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Skill Mismatch:

MEASUREMENT, DETERMINANTS, AND CONSEQUENCES

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Measurement, Determinants, and Consequences

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Content

"In a regime of ignorance, Enrico Fermi would have been a gardener,
Von Neumann a checkout clerk at a drugstore." (Stigler, 1962, p. 104)

Overview Article:

Skill Mismatch: Measurement, Determinants, and Consequences

1 Motivation

Skill mismatches are highly prevalent in today's labour market and affect workers across regions, countries, and economies (Allen, Levels, et al., 2013; Cedefop, 2018; Flisi et al., 2017; Perry et al., 2014). Different types of skill mismatches refer either to mismatches at the macroeconomic and company level or to mismatches at the level of individuals (McGuinness et al., 2018). At the macroeconomic and company level, skill mismatches typically refer to skill shortages (the demand for skills exceeds the supply of available individuals possessing these skills), skill surpluses (the supply of skills exceeds the demand for skills), or skill gaps (the required skills are not available in the workforce or on the labour market) (Cedefop, 2010, 2015). This thesis focuses on *individual-level skill mismatches* referring to the matching of skill levels between currently employed workers and their jobs (International Labour Office, 2018b). Workers are defined as *underskilled* when their level of skills is lower than the level of skills required by their job and as *overskilled* when their skill level is higher. Workers possessing the adequate skill level are considered to be *skill-matched*.

Previous research has shown that individual-level skill mismatches may cause serious consequences and costs for individuals, companies, and societies. For example, skill mismatches come with high financial burdens for societies in the form of wasted public education costs (Acosta-Ballesteros et al., 2018) or lost income taxes due to individuals' lower earnings (International Labour Office, 2018a). Further, skill mismatches are associated with reduced labour productivity (McGowan & Andrews, 2017) as well as with a lower gross domestic product (Mavromaras et al., 2007), and may pose a threat to the long-term growth and economic competitiveness of economies and states (Nikolov et al., 2018). They may also produce costs at the company level. On the one hand, underskilled workers may hamper a company's economic prosperity because they might be less productive and less capable of adapting to technological progress and changes (International Labour Office, 2018a). On the other hand, overskilled workers are more likely to leave their job (Allen & van der Velden, 2001; McGuinness & Wooden, 2009), which is associated with additional recruitment costs (European Commission, 2012). For individuals, skill mismatches are associated with considerable monetary and non-monetary penalties, such as lower wages (Allen, Levels, et al., 2013; Caroleo & Pastore, 2018) and lower job satisfaction (Mateos-Romero & Salinas-Jiménez, 2018). Moreover, skill mismatches are likely to persist in the long term, especially in the case of overskilling (Cedefop, 2015, 2018).

Consequently, it is not surprising that the matching between workers' skills and job requirements has been discussed for decades in academia and policymaking. As early as the 1940s, the International Labour Organization (1944) declared that workers need to be employed in occupations that offer them the opportunity to use their skills to the greatest extent possible. Beginning in the 1970s, the mismatch issue also came to the fore in academic discourse. Initial studies focused on educational qualification mismatches in the USA. These studies addressed, first and foremost, questions of lacking returns to education, or whether the United States has produced too many highly educated graduates which the marketplace is no longer able to absorb (Berg, 1970; Freeman, 1976). Hereafter, mismatch research focused primarily on educational qualification mismatches for a long time. This was mainly due to insufficient data and lack of suitable skill or skill mismatch measurements (Desjardins & Rubenson, 2011; Quintini, 2011). The concept of *educational qualification mismatch* differs from the concept of skill mismatch in that it bases the definition of mismatch on formal educational qualifications (educational level or field of education) instead of skill levels. An individual whose educational level does not match the required level of their job faces an *educational mismatch*, being either undereducated (the educational level is lower than required) or overeducated (the level of education is higher than required). Individuals whose field of education does not correspond to their occupational field exhibit a *field-of-education mismatch* (International Labour Office, 2018a). In light of the improved data accessibility on skills, the academic interest and research on mismatches have increasingly shifted from educational qualification mismatch to skill mismatch in recent years. Moreover, increasing doubts arise as to whether educational qualification mismatches pose a serious problem, given the heterogeneity of skills across educational qualifications (Allen, Badillo-Amador, et al., 2013).

Currently, the topic of skill mismatch is gaining further relevance. This is mainly due to on-going megatrends which engender substantial changes in the labour market, such as globalisation, demographic changes, migration, digitalisation, and technological innovation (Comyn & Strietska-Ilina, 2019; International Labour Organization, 2015). These trends pose continuous challenges to individuals, companies, and economies, as well as to the matching of skills. For example, today's skills may not match the jobs of tomorrow and newly acquired skills may quickly become obsolete (International Labour Organization, 2019). Workers may therefore have to adapt to new and fast-changing skill requirements (Comyn & Strietska-Ilina, 2019). Moreover, companies may have to continuously reskill and upskill their workforce due to ever-changing skill requirements within occupations (International Labour Organization, 2015), and societies face the challenge of skill shortages, having to adapt their education systems due to changing requirements. The efficient matching of skills has recently also been prominently addressed by the European Union. In her 2022 State of the European Union Address, President Ursula von der Leyen emphasized both the necessity and the objective to improve the skill matching of the European workforce (European Commission, 2022). For this purpose, the European Union's Agenda for New Skills and Jobs 2020 is followed by the European Year of Skills 2023.

Germany, the major economy within the European Union, is particularly affected by these significant shifts in the labour market, the economy, and society. For example, Germany faces major challenges due to demographic change and the resulting decline of the working-age population. This may exacerbate the already existing bottlenecks and shortages of skilled labour in the German labour market (Peichl et al., 2022), and may also amplify the issue of skill mismatches in the future. As a technologically advanced industrial country with strong economic relevance and a range of substantial challenges, Germany represents an interesting case for the analysis of individual-level skill mismatches. This promises to provide interesting insights and lessons for modern economies.

Targeted policymaking that addresses, prevents, and counteracts skill mismatches necessitates comprehensive insights into the incidence, causes, and consequences of skill mismatches in the labour market. In turn, detailed information on the extent of different types of skill mismatches, how they occur, and which consequences they entail is required. This dissertation is based on four studies which address these issues by examining different aspects of skill mismatch in the context of Germany. I aim to provide new insights into the skill mismatch issue by contributing to the following overarching questions:

(1) How can skill mismatches be adequately measured?

(2) What are the causes of skill mismatches and how can skill mismatches be explained?

(3) What are the (a) monetary and (b) non-monetary consequences of being skill-mismatched for individuals?

1.1 Measuring skill mismatches

In order to identify the incidence and causes of skill mismatches, and to address the potential consequences of skill mismatches, valid information on individuals' skill mismatch situations is first and foremost required. Effective policymaking necessitates and relies on reliable and valid information on the true incidence of skill mismatch. This is essential, for example, to implement prevention and counteracting policies, training programmes, or programmes for lifelong learning (International Labour Office, 2018a), or to define and adapt education and vocational education policies. The fundamental issue of whether to measure skill mismatches subjectively based on workers' self-assessments, or objectively based on skill tests, also plays a role here. *Subjective skill mismatch* measures ask workers whether they possess the required level of skills for their job. These subjective measures benefit from directly addressing individual workers, who might be best informed of the respective skill mismatch situation (European Training Foundation, 2012). However, such subjective assessments may be biased because workers tend to overstate their skills or upgrade their own position (Brunello & Wruuck, 2021; Hartog, 2000; McGuinness et al., 2018; Perry et al., 2014). In contrast, *objective skill mismatch* measures compare individuals' proficiency in skill tests with the levels of skills required in their job, usually defined as the average skills in an individual's occupation. These measures provide objective and precise information on individuals' skill levels (Green, 2013), but face the challenge of defining corresponding information on job requirements. By definition, objective skill mismatches can only be assessed in objectively testable skill domains (EuroStat, 2016). Moreover, objective skill mismatch measures usually only provide information on individuals' mismatch situations in single skill domains. It is doubtful whether this enables an overall assessment (Perry et al., 2014).

Previous research has demonstrated that subjective and objective measures result in significantly different incidences of skill mismatch (Pellizzari & Fichen, 2017; Perry et al., 2014). Subjective measures are usually characterised by very low underskilling in comparison to quite high overskilling ratios (Cedefop, 2015; McGuinness et al., 2018), whereas objective measures typically indicate the vast majority of individuals as matched (Allen, Levels, et al., 2013; Desjardins & Rubenson, 2011). In political discourses and the economy, the issues of underskilling and the necessity to upskill workers are discussed most prominently. This raises doubts about the plausibility and balance of employees' subjective assessments, given their exceptionally high report of overskilling, with hardly any reported underskilling.

Several approaches to *objective test-based measurement of skill mismatch* have been described and debated in the literature thus far, without an agreement on the best practice method. This is mainly due to the fact that the incidence of skill mismatch differs significantly even between different approaches of objective test-based measures (Flisi et al., 2017), while it remains unclear which measure provides the most valid information. Thus, a comprehensive comparative validation of different test-based measures of skill mismatch is required in order to determine which of these objective measures is most appropriate. Moreover, previous test-based measures only provide information on domain-specific skill mismatches in two skill domains (literacy and numeracy), owing to data limitations. This means that first, previous measures only cover a narrow spectrum of today's most relevant skills and that second, they have not addressed the multidimensional character of skills and skill mismatches thus far (Brunello & Wruuck, 2021).

The first article, *Test-based measurement of skill mismatch: A validation of domain-specific and multidimensional skill mismatch measures using the NEPS* addresses precisely these research gaps. This study provides a comparative empirical validation of five commonly used approaches to test-based measurement of skill mismatch and introduces a new test-based measure of multidimensional skill mismatch. The article presents five methods of test-based measurement of skill mismatch. These differ in how they operationalise skill requirement levels in occupations (*statistical approach:* average skills; *mixed approach:* average skills of subjectively well-matched workers; *job analysis approach*: expert-based assessment; *worker assessment approach*: worker-based assessment; *task approach:* complexity of job tasks). The study adds to previous literature by addressing, for the first time, the validity of the approaches' occupational skill requirement measures, which are essential for the operationalisation of the resulting skill mismatch measures. Moreover, it provides a comparative empirical validation of the five different approaches to test-based measurement of skill mismatch. For this purpose, it applies a range of validation methods, including the validation of the empirical distributions of the skill mismatch measures as well as their links to theoretically relevant predictors and labour market outcomes. Thus, this article evaluates which measurement approach provides the most valid information on individuals' skill mismatch. Furthermore, it introduces a new test-based measure addressing the multidimensional facet of skill mismatch based on the most valid measurement approach. A multidimensional view of skill mismatch is essential because domain-specific mismatches only provide evidence for single skills but not for the global mismatch situation of individuals. Conversely, this multidimensional skill mismatch measure considers individuals' skill mismatch situations in five different cognitive skill domains, i.e. reading, mathematics, information and communication technology (ICT), science, and reasoning. These skills are all highly relevant in today's world of work and thus represent a valuable complement to previous measures.

1.2 Determinants of skill mismatches

Previous research has shown that individuals' skill mismatches are caused by a range of determinants. Macroeconomic conditions such as slack labour market or skill shortages, institutional characteristics such as the vocational orientation of education systems, and social policy measures such as unemployment benefits and activating labour market measures all affect the likelihood of skill mismatches (Fregin et al., 2020; Livanos & Núñez, 2017).

There is also ample evidence that the risk of skill mismatch is associated with relevant individual-level and occupational characteristics. For example, women, older workers, and immigrants are more likely to be underskilled, whereas men, younger workers, and native residents are more likely to be overskilled (Cedefop, 2018; Desjardins & Rubenson, 2011; Livanos & Núñez, 2017; McGowan & Andrews, 2015; Rohrbach-Schmidt & Tiemann, 2016). In this context, the oldest workers (over 55 years old) are particularly affected by skill mismatch (Cedefop, 2018, 2022). Among immigrants, underskilling is particularly prevalent for those with better host language skills and native speakers (Budría & Martínez-de-Ibarreta, 2021; Perry, 2017). The evidence also shows that individuals' personalities affect their chances for skill matching, so that individuals with a more open or conscientious personality are more likely to be overskilled, whereas higher neuroticism is associated with a lower likelihood of overskilling (Esposito & Scicchitano, 2022).

In addition to individual characteristics, the likelihood of skill mismatch also links to occupational characteristics. For example, working in a job with higher occupational skill requirements signifies a lower chance of being overskilled, but a higher risk of being underskilled (Cedefop, 2022). Conversely, workers in low-skilled occupations are more likely to be overskilled, but less likely to be underskilled (Allen, Levels, et al., 2013; Cedefop, 2018). The risk of skill mismatch also varies considerably between occupational groups. For example, plant and machine operators as well as workers in elementary jobs are more likely to be overskilled, whereas managers and professionals are more likely to be underskilled (Cedefop, 2018). These findings suggest that working in more demanding jobs prevents overskilling while increasing the risk of workers to be underskilled, and vice versa for less demanding occupations. Further, working part-time or in the private sector entails a higher risk of overskilling (McGowan & Andrews, 2015).

Individual career experiences and stages are also relevant factors for skill mismatches. For instance, individuals who have previously been overskilled are also more likely to be overskilled in their current jobs (Mavromaras, Mahuteau, et al., 2013). Conversely, individuals with more experience and tenure in their current job face lower risks of being overskilled (Cedefop, 2022) or skill-mismatched (Albiol-Sánchez et al., 2021). While early skill mismatches may lead to path dependencies for individuals' later careers, their risks may also decrease with job experience.

Education may also play a significant role in the context of skill matching, given its exceptional relevance for individuals' participation and success in the labour market (cf. Gebel & Heineck, 2019 for an overview). Education aims to prepare graduates for the labour market and to provide skills that enable individuals to work in jobs matching their talents and interests (Autorengruppe Bildungsberichterstattung, 2018; van de Werfhorst, 2014). This might be particularly relevant in light of recent structural shifts, such as the educational expansion and digitalisation of the professional world, which have caused considerable changes in both the supply and demand for education and skills (Brunello & Wruuck, 2021; Cedefop, 2022). In view of today's broad variety of education and educational qualifications, it is worth examining how different facets and dimensions of education relate to skill mismatches. This is particularly interesting in the case of Germany, considering its highly differentiated education and training system and the strong relevance of educational credentials for individuals' success in the labour market.

Previous research on the relationship between education and skill mismatch has mainly focused on the role of different levels of education, vocational secondary education, or fields of study. These findings indicate that individuals with higher educational qualifications are less likely to be underskilled, but more likely to be overskilled (Cedefop, 2018; Flisi et al., 2017; McGowan & Andrews, 2015; Pellizzari & Fichen, 2017). Moreover, graduates of vocational secondary education programmes are less likely to be overskilled, but more likely to be underskilled in comparison to those with a general secondary education (Allen, Levels, et al., 2013; Verhaest et al., 2018). Conversely, tertiary graduates from presumably less specific fields (e.g. arts and humanities, social sciences, or business and economics) face a higher risk of being overskilled, whereas tertiary degrees in medicine and health tend to prevent overskilling (Assirelli, 2015; Berlingieri & Erdsiek, 2012; Caroleo & Pastore, 2018; Green & McIntosh, 2007; McGuinness & Byrne, 2015). These studies suggest that the risk of skill mismatch varies between different fields and education programmes. However, they do not provide insightful evidence on the underlying mechanism, namely the specificity of education. To gain insights into this black box, it is necessary to address precisely the specificity of education (e.g. vocational specificity and occupational specificity) as well as its link to skill mismatch. This issue is particularly relevant in recent times of higher specialisation and differentiation of education programmes. Moreover, given the increasing rates of lifelong learning, further education, upskilling, and educational reorientation, there is a need for detailed analysis of how the link between individuals' education and skill mismatch varies in the course of the careers.

The second study *The link between education and skill mismatches: An analysis of the role of vocational and occupational specificity from a career perspective* provides a comprehensive and differentiated analysis of how different facets of education (educational level, vocational specificity, and occupational specificity) are related to individuals' skill matching in the labour market. Moreover, this article analyses how these associations vary in the course of the career. The study thus sheds new light on unanswered questions regarding the association between education and skill mismatch, adding to previous literature in several ways. In contrast to earlier studies which have approached the implications of the specificity of education by different fields or education programmes, this study is the first to directly address how vocational specificity of education (i.e. the scope in which education imparts vocation-specific skills) and occupational specificity of education (i.e. how strongly education links to a specific set of occupations) are associated with skill mismatches. Based on specified gradual measures of both vocational and occupational specificity of education, this study provides initial insights into the black box of the specificity of education and its relevance for skill matching. Additionally, this study addresses the relationship between education and skill mismatches from a career perspective. In this way, it pioneers in considering the fact that the level of education as well as the vocational and occupational specificity of education might have different relevance and thus varying influence at diverse stages of individuals' careers. Therefore, this study provides new explanations and insights into which facets of education are more or less valuable for individuals' skill matching in general, and how these associations vary in the course of the career.

1.3 Consequences of skill mismatches

Working in a job that does not match one's skills may result in manifold penalties. Mismatched workers experience stronger work-life conflicts (Shevchuk et al., 2019) and show higher absenteeism in their job (Congregado et al., 2016). Moreover, they are less willing to continue working in their current workplace (Ju & Li, 2019) and are more likely to switch jobs (Guvenen et al., 2020). In this context, previous research has primarily focused on the implications of overskilling. With regard to job changes, for example, overskilled workers are more likely to seek another job (Allen & van der Velden, 2001) and to leave their jobs within the year following the time of the survey (McGuinness & Wooden, 2009). Overskilling may also result in long-term penalties for individuals, as, for example, overskilled workers face a higher risk of future unemployment (Mavromaras et al., 2015). Moreover, workers who are overskilled at the outset of their jobs are less likely to participate in training courses or informal learning opportunities, and show a lower level of skill growth over time (Ferreira Sequeda et al., 2017; van der Velden & Verhaest, 2017). Less evidence is available for the consequences of underskilling, which reveals a somewhat different picture. For example, underskilled workers are more likely to participate in employer-financed training measures (Desjardins & Rubenson, 2011). Being underskilled at the beginning of a job may even be advantageous for individuals' skill growth, as initially underskilled workers are more likely to improve their skills substantially over time (Ferreira Sequeda et al., 2017). This is especially true for those who possess slight skill deficits when starting their jobs (van der Velden & Verhaest, 2017). Both underskilling and overskilling may also affect aspects beyond individuals' working lives. For example, skill mismatch is associated with feelings of social trust, political efficacy, and self-efficacy (Ferrari, 2023; Fregin et al., 2018), and overskilled individuals report lower mental well-being (Zhu & Chen, 2016). These findings suggest that skill mismatches carry various implications for individuals, both inside and outside their professional lives.

Notwithstanding, the vast majority of previous studies on the individual-level consequences of skill mismatches have focused on how skill mismatches affect individuals' wages and job satisfaction. With regard to individuals' *monetary returns*, these studies find substantial wage benefits for underskilled workers and wage penalties for overskilled workers when compared to matched workers with the same level of education or skills (e.g. Allen, Levels, et al., 2013; Bönisch et al., 2019; Desjardins & Rubenson, 2011; McGuinness & Sloane, 2011; Perry et al., 2014; van der Velden & Bijlsma, 2019). While there is strong evidence on the monetary consequences of skill mismatches in general, less knowledge exists about the impact of skill mismatches on individuals' wages in different skill domains. This is because previous studies have only focused on skill mismatches in either literacy or numeracy. However, these two skill domains merely cover a narrow set of basic skills and fail to provide insights into further relevant skills essential for working in the modern economy, such as digital skills. Moreover, previous research has mainly focused on the implications of skill mismatches in only one domain. Thus, current literature does not address whether wage effects due to mismatches in one skill can compensate for those due to mismatches in another skill.

The third article *Which skills pay the bills? How mismatches in different skill domains affect wages and the special relevance of ICT* addresses these issues by analysing whether and how skill mismatches in reading, mathematics, ICT, science, and reasoning are differentially associated with individuals' wages. Moreover, this study investigates whether these wage effects can be compensated by opposing skill mismatches. It presents initial evidence on the link between skill mismatches in five different skill domains and individuals' wages, and accordingly provides the first comprehensive comparison to identify the skill domain in which deficits or surpluses have the strongest monetary implications. Further, the article pioneers in presenting first-time evidence of wage differences due to mismatches in ICT, science, and reasoning, in addition to reading and mathematics. These insights are particularly relevant in light of today's modern knowledge society and the increasingly digitalised world of work, in which these five skills constitute some of the most essential cognitive skills for successful labour market participation and employability (Cedefop & Eurofound, 2018; OECD, 2019; World Economic Forum, 2016). Additionally, this study is the first to investigate whether wage penalties due to domain-specific underskilling and wage benefits due to domain-specific overskilling are equalised by the opposing skill mismatch in ICT. This initial research reflects the fact that ICT skills are relevant across occupations and sectors (Cedefop, 2022), and provides new insights into the significance of digital skills for worker productivity. Furthermore, it considers the multifaceted nature of individuals' skill sets and the fact that skill surpluses in one domain may compensate for skill deficits in another domain, and vice versa.

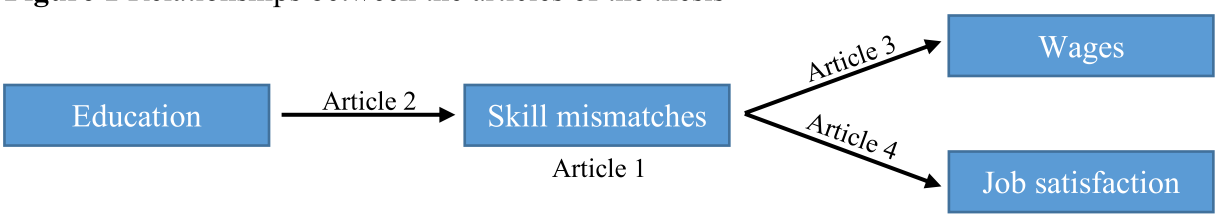
Skill mismatches are also known to affect workers' perceptions and evaluations of their working situation, for example, due to unrealised expectations or a loss of motivation (International Labour Office, 2018a). A broad range of previous studies has shown that underskilling, and especially overskilling, reduce workers' *job satisfaction* (e.g. Allen & van der Velden, 2001; Badillo-Amador et al., 2012; Badillo-Amador & Vila, 2013; Béduwé & Giret, 2011; Congregado et al., 2016; Green & Zhu, 2010; Mateos-Romero & Salinas-Jiménez, 2018; Mavromaras et al., 2012; Mavromaras, McGuinness, et al., 2013; Santiago-Vela & Hall, 2023; Shevchuk et al., 2019; Vieira, 2005). These studies provide evidence of the link between subjectively perceived skill mismatches and job satisfaction. However, the question of whether and in which ways objective skill mismatches affect job satisfaction has not been clearly answered (Allen, Levels, et al., 2013; Bönisch et al., 2019). In addition, this question has only been addressed so far in terms of objective skill mismatches in single skill domains, that is, literacy or numeracy. Recent evidence suggests that only the subjective perception of a mismatch, rather than the objective facts, might be relevant to individuals' job satisfaction (Fregin et al., 2018). This raises new questions about whether subjective and objective skill mismatches carry different implications, and about whether subjective skill mismatches are the only ones relevant to individuals' perceived job quality.

