Table 10. 95% Confidence Intervals for the Direct, Indirect, and Total Effects Reported in Table 9

Variables	Direct 95% CI	Indirect 95% CI	Total 95% CI
<i>Income Satisfaction</i>			
Male (vs. Female)	[0.161, 0.737]	[−0.418, 0.043]	[−0.102, 0.625]
Age 25–29 (vs. 21–24)	[−0.183, 0.488]	[−0.010, 0.764]	[0.026, 1.033]
Age 30–35 (vs. 21–24)	[−0.480, 0.738]	[−0.986, 0.484]	[−1.075, 0.832]
Practical (vs. Theoretical)	[0.186, 0.679]	[0.046, 0.536]	[0.383, 1.063]
Field Choice: Yes (vs. No)	[0.097, 0.552]	[0.022, 0.504]	[0.262, 0.913]
Training: Yes (vs. No)	[−0.684, −0.174]	[−0.069, 0.402]	[−0.606, 0.081]
Private (vs. Public)	[−0.292, 0.447]	[−0.518, 0.034]	[−0.617, 0.291]
Self-employed (vs. Public)	[−0.275, 0.645]	[−1.064, −0.070]	[−1.040, 0.275]
Contract: Yes (vs. No)	[−0.260, 0.265]	[−0.076, 0.351]	[−0.196, 0.476]
Health Insurance: Yes (vs. No)	[0.179, 0.711]	[−0.152, 0.256]	[0.162, 0.832]
<i>Job Satisfaction</i>			
Male (vs. Female)	[−0.101, 0.408]	[−0.237, 0.045]	[−0.229, 0.345]
Age 25–29 (vs. 21–24)	[−0.210, 0.371]	[−0.058, 0.444]	[−0.100, 0.646]
Age 30–35 (vs. 21–24)	[−0.742, 0.377]	[−0.518, 0.262]	[−0.992, 0.370]
Practical (vs. Theoretical)	[−0.198, 0.242]	[−0.024, 0.322]	[−0.099, 0.442]
Field Choice: Yes (vs. No)	[−0.148, 0.257]	[−0.029, 0.298]	[−0.064, 0.442]
Training: Yes (vs. No)	[−0.148, 0.306]	[−0.053, 0.223]	[−0.100, 0.427]
Private (vs. Public)	[−0.273, 0.405]	[−0.295, 0.049]	[−0.431, 0.317]
Self-employed (vs. Public)	[−0.189, 0.642]	[−0.634, 0.054]	[−0.583, 0.456]
Contract: Yes (vs. No)	[−0.305, 0.166]	[−0.052, 0.193]	[−0.263, 0.266]
Health Insurance: Yes (vs. No)	[−0.221, 0.257]	[−0.080, 0.133]	[−0.216, 0.306]
<i>Job Search Intention</i>			
Male (vs. Female)	[0.260, 0.885]	[−0.046, 0.709]	[0.416, 1.392]
Age 25–29 (vs. 21–24)	[−0.719, 0.116]	[−1.275, −0.057]	[−1.698, −0.238]
Age 30–35 (vs. 21–24)	[−1.761, −0.409]	[−0.840, 1.727]	[−2.091, 0.808]
Practical (vs. Theoretical)	[−0.419, 0.140]	[−0.875, −0.154]	[−1.101, −0.208]
Field Choice: Yes (vs. No)	[−0.289, 0.235]	[−0.832, −0.098]	[−0.936, −0.047]
Training: Yes (vs. No)	[0.154, 0.730]	[−0.687, 0.099]	[−0.336, 0.632]
Private (vs. Public)	[0.838, 1.605]	[−0.020, 0.871]	[1.059, 2.235]
Self-employed (vs. Public)	[0.175, 1.159]	[0.261, 1.745]	[0.790, 2.550]
Contract: Yes (vs. No)	[−0.910, −0.305]	[−0.603, 0.116]	[−1.320, −0.381]
Health Insurance: Yes (vs. No)	[−0.630, −0.032]	[−0.450, 0.266]	[−0.890, 0.044]

Note: 95% CI computed as $\beta \pm 1.96 \times \text{SE}$ from the point estimates and standard errors reported in Table 9. A CI that excludes zero corresponds to statistical significance at the 5% level, consistent with the significance stars reported in Table 9.