The fourth study of this thesis *Mismatched, but Not Aware of It? How Subjective and Objective Skill Mismatch Affects Employee Job Satisfaction* addresses these questions by focusing on job satisfaction, which is considered to be one of the most relevant aspect of individuals' subjective job quality. This study enriches previous research by indicating the interrelation between objective and subjective skill mismatch, illustrating whether individuals' subjective evaluations correspond to objective reality. In contrast to earlier studies which have addressed objective skill mismatches only in single skill domains (e.g. literacy or numeracy), this study uses a multidimensional measure to better approach individuals' overall objective skill mismatch situations. This facilitates the comparison of individuals' subjective and objective skill mismatches because both refer to overall assessments of individuals' skill mismatch situations. Moreover, it allows to examine, for the first time, whether the previously postulated findings on the link between objective skill mismatch and job satisfaction also apply to individuals' overall skill mismatch situations, or whether this only holds for single skill domains. Additionally, the research clarifies whether both subjective and objective skill mismatches are directly related to individuals' job satisfaction by disentangling the separate implications of both types of skill mismatch. In this way, it provides several new insights into whether both objective and subjective skill mismatch affect workers' job satisfaction, and into the question of which type of skill mismatch matters most for worker satisfaction. Therefore, this study demonstrates that mismatches can carry different implications for individuals' subjective job quality, depending on whether they are objectively given or subjectively perceived.

2 Structure

This thesis is a cumulative dissertation consisting of an introductory overview and four studies. It thereby aims to provide a comprehensive perspective on skill mismatch. With the *validation of skill mismatch measurements* in *Article 1*, education as a *determinant of skill mismatch* in *Article 2*, and *monetary* (wages) as well as *non-monetary* returns (job satisfaction) as *consequences of skill mismatch* in *Articles 3 and 4*, respectively, the four articles each cover different facets of skill mismatch. Figure 1 provides an overview of the structure of the cumulative dissertation, showing how the different aspects of skill mismatch and articles in the thesis are related.

Figure 1 Relationships between the articles of the thesis



Source: Own illustration.

The first article *Test-based measurement of skill mismatch: A validation of domain-specific and multidimensional skill mismatch measures using the NEPS* provides a validation of different test-based measures of skill mismatch. The main aims of this study are to evaluate which approach is best for test-based measurement of skill mismatches, and to introduce a new measure of multidimensional skill mismatch. By this means, the research presented in this first article constitutes the basic foundation of the entire thesis, as the most valid skill mismatch measures are also applied to the empirical analyses of the following articles.

In contrast to the first study, which mainly focuses on measurement methodologies, the following articles place a stronger emphasis on empirical analysis. The second article *The link between education and skill mismatches: An analysis of the role of vocational and occupational specificity from a career perspective* investigates the relevance of education for individuals' skill matching, aiming to explain how different facets of education relate to skill mismatches, and how these associations vary by career stage. In this way, this second study addresses the causes of skill mismatches and the question of how skill mismatches can be explained by individuals' education.

The third article *Which skills pay the bills? How mismatches in different skill domains affect wages and the special relevance of ICT* examines the monetary implications of skill mismatches. Its main objectives are to investigate in which domains skill mismatches have the strongest monetary implications, and to determine whether wage differences due to domain-specific skill mismatches can be compensated by the opposing skill mismatch in ICT. In contrast to the other articles of the thesis, this study emphasises the relevance of domain-specific skill mismatches.

The fourth article *Mismatched, but Not Aware of It? How Subjective and Objective Skill Mismatch Affects Employee Job Satisfaction* addresses affective implications for different types of skill mismatches, highlighting the need to differentiate between subjective and objective skill mismatches and their different meanings for worker satisfaction. Thus, this study illustrates that skill mismatches are also relevant for the subjective perception of job quality.

Overall, this thesis addresses the core issues of skill mismatch, namely how to adequately measure skill mismatch, the causes of individuals' skill mismatches, and which monetary and affective implications may result from them. It thus provides an umbrella view of the topic. Table 1 offers an overview on the four articles of the dissertation and their current publication state.

Table 1 Overview of the articles

Article	Author(s)/Share	Year	Title	Status/Journal
1	Bischof, S./ 100%	2023	Test-based measurement of skill mismatch: A validation of domain-specific and multidimensional skill mismatch measures using the NEPS	Submitted to *Journal for Labour Market Research*
2	Bischof, S./ 100%	2023	The link between education and skill mismatches: An analysis of the role of vocational and occupational specificity from a career perspective	Not published
3	Bischof, S./ 85% Van der Velden, R./ 15%	2023	Which skills pay the bills? How mismatches in different skill domains affect wages and the special relevance of ICT	Not published
4	Bischof, S./ 100%	2021	Mismatched, but Not Aware of It? How Subjective and Objective Skill Mismatch Affects Employee Job Satisfaction	Published in *Social Science*, 10(10) (389)

Source: Own illustration.

3 Theoretical background and hypotheses

This chapter provides a general and comprehensive theoretical framework on the causes and consequences of skill mismatches. Section 3.1 presents theoretical arguments explaining why skill matching between individuals and jobs does not always reach perfection in the labour market, and which determinants may contribute to mismatches. Section 3.2 issues theoretical considerations on why and how skill mismatches affect individuals; in other words, it explores the consequences of these mismatches. The chapter closes with a brief overview on the core theoretical arguments and hypotheses of the four studies of the thesis.

3.1 Why skill mismatches exist and how they arise

Individual-level skill mismatch can be attributed to several reasons. Various circumstances imply that it is not possible to completely avoid mismatches between individuals' skills and those required by their jobs. For example, no perfect fit exists between the skill supply of the working resp. employable population and skill demands in the labour market. Moreover, information on available jobs, skills, or skill requirements is usually imperfect on both the employers' and the employees' side. The job matching literature explains skill mismatches mainly by structural circumstances in society and the labour market, as well as by preferences, motivations, and interests of employees and employers, or by individual and firm characteristics.

Structural macroeconomic conditions and cyclical periods (e.g. economic crises, expansion, or recession) affect the demand for skills and labour, and may thus contribute to individual-level skill mismatches (Brunello & Wruuck, 2021). In addition, structural imbalances between the skill demand of firms and the skill supply of individuals, such as skill shortages and skill surpluses in the labour market, can cause skill mismatches. In view of demand and supply imbalances, individuals may have to accept jobs that do not perfectly match their skills, and firms may have to fill their vacancies with candidates who do not perfectly meet their requirements due to a lack of alternatives. Moreover, structural changes caused by digitalisation, technological advancement, an ageing society, migration, climate change, or exogenous shocks and crises such as the Covid-19 pandemic, may give rise to new or additional skill demand and supply. This may also change the value of certain skills and skill sets, thus further contributing to skill mismatches.

Both in the case of individuals and firms, there may also be interests and motivations for individuals to work in a job that does not match their skills, or for firms to employ skill-mismatched individuals or recruit skill-matched individuals for their vacancies. For example, individuals may select jobs that first and foremost fit their preferences, rather than their skills. They may thus consciously choose a job for which they are overskilled. Individuals might be motivated to make such a choice, for instance, by wanting to reduce stress and pressure, attain a higher job security, achieve a better work-life balance, secure an intrinsically rewarding and meaningful job, or simply because they do not care whether or not they can make use of their skills (Büchel, 2001; Cedefop, 2015; Desjardins & Rubenson, 2011). Firms may also consciously employ skill-mismatched individuals. On the one hand, they may choose to hire underskilled workers with strong growth potential as a cheaper alternative, trying to address their skill deficits through on-the-job training and investments in specific training (Livanos & Núñez, 2017). On the other hand, firms might be interested in hiring overskilled workers for their vacancies because they might be more productive than workers with matching skill levels, cause lower training costs, and bring additional skills to the company (Cedefop, 2012; García-Mainar & Montuenga-Gómez, 2020). Firm policy and a firm's recruitment, monitoring, and human resource development strategies might also affect the likelihood of skill mismatches. Moreover, both individuals and firms may accept a mismatched job or hire a mismatched applicant due to the temporary lack of suitable alternatives and, therefore, only as a second-best interim solution (Büchel, 2001; European Training Foundation, 2019). Imperfect information on the actual skill requirements of the job or on the skill set of the applicants may also play a role (Spence, 1973).

Furthermore, individuals' sociodemographic characteristics and social resources can affect the risk of skill mismatch. For example, any discrimination in access to jobs and job positions (e.g. due to gender, socioeconomic, or immigration background) may negatively affect skill matching in the labour market, thus increasing the risk of skill mismatches for those groups affected (European Training Foundation, 2012). In contrast, individuals with high social capital and supportive social networks might be more likely to find a job that matches their skills (Franzen & Hangartner, 2006; Granovetter, 1973, 1974; Mouw, 2003), due to proven information on job vacancies and potential employers, for instance.

Education is also presumed to be highly relevant to individuals' labour market success and skill matching. For example, the human capital theory (Becker, 1964) assumes that higher educational attainment increases individuals' human capital, skills, and productivity, and therefore their chances in the labour market. This may also improve individuals' likelihoods of securing a job that matches their skills. In contrast, the job-competition theory (Thurow, 1979) and the signalling theory (Spence, 1973) consider education as a positional good to which employers may refer, especially in the application process, due to a lack of information about the actual productivity of individuals. Higher educational attainment might signalise higher skills, productivity, learning, and adaptability potentials, but lower training costs. Therefore, individuals with a higher level of education might have better opportunities in the job market and may thus obtain a matching job more easily. Besides the level of education, skill matching may also be affected by the field of education, the specificity of the education programme, and the specificity of skills gained in education. On the one hand, less specific fields (e.g. sociology or philosophy) or general education programmes impart graduates with more general skills which are assumed to raise individuals' productivity in a broad set of skills and tasks (Becker, 1964). On the other hand, more specific fields (e.g. dentistry or pharmacy) or vocational education and training programmes provide graduates with specific skills. These skills are assumed to increase individuals' productivity in specific tasks. More specific education and more specific skills can thus be expected to better prepare graduates for their specific occupation, and to make them more employable and ready for the job (Gebel & Noelke, 2011; Kleinert & Jacob, 2019; Verhaest et al., 2018). This may also cause them to be more attractive to potential employers. Moreover, provided that graduates of a more specific field or education programme are employed in an occupation which matches their educational background, they are likely to have acquired the required specific skills in education, which also renders them less likely to be affected by skill mismatches. Graduates from different fields of education may also face unequal risks of mismatch due to field-specific under- or over-supply of skilled workers. In addition, the risks of skill mismatch may vary due to field-specific social closure policies that restrict access to certain occupations to graduates of the corresponding field or educational credentials, such as medicine, law, teaching, or through state examination (Barone & Schindler, 2014).

Skill mismatches may also arise, pass, and become more or less pronounced in the course of professional life, depending on the career stage. Especially for labour market entrants, skill mismatches may be more prevalent, as this group may possess skill deficits due to a lack of professional experience, or may accept a job below their skill level as a temporary stepping stone for their further career path (Sicherman & Galor, 1990). However, these higher risks may diminish over the course of a career, as both work experience and knowledge about the labour market increase. Initially mismatched individuals may, for example, transfer to matching jobs (Jovanovic, 1979), perform in-company transitions (Cedefop, 2018), or be dismissed by the employer. Even without internal or external job mobility, initially underskilled workers may compensate their skill deficits with time through on-the-job learning or further training measures, while initially overskilled workers may lose their skill surpluses if they do not make use of them (Bynner & Parsons, 1998; De Grip et al., 2008; Krahn & Lowe, 1998; Salthouse, 2006). Additionally, an age-related decline of skills (Desjardins & Warnke, 2012; Paccagnella, 2017) or changing external conditions may affect the likelihood of skill mismatch over time. These altered circumstances may involve, for example, a shifting relative value of skills and education due to technological changes and educational expansion (Acemoglu, 2002; Ortiz & Rodriguez Menés, 2016), skill obsolescence (Schultheiss & Backes-Gellner, 2023; van Loo et al., 2001), or changing occupational profiles and job tasks (Spitz-Oener, 2006).

In this context, the *varying relevance of education and skills over the course of a career* may also be of importance. For example, more specific education programmes and more specific skills might be beneficial to obtaining a matching job upon entering the labour market due to more ready-to-use skills (Rözer & Bol, 2019). However, this initial advantage may turn into a disadvantage for long-term matching due to a lower adaptability to changing demands in the course of the career (Forster et al., 2016; Hampf & Woessmann, 2017; Krueger & Kumar, 2004). In this way, the varying value and importance of education and skills at different stages of a career may influence the risk of skill mismatch.

3.2 Why and how skill mismatches affect individuals

Skill mismatches are assumed to affect individuals' professional lives in several ways. On the one hand, skill mismatches may influence individual job performance, labour market returns, and career paths. On the other hand, skill mismatches may also affect individuals' subjectively perceived job quality, i.e. how they think about and evaluate their employment situation.

With regard to career paths, skill mismatches may influence individual job mobility because mismatched workers might be more likely to either voluntarily change their jobs or to be dismissed than workers with matching skills are. For example, underskilled workers may suffer from skill deficits and may feel overchallenged by their job tasks and requirements. This renders them more likely to seek a job which better matches their skills. Employers may also lay off underskilled employees due to their lower productivity rates, instead hiring individuals with matching skills as a replacement if given the alternative. Conversely, overskilled employees may feel underchallenged and consider their current position as a "bad deal", for example, due to lower wages or poor opportunities for development and promotion in their further career. Therefore, overskilled workers may be more interested in leaving their jobs in favour of a better alternative.

Individuals' skill (mis)match situations may also affect their participation in further training. For example, underskilled workers might be interested in further training measures to address their skill deficits and cope with job challenges more effectively. Such training might also be beneficial for employers, as it reduces productivity losses due to employee skill deficiencies while increasing the productivity of their companies. In contrast, workers with matching skills, and especially those with skill surpluses, might be less motivated to participate in upskilling measures, given their potentially lower necessity or anticipated benefits.

The matching situation between individuals' skill levels and skill requirements in their jobs may also influence worker productivity and, thus, their monetary returns. In this context, the same skill (mis)match situation can have different implications depending on the reference. When comparing the *productivity of workers in jobs with the same skill requirements,* underskilled workers possess skill deficits and may be less productive, whereas overskilled workers have skill surpluses and may be more productive than workers with matching skills. However, the actual level of productivity may also depend on the level of complexity and skill requirements of the job, and on the extent to which workers can make use of their skills (Sattinger, 1993). When comparing the *productivity of workers with the same level of skills*, underskilled individuals work in jobs above their skill level. This may force them to put the full scope of their skills into productive use. Thus, they may be even more productive than they would be if working in a job with matching skill requirements (Quintini, 2011). In contrast, overskilled workers may face a productivity ceiling due to not being able to fully utilize their skills, potentially rendering them less productive than they would be in a job with matching skill requirements (Quintini, 2011).

Following the argumentation of human capital theory (Becker, 1964), *individuals' productivity determines their wages*. Given the reference of individuals working in jobs with the same level of skill requirements, underskilled workers are assumed to be less productive, while overskilled workers are assumed to be more productive than workers with matching skills. Therefore, the less productive underskilled workers may earn lower wages, whereas the more productive overskilled workers may earn higher wages than matched workers. Conversely, individuals with the same level of skills may be more productive when working in a job with requirements above their skill level (underskilled), but less productive when working in a job for which they are overskilled, than they would be in a job with matching skill requirements. Against this reference of individuals with the same level of skills, underskilled workers may thus earn higher wages, whereas overskilled workers may earn lower wages in comparison to workers with matching skills.

Following job competition theory (Thurow, 1975), in contrast, individuals' marginal productivity is relevant as a positional good in the job recruitment process, but not in terms of wages. This builds on the assumption that productivity and wages depend on job characteristics instead of workers' skills. Applied to the context of skill mismatches, matched and mismatched individuals working in the same job would therefore earn the same wages. However, among workers with the same level of skills, underskilled workers are expected to earn higher wages than matched workers, while overskilled workers are expected to earn lower wages. This is assumed due to the higher (underskilled) resp. lower (overskilled) job requirements.

Whether and to what extent skill deficits or surpluses affect worker productivity and wages may furthermore depend on the skill domain. Therefore, the monetary implications of skill mismatch may differ significantly across skill domains, depending, for example, on the relevance of the respective skill to the labour market. Given the highly technological and digitalised nature of today's working world, ICT skills may be of special relevance in this context.

How mismatched individuals handle and cope with their situation (e.g., by upskilling, reskilling, professional reorientation, or job quitting) may further depend on their subjective perception. This may also determine how the situation affects their *subjective job quality*.

According to person-environment fit theory, a mismatch between individuals' skills and job demands may cause stress and strain responses (Edwards, 1991, 1996; French et al., 1982). In this context, mismatches between individuals' skills and job demands are expected to constitute a burden if the job is either underchallenging or overchallenging (Csikszentmihalyi, 1975). While individuals enjoy challenges that are fairly balanced with their skills and may thus enter a state of flow, this is not the case for understraining or overstraining challenges (Csikszentmihalyi, 1990). On the one hand, underskilled workers may be strained by overchallenging job tasks or workloads. Given their skill deficits, underskilled workers might feel pressure, worry, or even anxiety; for example, if they cannot meet job requirements or if they may expect to be dismissed or replaced by matching individuals. On the other hand, overskilled workers might be bored, as they may not make use of their full scope of skills and may perceive their jobs as unchallenging. Both feelings of strain and boredom due to underskilling or overskilling may, for instance, reduce individual job satisfaction.

Moreover, skill mismatches may affect how workers cope with time- and strain-based work demands which might impact their work-life balance (Greenhaus & Beutell, 1985). For example, underskilled workers may have to spend comparatively more time and cognitive resources to meet their job demands, and may face trouble completing their tasks in the time allotted (Shevchuk et al., 2019). Additionally, underskilling may cause mental stress situations in professional life, such as exhaustion or anxiety, which might spill over to private life. In contrast, overskilled workers might face less overchallenging stress and may experience less burden in terms of working time. Accordingly, underskilled workers may be less, and overskilled workers more able to reconcile their professional and working life, and thus may have a lower resp. higher work-life balance.

However, objective conditions such as being underskilled or overskilled in the job neither necessarily affect workers' subjective perceptions in the same way, nor do they necessarily imply stressful reactions (Lazarus & Folkman, 1986). According to appraisal theory (Lazarus, 1991; Smith & Lazarus, 1990), objectively identical situations may cause different emotional reactions in different individuals. These reactions may depend on how the situation is appraised and on how much relevance is personally attributed to a certain matter. Furthermore, stressors presumably only trigger an affective reaction if the individual subjectively perceives and evaluates the stressor (Caplan, 1987; Lazarus & Folkman, 1986; Lazarus & Launier, 1978). Since the same stressor may be interpreted differently by different individuals, it may cause different emotions and reactions. For example, underskilled workers may perceive their skill deficits as a threat and stressor, a challenge, or an opportunity for personal development. This may imply, for example, that underskilling and overskilling do not necessarily affect individuals' subjective job quality per se. Moreover, individuals' affective implications may primarily depend on whether a skill mismatch is perceived as such and whether a person considers this situation as burdening.

In sum, the theories suggest that various factors driving skill mismatches exist, and that education may play a special role for individuals' matching, even over the course of their careers. Skill mismatches are also expected to affect individuals' labour market success and may influence their subjectively perceived job quality. Still, skill-mismatched workers may perceive and interpret their situation in different ways; for instance, as a challenge or a strain. Therefore, skill mismatches may have varying relevance to worker job quality under certain circumstances. Table 2 provides an overview of the core theoretical arguments and all hypotheses of Articles 2, 3, and 4, which address the determinants and consequences of skill mismatch.

Table 2 Overview on the theoretical arguments and hypotheses of the Articles 2, 3, and 4

Article	Theoretical argumentation	Hypotheses
2	Individuals with higher levels of education possess higher levels of skills, and are thus less likely to have skill deficits but more likely to have skill surpluses. Employers may prefer to hire individuals with higher levels of education because they signalise higher productivity even when the job is below their skill level.	**H1.** *Individuals with a higher level of education (upper secondary, post-secondary non-tertiary, tertiary education) are less likely to be underskilled for their job* **(H1a)** *but more likely to be overskilled for their job* **(H1b)** *than individuals with a lower level of education (lower secondary education).*
	More vocational-specific education provides more vocational-specific skills, which prepare graduates more specifically for specific job tasks in their profession. This increases the likelihood of ensuring that individuals possess the skills required by their job.	**H2.** *The higher the vocational specificity of an individual's education, the lower their likelihood to be underskilled for their job* **(H2a)** *and the lower their likelihood to be overskilled for their job* **(H2b)**.
	More occupation-specific education prepares graduates for a specific set of occupations and provides a strong link to occupational destinations. This increases graduates' chances to work in a matching occupation and reduces their risks of working in an occupation that does not match their educational resp. skill profiles.	**H3.** *The higher the occupational specificity of an individual's education, the lower their likelihood to be underskilled for their job* **(H3a)** *and the lower their likelihood to be overskilled for their job* **(H3b)**.
	Individuals with higher levels of education may be more likely to compensate for initial skill deficits, to adapt to new job requirements, and to show lower risks of skill depreciation. The higher risks of individuals with higher educational attainment for overskilling at the beginning of their career may decrease over time, given their better chances for upward mobility.	**H4.** *The longer the time since graduation, the less likely individuals with a higher level of education (upper secondary, post-secondary non-tertiary, tertiary education) are underskilled or overskilled for their job compared to individuals with a lower level of education (lower secondary education).*
	More vocational-specific education and skills provide graduates with more ready-to-use skills. These are beneficial when entering the labour market but disadvantageous in the long run, given their limited flexibility if skill demands change over time.	**H5.** *The longer the time since graduation, the weaker the preventive influence of vocational specificity of education on avoiding skill mismatch (underskilling or overskilling).*
	More occupational-specific education is beneficial for initial access to a job, but less relevant over the course of a career when flexibility and adaptability may gain importance.	**H6.** *The longer the time since graduation, the weaker the preventive influence of occupational specificity of education on avoiding skill mismatch (underskilling or overskilling).*

3	Underskilled workers are less productive and earn lower wages than matched workers in the same job, whereas overskilled workers are more productive and earn higher wages. Given the crucial relevance of ICT skills in today's world of work, ICT mismatches may be more relevant for worker productivity than mismatches in other skill domains. This is why wage penalties and wage benefits due to mismatches in ICT may be stronger than in other skill domains.	**H1a.** *Individuals underskilled in ICT suffer stronger wage penalties than individuals underskilled in other skill domains.* **H1b.** *Individuals overskilled in ICT receive stronger wage benefits than individuals overskilled in other skill domains.*
	ICT deficits may reduce workers' overall efficiency and productivity, and thus may eliminate wage benefits due to skill surpluses in other skill domains.	**H2a.** *Wage penalties due to ICT underskilling eliminate wage benefits due to overskilling in other skills.*
	ICT surpluses may enhance workers' overall efficiency and productivity, and thus may compensate for wage penalties due to skill deficits in other skill domains.	**H2b.** *Wage benefits due to ICT overskilling compensate for wage penalties due to underskilling in other skills.*
4	While matched workers may enter a state of flow, underskilled workers may be overchallenged and overskilled workers may be underchallenged. Subjectively mismatched workers may thus feel either stressed or bored and may be less satisfied with their job.	**H1.** *Subjectively skill mismatched employees show less job satisfaction compared to subjectively skill matched employees.*
	Objective skill mismatches may cause stressors, overstraining underskilled workers and impeding overskilled workers from using their full scope of skill potentials. This is why they may be less satisfied with their job.	**H2.** *Objectively skill mismatched (underskilled or overskilled) employees show less job satisfaction compared to objectively skill matched employees.*
	Workers who perceive themselves to be mismatched may feel overworked or bored, even if they are not mismatched under objective conditions. These perceptions may make them less satisfied with their job.	**H3.** *Subjectively skill mismatched employees show less job satisfaction compared to subjectively skill matched employees even when controlling for objective skill mismatch.*
	Objectively underskilled workers may face difficulties in dealing with job requirements, and objectively overskilled workers cannot make use of their skill potentials, irrespective of whether they perceive themselves to be mismatched. Objectively mismatched workers thus face objective stressors, which may make them less satisfied with their job.	**H4.** *Objectively skill mismatched (underskilled or overskilled) employees show less job satisfaction compared to objectively skill matched employees even when controlling for subjective skill mismatch.*

Source: Own illustration.

4 Research designs

This chapter presents the research designs of the four articles. Section 4.1 provides basic information on the German National Educational Panel Study (NEPS) Adult Cohort used for the empirical analyses of the four studies. This section highlights the benefits of these data for skill mismatch research and outlines the selection of the analytical samples. Section 4.2 describes the operationalisation of the different skill mismatch measures used in the four articles and provides a brief overview of the other independent and dependent variables of the articles. Section 4.3 presents the different analytical strategies and methods applied and provides a brief discussion on approaches to modern causal analysis. The chapter closes with a summarizing overview of the research designs and methods of the four articles.

4.1 Data and samples

The four articles rely on data from the German National Educational Panel Study (NEPS) Adult Cohort. In general, the NEPS provides rich information for investigating the relevance and implications of education in Germany throughout the life course (Blossfeld & Roßbach, 2019). Following a multicohort sequence design, the NEPS possesses longitudinal information on individuals' biographies through retrospective questioning, as well as annually conducted surveys on a large number of participants of different starting cohorts from new-borns to older adults. In this way, the NEPS provides comprehensive information on individuals' sociodemographic and socioeconomic background, personality, skills, educational attainment, returns to education, and labour market biographies throughout their life course (Blossfeld & Roßbach, 2019).

The empirical analyses of this thesis are based on the NEPS Adult Cohort. The first survey of the NEPS Adult Cohort named Working and Learning in a Changing World (ALWA) started in 2007 and consisted of adults living in Germany. The total sample of respondents of the NEPS Adult Cohort comprises adults born between 1944 and 1986 of three subsamples with a gross sample of 17,140 individuals (6,855 of the ALWA sample; 5,077 of the NEPS wave 2 enhancement and refreshment sample; 5,208 of the NEPS wave 4 refreshment sample) (NEPS Network, 2022). Given the extensive information on the educational and employment biographies of the respondents from different stages, the NEPS Adult Cohort allows to investigate the situation of employed individuals in the labour market, the role of education, and their labour market returns.

Moreover, the NEPS Adult Cohort offers particular opportunities for analysing the measurement, determinants, and consequences of skill mismatch. This is mainly due to test-based information on the skill levels of employed adults in five conceptually different skill domains (reading, mathematics, ICT, science, and reasoning), all of which are highly relevant for successful participation in today's labour market (Cedefop, 2022; OECD, 2019). This information on the skill levels of workers is essential to operationalise test-based measures of skill mismatch and allows for a multidimensional view of skills and skill mismatches, given the broad coverage of relevant cognitive skill domains. In addition to the various options for objective test-based measurement of skill mismatches, the NEPS Adult Cohort also provides information on subjective skill mismatch, enabling analyses of how both types of mismatch are interrelated and whether they have different implications. In some of the analyses, the NEPS Adult Cohort data is enriched by additional information from external data sources.

There are some basic criteria for the analysis samples across the articles, but there are also some minor variations in the sample selection procedure depending on the primary focus of the respective study. The empirical analyses of the four articles each draw on cross-sections of the NEPS Adult Cohort. This is due to the fact that there are no repeated measures of skill levels for most skill domains, and thus no skill mismatch information in the panel. Articles 1, 2, and 3 draw on cross-sections of the 2016 wave of the NEPS Adult Cohort because the most recent skill tests used for operationalising objective skill mismatch were conducted in this wave. Conversely, Article 4 uses a cross-section of the 2018 wave because it provides first-time information on workers' subjective skill mismatch. Across the four studies, the analysis sample is restricted to individuals currently employed at the time of the survey conduct. In this context, the analysis samples consistently focus on dependent-employed core workers. These are defined as having a maximum age of 65 years and being employed for at least 15 hours per week, while excluding self-employed individuals, those in pre-professional employment (e.g. internship, student assistant, etc.), as well as freelancers, family workers, and individuals employed in active labour market programmes or seasonal work. Given the age structure of participants in the NEPS Adult Cohort, the four studies do not include individuals under the age of 30.

4.2 Measurements

Skill mismatch is the central focus of all four articles. Across the individual studies, however, skill mismatch is operationalised in different ways. I use different skill mismatch measures, which represent both independent and dependent variables, depending on the main research interest of the article.

Test-based measures of skill mismatch are used in each of the four papers. These measures are characterised by comparing an individual's skill level (assessed through a skill test) to the level of skill requirements in their occupation. Workers with skills lower than those required for their job are defined as being underskilled, while those with skill surpluses are defined as being overskilled, and those with matching skills are defined as being matched. The NEPS Adult Cohort provides skill tests for the five cognitive skill domains of reading, mathematics, ICT, science, and reasoning.[1] Individuals' skill levels in the single skill domains are defined by their scores in the skill test. These scores are provided as weighted maximum likelihood estimates. The most recent skill tests were conducted in different waves depending on the skill domain (ICT and science in wave 2012; reasoning in wave 2014; reading and mathematics in wave 2016). I assume individuals' skill levels to remain constant between the most recent measurement and the time referred to by the analysis, given that the skill levels of adults do not essentially change over relatively brief periods (Lechner et al., 2021). Not all NEPS Adult Cohort participants were tested in all skill domains because some did not participate in each wave or refused in-person interviews. Moreover, all NEPS wave 4 refreshment sample participants were only tested in reading and reasoning, but not in mathematics, ICT, or science (FDZ-LIfBi, 2022). For those individuals affected, I imputed their skill level in the respective skill domain, following the multivariate imputation by chained equations approach (van Buuren & Groothuis-Oudshoorn, 2011).[2]

There are various approaches to test-based measurement of skill mismatch which differ in the way they operationalise the skill requirement levels per occupational group. Article 1 uses five different approaches (statistical, mixed, job analysis, worker assessment, and task approach) to test-based measurement of skill mismatch in mathematics. Additionally, this study introduces a multidimensional skill mismatch measure which applies the mixed approach. The five different measures of skill mismatch in mathematics are operationalised by comparing an

[1] The NEPS concept of cognitive basic skills includes reasoning and perceptual speed. However, previous research indicates that the general, domain-unspecific aspect of cognitive skills is best represented by reasoning skills (Brunner et al., 2014). Table A1 in the Appendix provides an overview of the NEPS definitions and conceptual frameworks of the five skill domains.

[2] For methodological reasons, different numbers of imputations had to be used for different skill domains: reading (19), mathematics (45), ICT (44), science (39), and reasoning (10). To ensure that for each individual, only one test score is assigned, the average of the imputed values per individual and per skill domain is defined as the relevant test score in the respective skill, following the OECD (2013) approach.

individual's skill level in mathematics with the level of mathematical skill requirements in their occupation. Following the respective procedure, the occupational skill requirements are defined as the average score in mathematics of workers belonging to the same occupational group plus and minus one standard deviation. Workers are classified as being underskilled, matched, or overskilled in mathematics, depending on whether they possess lower, higher, or matching levels of mathematical skills.

The multidimensional measure of skill mismatch is based on the mixed approach (cf. Pellizzari & Fichen, 2017) and considers individuals' mismatch situations in each of the five skill domains. First, the five skill mismatch measures in the single skill domains are operationalised. In this context, individuals are considered to be underskilled or overskilled if their skill level in the respective skill is more than one-half of a standard deviation below or above the average skill level of subjectively matched workers in their occupational group. If their skill level is within this range, individuals are considered to be matched. This means that each individual is classified as being underskilled, matched, or overskilled in each of the five single skill domains. Subsequently, the multidimensional skill mismatch measure defines individuals as being underskilled overall resp. overskilled overall if they are underskilled resp. overskilled in the majority of skills, that is, in at least three out of five skills. Individuals are considered as being matched overall if they are matched in the majority of skills, or if they are neither underskilled nor overskilled in at least three of the five skill domains.

Articles 1 and 2 use this multidimensional measure of skill mismatch which applies the mixed approach with plus and minus one-half of a standard deviation defining the threshold values. In Article 4, I also use a multidimensional measure of skill mismatch that follows the procedure of the mixed approach. However, the multidimensional measure in Article 4 differs from the multidimensional measures in Articles 1 and 2 in using one standard deviation instead of one-half of a standard deviation. For multidimensional measures, in contrast to domain-specific measures, it is beneficial to use one-half instead of one standard deviation because this method not only considers individuals with strong mismatches in individual skills. This ensures sufficient coverage of workers who are underskilled or overskilled overall in the multidimensional measure. By comparison, the one standard deviation method is more restrictive, meaning that only those individuals with a strong skill surplus or deficit in individual skills are considered as mismatched. Thus, only those with strong deficits or surpluses in the majority of skills are considered to be underskilled or overskilled overall. I apply the more restrictive one standard deviation method in the case of Article 4 to analyse whether relatively strong objective skill mismatches affect individuals' job satisfaction.[3]

Article 3 focuses on the implications of domain-specific skill mismatches, using five different skill mismatch measures for reading, mathematics, ICT, science, and reasoning. These five domain-specific skill mismatch measures are operationalised by applying the mixed approach, using plus and minus one standard deviation from the average skill level of subjectively matched individuals as a matching reference. Across the four articles, the skill mismatch variables enter the models as underskilling and overskilling dummy variables, irrespective of domain-specific or multidimensional skill mismatch.

In addition to the test-based measure of multidimensional skill mismatch, Article 4 includes a subjective skill mismatch measure. Individuals who somewhat agree or completely agree to the statement "The requirements of the job match my skills" are defined as subjectively skill-matched. Conversely, those who partly agree, somewhat disagree, or completely disagree are considered to be subjectively skill-mismatched. However, this measure does not provide any information on the direction of the mismatch; that is, whether mismatched individuals possess skill deficits or surpluses. Therefore, it does not allow the differentiation between underskilled and overskilled individuals among those who assess themselves as mismatched, but only between skill-matched and skill-mismatched workers. Table 3 provides an overview on the different skill mismatch measures of the four articles.

Table 3 Overview on the skill mismatch measures used for the main empirical analyses

Article	Dimension	Approach	Method	Categories
1	domain-specific	statistical (test-based) mixed (test-based) job analysis (test-based) worker a. (test-based) task (test-based)	mean ± 1 SD	US, MA, OS
	multidimensional	mixed (test-based)	mean ± 0.5 SD	US, MA, OS
2	multidimensional	mixed (test-based)	mean ± 0.5 SD	US, MA, OS
3	domain-specific	mixed (test-based)	mean ± 1 SD	US, MA, OS
4	multidimensional	mixed (test-based)	mean ± 1 SD	US, MA, OS
	global	subjective	self-assessment	MA, MIS

Notes: SD (standard deviation), US (underskilled), MA (matched), OS (overskilled), MIS (mismatched).
Source: Own illustration.

[3] Additionally, the Supplementary Material of Article 4 provides the main model based on the less restrictive one-half standard deviation method.

Furthermore, the analyses of the articles include determinants (independent variables) and consequences (dependent variables) of skill mismatch. In Article 1, the skill mismatch measures are validated with regard to their relation to relevant sociodemographic, educational, and occupational determinants (gender, age cohort, educational attainment, educational mismatch, and occupational level) and consequences (gross hourly wages). Article 2 addresses the relevance of different facets of education as determinants of skill mismatches, analysing the role of vertical education (level of education) and horizontal education (vocational specificity of education, occupational specificity of education), as well as the moderating role of time since educational graduation. Articles 3 and 4 address the consequences of skill mismatches, analysing the monetary (gross hourly wages) and non-monetary (job satisfaction) implications of being skill-mismatched. In addition, the regression models include a set of relevant control variables depending on the analysis strategy of the study. These cover, for example, sociodemographic, educational, and occupational characteristics as well as information on individuals' socioeconomic background or personality.

4.3 Analytical strategies

The four articles of this thesis pursue different analytical strategies and objectives, despite their basic similarities in methodological approaches.

The main purpose of *Article 1* is to evaluate the *validity of different test-based measures of skill mismatch*. This involves different validation methods. I evaluate the *plausibility of threshold values* of occupational skill requirements. These are essential for the resulting skill mismatch measures, as they determine the skill level at which individuals are defined as either underskilled or overskilled in the respective approach. Moreover, I analyse the *validity of the empirical distributions* of the different skill mismatch measures and assess their *construct validity* by testing whether they are associated with key sociodemographic and occupational predictors of skill mismatch in a theoretically expected manner. For this purpose, I run binary logistic regression models to analyse whether and how the theoretically assumed predictors are linked to underskilling and overskilling. I also test the *criterion-related validity* of the skill mismatch measures. To this end, I analyse how the different skill mismatch measures are related to a key labour market outcome. Based on OLS regressions, I test the relation of both underskilling and overskilling to individuals' wages by applying Duncan and Hoffman's (1981) so-called Overeducation-Required education-Undereducation (ORU) model, modified for skill mismatch. These ORU models include a set of relevant control variables, whose selection, however, does not follow causal methodological considerations. This is because Article 1 does not aim to explain causal relationships.

Conversely, the other studies of the thesis aim to eliminate non-causal associations in order to get closer to the *causal paths*. This concerns the paths between different facets of *education and skill mismatches (Article 2)*, between *skill mismatches and wages (Article 3)*, and between *skill mismatches and job satisfaction (Article 4)*. Of course, this is accompanied by problems of selection on observables, because analyses can only control for common causes which are observable.

Following the *methods of modern causal analysis*, regression analyses need to account for relevant factors that may affect both the respective treatment and outcome variables to prevent unbiased estimates (Elwert & Winship, 2014). Thus, by only controlling for the common causes, it is possible to avoid overcontrol bias and endogenous selection bias, and to identify the total effect of the treatment on the outcome (Elwert & Winship, 2014). Accordingly, in *Article 2*, the regression models only include control variables which are a common cause for the respective independent variable (e.g. educational level, vocational specificity, or occupational specificity) and the respective dependent variable (e.g. underskilling or overskilling). I apply separate binary logistic regression models indicating the average marginal effects for how individuals' educational level as well as vocational specificity and occupational specificity are linked to the likelihood of being underskilled resp. overskilled. Additionally, I estimate interaction models to indicate how the associations between educational levels, vocational specificity, and occupational specificity and skill mismatches vary with the years passed since individuals' educational graduation.

Article 3 aims to identify how skill mismatches in different skill domains affect individuals' wages, and whether wage differences due to ICT mismatches equalise wage differences due to opposing mismatches in another skill domain. For this purpose, my co-author and I first investigate how underskilling and overskilling in reading, mathematics, ICT, science, and reasoning affect individuals' wages, running separate OLS regressions for each of the five skill domains. We apply modified ORU models which account for individuals' occupational skill requirements in the respective skill domain, in order to identify how the wages of underskilled workers resp. overskilled workers differ from the wages of matched workers with the same occupational skill requirements. Additionally, we perform pairwise analyses, which simultaneously consider opposing skill mismatches in two skill domains. This is to investigate whether wage penalties due to ICT underskilling eliminate wage benefits due to overskilling in another domain, and whether wage benefits due to ICT overskilling compensate for wage penalties due to underskilling in another skill. Beyond the main analyses in Article 3, I provide some additional analyses in the Supplementary Material to address some aspects that have not yet been considered in the study. This comprises, for example, interaction models for interactions between single-domain overskilling and ICT underskilling resp. between single-domain underskilling and ICT overskilling, as well as models which additionally control for further observable confounding variables.

The objective of *Article 4* is to investigate the direct relationship between objective resp. subjective skill mismatches and job satisfaction using OLS regressions. In line with the methods of modern causal analysis, I only control for observable confounders that are likely to condition both the respective treatment (objective skill mismatch, subjective skill mismatch) and the outcome (job satisfaction). Moreover, I estimate an additional model which simultaneously includes objective and subjective skill mismatch in order to identify the separate effects of both types of skill mismatch while controlling for the other.

The analytical strategy in Articles 2, 3, and 4 is inspired by methods of modern causal analysis, which, notwithstanding their strengths, also contain limitations. For example, even when being able to control for all observable confounding variables, the possibility of further potential unobserved confounders still remains. Such unobserved confounders may affect both the treatment and the outcome, but cannot be conditioned on as they are not observed. For instance, individuals differ in how they value leisure time, work strain, and work-life balance. These might be common causes for selecting matching jobs and for job satisfaction, for example, but cannot be conditioned on in the analyses as they are not observed. Table 4 summarises the main analytical strategies and methods used in the four articles.

Table 4 Overview on the analytical strategies of the articles

Article	Data	Sample	Independent variables	Dependent variables	Methods
1	NEPS Adult Cohort, 2016 wave	Dependent-employed core workers, aged 30 to 65	Female, age cohort (36 to 45 y., 46 to 55 y., 56 to 65 y.), tertiary education, educational mismatch (undereducation, overeducation), high complex occupational level	US, OS (mathematics) US, OS (multidimensional)	Logistic regressions (predictors analysis)
			US, OS (mathematics) US, OS (multidimensional)	Ln gross hourly wages	OLS regressions (ORU model)
2	NEPS Adult Cohort, 2016 wave	Dependent-employed core workers, aged 30 to 65	Educational level (upper sec. educ., post-sec. non-tert. educ., tertiary educ.), vocational specificity of education, occupational specificity of education Moderator: time since graduation	US, OS (multidimensional)	Logistic regressions
3	NEPS Adult Cohort, 2016 wave	Dependent-employed core workers, aged 30 to 65	US, OS (reading, mathematics, ICT, science, reasoning)	Ln gross hourly wages	OLS regressions (ORU model)
			OS (reading, mathematics, science, reasoning), US (ICT) US (reading, mathematics, science, reasoning), OS (ICT)	Ln gross hourly wages	OLS regressions (compensation model) OLS regressions (compensation model)
4	NEPS Adult Cohort, 2018 wave	Dependent-employed core workers, aged 32 to 65	Subjective skill mismatch US, OS (multidimensional)	Job satisfaction	OLS regressions

Notes: US (underskilled), OS (overskilled).
Source: Own illustration.

5 Discussion and conclusion

The thesis provides a comprehensive overview on skill mismatches, addressing their measurements, determinants, and monetary as well as non-monetary consequences. Chapter 5.1 summarises the main findings of the four studies and provides answers to the central research questions of the thesis. Chapter 5.2 presents a general discussion on the findings and highlights the main conclusions and implications of the thesis. In Chapter 5.3, I discuss limitations of the four studies and present an outlook on potential future advancements and research.

5.1 Summary of main findings

The first objective of this thesis is to validate different measures of skill mismatch to determine *how skill mismatches can be adequately measured*. Focusing on objective skill mismatches, Article 1 provides a comparative empirical validation of five different approaches to test-based measurement of skill mismatch in mathematics. The validation illustrates that different measurement approaches may lead to quite different results, except in the case of the statistical and the mixed approach. The occupational skill requirement threshold values of these two approaches are more plausible than those of the other approaches, each of which possesses some thresholds that cannot, by definition, be fallen below or exceeded. Moreover, the skill mismatch measures of the statistical and the mixed approach show valid empirical distributions, as they significantly cover all skill (mis)match categories and indicate well-founded proportions of matched and mismatched workers. However, this is not the case for other approaches. The job analysis approach classifies the vast majority of workers as being mismatched, while the worker assessment and the task approach rarely categorise individuals as being underskilled (task approach) or overskilled (worker assessment approach). Furthermore, the statistical and the mixed approach possess high construct validity as well as the highest criterion-related validity. The job analysis approach also possesses high construct and criterion-related validity, both of which are considerably lower for the worker assessment and the task approach. In sum, the statistical and the mixed approach provide the most valid measures of domain-specific skill mismatch. However, the findings might differ when using other data because the occupational skill requirement scales of the statistical and the mixed approach perfectly match the skill level scale, which is not the case for other approaches.

Additionally, Article 1 introduces a new measure of multidimensional skill mismatch which considers individuals' skill mismatch situations in five different skill domains (reading, mathematics, ICT, science, and reasoning) by applying the mixed approach. The validation indicates that the multidimensional measure also possesses valid empirical distributions similar to previously well-established domain-specific measures. Further, it shows high construct and criterion-related validity and thus represents a valid test-based measure of skill mismatch. This multidimensional measure provides a more comprehensive assessment of individuals' skill mismatch situations. Thereby, it poses an alternative and complements the previous domain-specific measures. Either domain-specific or multidimensional measures of skill mismatch can thus be employed, depending on the research desideratum.

The second aim of this thesis is to provide new insights into *the causes of skill mismatches and how skill mismatches can be explained*. Article 2 focuses on education as a determinant of skill mismatches. This study investigates how individuals' level of education as well as vocational specificity and occupational specificity of education are associated with the likelihood of being underskilled or overskilled. Moreover, it analyses how these associations vary by career stage. My findings show that individuals with a higher level of education (upper secondary, post-secondary non-tertiary, tertiary education) face substantially lower risks of being underskilled than individuals with a lower secondary education do. Conversely, post-secondary non-tertiary graduates as well as tertiary graduates are considerably more likely to be overskilled than individuals with a lower secondary education. Upper secondary graduates face also slightly higher overskilling risks, but these are not statistically significant. The same pattern holds for individuals with a higher occupational specificity of education, which also face statistically significantly lower underskilling but higher overskilling risks. In contrast, a higher vocational specificity of education is associated with lower risks of both underskilling and overskilling, although the relationship is not statistically significant in the case of underskilling.

Moreover, Article 2 indicates that the role of education changes over the course of a career, depending on the time passed since the educational graduation. For example, the risk of being underskilled or overskilled decreases for individuals with a higher educational level (upper secondary, post-secondary non-tertiary, tertiary education) in comparison to those with a lower secondary education over the course of the career. Furthermore, the mismatch-preventing influences of vocational specificity and occupational specificity on underskilling increase with more time passed since educational graduation. Conversely, the mismatch-preventing influences of vocational and occupational specificity on overskilling decrease over the course of the career. Considering the career perspective, the findings also suggest trade-offs for the influence of vocational specificity on underskilling as well as for the influence of occupational specificity on overskilling. In approximately the first 27 years after educational graduation, there is a mismatch risk-increasing influence of vocational specificity on underskilling, which becomes a mismatch-preventing influence afterwards. In contrast, a mismatch-preventing influence of occupational specificity on overskilling can be observed in the first five years after graduation, turning into an overskilling risk-increasing influence in the further course of the career. Therefore, Article 2 uncovers how different facets of education are related to skill mismatches and how their role varies over the course of the career.

The third main issue of this thesis is to analyse *individuals' monetary and non-monetary consequences of being skill-mismatched*. Article 3 explores the monetary returns for underskilled or overskilled workers in occupations with the same job requirements, focusing on mismatches in single skill domains. When compared to individuals with matching skills and the same occupational requirements, underskilling is associated with substantially lower wages across all skill domains. Conversely, overskilling substantially pays off especially in ICT, but also in reading and mathematics, while the overskilling wage benefits in science and reasoning are only slight and not statistically significant. The findings illustrate that both the strongest wage penalties and benefits are evident for skill mismatches in ICT. Article 3 further indicates that ICT skill mismatches can compensate for wage penalties or benefits due to opposing mismatches in other skill domains. On the one hand, wage penalties associated with ICT underskilling fully eliminate wage benefits from overskilling in any of the other skill domains. On the other hand, wage benefits due to ICT overskilling are likely to fully compensate for wage penalties associated with underskilling in reading, mathematics, and reasoning, and also in large part for being underskilled in science. Thus, this study demonstrates the substantial monetary consequences of skill mismatches. It shows that, given a certain level of occupational requirements, skill surpluses pay off, whereas skill deficits are associated with wage losses for individuals. These substantial monetary implications of skill mismatches are evident across cognitive skill domains, but they are most pronounced in the ICT domain.