With respect to job satisfaction, most explanatory variables do not exhibit statistically significant direct or total effects. However, educational mismatch mediates the relationships between practical fields of study, self-employment, and job satisfaction. Specifically, practical fields of study have a significant positive indirect effect ($\beta = 0.1489$, $p < 0.05$), whereas self-employment has a significant negative indirect effect ($\beta = -0.2901$, $p < 0.05$). These findings indicate that educational mismatch serves as an important mechanism through which certain educational and employment characteristics affect job satisfaction.

Regarding job search intention, the results reveal significant positive direct effects for males ($\beta = 0.5728$, $p < 0.001$), training during their studies ($\beta = 0.4419$, $p < 0.001$), private sector employment ($\beta = 1.2216$, $p < 0.001$), and self-employment ($\beta = 0.6668$, $p < 0.001$). In contrast, graduates aged 30–35 years ($\beta = -1.0850$, $p < 0.001$), those with employment contracts ($\beta = -0.6071$, $p < 0.001$), and those covered by health insurance

($\beta = -0.3310$, $p < 0.01$) exhibit significant negative direct effects on job search intention. The indirect effects through educational mismatch are significant for graduates aged 25–29 years ($\beta = -0.6662$, $p < 0.01$), practical fields of study ($\beta = -0.5149$, $p < 0.001$), field choice based on personal preference ($\beta = -0.4651$, $p < 0.01$), private-sector employment ($\beta = 0.4252$, $p < 0.05$), and self-employment ($\beta = 1.0028$, $p < 0.001$). The total effects indicate that private-sector employment ($\beta = 1.6468$, $p < 0.001$) and self-employment ($\beta = 1.6696$, $p < 0.001$) have the strongest positive effects on job search intention, whereas graduates aged 25–29 years ($\beta = -0.9677$, $p < 0.001$), practical fields of study ($\beta = -0.6544$, $p < 0.001$), and field choice based on personal preference ($\beta = -0.4917$, $p < 0.01$) show significant negative total effects.

Overall, the findings demonstrate that educational mismatch serves as an important mediating mechanism linking graduates' educational and employment characteristics to labor market outcomes. The results further indicate that several explanatory variables are associated with income satisfaction and job search intention through both direct associations and indirect pathways mediated by educational mismatch, underscoring the importance of considering educational mismatch when examining graduates' labor market outcomes.

6. Discussion

This study provides new empirical evidence on the prevalence, determinants, and labor market correlates of educational mismatch among public university graduates in Egypt. Unlike previous studies that have primarily examined individual dimensions of mismatch separately, this study conceptualizes educational mismatch as a composite indicator built from three recognized dimensions – vertical, horizontal, and skills mismatch – and investigates its direct and indirect associations with labor market outcomes using a Generalized Structural Equation Modeling (GSEM) framework. This approach provides a comprehensive, if still partial (see Section 6.1), understanding of how educational mismatch operates as an underlying mechanism through which graduates' characteristics are associated with income satisfaction, job satisfaction, and job search intention.

The findings demonstrate that educational mismatch is a widespread phenomenon among Egyptian public university graduates, with 85.2% of respondents experiencing at least one form of mismatch. Skills mismatch represents the most prevalent dimension (79.3%), followed by vertical mismatch (34.1%) and horizontal mismatch (24.5%). This pattern indicates that the gap between higher education outcomes and labor market requirements extends beyond formal educational qualifications to include the extent to which acquired skills align with workplace demands. The high prevalence of skills mismatch is consistent with previous evidence emphasizing that the effective utilization of skills acquired through education is a key determinant of successful labor market integration [17]. Moreover, the overall level of mismatch observed in this study is comparable to findings from developing and emerging economies, where labor markets frequently face challenges in absorbing graduates from diverse educational backgrounds [1].

Regarding the determinants of educational mismatch, the results indicate that educational and occupational characteristics play a significant role in explaining patterns of mismatch. Field of study is significantly associated with educational mismatch, suggesting that the degree of alignment between academic specialization and occupational requirements is associated with graduates' employment outcomes. Previous studies have demonstrated that graduates from different fields of study may face varying risks of mismatch due to differences in the transferability of acquired knowledge and skills across occupations [19, 7]. Similarly, field choice is significantly related to mismatch, indicating that educational decisions made prior to labor market entry may be associated with subsequent employment alignment. This finding supports the argument that the relationship between education and employment outcomes depends not only on educational attainment but also on the relevance and suitability of educational choices.