In Article 4, I analyse how objective and subjective skill mismatches affect individual job satisfaction. Although the proportion of subjectively mismatched individuals roughly corresponds to the proportion of objectively mismatched individuals, major intra-individual differences exist between individuals' objective mismatches and their subjective assessments. This discrepancy between objective situation and subjective perception means that the majority of objectively skill-mismatched workers are not aware of being mismatched, and that most subjectively skill-mismatched workers objectively possess the required level of skills. My findings show that subjectively skill-mismatched workers exhibit quite substantially lower job satisfaction than subjectively skill-matched workers. Moreover, the results indicate that objectively underskilled workers are noticeably less satisfied with their jobs in comparison to objectively matched workers. Objectively overskilled workers show only marginally lower job satisfaction than workers with objectively matching skills. In contrast to the findings on subjective skill mismatch, however, these results are not statistically significant. The substantial job satisfaction penalty for subjectively skill-mismatched workers decreases only marginally when controlling for objective skill mismatch. Therefore, my findings suggest that only the subjective skill mismatch significantly reduces individuals' job satisfaction. Additionally, subjectively perceived skill mismatch harms workers' job satisfaction, irrespective of whether these individuals are mismatched under objective criteria. Objective skill mismatches, however, do not significantly affect this non-monetary aspect of individuals' job quality.

5.2 General discussion and conclusions

This thesis and the findings of the studies allow for some overarching conclusions to be drawn and policy implications to be derived. In total, I offer seven general conclusions.

First, *the measurement matters!* Choosing an adequate skill mismatch measure for the respective research question is decisive because different approaches to measuring skill mismatch produce highly differing incidences of skill mismatch. This, in turn, may result in different findings and conclusions. Accordingly, whether an individual is underskilled, matched, or overskilled strongly depends on the underlying measurement approach. Moreover, the skill mismatch proportions may significantly vary even when applying the same measurement method (test-based measurement of skill mismatch, mixed approach). Article 1, for example, illustrates that an individual's skill mismatch situation is inconsistent across skill domains, and that the intra-individual skill mismatch situation in diverse skill domains only correlates moderately with each other. Furthermore, all four articles indicate that skill mismatches may have quite different causes or consequences, depending on the skill domain. For example, Article 3 demonstrates that the impact of skill mismatches on monetary returns differs considerably, depending on the skill domain, and that the relevance of mismatches depends on the skill domain concerned. Article 4 underlines the need to differentiate between subjective and objective skill mismatches. Hardly any correspondence exists between subjective perception and objective circumstances in individuals' skill mismatch situations, and depending on the measurement method, different results and implications follow. This highlights the decisive relevance of identifying an adequate skill mismatch measure. However, there is no one-size-fits-all solution, as the adequacy of a measure may differ depending on the available database and the research question at hand. Researchers should thus be aware of the crucial relevance of selecting adequate skill mismatch measures and consequently pose a strong reflection on their respective findings.

Second, *education matters for skill (mis)matching!* This thesis points out the key role of education for individuals' matching in the labour market, highlighting the relevance of both the vertical and horizontal dimension of education. The findings of Article 2 demonstrate the necessity of differentiating between distinct facets of education and of considering the consequences of education in a differentiated way. This is essential because one and the same education can be associated with an increased or decreased risk of skill mismatch, depending on the skill mismatch type (underskilling or overskilling). Additionally, this thesis illustrates that the role and value of education may change over the course of a career and with changing circumstances in the labour market and society. In this context, it becomes obvious that the relationship between education and skill mismatches should not only be considered in terms of securing a matching job, but also with respect to education's role in staying in a matching job or remaining matched in a job. In light of the increasing emphasis on lifelong learning and adapting to new technologies and skill requirements in today's labour market, education plays a key role in matching individuals' skills throughout their careers. Moreover, education may affect how individuals deal with mismatches in the long term, as it may influence their intention and readiness to participate in further training or upskilling measures.

Third, *skill mismatches matter for individuals' labour market returns!* This thesis underlines the substantial and broad relevance of skill mismatches for individuals in the labour market, both in monetary and non-monetary terms. The articles indicate that skill mismatches may not only affect individuals' wages and job satisfaction, but also workers' productivity and long-term coping in the job. Further, Article 3 illustrates that skill mismatches do not necessarily have only negative consequences, but may also be beneficial for individuals (i.e. with respect to their wages), depending on the type of mismatch and the context. Interestingly, Article 4 also shows that subjectively perceived skill mismatches may affect individuals' job satisfaction, even if they are not mismatched according to objective standards. Irrespective of underskilling or overskilling, whether subjectively or objectively mismatched, and whether mismatched overall or only in certain skills: skill mismatches carry strong implications for individuals.

Fourth, *the skill domain matters!* The findings of the four studies show that it not only matters whether an individual is underskilled, matched, or overskilled, but that the skill domain in which the mismatch exists also plays a role. Individuals are more or less skilled in different skills, which are more or less relevant in different occupations and jobs. Accordingly, individuals can be underskilled in one skill domain, but matched or even overskilled in others. However, the causes and consequences of skill mismatches also depend on the skill domain in question. For example, Article 2 demonstrates that individuals with a certain educational profile are more or less prepared for the occupational skill requirements of their job, depending on the skill domain. Therefore, individuals with the same educational profile are more likely to be underskilled or overskilled in one skill, but less likely in other domains. How education relates to skill mismatches thus depends on the skill domain in question. Further, the significance of skill domains is especially true for the association between skill mismatches and wages, as highlighted in Article 3. The domain of skill therefore plays a central role in determining who is affected by skill mismatch, and for the consequences of skill mismatches. This is because some skills are more beneficial, more in demand, and more relevant in today's world of work than others. In this context, ICT skills play an exceptionally critical role.

Fifth, *individuals' subjective perceptions matter!* This thesis illustrates the crucial importance of individuals' subjective assessments, and the fact that they can have a significant meaning in themselves, regardless of the objective situation. The findings of Article 4 highlight the special nature of subjective skill mismatch measures, indicating that individuals' subjective assessments mainly contradict their objective skill mismatch situations. Thus, subjective skill mismatch measures might be biased by subjective perceptions, and they may therefore need to be interpreted with caution. Moreover, subjective perceptions matter for individuals' subjective job quality. Article 4 indicates that the subjective feeling of being mismatched is more relevant to individuals' job satisfaction than the objective skill mismatch situation. Therefore, not only objective facts, but also subjective perceptions of skill mismatches may affect workers. For more precise and comprehensive insights into the implications of skill mismatches, both facets should thus be considered.

Sixth, *the context of skill mismatches matter!* The thesis at hand illustrates the relevance of considering and reflecting upon the specific context of skill mismatches, as each context may provide different conclusions. Skill mismatches may have varying implications for different subgroups, labour market segments, economic sectors, or at different times of the career. For example, Article 2 illustrates that the specificity of education has distinct implications for individuals' skill matching depending on the educational level context. While more vocational-specific education is beneficial for preventing skill mismatches among secondary education graduates or tertiary education graduates, it increases the skill mismatch risks among post-secondary education graduates. Further, Article 3 demonstrates that wage benefits and penalties associated with domain-specific mismatches may vary considerably depending on gender, sector, and contract of employment. This results in partially different implications that are relative to the context. It is therefore highly relevant to reflect upon the specific context when drawing general conclusions.

And seventh, *a holistic perspective on skill mismatch matters!* This thesis demonstrates why the issue of skill mismatch deserves consideration from a comprehensive perspective. If skill mismatches are not measured adequately, incorrect conclusions about their determinants and consequences are likely to be drawn. To analyse the consequences of skill mismatches, it is also essential to be aware of their determinants. And vice versa: to identify the causes of skill mismatches and to understand, for example, which group of people selects into mismatched jobs, it is necessary to consider the negative and positive implications of skill mismatches. The articles also highlight the need for an overall view of the individual facets, for example, because situations and associations can change over time. This suggests that skill mismatches may be a lifelong issue for individuals that might be more or less prevalent depending on their life situation, external circumstances, and career stage. To mitigate the negative consequences of skill mismatches, the causes of skill mismatches need to be addressed as well. This requires, in turn, a holistic view of the issue.

These insights also provide some important implications for policymaking. For an improved overview and a deeper understanding of the current extent of skill mismatches in the labour market, it might be advisable to implement analyses on workers' skill mismatch in firms. Additionally, skill matching assessments could also be implemented in educational and training systems to address potential deficiencies at an early stage. Policymakers may also need to place a stronger focus on close-mesh skill forecasting in order to identify the current and future skill demands for specific sectors and regions. This might provide valuable information to prepare the future workforce for these specific skill requirements from their training phase onwards.

Skill mismatches do not only result from imbalances in the supply and demand of skills or skilled labour, but also from limited information on the side of employees, applicants, or the firm. Therefore, policymaking should implement targeted measures to reduce information deficits on both the employer's and the employee's side, thus decreasing the likelihood of mismatches. For example, career guidance measures for education graduates should be improved, and more high-quality career guidance services in schools, training institutions, and universities should be implemented. The fact that tertiary education graduates are strongly affected by overskilling highlights that these measures are not only relevant for lower education graduates, but especially for higher education graduates. It might also be advisable to enforce compulsory internships across education and training systems and school systems, as this may reduce information gaps between individuals and firms and could provide individuals with some first occupation-specific skills. In this way, individuals are able to gain insights into which skills are in demand before they enter the regular labour market and can thus obtain a better awareness of their own skills.

Addressing the skill mismatch issue in the long term requires fundamental reforms in the skills policy. Given the special relevance of education for skill matching, fundamental reforms of the education system should be addressed. The education system should place a stronger focus on teaching vocational skills, since a more vocational-specific education reduces the risk of skill mismatch. This applies even to Germany, known for its highly vocation-oriented training. Furthermore, there is a need for a digital reformation of the entire education system. ICT skills are essential for productivity and competitiveness in today's and tomorrow's professional world. Therefore, a special focus should be placed on acquiring these crucial skills in education, so that the acquisition of sufficient ICT skills should be one of the main objectives of educational and training programmes in future. Moreover, policymaking should promote ICT training for the current workforce and incentivise their participation.

Given the high prevalence of skill mismatches in the labour force, policies should encourage and subsidise the reskilling and upskilling measures of individuals, and should also fund companies in this regard. Meanwhile, policymakers should place greater responsibility on the companies themselves to address their skilled workers' shortages and in-house skill deficiencies through retraining, in order to make more use of the skill potentials of their own staff. However, this requires a stronger political prioritisation of individual-level skill matching, an issue that seems to be somewhat neglected in the current discourse in light of the overriding macro-level issue of skilled labour shortages.

Much like all empirical studies, the four articles and, accordingly, the thesis as a whole face some limitations which need to be considered when interpreting the results and deriving implications. The NEPS in general and the NEPS Adult Cohort in particular provide comprehensive information and rich data on individuals' sociodemography, biography, skill levels, education, and labour market history. Nonetheless, the empirical analyses might be subject to biases due to unobserved confounding variables, which could not be accounted for in the individual articles and analyses. In the context of skill mismatches, this particularly concerns the incomplete information on the characteristics, interests, and motivations of the employers. This may involve recruitment procedures, payment policies, feedback culture, workplace atmosphere, or the general purpose of the firms. Moreover, the four studies do not provide evidence for young labour market entrants since there are no individuals under the age of 30 in the NEPS Adult Cohort samples that are relevant for the analyses. Given that the NEPS and therefore the four studies focus on the context of Germany and the German labour market, no general cross-national and cross-contextual conclusions can be drawn.

The NEPS Adult Cohort also faces some limitations with regard to skill mismatch measurement despite its extensive scope. For example, no sufficiently differentiated subjective skill mismatch measure exists in the NEPS Adult Cohort to date. While the existing subjective skill mismatch measure allows differentiating between subjectively matched and subjectively mismatched individuals, it is not possible to distinguish between underskilled and overskilled individuals within the group of subjectively mismatched individuals. Even the objective test-based measurements of skill mismatch still feature some restrictions. Given that not all participants in the NEPS Adult Cohort were tested in all skill domains due to their respective subsample affiliation, some of the skill level information had to be imputed for several individuals. I conducted cross-sectional analyses in each of the four studies, owing to the lack of repeated skill level measurements in the panel for the majority of skill domains, and the lack of information on individuals' skill mismatch situation in the panel. However, cross-sectional analyses are subject to limitations with regard to causal conclusions.

This illustrates the general limitations of skill mismatch measurement per se. Ideally, skill mismatches would be measured both subjectively and objectively in each skill domain relevant to the labour market, at the same point in time in the panel design. In a perfect scenario, subjective skill mismatch measures would not be biased by individuals' subjective perceptions. Further, test-based measures of skill mismatches would not only draw on general cognitive skills but also on a broader range of skill domains (e.g. communication, problem-solving, consulting, technical, management, and manual skills) that are relevant to labour market success. These test-based measures would be based on precise and valid information on skill requirements in the individual's specific job. Unfortunately, this perfect scenario is not the reality in the NEPS Adult Cohort or in any other survey. Therefore, any skill mismatch measurement or analysis is subject to certain limitations.

5.3 Outlook

This thesis provides comprehensive insights into individual-level skill mismatches, but it also raises new questions on this topic. One question of obvious importance is whether the findings are transferable to other countries. This is particularly interesting with regard to the test-based measurement of skill mismatches as well as regarding the link between education and skill mismatches. In both cases, the conclusions might strongly depend on the underlying country-specific data and country-specific education system. Another issue is whether and to what extent the findings and conclusions of the four studies also apply to young labour market entrants under the age of 30. This might be of particular relevance to the link between education and skill mismatches, as educational certificates are expected to be of more importance for the matching of young labour market entrants than for older workers or individuals with more professional experience (cf. Altonji & Pierret, 2001). Young labour market entrants may also be more likely affected by skill deficits at the beginning of their careers, but may perceive this situation as less problematic due to their low level of work experience and different expectations. This might imply that skill mismatches affect job satisfaction differently for younger workers than for prime-age workers. Therefore, future research could replicate the findings of the studies in other country-specific education and labour market contexts, as well as for young labour market entrants or individuals in vocational training, in order to test their general validity.

Some issues remain unresolved despite the rich findings of this thesis on the measurement, determinants, and consequences of skill mismatches. With regard to skill mismatch measurement, for example, it remains unclear whether subjective skill mismatch measures provide valid information and which subjective measures are useful. There are also some unanswered questions concerning the association between education and skill mismatch. Future research might address, for example, how the school entry age of students or their final grades affects the likelihood of skill mismatches at the start of their careers. Subsequent research may also analyse whether first-generation academics are more likely to be mismatched than tertiary graduates from families with an academic background. Moreover, the implications of the Covid-19 pandemic for the education system, such as home schooling or studying from home, may also affect the education-skill matching nexus. Therefore, future research could investigate, for example, whether individuals who attended school, vocational training, or tertiary education during the Covid-19 pandemic are comparatively more likely to be affected by skill mismatches. This thesis also demonstrates that the link between education and skill mismatches may vary depending on the time passed since educational graduation. Drawing on this finding, subsequent research may analyse whether and how both the monetary and non-monetary consequences of skill mismatches differ by individuals' career stages. Several more questions remain open regarding ICT skill mismatches, such as whether and how mismatches in ICT contribute to the gender digital gap and gender wage gap.

Future research may also build on this thesis and benefit from the option of multidimensional test-based measurement of skill mismatch. For example, more finely differentiating measures of multidimensional skill mismatch could be conceptualised in order to address the heterogeneous skill mismatch situations of individuals in different skill domains in more detail. This might provide interesting insights for research and employers dealing with issues of organisational sociology, sociology of work, and human resource decision-making, for example, to obtain more differentiated and accurate information about individuals' skill portfolios in the recruitment process. Future research may also pay closer attention to self-selected skill mismatches, given the substantial changes in demographics, work patterns, labour market participation, and the meaning attached to work in society. In this context, individuals' personal work preferences (e.g. how they value maintaining a work-life balance, making a career, or having a meaningful job), their generational affiliation, family model, socioeconomic background, and financial wealth and resources might provide interesting insights. Additionally, the role of firm-level characteristics could be specifically analysed in the future. This might involve evaluations of the significance of assessment centres, different human resource practices, or firm cultures on attracting and long-term holding of matching workers. Subsequent research may also further explore the domain-specific consequences of skill mismatches, for example, to investigate in which skill domains mismatches are most relevant for job quitting, or to participate in upskilling or further training measures. Furthermore, future research might investigate whether subjective and objective skill mismatches not only have different implications for job satisfaction, but also for other affective facets of job quality, such as feelings of overload, pressure, overstraining, job security, or work-life conflict.

Considering the current changes and developments taking place in both society and the labour market such as technological innovation, digital transformation, and artificial intelligence, there is much to suggest that skill matching will continue to be of significant relevance in the future. This might also affect the different aspects of skill mismatch addressed in this thesis. For example, some new approaches to test-based measurement of skill mismatches might gain relevance which builds on big data, real-time labour market information, and online job vacancies to assess occupational skill requirements (Cedefop, 2019). In addition, existing methods to test-based measurement of skill mismatch in occupation-specific skills may be further developed and implemented in large-scale surveys (cf. Abele et al., 2016, 2021; Beck et al., 2016).

The digitalisation of society and the labour market provides special opportunities for improved skill matching in today’s and tomorrow’s world of work. Online professional networks and job search platforms such as LinkedIn, Xing, or Indeed may become increasingly relevant in the skill matching process. They may further enhance transparency regarding the skills of workers or applicants, and the skill requirements of firms. Additionally, they may reduce information deficits on both the employee’s and the employer’s side. Cross-sectoral skill matching platforms might, moreover, be implemented more frequently in the future, connecting jobseekers to vacancies by matching skill demands and supply. These trends could further increase the relative meaning of skills compared to educational credentials and increase individual-level skill matching.

Conversely, temporary skill mismatches may become less critical for individuals’ job quality and labour market success in the future. This may be, for example, due to increasing prevalence and relevance of lifelong learning, skill adaptation, upskilling, and reskilling over the course of a career. Especially underskilled workers may face minor penalties in the future if ever-cycling skill matching becomes the new standard, coming to be considered less of a flaw and more of a normality.

6 References

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7 Appendix

Table A1 Definition and conceptual framework of skill domains in the NEPS

	Reading	**Mathematics**	**ICT**	**Science**	**Cognitive basic skills (reasoning)**
Definition	… the ability to read a written text and understand it	… the ability to use and apply mathematics	… the ability to search for information and to handle information and communication technologies	… the ability to transfer and apply scientific knowledge to situations in life involving science	… the ability to deal with complex information and processing general cognitive information
Conceptual framework	Text functions • commenting • information • literary • instruction • advertising Cognitive requirements • finding information in text • drawing text-related conclusions • reflecting and assessing	Content areas • quantity • change and relations • space and shape • data and chance Cognitive components • mathem. communication • mathem. argumentation • modelling • using repres. forms • mathem. problem solving • technical abilities and skills	Software applications • word processing • spreadsheet • presentation software • email • search engines Process components • define • access • manage • create • integrate • evaluate • communicate	Knowledge of science (health, environment, technology) • matter • systems • development • interactions Knowledge about science (health, environment, technology) • scientific enquiry • scientific reasoning	Matrix test

Sources: Gehrer et al. (2013) for reading, Schnittjer and Duchhardt (2015) and Neumann et al. (2013) for mathematics, Senkbeil et al. (2013) for ICT, Bybee et al. (2009) and Hahn et al. (2013) for science, Gottfredson (1997) and Autorenteam Kompetenzsäule (2020) for cognitive basic skills (reasoning). Own illustration.

Article 1:

Test-based measurement of skill mismatch: A validation of domain-specific and multidimensional skill mismatch measures using the NEPS

Status: Submitted to *Journal for Labour Market Research*

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Abstract

Skill mismatch is a key indicator of labour market research that has received significant attention. To date, various approaches of test-based measurement of skill mismatch have been used in research, generating differing results and usually restricting themselves to mismatches in single skill domains. This study provides a comparative validation of five commonly used approaches to test-based measurement of skill mismatch and introduces a new multidimensional measure that considers individuals' skill mismatch situations in five cognitive skill domains. Drawing on the 2016 wave of the German National Educational Panel Study (NEPS) Adult Cohort, I find significantly varying distributions for the different measurement approaches, and highly valid skill mismatch measures for the statistical and the mixed approach. The new multidimensional measure of skill mismatch also possesses high validity and represents a major complement and alternative to domain-specific skill mismatch measures. The findings highlight the special relevance of measurement approaches for skill mismatch research.

1 Introduction

Skill mismatch is a significant determinant of labour market returns which contributes, for example, to differences in job satisfaction and wages (Mateos-Romero & Salinas-Jiménez, 2018; McGuinness et al., 2018; Rohrbach-Schmidt & Tiemann, 2016). The major relevance of this issue has recently been underlined by the European Commission's declaration of the European Year of Skills 2023, with the objective of improving workforce skill matching (European Commission, 2022). As a central indicator of labour market research, skill mismatch measures are crucial for identifying which individuals are affected by mismatches, and for analysing how mismatches affect these individuals. Thus, both policymaking and research require accurate and valid information on the incidence and type of individual-level skill mismatches (Flisi et al., 2017).

Previous studies on the validation of mismatch indicators have mainly focused on qualification mismatch measures (e.g. Capsada-Munsech, 2019 for overeducation). In contrast to the concept of qualification mismatch which defines mismatches based on educational qualifications (educational level or field of education), skill mismatches refer to the matching of workers' skill levels to their jobs (International Labour Office, 2018). Typically, skill mismatch measures are either based on workers' subjective self-assessments of their skill mismatch situation, or on objective (test-based) approaches that compare individuals' skill levels measured by skill tests to the level of skill requirements in their occupational group. This study focuses on test-based measures of skill mismatch which are considered to be less biased. Such test-based measures can draw on valid information about workers' skills in specific skill domains. However, they lack perfectly corresponding information on the level of skill requirements within these domains in individuals' occupations (Pérez Rodríguez et al., 2022).

To date, various approaches have been used to proxy the skill requirements in occupations and consequently, approaches to test-based measurement of skill mismatch also vary. Five commonly used approaches in the literature operationalise skill requirements in occupations. They are based on the average skills of all workers *(statistical approach)* resp. of subjectively well-matched workers only *(mixed approach)*, or on expert-based assessments *(job analysis approach)*, worker-based assessments *(worker assessment approach)*, or the complexity of job tasks *(task approach)*. However, these approaches in part indicate highly different patterns of skill mismatches (cf. Flisi et al., 2017; Pérez Rodríguez et al., 2022; Perry et al., 2014), and so far, no common consensus exists on which of them is most appropriate. Moreover, previous research on test-based measurement of skill mismatch usually addresses mismatches from a domain-specific perspective focusing on mismatches in single general skills. Critics have argued that this perspective overlooks the multifaceted structure of workers' and occupations' skill profiles (Kracke et al., 2018) as well as the potential variation in an individual's skill mismatch situation across different domains. Single-domain classifications might thus provide a misleading picture of individuals' overall mismatch situations (Perry et al., 2014). Therefore, the evaluation of an individual's overall skill mismatch status necessitates a holistic approach which acknowledges skill mismatch as a multidimensional phenomenon and considers a broader set of skills relevant to the labour market. This raises questions on which of the approaches are appropriate for test-based measurement of skill mismatch, and on how test-based measures of skill mismatch may consider and properly address the multifaceted composition of workers' and occupations' skill sets.

This study provides a comparative empirical evaluation of five commonly used approaches to test-based measurement of skill mismatch and introduces a new measure for multidimensional skill mismatch. It adds to the previous literature in several ways. First, this study pioneers in empirically analysing different methods of measuring occupational skill requirements. Previous studies have only validated the resulting skill mismatch measures. However, this overlooks the decisive relevance of valid occupational skill requirements for the quality of the resulting test-based measures of skill mismatch (for example, determining the skill level required for workers in a given occupation and establishing the level at which workers are categorized as either underskilled or overskilled). In contrast, I empirically validate five different occupational skill requirement measures, underlining their relevance as an essential component for valid test-based measures of skill mismatch.

Second, this study is the first to provide a comprehensive comparative validation of five different test-based measurement approaches for skill mismatch in order to test the quality of the measures based on empirical analyses. Some previous studies have validated single approaches of test-based measurement of skill mismatch (cf. Allen et al., 2013; Desjardins & Rubenson, 2011; Pellizzari & Fichen, 2017). However, these studies lack comparison to other measures or restrict to single facets of the mismatch (e.g. Flisi et al., 2017 for overskilling). Furthermore, three studies to date provide comparative analyses of different approaches to test-based measurement of skill mismatch. They validate the different measures based on their link to key labour market outcomes such as wages or job satisfaction (cf. Pérez Rodríguez et al., 2022 for the statistical, mixed, and job analysis approach; Perry et al., 2014 for the statistical, mixed, and skill use approach; van der Velden & Bijlsma, 2019 for the statistical, mixed, and effective skill approach). These studies demonstrate that the incidence of skill mismatches and their link to labour market outcomes are highly dependent on the underlying measurement approach. However, they do not suggest how these skill mismatches are explained by relevant characteristics of workers and occupations. This study, by contrast, applies a range of validation methods to assess and compare the validity of five different skill mismatch measures based on the statistical, mixed, job analysis, worker assessment, and task approach.

Third, this study introduces a new multidimensional measure of skill mismatch that considers an individual's mismatch situation in five different skill domains. Previous studies using test-based measures of skill mismatch usually refer to individuals' mismatch in single skill domains based on the Programme for the International Assessment of Adult Competencies (PIAAC) (e.g. Allen et al., 2013). However, the PIAAC only provides valid information on skill levels for the two general skill domains literacy and numeracy,[1] which show extremely high correlations exceeding 0.90 (Levels et al., 2014). Therefore, they do not allow for a multidimensional perspective on skills and skill mismatch. In contrast, this study draws on the German National Educational Panel Study (NEPS) Adult Cohort which provides test-based information on workers' skills in five conceptually different domains of reading, mathematics, ICT, science, and reasoning.[2] This enables a multidimensional view of skill mismatch, covering skills which are highly relevant in today's professional world, and essential across occupational sectors and professions.

The remainder of this paper is organised as follows. Chapter 2 discusses the five approaches to test-based measurement of skill mismatch. Chapter 3 presents the data and describes the operationalisation of the central measures and the analytical plan. This is followed by the empirical validation of the occupational skill requirement measures and the resulting domain-specific skill mismatch measures of the five approaches in Chapter 4. Chapter 5 introduces and validates the new measure of multidimensional skill mismatch. Finally, Chapter 6 discusses the findings and limitations, and provides an outlook and implications for future research.

[1] The PIAAC also provides a measure on individuals' skills in problem-solving in technology-rich environments but this measure comes with considerable limitations (cf. Flisi et al., 2017 for detailed information).
[2] The correlations between an individual's skill levels are also high in the NEPS, with a maximum value of 0.66. Yet, this still suggests covering conceptually different domains, which is not the case with the overwhelming correlations in PIAAC.

2 Test-based measurement of skill mismatch

Test-based measures of skill mismatch compare an individual's skill level assessed by skill tests to the level of skill requirements in their occupation. An individual is categorized as being underskilled if their skill level in the specific skill is lower than the level of skill requirements in their occupational group, and as being overskilled if their skill level is higher. Individuals possessing the required level of skills are categorized as being matched. Large-scale surveys such as PIAAC or NEPS provide information on the supply side of skills, i.e. the skill levels of individuals, but not on the demand side of skills, i.e. the level of skills required in their respective jobs. Previous literature has discussed various methods for the operationalisation of occupational skill requirements and thus for test-based measurement of skill mismatch (e.g. McGuinness et al., 2018).

This study analyses five commonly used approaches to operationalising occupational skill requirements and their resulting skill mismatch measures. The *statistical approach (STA)* defines occupational skill requirements based on the averaged test scores of workers in occupations which belong to the same occupational group. Similarly, the *mixed approach (MA)* defines occupational skill requirements based on the averaged test scores of workers within the same occupational group, but only considers those individuals who subjectively assess themselves as having an adequate skill level for their job (cf. Pellizzari & Fichen, 2017). These two approaches possess a high level of objectivity, as the occupational skill requirements are based on objective test scores. Moreover, the MA prevents biases through test scores of mismatched workers, as it only considers subjectively matched workers. Both approaches, however, have been criticised for defining the average worker as being matched, which might not necessarily represent the actual skill requirements in a job (van der Velden & Bijlsma, 2019). In the *job analysis approach (JA)*, the level of occupational skill requirements is assessed by professional experts. This approach benefits from the high field expertise of occupational experts and from a transparent and objective evaluation process (McGuinness et al., 2018). However, expert-based ratings may also involve subjective bias or fallible human judgement (Morgeson & Campion, 1997). The *worker assessment approach (WA)* uses subjective evaluations of workers on the level of skills required to perform their job, defining the occupational skill requirements by the averaged self-assessed scores of workers belonging to the same occupational group. The direct questioning of workers offers the opportunity to promptly identify current trends and changes in occupational requirements (Hartog, 2000). On the other hand, workers' subjective assessments lack objectivity. This might lead to biases since workers may tend to overstate their job requirements in order to upgrade their status (Handel, 2016; Sparreboom & Tarvid, 2016). The *task approach (TA)* refers to workers' subjective assessments on the complexity of tasks they regularly employ in their job. Occupational skill requirements are defined by the average complexity-of-tasks scores of employees working in the same occupational group. This provides reliable information on the complexity of job tasks in occupations (Kracke & Rodrigues, 2020). However, concerns exist about the appropriateness of this measure to represent occupational skill requirements, since the complexity of job tasks is conceptually different from the level of skill requirements. Table 1 provides an overview of the operationalisation method as well as the strengths and limitations of the five different approaches.

Table 1 Five approaches to measuring occupational skill requirements

	STA	MA	JA	WA	TA
Skill requirement proxy	Averaged test scores of all workers of the same occup. group	Averaged test scores of subjectively matched workers of the same occup. group	Experts' ratings on skill requirements in the occup. group	Averaged ratings on skill requirements of all workers of the same occup. group	Averaged ratings on complexity of job tasks of all workers of the same occup. group
Pros	High objectivity	High objectivity Preventing bias due to mismatched workers	High field expertise	Direct addressing of workers Quick identification of new or changing skill requirements	Direct addressing of workers Reliable assessments
Cons	Data-driven	Data-driven	Subjective bias	Subjective bias	Different concept

Source: Own illustration.

3 Data and methods

3.1 Data and samples

The empirical analyses of this study are based on the NEPS Adult Cohort which comprises extensive information on educational and employment biographies of adults in Germany from several waves (Blossfeld & Roßbach, 2019; NEPS Network, 2018). This data provides test-based information on skill levels of employed adults in five different skill domains, which is essential to operationalise test-based measures of skill mismatch. The main empirical analyses draw on cross-sections of the 2016 wave of the NEPS Adult Cohort since the most recent skill tests were carried out in this wave. This wave comprises adults born between 1944 and 1986 within three subsamples with a gross sample of 10,078 individuals (4,427 of the

ALWA sample; 2,641 of the NEPS wave 2 enhancement and refreshment sample; 3,010 of the NEPS wave 4 refreshment sample). I restrict the analytical samples to dependent-employed core workers defined as having a maximum age of 65 years, being employed for at least 15 hours per week, and excluding the self-employed, persons in pre-professional employment (e.g. internship, student assistant, etc.), freelancers, family workers, and individuals employed in active labour market programmes or seasonal work. Additionally, I exclude individuals with missing values in any of the required variables or those who did not participate in the 2016 wave. This results in gross sample sizes between 4,388 and 4,922 individuals, depending on the measurement approach.

3.2 Measurements

I use five different measures of *occupational skill requirements*, exemplified by the skill domain of mathematics.[3] The operationalisation of each measure is based on different data, due to the fact that the relevant information is either provided in different waves of the NEPS Adult Cohort or had to be gathered from external data. Given the use of different sources which vary in the richness and accuracy of available data, information on skill requirements refers to the ISCO-08 two-, three-, or four-digit occupational groups, depending on the approach. In this context, ISCO-08 occupational unit groups (four-digits) provide the most specific information because of their high within-occupational group homogeneity of occupations, which is also high for ISCO-08 occupational minor groups (three-digits). Conversely, the skill requirement information for ISCO-08 occupational sub-major groups (two-digits) is considerably less specific, which may result in aggregation biases (Pérez Rodríguez et al., 2022).

The *STA occupational skill requirement measure* is based on the 2016 wave of the NEPS Adult Cohort and refers to the average skill level of all dependent-employed core workers of the same ISCO-08 three-digit occupational minor group plus and minus one standard deviation.[4] Based on the 2018 wave of the NEPS Adult Cohort, the *MA occupational skill requirement measure* is defined by the average skill level plus and minus one standard deviation of

[3] I validate the five approaches to measuring occupational skill requirements and skill mismatches using the skill domain of mathematics. This is because across the five approaches, only data for reading and mathematics is available. Moreover, there are stronger theoretical assumptions regarding the associations between the predictors and skill mismatch in mathematics compared to reading, which I refer to in the validation process.

[4] In the NEPS Adult Cohort, individuals' skill levels are measured by skill tests providing weighted maximum likelihood estimates (WLE) scores. I transform these WLE scores into scales from 0 to 100, defining the starting and end points of the scales by the empirically lowest resp. highest test score.

dependent-employed core workers belonging to the same ISCO-08 three-digit occupational minor group, who subjectively assess that their skills match the requirements of their job.[5]

The *JA occupational skill requirement measure* builds on expert-based information on the critical level of skill requirements in ISCO-08 four-digit occupational unit groups in the OECD countries including Germany (Pérez Rodríguez et al., 2022). Given that the information on skill requirements refers to OECD countries in general, it does not provide country-specific information for the German labour market context. I transform the original eleven-point scale (level 0, level 0.5, level 1, etc. to level 5) into a scale from 0 to 100 and define the occupational skill requirements as the transformed expert-based score per ISCO-08 four-digit occupational unit group plus and minus one standard deviation.

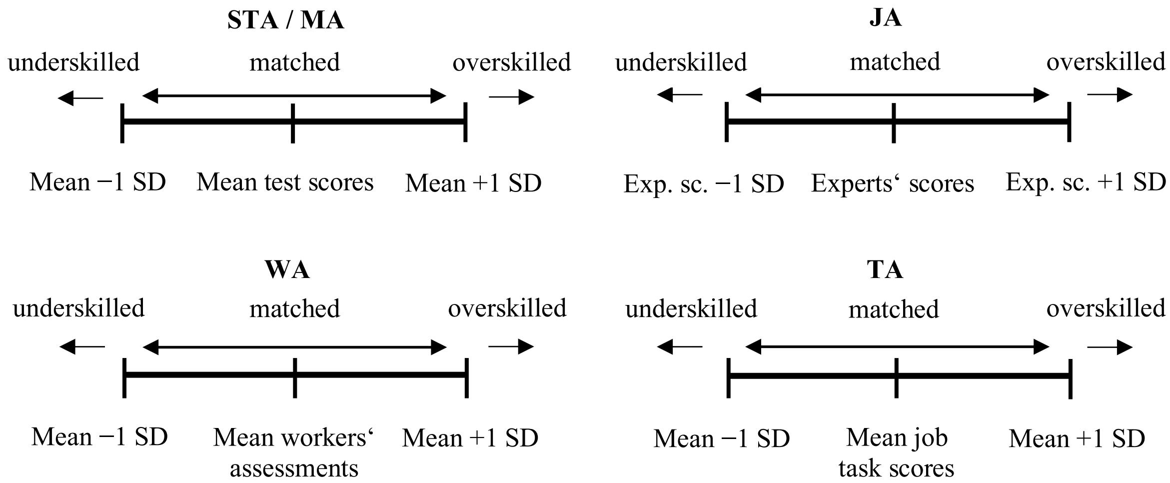
The *WA occupational skill requirement measure* is based on the 2014 wave of the European Skills and Jobs Survey (ESJS) restricted to the sample of Germany. I build on worker's self-assessed level of mathematical skill requirements in their job, distinguishing three levels (0: not required, 1: basic level, 2: advanced level).[6] I transform the three-point scale into a scale from 0 to 100 and define the occupational skill requirement level as the average self-assessed score of dependent-employed core workers belonging to the same ISCO-08 two-digit occupational sub-major group plus and minus one standard deviation.

The *TA occupational skill requirement measure* builds on the 2019 wave of the NEPS Adult Cohort. In a first step, I calculate the complexity-of-mathematical-tasks score per individual by aggregating information from several items on mathematical job tasks into a five-point scale (1: not required, 2: low complexity, 3: moderate complexity, 4: advanced complexity, 5: high complexity). This follows the procedure of Matthes et al. (2014).[7] Subsequently, I transform the five-point scale into a scale from 0 to 100, defining the occupational skill requirements as the average complexity-of-mathematical-tasks score of dependent-employed core workers working in the same ISCO-08 three-digit occupational minor group plus and minus one standard deviation.[8]

[5] Workers who "rather agree" or "completely agree" with the statement "The requirements of the job match my skills" are defined to be subjectively matched and therefore considered as a reference for calculating the occupational skill requirements, whereas workers who "completely disagree", "rather disagree" or "partly agree" are not considered.
[6] See Table A1 in the Appendix for detailed information on the operationalization procedure of the WA.
[7] See Table A2 in the Appendix for detailed information on the operationalization procedure of the TA.
[8] Note that the original scales of occupational skill requirement measures are transformed into scales from 0 to 100 in order to enable comparison to the scaling metric of individuals' skill levels. If there are not at least 20 observations available per ISCO-08 three-digit minor group in the STA, MA, and TA, I use the respective ISCO-08 two-digit sub-major group as a reference.

The five measures of *skill mismatch* in mathematics are operationalised by comparing an individual's skill level in mathematics with the level of mathematical skill requirements in their occupational group. Workers are categorized as being underskilled, matched, or overskilled depending on whether they possess lower, higher, or the required level of skills (see Figure 2).

Figure 2 Operationalisation of skill mismatch measures



Source: Own illustration.

3.3 Analytical strategy

The study provides empirical validations of five different measures of occupational skill requirements, test-based measures of skill mismatch, and a new multidimensional measure of skill mismatch. This involves four validation methods. First, I evaluate the *plausibility of threshold values of occupational skill requirement measures (1)*. This entails an assessment of whether the distributions of the occupational skill requirements' lower and upper limit values vary across occupational groups in line with theoretical expectations, and whether the threshold values allow for differentiation at both ends of the scale. Next, a *validation of the empirical distributions of skill mismatch measures (2)* involves analyses of whether the skill mismatch measures possess significant coverage of all categories and a meaningful proportion between matched and mismatched individuals. Subsequently, I assess the *construct validity of skill mismatch measures (3)* by testing whether they link to key predictors of skill mismatch in a theoretically expected manner (Döring & Bortz, 2016). For this purpose, I run separate logistic regression models for both underskilling *(US_i)* and overskilling *(OS_i)* to test how they relate to five core sociodemographic and occupational predictors of skill mismatch (cf. Equations 1a and 1b). These predictors include individuals' age cohort *($agec_i$)* (up to 35 years, 36-45 years, 46-55 years, 56-65 years) and educational mismatch *($educmis_i$)* (undereducation, education match, overeducation), as well as dummies for female *($gender_i$)*, tertiary education *($terteduc_i$)* (ISCED-1997: 5A, 6), and high complex occupational level *($highocc_i$)* (working in an occupation with highly complex tasks defined by the fifth-digit classification of the German Classification of Occupations 2010).

Equation 1a Logistic regression models for predicting underskilling vs. not

$$US_i = \alpha + \beta_1 gender_i + \beta_2 agec_i + \beta_3 terteduc_i + \beta_4 educmis_i + \beta_5 highocc_i + \varepsilon$$

Equation 1b Logistic regression models for predicting overskilling vs. not

$$OS_i = \alpha + \beta_1 gender_i + \beta_2 agec_i + \beta_3 terteduc_i + \beta_4 educmis_i + \beta_5 highocc_i + \varepsilon$$

Finally, I test the *criterion-related validity of skill mismatch measures (4)* by analysing how they are associated with individuals' wages, which represent a central labour market outcome (Döring & Bortz, 2016). Therefore, I run OLS regressions based on the so-called Overeducation-Required education-Undereducation (ORU) model of Duncan and Hoffman (1981), modified for skill mismatches. I test how both underskilling and overskilling relate to individuals' ln gross hourly wages *(W_i)*, measured by respondents' self-reported gross income divided by their contractual monthly working hours and trimmed by dropping the 1st and 99th percentiles. The ORU models include information on the skill requirement level in an individual's occupational group *(RS_i)* and a set of relevant control variables *(C_i)* (cf. Equation 2).

Equation 2 Specification of the ORU model modified for skill mismatches

$$W_i = \alpha + \beta_1 US_i + \beta_2 OS_i + \beta_3 RS_i + \beta_4 C_i + \varepsilon$$

These control variables cover female (as opposed to male), age (in years), immigration background (individuals of the first and second generation), education level (lower secondary, upper secondary, post-secondary non-tertiary, tertiary), field of education (general, STEM, humanities/social sciences, business/law/services, education, health/welfare, unknown), part-time work (as opposed to full-time), public sector work (as opposed to private sector), economic sector (agriculture/industry, services, information sector, public administration, unknown), workplace (East Germany, West Germany incl. Berlin, unknown), and job experience (number of years in the current job). Table A3 in the Appendix provides an overview of the descriptive sample statistics.

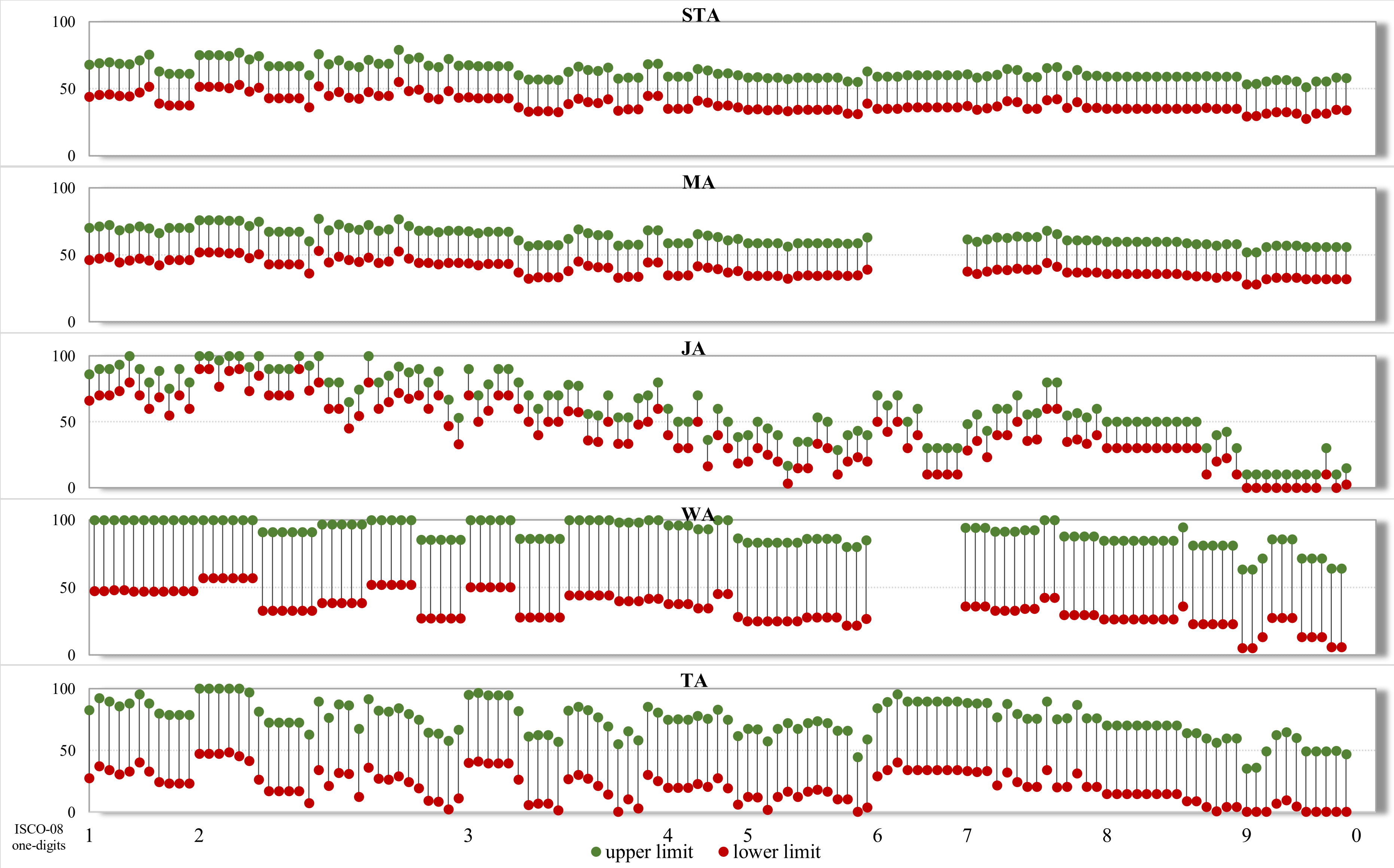
4 Validation of the five approaches

4.1 Occupational skill requirements

The occupational skill requirement measures are validated with regard to their *plausibility of threshold values (1)*. Plausible threshold values indicate relatively higher skill requirement levels in occupational groups that are perceived to possess higher skill levels and need to allow for differentiation in both directions. Therefore, threshold values that cannot by definition fall below or exceed are problematic. Figure 3 presents the threshold values of the occupational skill requirements in mathematics (vertical axis) of the different occupational minor groups (horizontal axis) for each approach.[9]

[9] The reference level for the skill requirements of the occupational groups differ between the approaches (two-digits for WA; three-digits for STA, MA, TA; four-digits for JA). For reasons of better comparability, Figure 3 presents the threshold values consistently for all approaches based on ISCO-08 minor groups (three-digits).

Figure 3 Occupational skill requirement threshold values in mathematics per ISCO-08 minor group (three-digits)



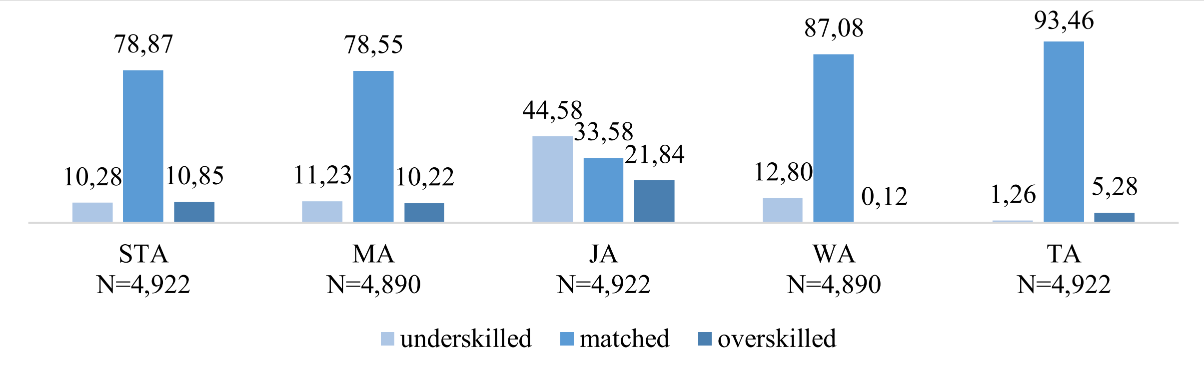
Sources: NEPS Adult Cohort (SC6: 9.0.1; SC6: 11.1.0; SC6: 12.0.1), Pérez Rodríguez et al. (2022), ESJS (2014), own illustration.