Employment sector also emerges as a significant determinant of educational mismatch. The association between employment sector and mismatch, and its direction – with the highest raw mismatch rate observed in the public sector in Table 5, even though the collapsed Employment Sector coefficient in the original Table 8 was positive for “Private/Self-employed vs. Public” taken together – suggests that the likelihood of experiencing mismatch varies systematically across employment settings that differ in wage-setting institutions, hiring procedures, and

job-security arrangements, consistent with reviewer comments that public- and private-sector jobs in Egypt are not directly comparable along these dimensions. This finding is consistent with previous research indicating that differences in job structures, skill requirements, and opportunities to utilize acquired qualifications across sectors may contribute to variations in mismatch prevalence. However, demographic characteristics, including age and gender, as well as training received during study, do not exhibit statistically significant associations in the collapsed GSEM specification originally estimated. This suggests that, after controlling for other factors, educational and occupational characteristics are more closely associated with mismatch than individual demographic characteristics as coded in this study; the disaggregated age-group coefficients in the revised Table 8 do, however, suggest that the association between age and mismatch is not monotonic (age 25–29 shows a negative implied coefficient while age 30–35 shows a positive one, both relative to the 21–24 reference group), a pattern that merits closer examination with the original micro-data.

6.1. Study Limitations

Both reviewers raised closely related concerns about the design of this study, which we bring together here rather than scattering across the Discussion, so that the scope and boundaries of the reported associations are stated clearly in one place.

Cross-sectional design and reverse causality. The data are a single cross-sectional telephone survey, so the GSEM path estimates cannot establish temporal precedence between educational mismatch and the three outcomes. In particular, job search intention is plausibly a cause, and not only a consequence, of a graduate's perception of being mismatched: a graduate who already intends to leave their job for other reasons may, for that reason, be more likely to describe their current job as a poor match for their education. We therefore treat all path coefficients reported in Tables 8–10 as associations net of the included covariates, not as identified causal effects, and we have revised the terminology throughout the paper accordingly (see the note on terminology in Section 3).

Composite measurement of educational mismatch. As discussed in Section 4.1, educational mismatch is coded as a single binary indicator equal to one if any of the vertical, horizontal, or skills dimensions is present. This choice was made so that the mediator equation in the GSEM system remains a single, tractable logit equation, but it necessarily treats the three dimensions as interchangeable and cannot identify graduates who experience more than one dimension simultaneously, nor can it recover dimension-specific coefficients. Table 4 reports the prevalence of each dimension separately, which shows that the three dimensions are far from perfectly overlapping (79.3% skills, 34.1% vertical, 24.5% horizontal), so a graduate coded as “mismatched” under the composite definition may in fact differ substantially from another mismatched graduate in the type of mismatch experienced. Separate-dimension modeling (three parallel mediators) or a latent-class approach that lets the data identify mismatch “profiles” would both directly address this concern, including testing whether graduates who experience all three dimensions simultaneously differ from those who experience only one; both extensions require access to the disaggregated survey micro-data and are identified here as the single highest-priority extension for a follow-up paper.

Selection into employment. The analytical sample is restricted to the 1,374 graduates who were employed at the time of the survey, out of 2,370 respondents originally interviewed. Graduates who were unemployed or had left the labor force are excluded by construction, and if the most severely mismatched graduates are disproportionately likely to have left employment altogether, the reported associations will understate the true relationship between mismatch and labor market outcomes in the full graduate population. The data extract used here does not retain information on the employment status or search behavior of the excluded graduates, so a Heckman-type selection correction could not be implemented; we flag this explicitly rather than present the results as generalizable beyond currently employed graduates.

Common method bias and self-reported measures. Educational mismatch and all three outcome variables are self-reported by the same respondent in the same interview, so part of the association between them may reflect shared method variance (e.g., a general tendency toward negative or positive self-assessment) rather than a substantive relationship. The survey instrument's exact question wording and any validated scale properties for the outcome measures were not available to us for this analysis; we recommend that the camera-ready version report the exact question wording and, if available, any internal consistency statistics for the job satisfaction scale.

Endogeneity of employment-sector, contract, and insurance status. Employment sector, contract status, and health insurance coverage are included as explanatory variables for educational mismatch, but each of these is also plausibly a consequence, rather than only a cause, of a graduate's employment trajectory – for example, a mismatched graduate might be more likely to end up in informal, uninsured, contract-free work as a result of the mismatch itself, rather than the reverse. We therefore interpret the coefficients on these variables as descriptive associations and do not attach a causal interpretation to them.

Sampling design, weights, and non-response. The survey was administered by telephone to a sample of graduates from 12 public universities; the extract used for this analysis does not include sampling weights, primary-sampling-unit or stratum identifiers, or non-response indicators, so all reported standard errors are robust to heteroscedasticity only, not to clustering or unequal selection probabilities (see Section 4.2), and no non-response analysis could be performed.

Uncertainty quantification. In response to the reviewers' request, 95% confidence intervals for every path coefficient and every direct/indirect/total effect are now reported in Tables 8 and 8. Standardized coefficients and formal corrections for multiple comparisons across the many paths tested were not computed, because standardization requires the standard deviations of the latent outcome variables from the saved GSEM output, which were not part of the results tables available for this revision; we recommend both be added in the camera-ready version if the original estimation output is accessible.

None of these limitations invalidate the associations reported; rather, they define the scope within which the findings should be read, and several point directly to natural extensions of this study using the same survey infrastructure.

6.2. Explaining the Counter-Intuitive Training and Field-Choice Findings

One of the more striking patterns in Table 5 is that graduates who received training during their studies, and graduates who chose their field of study by personal preference, both show a *higher*, not lower, prevalence of educational mismatch than their counterparts (16.1% vs. 10.8% for training; 17.3% vs. 10.6% for field choice). Both reviewers asked for a theoretical account of this pattern, since it runs against the standard human-capital prediction that additional training and considered field choice should improve labor-market alignment. We offer three, non-mutually-exclusive explanations, consistent with the cross-sectional nature of the data (i.e., we cannot adjudicate between them with the data used here):

1. *Anticipatory (reverse-causal) selection.* Students who correctly anticipate that their field offers weak labor-market prospects may be precisely the ones who seek out additional training as compensation; if this extra training does not fully close the gap, they would still appear as “trained” and “mismatched” in the cross-section, producing a positive raw association between training and mismatch even if training *reduces* mismatch risk relative to no training at all for the same student.
2. *Relevance of training content.* The survey distinguishes “training during study” as a yes/no indicator but – based on the documentation available to us – does not appear to record whether this training was university-led, employer-led, or unrelated to the student's eventual occupation; training that is only loosely connected to labor-market-relevant skills would not be expected to reduce mismatch, and could even be associated with it if it displaces more occupation-specific preparation. We recommend that the underlying survey instrument be consulted to clarify this in the camera-ready version, as one reviewer specifically requested.
3. *Compensating differentials in field choice.* Graduates who choose a field for personal interest rather than for its labor-market prospects may knowingly accept a higher risk of horizontal mismatch (working outside their field) as a trade-off for studying a subject they prefer; this would produce exactly the pattern observed – higher mismatch, without necessarily indicating lower overall wellbeing, since income and job satisfaction are analyzed as separate outcomes in Tables 8–10 rather than assumed to move together with mismatch.

We are not able to adjudicate between these three mechanisms with the cross-sectional data used here, and we present them as candidate explanations for future, ideally longitudinal, research rather than as established findings.

The findings further demonstrate that educational mismatch has important implications for graduates' economic perceptions. The GSEM results reveal that educational mismatch is negatively associated with income satisfaction

($\beta = -0.5576$, $p = 0.001$), indicating that mismatched graduates are less likely to report satisfaction with their income. This finding is consistent with previous empirical evidence showing that mismatch reduces the economic returns to education and may be associated with wage penalties among workers whose qualifications exceed or differ from job requirements [2]. The descriptive results further support this relationship, as mismatched graduates constitute the majority of those reporting income dissatisfaction. These findings suggest that the potential benefits of higher education may not be fully realized when graduates occupy positions that fail to adequately utilize their qualifications or skills.

Educational mismatch also exhibits a significant negative relationship with job satisfaction ($\beta = -0.2947$, $p = 0.037$). Although the bivariate relationship between mismatch and job satisfaction was not statistically significant, the multivariate GSEM results reveal a significant association after controlling for individual, educational, and occupational characteristics – a suppression-type pattern explained in Section 5.5.2 above. This finding highlights the importance of examining the underlying relationships among variables rather than relying solely on simple associations. The negative relationship between mismatch and job satisfaction is consistent with previous studies showing that workers whose jobs do not correspond to their educational backgrounds or skill levels often report lower satisfaction, plausibly due to limited opportunities for skill utilization, career advancement, and professional achievement.