The STA and MA occupational skill requirements vary in a moderate range, with minimum lower limit values of about 30 and maximum upper limit values of about 80. Conversely, the JA, WA, and TA mark job requirements across the full spectrum of the scale. The JA shows comparatively small bandwidths, whereas the WA and TA show significantly broader bandwidths. This might reduce differentiability as almost all workers might be classified as being matched by definition. Moreover, the JA, WA, and TA each possess several absolute thresholds (lower limit values of 0 resp. upper limit values of 100), which cannot be fallen below or exceeded by definition. This is problematic because even workers with extraordinarily low or high skill levels cannot be categorized as being underskilled or overskilled in the occupational groups concerned. The distributions of skill requirement values mostly confirm the theoretical assumptions (International Labour Office, 2018). This signifies extended mathematical requirements in occupational minor groups belonging to the ISCO-08 one-digit major groups 1 (managers) and 2 (professionals), high mathematical requirements in 3 (technicians and associate professionals), moderate mathematical requirements in 4 (clerical support workers), 5 (services and sales workers), 6 (skilled agricultural, forestry and fishery workers), 7 (craft and related trades workers), and 8 (plant and machine operators and assemblers), as well as basic mathematical requirements in 9 (elementary occupations). This is particularly reflected in the distributions of the JA. The STA and MA possess more compressed middle-ranging thresholds across each occupational group, which classify workers with skill levels in the lower or upper quintile in each occupational group as underskilled resp. overskilled. Overall, STA and MA have a comparatively higher plausibility of threshold values as they do not possess any problematic absolute threshold values.

4.2 Domain-specific skill mismatch

The five measures of skill mismatch in mathematics are validated with regard to their empirical distributions, construct validity, and criterion-related validity. *Valid empirical distributions (2)* of skill mismatch possess significant coverage for all categories of the measure. Moreover, valid empirical distributions correspond to major expectations of skill mismatch; that is, the majority of workers are matched. Figure 4 presents the empirical distributions of the five domain-specific skill mismatch measures.

Figure 4 Distributions of skill mismatch (mathematics)



Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

The distributions significantly differ between the five approaches, except for the STA and MA. The proportions of underskilling range from 1.26 percent in the TA to 44.58 percent in the JA resp. for overskilling from 0.12 percent in the WA to 21.84 percent in the JA. There are also striking variations for the proportions of matched workers from 33.58 percent (JA) to 93.46 percent (TA), with the majority of individuals being categorized as matched. The exception is the JA which classifies about two-thirds of workers as mismatched. By contrast, both the WA and TA indicate very high proportions of matched individuals but rarely categorize individuals as being underskilled (TA) resp. overskilled (WA). Both the STA and MA classify about three-fourths of workers as being matched, provide a significant coverage of all skill (mis)match categories, and show fairly balanced ratios between underskilling and overskilling. Therefore, the empirical distributions of the STA and MA correspond most closely to previous findings on test-based measures of skill mismatch (e.g. Allen et al., 2013; Pérez Rodríguez et al., 2022; Perry et al., 2014).

Subsequently, I assess the *construct validity (3)* of the five skill mismatch measures by analysing their link to relevant sociodemographic and occupational predictors. For each approach, I run separate logistic regression models for underskilling and overskilling to examine whether individuals' gender, age cohort, education, educational mismatch, and occupational level predict both types of mismatches in a theoretically expected manner. Following theoretical expectations (cf. Becker, 1964; Sicherman & Galor, 1990) and previous empirical findings on determinants of skill mismatches (e.g. Pellizzari & Fichen, 2017 for gender and for tertiary education; Desjardins & Rubenson, 2011 for age; Allen et al., 2013 for educational mismatches and for occupational level), I expect *female workers, older workers, undereducated workers, and individuals working in a job with a highly complex occupational level more likely to be underskilled but less likely to be overskilled.* In contrast, *workers with* *tertiary education and overeducated workers are assumedly less likely to be underskilled, but more likely to be overskilled.* Table 2 and Table 3 present the associations between the predictors and underskilling resp. overskilling separately for each approach.

Table 2 The association between sociodemographic and occupational characteristics and underskilling in mathematics, logistic regressions

	Underskilled (mathematics)				
	STA	**MA**	**JA**	**WA**	**TA**
Female	0.090***	0.103***	0.038**	0.090***	0.004
(ref. male)	(0.009)	(0.009)	(0.013)	(0.009)	(0.003)
Age cohorts					
(ref. up to 35 years old)					
36 to 45 years old	−0.001	0.012	0.036	0.016	0.002
	(0.013)	(0.013)	(0.023)	(0.014)	(0.004)
46 to 55 years old	0.035**	0.046***	0.074***	0.062***	0.007
	(0.013)	(0.012)	(0.020)	(0.013)	(0.004)
56 to 65 years old	0.090***	0.115***	0.125***	0.111***	0.013*
	(0.015)	(0.015)	(0.022)	(0.015)	(0.005)
Tertiary education	−0.059***	−0.066***	−0.038	−0.064***	−0.009
(ref. non-tertiary education)	(0.013)	(0.013)	(0.020)	(0.014)	(0.005)
Educational mismatch					
(ref. education-matched)					
undereducated	0.025	0.010	0.168***	0.054***	0.002
	(0.013)	(0.013)	(0.019)	(0.015)	(0.005)
overeducated	−0.036***	−0.025*	0.067***	−0.056***	−0.006
	(0.010)	(0.011)	(0.015)	(0.011)	(0.003)
High complex occupational level	0.067***	0.087***	0.503***	0.039*	0.012
(ref. unskilled, skilled, complex level)	(0.016)	(0.018)	(0.018)	(0.016)	(0.007)
R-squared (McFadden)	0.078	0.080	0.162	0.079	0.038
N	4,889	4,857	4,889	4,857	4,889

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate average marginal effects, standard errors in parentheses.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

For underskilling, similar results show across the different approaches, excepting the TA. In the case of the STA, MA, JA, and WA, females, workers of older age cohorts, and workers in highly complex occupations are statistically significantly more likely to be underskilled, whereas tertiary-educated workers are statistically significantly less likely to be underskilled (excepting the JA). Moreover, undereducated workers are somewhat (WA 5.4 percentage points) resp. strongly (JA 16.8 percentage points) more likely to be underskilled in comparison to workers with a matching education. Interestingly, overeducated workers are statistically significantly less likely to be underskilled in the STA, MA, and WA, but more likely to be underskilled in the JA.

Table 3 The association between sociodemographic and occupational characteristics and overskilling in mathematics, logistic regressions

	Overskilled (mathematics)				
	STA	**MA**	**JA**	**WA**	**TA**
Female	−0.091***	−0.085***	−0.034**	−0.002	−0.008
(ref. male)	(0.009)	(0.008)	(0.011)	(0.001)	(0.006)
Age cohorts					
(ref. up to 35 years old)					
36 to 45 years old	−0.049**	−0.054**	−0.038	.	−0.029*
	(0.017)	(0.017)	(0.022)		(0.013)
46 to 55 years old	−0.053**	−0.058***	−0.048*	.	−0.030*
	(0.016)	(0.016)	(0.020)		(0.012)
56 to 65 years old	−0.111***	−0.114***	−0.078***	.	−0.044***
	(0.016)	(0.016)	(0.021)		(0.012)
Tertiary education	0.125***	0.127***	0.042**	0.004	0.078***
(ref. non-tertiary education)	(0.015)	(0.015)	(0.017)	(0.003)	(0.014)
Educational mismatch					
(ref. education-matched)					
undereducated	0.020	0.030	−0.142***	.	0.012
	(0.016)	(0.016)	(0.013)		(0.011)
overeducated	0.070***	0.050***	0.001	−0.000	−0.012
	(0.013)	(0.012)	(0.012)	(0.002)	(0.007)
High complex occupational level	−0.042***	−0.050***	−0.307***	−0.001	−0.056***
(ref. unskilled, skilled, complex level)	(0.011)	(0.011)	(0.011)	(0.002)	(0.008)
R-squared (McFadden)	0.107	0.101	0.166	0.112	0.038
N	4,889	4,857	4,889	3,475	4,889

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate average marginal effects, standard errors in parentheses.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

With respect to overskilling, similar findings exist for STA and MA, which indicate statistically significantly lower risks of being overskilled for female workers, older age cohorts, and workers in highly complex occupations, but higher risks for workers with a tertiary education as well as for overeducated workers. The results for overskilling in the JA and TA differ from the other approaches insofar as they do not show a statistically significantly higher likelihood of being overskilled for overeducated workers. Additionally, undereducated workers face a 14.2 percentage points lower likelihood of being overskilled in the JA than properly educated workers, and female workers are not statistically significantly less likely to be overskilled than male workers in the TA. The WA fails to provide estimations for some predictors, given the very small number of workers categorized as being overskilled. Overall, the predictions of skill mismatches in STA, MA, and JA are most consistent with theoretical expectations. This suggests that the STA, MA, and JA possess the highest construct validity.

Finally, I test the *criterion-related validity (4)* of the five domain-specific skill mismatch measures based on their association with individuals' wages which represents a key labour market outcome (cf. Table 4). I expect *underskilled workers to earn lower wages and* *overskilled workers to earn higher wages than matched workers with similar skill requirements* (Verhaest & Omey, 2006).

Table 4 The association between skill mismatches in mathematics and ln gross hourly wages, OLS regressions

	Ln gross hourly wages				
	STA	**MA**	**JA**	**WA**	**TA**
Skill mismatch					
(ref. matched)					
underskilled	−0.076***	−0.091***	−0.018	−0.074***	−0.151***
	(0.019)	(0.018)	(0.015)	(0.018)	(0.052)
overskilled	0.031	0.030	0.089***	−0.012	−0.008
	(0.018)	(0.018)	(0.018)	(0.199)	(0.027)
R-squared	0.459	0.458	0.453	0.436	0.426
N	3,921	3,893	3,921	3,893	3,921

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in mathematics, female, age, immigration background, educational level, field of education, part-time work, public sector, workplace, economic sector, job experience in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Across the approaches, underskilled workers earn lower wages than matched workers with similar occupational requirements. These underskilling wage penalties are statistically significant with the exception of the JA and range from approx. 1.8 percent (JA) to approx. 15.1 percent (TA) lower wages. Conversely, overskilled workers earn higher wages than matched workers with similar occupational requirements in the STA, MA, and JA, but lower wages in the WA and TA. The overskilling wage benefits are only statistically significant in the case of the JA and vary between approx. 3.0 percent (MA) and approx. 8.9 percent (JA). Thus, the STA, MA, and JA show the expected underskilling wage penalties and overskilling wage benefits, but none of them presents statistically significant results for both. The findings indicating stronger consequences for underskilling than for overskilling align with assumptions that skill deficits substantially decrease worker productivity in any case. However there are ceiling effects of worker productivity due to skill surpluses, since people cannot perform their jobs beyond excellence (Humburg et al., 2013). I conclude that the wage differences resulting from skill mismatches are most convincing in the STA and MA, and therefore possess the highest criterion-related validity.[10]

Overall, the empirical validations illustrate that different approaches may produce quite different results. This is particularly evident from the significantly varying distributions of the

[10] The STA and MA also show the most valid empirical distributions and possess the highest construct and criterion-related validity in the case of skill mismatch in reading (cf. Figure S1 and Table S1 to Table S3 in the Supplementary Material).

measures. The STA and MA possess valid empirical distributions as well as high construct and criterion-related validity. The JA also possesses high construct validity but classifies only one-third of workers as well-matched, which is significantly different from previous findings. Both WA and TA do not sufficiently cover each skill mismatch category and possess considerably lower construct validity. The STA and MA thus provide the most convincing results.

5 Multidimensional measure of skill mismatch

The previous analyses focus on skill mismatch in a single skill domain, exemplified for mathematics. This is in line with existing research which usually operationalises test-based measures of skill mismatch based on single domains (e.g. Allen et al., 2013; Flisi et al., 2017; van der Velden & Bijlsma, 2019). However, this method ignores the fact that both the skill sets of individuals and the occupational requirements cover various domains, and that an individual's skill mismatch situation might vary between different domains. This becomes even more evident when considering the within-individual correlation and correspondence between the skill mismatch measures in the single domains (cf. Table 5 and Table 6 exemplified for the MA).

Table 5 Spearman's correlation between skill mismatches in different skill domains based on the MA

	(1)	(2)	(3)	(4)	(5)
(1) reading	1				
(2) mathematics	0.285***	1			
(3) ICT	0.298***	0.347***	1		
(4) science	0.272***	0.349***	0.377***	1	
(5) reasoning	0.235***	0.256***	0.263***	0.217***	1

Notes: N=4,388. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table 6 Correspondence between skill mismatches in different skill domains based on the MA

	reading			ICT		
mathematics	US	MA	OS	US	MA	OS
US	34.00 % (N=169)	63.38 % (N=315)	2.62 % (N=13)	35.21 % (N=175)	63.58 % (N=316)	1.21 % (N=6)
MA	11.41 % (N=392)	78.52 % (N=2,697)	10.07 % (N=346)	8.79 % (N=302)	82.88 % (N=2,847)	8.33 % (N=286)
OS	4.17 % (N=19)	62.06 % (N=283)	33.77 % (N=154)	1.97 % (N=9)	60.75 % (N=277)	37.28 % (N=170)
	science			**reasoning**		
mathematics	US	MA	OS	US	MA	OS
US	34.41 % (N=171)	63.78 % (N=317)	1.81 % (N=9)	37.42 % (N=186)	57.55 % (N=286)	5.03 % (N=25)
MA	8.53 % (N=293)	83.73 % (N=2,876)	7.74 % (N=266)	14.99 % (N=515)	70.98 % (N=2,438)	14.03 % (N=482)
OS	2.63 % (N=12)	58.33 % (N=266)	39.04 % (N=178)	3.07 % (N=14)	65.13 % (N=297)	31.80 % (N=145)

Notes: N=4,388, US (underskilled), MA (matched), OS (overskilled).
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Skill mismatches between the five different domains are only moderately or even weakly correlated, and the correspondence of mismatches between the different domains is also low. For example, only one-third of all workers who are underskilled in mathematics is also underskilled in another domain. The majority of workers who are underskilled in one domain are matched or even underskilled in another, and the same applies to overskilling. Classifying an individual to be underskilled, matched, or overskilled overall while taking only one domain into account might thus be misleading.

For this reason, I introduce a multidimensional measure of skill mismatch that considers mismatches from five different skill domains in order to address the overall profile of an individual's skill mismatch situation more comprehensively. Taking into account an individual's mismatch situation in a range of skill domains strengthens the robustness of the classification by reducing the susceptibility to outliers in single skills, and provides a methodologically broader foundation in comparison to single-domain measures. In this way, the measure considers intrapersonal heterogeneity in skills and mismatch situations, and may provide a more valid approximation to individuals' overall skill mismatch profiles. I apply the MA instead of the STA method for this purpose, as it uses the average skill levels of only subjectively matched workers as a reference. Under theoretical considerations, this may represent a more accurate proxy for skill requirements.

5.1 Operationalisation

The multidimensional measure of skill mismatch takes into account individuals' mismatch situations in each of the five skill domains reading, mathematics, ICT, science, and reasoning. In a first step, the five skill mismatch measures in the single skill domains are operationalised based on the MA procedure.[11] Workers are categorized as being underskilled, matched, or overskilled in each of the skill domains, depending on whether their skill level in the respective domain is more than one-half of a standard deviation[12] below (underskilled) or above (overskilled) the average skill level of subjectively matched workers in their occupational group, resp. in between the range (matched). Consequently, any individual is categorized as being underskilled, matched, or overskilled in each of the five single skill domains. The multidimensional skill mismatch measure is then generated, categorizing individuals to be underskilled resp. overskilled overall if they are underskilled resp. overskilled in the majority of skills, i.e. at least three out of five. Individuals who are considered to be matched overall are those who are matched in the majority of skills or are not classified as underskilled or overskilled in at least three out of five skills.

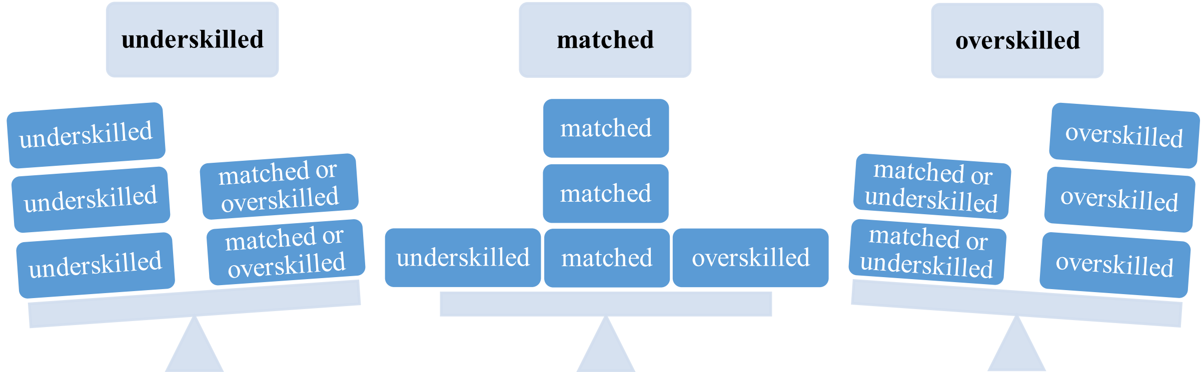
The resulting multidimensional measure of skill mismatch is conceptually based on the principle of a scale that only tips to one of the two edge sides (underskilled resp. overskilled) if the total balance is no longer maintained (cf. Figure 5). Individuals are therefore only defined as being underskilled resp. overskilled if the majority of the evidence speaks in favour of this classification and — metaphorically speaking — the scale tilts towards one of these two sides. This premise intends to ensure that only those workers are categorized as being underskilled or overskilled who possess significant skill deficits resp. skill surpluses across several skill domains. Otherwise, the scale remains in balance and individuals are considered to be matched overall.[13]

[11] The skill tests were assessed in different waves, depending on the skill domain (ICT and science in wave 2012; reasoning in wave 2014; reading and mathematics in wave 2016). Given that adults' skill levels do not essentially change over relatively short periods (cf. Lechner et al., 2021), individuals‘ skill levels are assumed to remain constant. Moreover, not all individuals were tested in each skill domain because participants of the NEPS wave 4 refreshment sample were only tested in reading and reasoning, but not in mathematics, ICT, and science, and because some individuals did not participate in each wave or refused to be interviewed in person. I imputed an individual's skill level in a skill domain if the individual had not previously been tested in the respective skill domain, following the multivariate imputation by chained equations approach.

[12] I use plus and minus one-half of a standard deviation instead of plus and minus one standard deviation. This is beneficial for the multidimensional measure because it also affects individuals with slight mismatches in single skills, ensuring sufficient coverage of workers who are underskilled, matched, or overskilled overall.

[13] Each of the three classifications (underskilled, matched, overskilled) is based on very heterogeneous skill mismatch situations in the single domains (cf. Table A4 in the Appendix for an overview on the empirically evident combinations).

Figure 5 Operationalisation of multidimensional skill mismatch

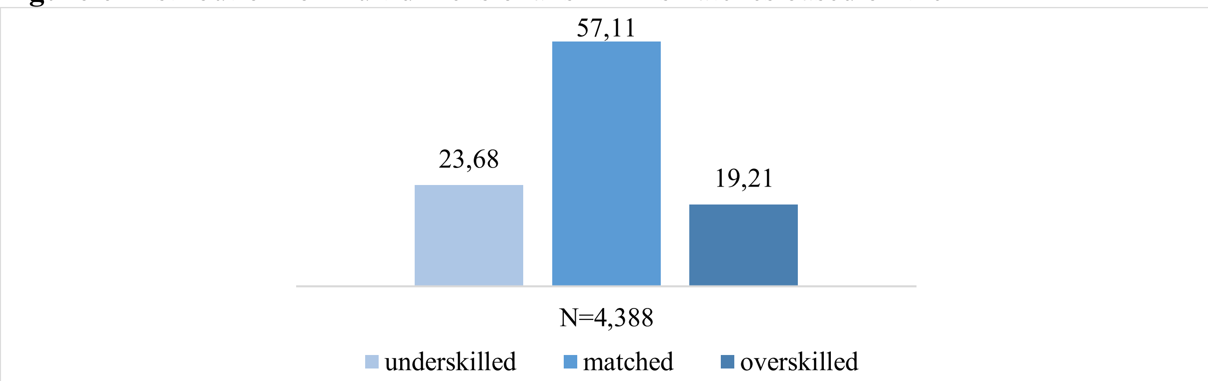


Source: Own illustration.

5.2 Validation

Following the procedure applied to the five different domain-specific measures, the new multidimensional measure of skill mismatch is validated in terms of empirical distribution, construct validity, and criterion-related validity. Figure 6 presents the multidimensional skill mismatch measure, which indicates *valid empirical distributions (2)*.

Figure 6 Distribution for multidimensional skill mismatches based on the MA



Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

With approximately 57 percent, the majority of workers are categorized to be matched overall. Moreover, the measure demonstrates a significant coverage of all classifications and a balanced proportion between underskilled and overskilled workers. Compared to the domain-specific measure of skill mismatch in mathematics based on MA, the multidimensional measure shows a considerably higher proportion of mismatched workers (both underskilled and overskilled) and a lower proportion of matched workers.[14] The empirical distribution of the multidimensional measure is similar to previous findings on test-based skill mismatches in

[14] Note that the comparatively higher rates of mismatched workers in the multidimensional measure are mainly due to using one-half of a standard deviation instead of one standard deviation to determine the lower limit and upper limit values in the single skill domains. Applying the one-standard deviation method to the multidimensional measure, 6.70 percent are underskilled, 87.74 percent matched, and 5.56 percent overskilled overall.

literacy and numeracy by Desjardins and Rubenson (2011), who also indicate approximately 60 percent of matched workers and somewhat higher underskilling than overskilling ratios.

As with the domain-specific skill mismatch measures, I test the *construct validity (3)* of the multidimensional skill mismatch measure (cf. Table 7).

Table 7 The association between sociodemographic and occupational characteristics and multidimensional skill mismatches based on the MA, logistic regressions

	Underskilled	**Overskilled**
Female	0.138***	−0.120***
(ref. male)	(0.012)	(0.011)
Age cohorts		
(ref. up to 35 years old)		
36 to 45 years old	0.020	−0.120***
	(0.018)	(0.026)
46 to 55 years old	0.121***	−0.202***
	(0.017)	(0.023)
56 to 65 years old	0.306***	−0.304***
	(0.020)	(0.022)
Tertiary education	−0.163***	0.159***
(ref. non-tertiary education)	(0.018)	(0.019)
Educational mismatch		
(ref. education-matched)		
undereducated	0.016	−0.021
	(0.018)	(0.018)
overeducated	−0.088***	0.101***
	(0.014)	(0.015)
High complex occupational level	0.120***	−0.086***
(ref. unskilled, skilled, complex level)	(0.021)	(0.015)
R-squared (McFadden)	0.133	0.141
N	4,361	4,361

Notes: * p < 0.05, ** p < 0.01, *** p < 0.001. Results indicate average marginal effects, standard errors in parentheses.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

In line with the assumptions, women, older workers, and individuals working in highly complex occupations are statistically significantly more likely to be underskilled, whereas tertiary education graduates and overeducated workers are statistically significantly less likely to be underskilled. This is consistent with the findings of the MA domain-specific skill mismatch in mathematics. In addition, the multidimensional measure essentially provides the same results for overskilling as for the MA domain-specific measure, which is also consistent with expectations and testifies to a high construct validity. In this context, the multidimensional skill mismatch findings consistently demonstrate considerably higher average marginal effects than the findings for domain-specific skill mismatch in mathematics.

Finally, I test the *criterion-related validity (4)* of the multidimensional skill mismatch measure. Table 8 indicates that underskilled workers earn approx. 4.2 percent lower wages than matched workers with similar occupational requirements, whereas overskilled workers earn approx. 5.3 percent higher wages.[15] Both underskilling wage penalties and overskilling wage benefits are statistically significant. Surprisingly, in contrast to the wage effects of skill mismatches in mathematics, the wage benefit for multidimensional overskilling is somewhat stronger than the wage penalties for underskilling. This might suggest that workers who possess skill surpluses across several skills are particularly valued by employers, and therefore earn significantly higher wages, for instance, as an incentive to retain them in the company.[16]

Table 8 The association between multidimensional skill mismatches based on the MA and ln gross hourly wages, OLS regressions

	Ln gross hourly wages
Skill mismatch	
(ref. matched)	
underskilled	−0.042*
	(0.021)
overskilled	0.053*
	(0.022)
R-squared	0.362
N	3,872

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in reading, mathematics, ICT, science, and reasoning, female, age, immigration background, educational level, field of education, part-time work, public sector, workplace, economic sector, job experience in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

The findings of both statistically significant underskilling wage penalties and overskilling wage benefits are in line with theoretical assumptions, suggesting high criterion-related validity of the multidimensional skill mismatch measure.

Altogether, multidimensional and domain-specific skill mismatch measures complement each other as they cover conceptually different aspects. On the one hand, a multidimensional skill mismatch measure provides conceptual advantages over domain-specific measures regarding the global assessment of an individual's skill mismatch situation. This is underlined by the rather weak intra-individual associations between skill mismatch measures in different skill domains. An individual's mismatch situation in one skill therefore does not necessarily coincide with their mismatch situation in other skills, or even their overall mismatch. On the other hand,

[15] Applying the formula of Benoit (2011), this corresponds to an underskilling wage penalty of 4.1 percent and an overskilling wage benefit of 5.4 percent.
[16] The multidimensional skill mismatch measure can also be operationalised using the STA, which shows almost identical validity to the MA (cf. Table S4 and Table S5 in the Supplementary Material). I conclude that the STA is also suitable for the test-based measurement of multidimensional skill mismatches.

domain-specific measures might be useful to address questions explicitly referring to skill-specific mismatches. Table 9 provides a summarising comparison of domain-specific and multidimensional skill mismatch measures.

Table 9 Summary on domain-specific and multidimensional skill mismatch measures

	Domain-specific skill mismatch	**Multidimensional skill mismatch**
Pros	Specific focus on mismatches in single skill domains High validity regarding individuals' skill specific mismatch situations	Broader coverage of skill domains Considering individuals' intrapersonal variations between single skill domains Closer approximation to individuals' overall mismatch profiles High validity regarding individuals' overall skill mismatch situations
Cons	Low validity on individuals' overall mismatch situation High sensitivity for outliers in single skill domains	Heterogeneous composition of categories
When to use	Research questions focusing on determinants or consequences of mismatches in specific skill domains or addressing differences in mismatches between the skill domains	Research questions focusing on determinants or consequences of individuals' overall skill mismatch situation

Source: Own illustration.

6 Discussion and conclusions

This study provides a comparative empirical validation of five different approaches to measuring occupational skill requirements as well as test-based measures of skill mismatch to analyse which approaches are adequate to measuring skill mismatches. Furthermore, it introduces a new measure of multidimensional skill mismatch that considers individuals' skill mismatch situations in five different cognitive skill domains. Drawing on the 2016 wave of the NEPS Adult Cohort, it validates the five different approaches with regard to the empirical distributions of their occupational skill requirement and skill mismatch measures, as well as their skill mismatch measure's link to relevant sociodemographic and occupational predictors and labour market outcomes. The findings illustrate significant variances between the different approaches, which underlines the need for careful reflection when choosing skill mismatch measures for analyses. Given their plausible distributions of occupational skill requirements and skill mismatches, and their high construct and criterion-related validity, the skill mismatch measures of the STA and MA are considered most valid overall. In contrast, the skill mismatch measures of the other approaches are less valid, for example, due to classifying the vast majority of workers as being mismatched (JA), or because they possess considerably lower construct and criterion-related validity (WA and TA).

The new measure of multidimensional skill mismatch also exhibits valid empirical distributions as well as high construct and criterion-related validity. It complements domain-specific measures by addressing the multifaceted composition of workers' and occupations' skill sets more accurately, thereby providing a more comprehensive assessment of individuals' skill mismatch. Given that individuals' skill mismatch situations vary considerably between different skills, this study suggests carefully differentiating between domain-specific and multidimensional measures and applying the appropriate one to the respective research question.

Nevertheless, this study has some limitations. The quality of the different approaches to test-based measurement of skill mismatch is evaluated using the NEPS Adult Cohort, but the implications cannot be transferred one-to-one to other contexts or other data. This is particularly evident for JA, WA, and TA, whose scaling of the occupational skill requirements does not perfectly match the metric of the NEPS skill level scaling, which might mainly drive their empirical shortcomings in this study. This implies that these three approaches should not be considered unsuitable for test-based measurement of skill mismatch in general, but rather in the specific context of NEPS. Moreover, this study illustrates that test-based measurement of skill mismatch is always associated with some degree of arbitrariness regarding the definition of threshold values, the skill domains used, or the selection of measurement approach. Considering that the incidence of skill mismatches and the resulting conclusions are highly driven by these arbitrary choices, results and conclusions should be interpreted with caution and in reflection of the measure which is used.

Future research might build on these findings, for example, to test the validity of the different approaches using other data or in another country-specific context. Subsequent skill mismatch research could benefit if large-scale surveys were to capture fitting information on occupational skill requirements in addition to skill tests and would cover a broader range of skill domains relevant to the labour market, such as communication skills or technical skills. The new multidimensional measure of test-based skill mismatch could also provide some new insights. Therefore, previous conclusions based on domain-specific skill mismatch might be reconsidered or rechecked to determine whether they still hold for a more general assessment of skill mismatch.

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8 Appendix

Table A1 Operationalization of the highest level of skills (numeracy), ESJS 2014

Question	Scale	Score
"Which of the following best describes the highest level of numeracy skills required for doing your job?"	1: Basic numeracy (e.g. Calculations using decimals, percentages or fractions, understanding tables and graphs)	1: Basic level
	2: Advanced numeracy (e.g. Calculations using advanced mathematical or statistical procedures)	2: Advanced level
	88: Not applicable/Numeracy skills are not required	0: Low level
	99: Don't know	Missing

Sources: Cedefop (2015), own illustration.

Table A2 Operationalization of job tasks score (mathematics), NEPS Adult Cohort

Item / Question	Scale	Filtering
Item 1: As a part of your job, do you apply any mathematical skills or do you have to deal with numbers?	1: yes 2: no −98: don't know	→ item 4 → item 2 → item 2
Item 2: Do you work at a cash register or do you in any other way work with cash?	1: yes 2: no −98: don't know	→ exit → item 3 → item 3
Item 3: Do you have to measure or count anything?	1: yes 2: no −98: don't know	→ exit → exit → exit
Item 4: As a part of your job, do you have to perform any simple calculations such as adding things up or subtracting, multiplying or dividing them?	1: yes 2: no −98: don't know	→ item 5 → exit → exit
Item 5: As a part of your job, do you use fractions or percentages?	1: yes 2: no −98: don't know	→ item 6 → item 6 → item 6
Item 6: As a part of your job, do you have to calculate areas, circles or volumes?	1: yes 2: no −98: don't know	→ item 7 → item 7 → item 7
Item 7: As a part of your job, do you have to apply advanced mathematics such as e.g. calculus, inferential statistics or regression analysis?	1: yes 2: no −98: don't know	→ exit → exit → exit
Score	**Recoding**	
1: Not required	Item 1 "no", Item 2 "no", Item 3 "no"	
2: Low complexity	Item 1 "yes" or Item 2 "yes" or Item 3 "yes" or Item 4 "yes", Items 5-7 "no"	
3: Moderate complexity	Item 5 "yes", Item 6 "no", Item 7 "no"	
4: Advanced complexity	Item 6 "yes", Item 7 "no"	
5: High complexity	Item 7 "yes"	

Sources: Matthes et al. (2014), own illustration.

Table A3 Descriptive sample statistics

Variables	Mean	SD	Min	Max	N
Occupational skill requirements					
STA	52.317	6.198	39.420	67.100	4,922
MA	52.834	6.218	40.200	65.130	4,890
JA	57.743	23.701	0	100	4,922
WA	66.156	8.930	34.280	78.490	4,890
TA	49.018	13.345	17.640	74.260	4,922
Skill mismatch					
STA					
underskilled	0.103	0.304	0	1	4,922
matched	0.789	0.408	0	1	4,922
overskilled	0.108	0.311	0	1	4,922
MA					
underskilled	0.112	0.316	0	1	4,890
matched	0.785	0.411	0	1	4,890
overskilled	0.102	0.303	0	1	4,890
JA					
underskilled	0.446	0.497	0	1	4,922
matched	0.336	0.472	0	1	4,922
overskilled	0.218	0.413	0	1	4,922
WA					
underskilled	0.128	0.334	0	1	4,890
matched	0.871	0.336	0	1	4,890
overskilled	0.001	0.035	0	1	4,890
TA					
underskilled	0.013	0.112	0	1	4,922
matched	0.935	0.247	0	1	4,922
overskilled	0.053	0.224	0	1	4,922
Predictors					
female	0.489	0.499	0	1	4,922
age cohorts					
up to 35 y.	0.115	0.319	0	1	4,922
36 to 45 y.	0.197	0.398	0	1	4,922
46 to 55 y.	0.413	0.492	0	1	4,922
56 to 65 y.	0.275	0.447	0	1	4,922
tertiary education	0.324	0.468	0	1	4,922
educational mismatch					
undereducated	0.188	0.391	0	1	4,889
matched	0.542	0.498	0	1	4,889
overeducated	0.269	0.444	0	1	4,889
high complex occup. level	0.313	0.464	0	1	4,922
Outcome					
ln gross hourly wages	4.537	0.457	1.544	5.991	3,953
Controls					
age	49.434	8.966	30	65	4,922
immigration background	0.152	0.359	0	1	4,922
educational level					
lower sec. educ.	0.028	0.166	0	1	4,922
upper sec. educ.	0.362	0.481	0	1	4,922
post-sec. non-tert. educ.	0.286	0.452	0	1	4,922
tertiary educ.	0.324	0.468	0	1	4,922

field of education					
general education	0.046	0.208	0	1	4,922
STEM	0.356	0.479	0	1	4,922
humanities, social sciences	0.088	0.283	0	1	4,922
busin., admin., law, services	0.293	0.455	0	1	4,922
education	0.056	0.229	0	1	4,922
health, welfare	0.094	0.291	0	1	4,922
field unknown	0.069	0.253	0	1	4,922
part-time job	0.324	0.468	0	1	4,911
public sector	0.315	0.464	0	1	4,886
economic sector					
agriculture, industry	0.291	0.454	0	1	4,922
services	0.197	0.398	0	1	4,922
information sector	0.220	0.414	0	1	4,922
public administration	0.244	0.429	0	1	4,922
unknown	0.049	0.215	0	1	4,922
workplace					
East Germany	0.133	0.339	0	1	4,922
West Germany	0.746	0.435	0	1	4,922
unknown	0.121	0.327	0	1	4,922
job experience	11.847	10.384	0	46	4,922

Source: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

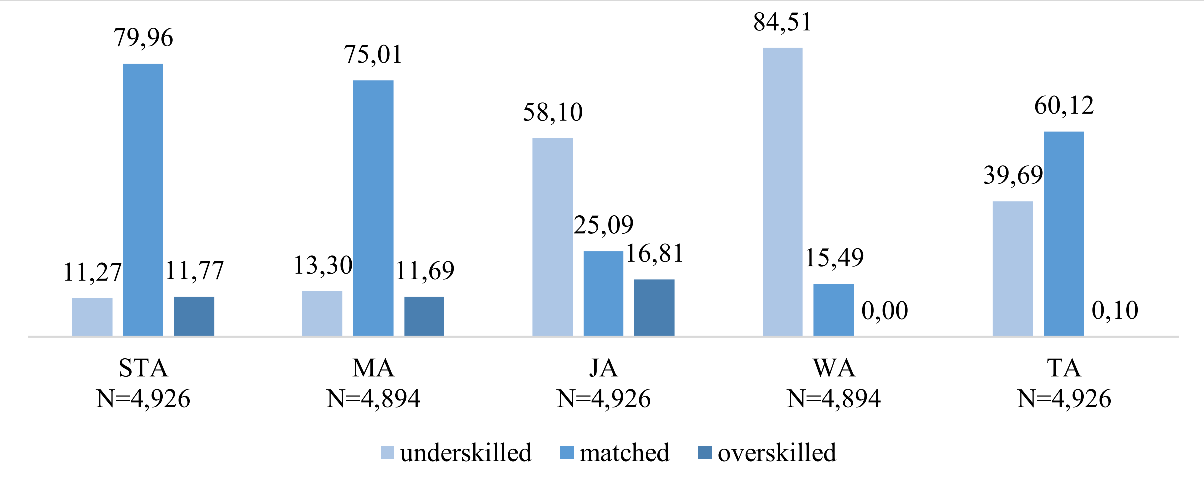
Table A4 Typology and empirical incidence of multidimensional skill mismatch combinations

Classification	Combination	Percent	N
Underskilled	5× US	4.81	211
	4× US / 1× MA	6.27	275
	4× US / 1× OS	0.71	31
	3× US / 2× MA	9.18	403
	3× US / 1× MA / 1× OS	2.46	108
	3× US / 2× OS	0.25	11
Matched	5× MA	4.06	178
	4× MA / 1× US	8.91	391
	4× MA / 1× OS	8.32	365
	3× MA / 1× US / 1× OS	7.22	317
	3× MA / 2× US	9.34	410
	3× MA / 2× OS	7.91	347
	2× MA / 2× US / 1× OS	5.13	225
	2× MA / 2× OS / 1× US	4.35	191
	1× MA / 2× US / 2× OS	1.87	82
Overskilled	5× OS	3.12	137
	4× OS / 1× MA	5.77	253
	4× OS / 1× US	0.64	28
	3× OS / 2× MA	7.18	315
	3× OS / 1× MA / 1× US	2.19	96
	3× OS / 2× US	0.32	14

Notes: N=4,388, US (underskilled), MA (matched), OS (overskilled).
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

9 Supplementary Material

Figure S1 Distributions of skill mismatch (reading)



Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S1 The association between sociodemographic and occupational characteristics and underskilling in reading, logistic regressions

	Underskilled (reading)				
	STA	**MA**	**JA**	**WA**	**TA**
Female	0.004	0.009	−0.017	0.042***	−0.042***
(ref. male)	(0.009)	(0.010)	(0.011)	(0.010)	(0.012)
Age cohorts					
(ref. up to 35 years old)					
36 to 45 years old	0.020	0.018	0.014	−0.014	0.027
	(0.014)	(0.015)	(0.021)	(0.021)	(0.021)
46 to 55 years old	0.029*	0.029*	0.027	0.022	0.056**
	(0.013)	(0.014)	(0.019)	(0.019)	(0.019)
56 to 65 years old	0.107***	0.125***	0.064**	0.087***	0.156***
	(0.015)	(0.016)	(0.020)	(0.019)	(0.020)
Tertiary education	−0.071***	−0.081***	0.054**	0.023	0.100***
(ref. non-tertiary education)	(0.013)	(0.014)	(0.018)	(0.015)	(0.021)
Educational mismatch					
(ref. education-matched)					
undereducated	0.012	0.016	0.291***	0.107***	0.281***
	(0.013)	(0.014)	(0.015)	(0.011)	(0.019)
overeducated	−0.051***	−0.062*	0.013	0.012	−0.068***
	(0.010)	(0.011)	(0.013)	(0.011)	(0.016)
High complex occupational level	0.040*	0.039*	0.545***	0.134***	0.358***
(ref. unskilled, skilled, complex level)	(0.016)	(0.017)	(0.012)	(0.013)	(0.022)
R-squared (McFadden)	0.047	0.053	0.314	0.079	0.209
N	4,893	4,861	4,893	4,861	4,893

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate average marginal effects, standard errors in parentheses.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S2 The association between sociodemographic and occupational characteristics and overskilling in reading, logistic regressions

	Overskilled (reading)				
	STA	**MA**	**JA**	**WA**	**TA**
Female	0.004	0.003	0.012	.	−0.001
(ref. male)	(0.009)	(0.009)	(0.010)		(0.002)
Age cohorts					
(ref. up to 35 years old)					
36 to 45 years old	0.016	0.012	−0.005	.	.
	(0.019)	(0.019)	(0.021)		
46 to 55 years old	−0.016	−0.021	−0.011	.	.
	(0.016)	(0.016)	(0.019)		
56 to 65 years old	−0.099***	−0.100***	−0.043*	.	.
	(0.016)	(0.016)	(0.019)		
Tertiary education	0.080***	0.084***	−0.037*	.	0.001
(ref. non-tertiary education)	(0.015)	(0.015)	(0.014)		(0.003)
Educational mismatch					
(ref. education-matched)					
undereducated	−0.016	−0.010	−0.115***	.	.
	(0.014)	(0.015)	(0.011)		
overeducated	0.049***	0.048***	−0.026*	.	−0.000
	(0.012)	(0.012)	(0.011)		(0.002)
High complex occupational level	−0.025	−0.026***	−0.232***	.	.
(ref. unskilled, skilled, complex level)	(0.013)	(0.013)	(0.009)		
R-squared (McFadden)	0.056	0.055	0.173	.	0.019
N	4,893	4,861	4,893	.	2,528

Notes: * p < 0.05, ** p < 0.01, *** p < 0.001. Results indicate average marginal effects, standard errors in parentheses.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S3 The association between skill mismatches in reading and ln gross hourly wages, OLS regressions

	Ln gross hourly wages				
	STA	**MA**	**JA**	**WA**	**TA**
Skill mismatch					
(ref. matched)					
underskilled	−0.079***	−0.074***	−0.024	−0.081***	−0.035*
	(0.018)	(0.017)	(0.017)	(0.018)	(0.014)
overskilled	0.038*	0.041*	0.055**	.	−0.019
	(0.017)	(0.017)	(0.019)		(0.237)
R-squared	0.459	0.452	0.468	0.447	0.464
N	3,921	3,893	3,921	3,893	3,921

Notes: * p < 0.05, ** p < 0.01, *** p < 0.001. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in reading, female, age, immigration background, educational level, field of education, part-time work, public sector, workplace, economic sector, job experience in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S4 The association between sociodemographic and occupational characteristics and multidimensional skill mismatches based on the STA, logistic regressions

	Underskilled	**Overskilled**
Female	0.115***	−0.118***
(ref. male)	(0.012)	(0.012)
Age cohorts		
(ref. up to 35 years old)		
36 to 45 years old	0.022	−0.112***
	(0.016)	(0.026)
46 to 55 years old	0.117***	−0.190***
	(0.016)	(0.023)
56 to 65 years old	0.272***	−0.308***
	(0.018)	(0.023)
Tertiary education	−0.133***	0.163***
(ref. non-tertiary education)	(0.017)	(0.020)
Educational mismatch		
(ref. education-matched)		
undereducated	0.045	−0.045*
	(0.018)	(0.018)
overeducated	−0.078***	0.114***
	(0.013)	(0.016)
High complex occupational level	0.081***	−0.064***
(ref. unskilled, skilled, complex level)	(0.020)	(0.016)
R-squared (McFadden)	0.125	0.134
N	4,394	4,394

Notes: * p < 0.05, ** p < 0.01, *** p < 0.001. Results indicate average marginal effects, standard errors in parentheses.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S5 The association between multidimensional skill mismatches based on the STA and ln gross hourly wages, OLS regressions

	Ln gross hourly wages
Skill mismatch	
(ref. matched)	
underskilled	−0.051*
	(0.022)
overskilled	0.058*
	(0.021)
R-squared	0.359
N	3,872

Notes: * p < 0.05, ** p < 0.01, *** p < 0.001. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in reading, mathematics, ICT, science, and reasoning, female, age, immigration background, educational level, field of education, part-time work, public sector, workplace, economic sector, job experience in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Article 2:

The link between education and skill mismatches: An analysis of the role of vocational and occupational specificity from a career perspective

Status: Not published

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Abstract

Previous research has demonstrated that individuals' level of education is associated with skill mismatch, but knowledge about the influence of horizontal dimensions of education and education's variation throughout the career is limited. Drawing on the 2016 wave of the German National Educational Panel Study (NEPS) Adult Cohort, this study analyses the link between education and skill mismatch by considering the influence of educational levels, vocational specificity, and occupational specificity from a career perspective. The findings show that individuals with a higher level of education or a higher occupational specificity of education are less likely to be underskilled, but more likely to be overskilled. Conversely, overskilling is less likely for individuals with a higher vocational specificity of education. The results also highlight that the link between education and skill mismatch varies depending on the time passed since graduation. Both the underskilling and overskilling risks of higher-educated individuals compared to those with a lower secondary education decline over time. Moreover, the mismatch-preventing influence of vocational and occupational specificity on underskilling increases, whereas their mismatch-preventing influence on overskilling decreases over the course of the career.

1 Introduction

Skill mismatches, defined as mismatches between employees' skills and the skills required for their jobs (International Labour Office, 2018), constitute significant challenges for individuals, firms, and societies. This encompasses wage penalties (Caroleo & Pastore, 2018; Kracke et al., 2018), reduced job satisfaction (Mateos-Romero & Salinas-Jiménez, 2018), productivity gaps, and diminished economic competitiveness (Brunello & Wruuck, 2021). Education is a crucial determinant for successful participation in the labour market and a key factor in addressing social inequalities, but the link between education and skill mismatch has hardly been explicitly investigated so far. Recent structural changes, such as the educational expansion and technological innovations, have led to significant shifts in both the supply and demand for education. These changes raise further questions about the significance of education for individuals' matching in the labour market.

Thus far, the link between education and skill mismatch has mainly been analysed in terms of the vertical dimension of education; that is, how different levels of education are associated with skill mismatch. Considering higher specialisation opportunities within the same educational level, however, the complete picture is no longer solely captured by the influence of vertical education. This is due to the fact that individuals' labour market success is also significantly affected by horizontal variations of education (Gerber & Cheung, 2008). On the horizontal dimension, education programmes differ, for instance, in vocational specificity (i.e. to what extent they impart vocation-specific skills) and occupational specificity (i.e. how strongly they link to a specific set of occupations). Education characterised by a high vocational specificity equips graduates with specific skills which increase their productivity in specific work tasks (Middeldorp et al., 2019), while highly occupational-specific education programmes link to a rather limited number of occupational groups (Geven & Spörlein, 2023). In this way, both high vocational and occupational specificity of education may facilitate individuals' transition into matching jobs, especially in early career stages (Rözer & Bol, 2019). To date, however, there is little evidence on whether vocational and occupational specificity of education affect individuals' skill matching and how this varies over the course of the career.

This study provides ample evidence on how different facets of education are associated with skill mismatch. In it, I analyse the relationship between education and skill mismatch, considering both the role of vertical (educational levels) and horizontal (vocational and occupational specificity) dimensions of education from a career perspective and thus contributing to the literature in several ways.

First, this study investigates the link between education and skill mismatch based on a multidimensional skill mismatch measure that accounts for (mis)matches in several skills. So far, some cross-sectional studies have shown that individuals with higher levels of education are less likely to be underskilled but more likely to be overskilled. For instance, Pellizzari and Fichen (2017) compare tertiary with non-tertiary educated workers for underskilling and overskilling in literacy and numeracy, while Flisi et al. (2017) compare upper secondary, post-secondary, and tertiary with lower secondary educated workers for overskilling in literacy and numeracy. However, as these studies focus on mismatches in single skill domains, they may convey an inaccurate picture of individuals' overall mismatch, given the intrapersonal heterogeneity between different skills. By contrast, the multidimensional skill mismatch measure used in this study addresses this issue by taking into account (mis)matches in five different skill domains (reading, mathematics, ICT, science, and reasoning) to provide a more valid overall (mis)match assessment.