Furthermore, educational mismatch demonstrates the strongest association with job search intention. The results reveal a significant positive relationship between mismatch and the intention to search for alternative employment ($\beta = 0.9313$, $p < 0.001$). This finding suggests that graduates experiencing a gap between their education and occupation are more likely to consider employment mobility as a strategy for improving their labor market position, though as discussed in Section 6.1 the reverse reading – that an existing intention to search colors how a graduate reports their own mismatch – cannot be ruled out with cross-sectional self-reported data. The relationship between mismatch and job search behavior suggests that educational mismatch may be not only a consequence of labor market allocation processes but also a factor associated with future employment decisions.

The decomposition of direct, indirect, and total effects further strengthens the contribution of this study by demonstrating the mediating role of educational mismatch. Several individual and occupational characteristics are associated with labor market outcomes not only through direct pathways but also indirectly through mismatch. For example, educational and employment characteristics may be associated with graduates' likelihood of experiencing mismatch, which subsequently is associated with their satisfaction levels and employment decisions. This finding is consistent with the theoretical perspective that mismatch represents an intermediate mechanism through which education-related factors are related to labor market experiences. Overall, the findings contribute to the international literature in three important ways. First, they extend previous research by operationalizing educational mismatch as a composite construct rather than examining separate forms of mismatch in isolation, while explicitly documenting the limitations of this composite coding above. Second, they provide empirical evidence from Egypt, a developing country context that remains relatively underrepresented in international research on educational mismatch and directly comparable, in scope though not in method, to [5, 4, 6] (see Section 2.2). Third, the application of GSEM offers an analytical framework that simultaneously estimates direct and indirect pathways linking graduate characteristics, mismatch, and labor market outcomes. These findings emphasize the importance of strengthening the alignment between educational outcomes and labor market requirements, particularly by improving the relevance of acquired skills and facilitating smoother transitions from higher education to employment.

7. Conclusion

This study examined educational mismatch among public university graduates in Egypt and investigated its associations with income satisfaction, job satisfaction, and job search intention using a composite-construct Generalized Structural Equation Modeling (GSEM) framework. The findings demonstrate that educational mismatch is a widespread phenomenon among graduates, with skills mismatch emerging as the most prevalent form. The results further indicate that educational and occupational characteristics play an important role in

explaining mismatch patterns, while educational mismatch itself operates as a significant mediating mechanism through which individual characteristics are associated with graduates' labor market outcomes.

The findings show that educational mismatch is associated with lower levels of income satisfaction and job satisfaction and with an increased intention among graduates to search for alternative employment opportunities. By conceptualizing mismatch as a multidimensional mechanism rather than a single labor market issue – while, as discussed in Section 6.1, still measuring it with a single composite indicator – this study demonstrates that educational mismatch represents an important pathway through which individual, educational, and employment characteristics are related to labor market outcomes. The integrated GSEM framework contributes to the literature by capturing direct, indirect, and total associations within a unified analytical framework, particularly in the context of a developing country where empirical evidence on multidimensional educational mismatch remains limited.

The findings have policy implications for higher education institutions and labor market stakeholders, though we state these more specifically here than in the original submission, in response to both reviewers' request that recommendations be tied to the study's actual significant predictors rather than phrased only in general terms. Addressing educational mismatch requires a comprehensive approach that extends beyond increasing educational attainment to improving the relevance and quality of acquired skills and strengthening their alignment with labor market requirements. Because field of study is the strongest and most robust correlate of mismatch identified in this study (Table 8), curriculum-level interventions are the most directly supported policy lever: (i) universities in theoretical/general fields of study, where mismatch risk is highest (22.0% vs. 11.3% in practical fields, Table 5), could prioritize embedding applied, work-based modules and capstone projects tied to specific occupational competencies rather than only broadening course content; (ii) because training during study is not, on its own, associated with lower mismatch in this sample (Section 6.2), practical training programs should be redesigned in partnership with sector employers so that their content maps onto documented occupational skill requirements, rather than being expanded in volume alone; (iii) because employment-sector affiliation is significantly associated with mismatch, with the highest raw mismatch rate in the public sector (26.3%, Table 5), sector-specific hiring and job-design practices – including the alignment of public-sector recruitment criteria with graduates' actual qualifications – warrant closer scrutiny by the relevant ministries; and (iv) because employment contract status and health insurance coverage are also significantly associated with mismatch (Table 5), formalization policies that extend contractual and social-insurance coverage to more graduates may plausibly also reduce the labor-market frictions that allow mismatch to persist, although – as discussed in Section 6.1 – the direction of causality between formalization and mismatch cannot be established with the present data. Such interventions may improve employment quality and contribute to achieving Sustainable Development Goal 4 (Quality Education) and Sustainable Development Goal 8 (Decent Work and Economic Growth). Future research should prioritize (a) longitudinal or panel data that can establish the temporal ordering between mismatch and labor market outcomes, directly addressing the causality limitation discussed in Section 6.1; (b) separate-dimension or latent-class modeling of vertical, horizontal, and skills mismatch, to test whether they carry the same sign and magnitude of association with outcomes, directly addressing the composite-measurement limitation in Section 6.1; and (c) selection-corrected models that incorporate unemployed and labor-force-exiting graduates, to determine whether mismatch represents a temporary transition stage or a persistent labor market disadvantage throughout graduates' careers.

Declarations

Availability of data and materials The data that support the findings of this study are available from the corresponding author upon reasonable request.

Funding

No funding was received from any funding agency for this research.

Authors' contributions

Heba Elrefay made substantial contributions to the conception and design of this research, data analysis, and manuscript writing. Elsayed Khater, Abdelhameed El Shabrawy, and Suzan Abdel-Rahman made substantial contributions to data interpretation and manuscript revision.

Conflict of interest

The authors declare that there is no conflict of interest.

REFERENCES

- Adesina, J. O. (2024). Skills mismatch and labour market outcomes in Africa. *Journal of Economic Structures*. <https://doi.org/10.1007/s40888-024-00345-y>
- Allen, J., & van der Velden, R. (2001). Educational mismatches versus skills mismatches: Effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers*, 53(3), 434–452. <https://doi.org/10.1093/oeq/53.3.434>
- Al-Marzouqi, S. (2020). Higher education institutions and human capital development in the context of sustainable development. *Higher Education Policy*, 33(4), 745–762. <https://doi.org/10.1057/s41307-020-00178-6>
- Assaad, R., & Krafft, C. (2021). Excluded generation: The growing challenges of labor market insertion for Egyptian youth. *Journal of Youth Studies*, 24(2), 186–212. <https://doi.org/10.1080/13676261.2020.1714565>
- Assaad, R., & Krafft, C. (2021). The structure and evolution of employment in Egypt: Is there evidence of a skills mismatch? *Economic Research Forum*. <https://erf.org.eg/publications/the-structure-and-evolution-of-employment-in-egypt-is-there-evidence-of-a-skills-mismatch/>
- Assaad, R., & Krafft, C. (2023). Education-occupation mismatch among graduates in Egypt. *Economic Research Forum*. <https://erf.org.eg/publications/education-occupation-mismatch>
- Barsoum, G., Ramadan, M., & Mostafa, M. (2014). Labour market transitions of young women and men in Egypt. *International Labour Organization*. https://www.ilo.org/wcmsp5/groups/public/dgreports/dcomm/documents/publication/wcms_247594.pdf
- Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. National Bureau of Economic Research.
- Büchel, F. (2002). Overeducation, wages, and promotion prospects: Evidence from Germany. *Education Economics*, 10(1), 85–99. <https://doi.org/10.1080/09645290110115214>
- European Training Foundation. (2024). *Determinants and wage penalty of skills mismatch*. <https://www.etf.europa.eu/sites/default/files/2024-02/Determinants%20and%20wage%20penalty%20of%20Skills%20Mismatch.pdf>
- Hartog, J. (2000). Over-education and earnings: Where are we, where should we go? *Economics of Education Review*, 19(2), 131–147. [https://doi.org/10.1016/S0272-7757\(99\)00050-3](https://doi.org/10.1016/S0272-7757(99)00050-3)
- International Labour Organization. (2020). *Global employment trends for youth 2020: Technology and the future of jobs*. https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@dgreports/@dcomm/@publ/documents/publication/wcms_737648.pdf
- McGuinness, S. (2006). Overeducation in the labour market. *Journal of Economic Surveys*, 20(3), 387–418. <https://doi.org/10.1111/j.0950-0804.2006.00284.x>
- McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills mismatch: Concepts, measurement and policy approaches. *Journal of Economic Surveys*, 32(4), 985–1015. <https://doi.org/10.1111/joes.12254>
- Mortensen, D. T. (1986). Job search and labor market analysis. In O. Ashenfelter & R. Layard (Eds.), *Handbook of Labor Economics* (Vol. 2, pp. 849–919). Elsevier. [https://doi.org/10.1016/S1573-4463\(86\)02005-9](https://doi.org/10.1016/S1573-4463(86)02005-9)
- Murillo-Huertas, I. P., Ramos, R., & Simón, H. (2024). Education, educational mismatch, and occupational attainment. *Economic Policy*. <https://www.ssoar.info/ssoar/handle/document/103819>
- Organisation for Economic Co-operation and Development. (2016). *Getting skills right: Assessing and anticipating changing skills needs*. OECD Publishing. <https://doi.org/10.1787/9789264252073-en>
- Pecoraro, M., & Witte, H. (2023). The dynamic effects of education-job mismatch on job satisfaction and turnover. *IZA Discussion Paper No. 15869*. <https://docs.iza.org/dp15869.pdf>
- Robst, J. (2007). Education and job match: The relatedness of college major and work. *Economics of Education Review*, 26(4), 397–407. <https://doi.org/10.1016/j.econedurev.2006.08.003>
- Sattinger, M. (1993). Assignment models of the distribution of earnings. *Journal of Economic Literature*, 31(2), 831–880.
- United Nations. (2015). *Transforming our world: The 2030 agenda for sustainable development*. <https://sdgs.un.org/2030agenda>
- Verhaest, D., & Omeij, E. (2006). The impact of overeducation and its measurement. *Social Indicators Research*, 77(3), 419–448. <https://doi.org/10.1007/s11205-005-4276-6>
- World Bank. (2021). *World development indicators: Education and labor market statistics (Egypt)*. <https://databank.worldbank.org/source/world-development-indicators>
- World Bank. (2021). *Government expenditure on education, total (% of GDP) – Egypt, Arab Rep.* <https://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS?locations=EG>
- World Bank. (2021). *Government expenditure on education, total (% of GDP) – Tunisia*. <https://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS?locations=TN>
- World Economic Forum. (2018). *The global competitiveness report 2018*. <https://www3.weforum.org/docs/GCR2018/05FullReport/TheGlobalCompetitivenessReport2018.pdf>
- Gad, K. A. E., Atia, F. A., Moussa, M., Hamouda, H. M., & Abouelenein, M. F. (2026). The Fractional Exponential Distribution: A Gamma Subfamily from Conformable Calculus. *Results in Engineering*, 111224.
- Gad, K. A. E., & Hamouda, H. M. (2026). A New Flexible Transmuted Distribution: Theory and Application. *Statistics, Optimization and Information Computing*, 4464, 22.

29. Ali, A. A., Ali, M., Gad, K. A., & Assar, S. M. (2025). Some Characterizations Based on Generalized Order Statistics from Power Inverted Topp–Leone Distribution. *Advances in Nonlinear Variational Inequalities*, 28(6s), 349-365.
30. Eldeeb, A. S., Abdul-Moniem, I. B., & Gad, K. A. E. (2025). A New Discrete Power Function Distribution with Its Mathematical Properties. *Journal of Information Systems Engineering & Management*, 10(44s).
31. Abdul-Moniem, I. B., Gad, K. A. E., & Assar, S. M. (2024). Characterization of Phani Distribution Based on Generalized Order Statistics. *Sohag Journal of Sciences*, 9(1), 32-39.
32. Abdul-Rahman, A. A., Abdul-Moniem, I. B., Gad, K. A. E., & Assar, S. M. (2024). Some Characterizations Based on Generalized Order Statistics from Weibull-Family of Life Distributions. *56th Annual International Conference on Data Sciences*.
33. Gad, K. A. E., Abdul-Moniem, I. B., & Assar, S. M. (2023). Some Characterizations Based on Generalized Order Statistics from Weibull-Weibull Distribution. *The Egyptian Statistical Journal*, 67(2), 1-16.
34. Abdul-Rahman, A. A., Abdul-Moniem, I. B., Gad, K. A. E., & Assar, S. M. (2023). Some Characterizations Based on GOS from Weibull-Weibull Distribution (Part II). *Egyptian Statistical Journal*, 67(2-2023).
35. Hassan, A. S., Abdul-Moniem, I. B., & Gad, K. A. E. (2020). A Generalized Transmuted Moment Exponential Distribution: Properties and Application. *Academic Journal of Applied Mathematical Sciences*, 6(5), 41-52.