Secondly, this study offers a differentiating view on the relationship between vocational specificity and skill mismatch. It achieves this by addressing vocational specificity across several educational levels using a specified gradual measure. Previous studies have analysed the association between vocational specificity and skill mismatch by differentiating vocational from general education programmes or by distinguishing between different fields of study. These cross-sectional studies have provided first indications that secondary graduates of vocational programmes are less likely to be overskilled but more likely to be underskilled in literacy and numeracy (Allen et al., 2013). They also signal that graduates of specific or workplace learning vocational programmes are less likely to be overskilled but more likely to be underskilled (Verhaest, Lavrijsen, et al., 2018), and that overskilling is more likely in tertiary graduates of unspecific fields (e.g. arts and humanities) (Assirelli, 2015). However, these approaches disregard the gradual character of vocational specificity, ignoring the heterogeneity within vocational programmes and fields. Moreover, they do not specifically address the underlying mechanisms (DiPrete et al., 2017). This study, in contrast, aims to obtain insights into this black box by directly addressing the underlying dimension of vocational specificity of education programmes based on a gradual measure.

Thirdly, this study is the first to analyse the link between occupational specificity and skill mismatch. Two studies so far have provided initial evidence on how occupational specificity of education links to mismatches in the level of education, indicating that graduates with a higher occupational specificity experience lower mismatching risks in their first significant job. In the first, Klein (2011) uses a gradual measure indicating the narrowness of an educations' job profile, showing lower risks of overeducation for higher occupational specificity. In the second, Vogtenhuber (2014) shows that graduates of more occupational-specific programmes are less likely to be undereducated or overeducated, using a gradual measure that indicates the extent of an education's dispersion over different occupations. I complement these studies by providing first evidence on how occupational specificity is associated with skill mismatch, based on a gradual measure that indicates the extent to which graduates of a specific education are clustered or spread across different occupations.

Fourth, this study analyses the link between education and skill mismatch from a career perspective, considering the varying influence of education at different stages of the career. Recent literature has discussed the relevance of a career perspective on education, for example, due to variations or even trade-offs in returns to education over the life course (e.g. Hanushek et al., 2017). Verhaest et al. (2018) are the first to analyse how the association between vocational specificity and skill mismatch is influenced by time since graduation. Based on a cross-sectional design, they show that vocational education graduates are less likely to be overskilled and more likely to be underskilled than general education graduates, but both of these likelihoods change in the course of the career. With increasing time, vocational education graduates become more likely to be overskilled, but less likely to be underskilled compared to individuals with a general education. Building on this study, I analyse how the associations between educational levels, vocational specificity, occupational specificity, and skill mismatch are moderated by the time passed since educational graduation.

Finally, this study builds on the German National Educational Panel Study (NEPS), which provides extensive information about individuals' education and employment biographies, as well as skill levels in a broad range of essential skill domains and potentially confounding characteristics. This comprehensive data set thus enables differentiated analyses of the relationship between education and skill mismatch. I address this relationship by drawing on the 2016 wave of the NEPS Adult Cohort, estimating logistic regression models to analyse the individual associations between educational levels, vocational specificity, occupational specificity, and underskilling resp. overskilling. I also consider the career perspective by investigating how these associations are moderated by time since graduation. Germany is a very interesting case in this regard, given its highly differentiated education system, the strong link between education and occupations, and the significant relevance of educational certificates for labour market success (Rözer & van de Werfhorst, 2020).

2 Theory and hypotheses

2.1 Educational levels and skill mismatch

Several approaches explain how education affects individuals' matching in the labour market. Following the human capital theory, education provides knowledge which enhances individuals' skills and productivity and therefore their chances on the labour market (Becker, 1993). Higher levels of education are assumed to be associated with higher levels of skills, which is why individuals with a higher educational achievement may be less likely to be underskilled but more likely to be overskilled.

Individual-level approaches highlighting the employer's perspective consider education as a positional good which serves as a proxy for applicants' skills or future trainability (Spence, 1973; Thurow, 1975). Following these approaches, a higher level of education signals higher productivity to employers, signifying a relatively better positioning in the job market. Employers might thus prefer to recruit applicants with the highest educational attainment. This decreases the likelihood for individuals with higher levels of education to be forced into jobs for which they are underskilled, but increases their likelihood to be hired for jobs for which they are overskilled (Verhaest, Bogaert, et al., 2018).

Additionally, individual-level associations between education and skill mismatch might be driven by the supply and demand for education. On the one hand, an oversupply of workers with a specific level of education (labour surpluses) and the associated undersupply of adequate employment might force individuals to enter jobs that do not match their skills. On the other hand, when there is an undersupply of workers with a specific education (labour shortages), employers may find themselves compelled to fill their vacancies with inadequately qualified applicants because they lack suitable alternatives. In Germany, the proportion of lower-educated individuals has decreased in recent decades, whereas the proportion of higher-educated individuals has significantly increased (Autorengruppe Bildungsberichterstattung, 2018). Insofar as this results in skill shortages among lower-educated individuals, employers may be forced to hire low-educated workers who do not possess the appropriate level of skills. By contrast, an oversupply of high education levels might coerce highly educated individuals to transition into low-level professions. This leads to the following hypotheses:

H1. *Individuals with a higher level of education (upper secondary, post-secondary non-tertiary, tertiary education) are less likely to be underskilled for their job* **(H1a)** *but more likely to be overskilled for their job* **(H1b)** *than individuals with a lower level of education (lower secondary education).*

2.2 Vocational specificity and skill mismatch

Education varies in the extent to which it provides vocational-specific skills. More vocational-specific education programmes (e.g. hairdressing, law) impart individuals with more specific skills to prepare them for specific job tasks. In contrast, less vocational-specific programmes, such as industrial business management or philosophy, teach rather general skills that are applicable to a broader range of occupations (Noelke et al., 2012). Graduates of more vocational-specific programmes may benefit from a closer fit between skills learned in education and requirements to be met on the job (Wolbers, 2003). Moreover, they may be less likely to face unfamiliar challenges not acquired during education, or job demands that they cannot cope with, provided that their job corresponds to their professional education.

Additionally, signalling and job competition approaches assume relative advantages for applicants of highly vocational-specific education, as they may signalise more specific and clearer skill sets and lower expected training costs to potential employers (Ortiz & Rodriguez Menés, 2016). A higher vocational specificity might thus be beneficial to being hired for matching jobs. It may also decrease the likelihood of individuals being forced to switch to less demanding jobs outside their subject or main expertise, or to jobs below their skill level. The following hypotheses are derived from these assumptions:

H2. *The higher the vocational specificity of an individual's education, the lower their likelihood to be underskilled for their job* **(H2a)** *and the lower their likelihood to be overskilled for their job* **(H2b)**.

2.3 Occupational specificity and skill mismatch

Educational programmes also differ in occupational specificity, i.e. how they link to a specific set of professions. Education characterised by high occupational specificity (e.g. early childhood education, medicine) link graduates to specific professions or a rather narrow set of occupations. Conversely, educational programmes with low occupational specificity, such as media design or arts and humanities, prepare graduates for a broader set of occupations. As a result of having stronger ties to specific occupations, graduates with a higher occupational specificity disperse to a smaller range of occupations (Rözer & van de Werfhorst, 2020).

Additionally, they face a higher chance to work in an occupation that matches their education (Geven & Spörlein, 2023).

The strength of occupational specificity is shaped, for example, by occupational closure mechanisms (DiPrete et al., 2017). For instance, highly occupation-specific programmes artificially restrict the supply of potential workforce by selective access criteria (e.g. based on the numerus clausus for studies) or through licensed access procedures to occupational destinations (e.g. state examination degrees for specific occupations) (Weeden, 2002). These closure mechanisms lower the risks of labour surpluses in highly occupation-specific programmes and smooth their graduates' transitions into the job by facilitating their access to matching occupations (Barone & Schindler, 2014). A stronger occupational specificity thus provides a stronger link between individuals' education and occupational destination, making graduates less likely to work in a job that does not match their subject or skill profiles. From this, the following hypotheses are derived:

H3. *The higher the occupational specificity of an individual's education, the lower their likelihood to be underskilled for their job* **(H3a)** *and the lower their likelihood to be overskilled for their job* **(H3b)**.

2.4 Education and skill mismatch – the moderating role of time since graduation

The risk for skill mismatch may vary between different stages of the career since individuals may acquire or lose skills over time. For example, individuals might be underskilled at the time of their job entry immediately following graduation due to lacking practical experience, but they may reduce such deficits over time through on-the-job learning (Ferreira Sequeda et al., 2017). On the other hand, skills acquired in education might become obsolete at a later point in the career, e.g. certain skills may no longer be required due to technological innovations or changing job tasks.

Moreover, the influence of education on skill mismatch may vary over an individual's career due to differing implications of education at different times of the career (Hanushek et al., 2017). Following the career mobility theory (Sicherman & Galor, 1990), individuals with higher levels of education face higher overskilling risks at the beginning of their career, but are more likely to arrive at a matching job in the long run due to their better upward mobility prospects. Conversely, highly vocational-specific programmes are assumed to be beneficial to skill matching upon entry due to more ready-to-use skills, but disadvantageous in the long-run due to limited flexibility and adaptive capacity if skill demands change (Rözer & Bol, 2019).

Similarly, the benefits of a higher occupational specificity in education might also be limited to the initial entry into a job, becoming less relevant over the course of a career when higher flexibility may gain importance.

Moreover, individuals' long-term coping in the job and labour market could be influenced by education, due to their varying adaptive capacities to changing demands. For example, both individuals with higher levels of education and graduates of more generic education may be more capable to compensate for initial skill deficits over time, and more capable to acquire new skills or to adapt to new conditions (Middeldorp et al., 2019). In contrast, individuals with a higher vocational specificity of education may be highly susceptible to skill depreciation when job-specific skill demands change. Moreover, higher-educated individuals might be less affected by long-term skill depreciation, as they are more likely to proactively counter deficits by participating in further education, training, and updating of skills (Ferreira Sequeda et al., 2017). This may also apply to graduates of less specific programmes who possess more on-the-job learning and participate more frequently in trainings than individuals with more vocational-specific education, especially at the start of the career (Tobback et al., 2023).

The varying influence of education on skill mismatch depending on the time passed since graduation might also be explained by structural changes in the supply and demand for education in recent decades. On the one hand, the demand for education has changed over time due to technological innovations and shifts in job demands. For example, the skill-biased technological change theory argues for changes in favour of high-skilled rather than low-skilled labour. This is assumed to be due to computerisation and digitalisation which have resulted in a higher demand for high-skilled workers and a lower demand for low-skilled workers in the past decades (Acemoglu, 2002). On the other hand, the supply of skilled labour, and therefore the relative value of higher educational attainment, has significantly changed given the steady increase in higher-educated individuals. In Germany, the share of individuals with lower secondary education has steadily declined in the relevant period between 1976 and 2016, while upper secondary and post-secondary non-tertiary education has grown and tertiary education has more than tripled (Statistisches Bundesamt, 2020). Therefore, the relative value and returns to recent higher educational attainment and especially tertiary degrees may be decreased in comparison to their value a few decades ago. Additionally, the expansion of higher-educated graduates might have affected the returns to vocational-specific education, for example, by increasing the signalling value of highly vocational-specific education (Klein, 2011), or by decreasing the relative value of less specific degrees (Ortiz & Rodriguez Menés, 2016). The following hypotheses are thus derived:

H4. *The longer the time since graduation, the less likely individuals with a higher level of education (upper secondary, post-secondary non-tertiary, tertiary education) are underskilled or overskilled for their job compared to individuals with a lower level of education (lower secondary education).*

H5. *The longer the time since graduation, the weaker the preventive influence of vocational specificity of education on avoiding skill mismatch (underskilling or overskilling).*

H6. *The longer the time since graduation, the weaker the preventive influence of occupational specificity of education on avoiding skill mismatch (underskilling or overskilling).*

3 Data and Methods

3.1 Data

The following analyses are based on the NEPS Adult Cohort Version 9.0.1 (Blossfeld & Roßbach, 2019; NEPS Network, 2018). The total sample of respondents of the NEPS Adult Cohort begun in 2007 (wave 1) consists of adults living in Germany who were born between 1944 and 1986. The NEPS Adult Cohort offers rich information on the educational and employment biographies of the respondents from different waves. It also provides skill tests in several skill domains relevant to the labour market, preconditioned to analysing the link between education and skill mismatch. This study draws on a cross-section of the 9th wave of the NEPS Adult Cohort, since the latest skill tests were carried out in this wave. In addition to the cross-section information from wave 9, variables from previous waves of the panel data are also used if the relevant information was collected in those waves, but not in the 2016 wave. This concerns the information regarding some of the respondents' skill levels, since the most recent skill tests were conducted in different waves, depending on the skill domain (ICT and science in wave 2012, reasoning in wave 2014, reading and mathematics in wave 2016).[1] Given that adults' skill levels do not essentially change over relatively short periods of time (cf. Lechner et al., 2021), individuals‘ skill levels are assumed to remain constant.

[1] Given the sampling strategy of the NEPS Adult Cohort, some respondents are not tested in each skill domain. I impute individuals' skill levels in the missing skill for those who had not previously been tested in the respective domain.

3.2 Sample

The analysis sample is based on individuals who participated in the 2016 wave of the NEPS Adult Cohort. I restrict the sample to include only dependent-employed core workers aged up to 65 years, who work for at least 15 hours per week. The sample excludes self-employed individuals, those in pre-professional employment (e.g. internship, student assistant, etc.), freelancers, family workers, and individuals employed in active labour market programmes or seasonal work. Migrants who have attained their last education abroad are also excluded, because their educational qualifications cannot be equated with those acquired in Germany. Furthermore, I restrict the sample to individuals with a maximum of 40 years passed since graduation to prevent an overrepresentation of low-educated individuals among those with a longer time since graduation. Moreover, I exclude individuals with primary education or without educational qualification (ISCED-1997: 0/1) due to insufficient numbers of observations, and individuals with missing values in any of the required variables. The final sample consists of a total of 3,687 respondents.

3.3 Measurements

The dependent variables *underskilling* and *overskilling* are operationalised based on a multidimensional concept which considers mismatches in five different skill domains (reading, mathematics, ICT, science, and reasoning). Given their higher objectivity, I use test-based measures of skill mismatch instead of worker self-assessments which might be biased by subjective perceptions. In a first step, I derive the five single skill mismatch indicators by comparing individuals' levels of skills to the level of skills required in their occupational group in the relevant skill domain. The skill requirements are defined for the reference group of regular dependent workers with a maximum age of 65 working at least 15 hours per week, who subjectively assess that their skills match the requirements of their job (cf. Pellizzari & Fichen, 2017).[2] For each skill domain, the skill requirements are defined as the average skill level of these subjectively matched workers in the same ISCO-08 three-digit occupational minor group based on a minimum of 20 observations.[3] In a second step, workers are categorized as underskilled, matched, or overskilled in each of the five domains. This classification is based on whether their skill level in the respective skill domain lies more than one-half of a standard

[2] This subjective assessment refers to workers' general skill mismatch. Individuals who "rather agree" or "completely agree" that "The requirements of the job match my skills" are considered to be subjectively matched and thus applied as reference group to estimate the occupational skill requirements.

[3] In the case of not at least 20 observations for a three-digit minor group, I use the respective ISCO-08 two-digit sub-major group as a reference.

deviation below (underskilled) or above (overskilled) the averaged level of skills in their occupational group, regardless of how they subjectively assess their skill matching situation. All others are classified as being matched. This results in five skill mismatch measures, each differentiating between underskilling, match, and overskilling. Finally, the multidimensional skill mismatch measure is generated, classifying individuals as underskilled resp. overskilled overall based on whether they are underskilled resp. overskilled in the majority, i.e. at least three out of five skills. Individuals who are considered as matched overall are those who are matched in the majority of skills or are not classified as underskilled or overskilled in at least three out of five skills. Based on this, both dependent variables underskilling and overskilling are operationalised as dummy variables.

The first independent variable *level of education* refers to individuals' last successfully completed educational qualification before wave 9 survey. I prefer the last to the highest successfully completed education, since the last education is considered more relevant for an individual's current employment situation. The level of education differentiates four categories: lower secondary education (ISCED-1997: 2), upper secondary education (ISCED-1997: 3), post-secondary non-tertiary education (ISCED-1997: 4/5B), and tertiary education (ISCED-1997: 5A/6).

The second independent variable *vocational specificity of education* indicates the extent to which the utilisation of knowledge and skills acquired in education is linked to the profession learned. The vocational specificity of education is calculated using the 2006, 2012, and 2018 versions of the BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany (Hall et al., 2020), applying the vocational specificity index of Hall (2011), cf. Equation 1.

Equation 1 Index for vocational specificity of education

$$VSe = \frac{(HUce - HUne)}{HUce}$$

VSe = Vocational specificity of education e
HUce = Share of individuals with high utilisation of the vocational knowledge and skills acquired during education e in current occupational activity that corresponds to the profession trained
HUne = Share of individuals with high utilisation of the vocational knowledge and skills acquired during education e in current occupational activity that is unrelated to the profession trained

The vocational specificity of education refers to individuals' last successfully completed education (e.g. vocational education, academic degree) separated by level of education (upper secondary ISCED-1997 3B/3C, post-secondary non-tertiary ISCED-1997 4/5B, tertiary ISCED-1997 5A/6) and field of education (KldB-2010 two-digits). I calculate the share of workers highly utilising vocational knowledge and skills learned in education, differentiating between those individuals currently working in an occupation corresponding their education and those who are not. The utilisation of vocational knowledge and skills acquired during education is defined as high if workers can use “some”, “quite a lot” or “very much” of it in their current job.[4] The resulting vocational specificity measure indicates both the extent to which single education programmes (e.g. vocational trainings or academic degrees) provide graduates with vocationally specific knowledge and skills, and the extent to which the skills acquired in education are bound to the learned occupation (cf. Appendix Table A1). A high vocational specificity indicates that the knowledge and skills acquired in the respective education programme can be highly applied in the learned occupation, but have limited transferability to other professions.

The third independent variable *occupational specificity of education* indicates the extent to which individuals’ level and field of education are clustered in or spread over specific occupations. I build on the measure of DiPrete et al. (2017) who use the German Microcensus 2006, indicating the occupational specificity by fields and levels of education in Germany (cf. Appendix Table A2). The occupational specificity of education refers to the last successfully completed education programme separated by level of education (lower secondary ISCED-1997 2, upper secondary ISCED-1997 3, post-secondary non-tertiary ISCED-1997 4/5B, tertiary ISCED-1997 5A/6), and field of education (ISCED-F 2013 two-digits). A high occupational specificity indicates that individuals with this education do not highly disperse over different occupational groups and are instead clustered in a narrow range of occupations (DiPrete et al., 2017).[5]

The moderator variable *time since graduation* states the number of years passed between the last successfully completed education and the wave 9 survey. I further draw on control variables that are likely to condition both the independent and the dependent variables in order to prevent endogenous selection bias (Elwert & Winship, 2014). These include dummies for male opposed to female, categorised birth cohorts, immigration background (only defining first and second generation migrants as having an immigration background), last educational qualification in

[4] Vocational specificity is only determined for educational qualification groups with at least 20 observations on the relevant question.

[5] Ideally, vocational and occupational specificity indicators would be based on subjective assessments directly questioning the respondents about the specificity of skills learned in training or the occupational specificity of the training content. However, I cannot build on such indicators due to lacking data for Germany.

former German Democratic Republic (as opposed to Federal Republic of Germany),[6] and high social background (defined as having at least one parent with tertiary education). Table 1 provides an overview of the descriptive sample statistics including all variables used in the study.

Table 1 Descriptive sample statistics

Variables	Mean	SD	Min	Max
Dependent variables				
underskilled	0.213	0.410	0	1
overskilled	0.204	0.403	0	1
Independent variables				
educational level				
lower secondary education	0.022	0.150	0	1
upper secondary education	0.353	0.478	0	1
post-sec. non-tert. education	0.292	0.455	0	1
tertiary education	0.333	0.471	0	1
vocational specificity	0.523	0.150	0	0.871
occupational specificity	1.223	0.642	0.270	3.420
Moderator variable				
time since graduation	22.395	11.096	0	40
Control variables				
male	0.512	0.500	0	1
birth cohort				
1950s	0.195	0.396	0	1
1960s	0.456	0.498	0	1
1970s	0.222	0.416	0	1
1980s	0.127	0.333	0	1
immigration background	0.154	0.361	0	1
educ. qualification in former GDR	0.085	0.279	0	1
high social background	0.210	0.408	0	1

Note: N=3,687.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

3.4 Analytical strategy

The following analyses demonstrate the associations between different facets of education and skill mismatch. Given the cross-sectional design and the two dichotomous dependent variables, I conduct logistic regression models indicating average marginal effects. First, I examine the link between educational levels and underskilling resp. overskilling. Subsequently, the associations between vocational resp. occupational specificity and skill mismatch are investigated. This is done by gradually introducing them to the models to distinguish their separate and combined influence on underskilling and overskilling. Subsequently, I estimate

[6] Last educational qualifications acquired after German reunification (i.e. in the reunified Federal Republic of Germany) are considered as educational qualifications in the Federal Republic of Germany regardless of whether they were acquired in East Germany or West Germany.

how educational levels, vocational specificity, and occupational specificity interact with the factor of time since graduation.

4 Findings

4.1 Educational level, vocational specificity, occupational specificity and skill mismatch

Table 2 illustrates the associations between educational levels and underskilling as well as overskilling.

Table 2 The associations between educational levels and skill mismatch, logistic regressions

	Underskilling		**Overskilling**	
	Model 1		Model 2	
	AME	SE	AME	SE
Educational level				
(ref. lower sec. education)				
upper sec. education	−0.170**	0.052	0.026	0.040
post-sec. non-tert. educ.	−0.203***	0.053	0.087*	0.040
tertiary education	−0.263***	0.053	0.136**	0.041

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate average marginal effects. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background, time since graduation.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

I find substantially lower underskilling risks for individuals with a higher educational attainment compared to lower secondary graduates. In line with Hypothesis 1a, employees with a higher level of education are statistically significantly less likely to be underskilled for their job. Compared to individuals with a lower secondary education, the average probability of being underskilled decreases by 17.0 percentage points for upper secondary education, by 20.3 percentage points for post-secondary non-tertiary education, and by 26.3 percentage points for tertiary education graduates. Conversely, individuals with a higher level of education are more likely to be overskilled than lower secondary graduates, although this is not statistically significant for those with upper secondary education. However, graduates with post-secondary and tertiary education face statistically significantly higher risks of being overskilled for their jobs. Their average probability of being overskilled is substantially higher when compared to individuals with lower secondary education (8.7 percentage points for post-secondary education and 13.6 percentage points for tertiary education graduates). Both Hypotheses 1a and 1b are therefore not rejected.

The associations between vocational resp. occupational specificity and skill mismatch are addressed in Table 3 and Table 4. Models 1 and 2 each provide separate analyses on the associations between vocational resp. occupational specificity and underskilling or overskilling. Model 3 takes both vocational and occupational specificity into account.

Table 3 The associations between vocational specificity, occupational specificity, and underskilling, logistic regressions

	Underskilling					
	Model 1		Model 2		Model 3	
	AME	SE	AME	SE	AME	SE
Vocational specificity	−0.025	0.042			−0.017	0.041
Occupational specificity			−0.045***	0.012	−0.045***	0.012

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate average marginal effects. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background, time since graduation.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table 3 indicates lower underskilling risks for individuals with a more vocational-specific education. However, the associations are not statistically significant and Hypothesis 2a is therefore rejected. In line with Hypothesis 3a, individuals with a higher occupational specificity are statistically significantly less likely to be underskilled. With a hypothetical one-point increase in the occupational specificity of education, which is scaled from 0.270 to 3.420, the average probability of being underskilled decreases by 4.5 percentage points. Accordingly, Hypothesis 3a is not rejected.

Table 4 The associations between vocational specificity, occupational specificity, and overskilling, logistic regressions

	Overskilling					
	Model 1		Model 2		Model 3	
	AME	SE	AME	SE	AME	SE
Vocational specificity	−0.088*	0.043			−0.089*	0.044
Occupational specificity			0.026*	0.010	0.025*	0.010

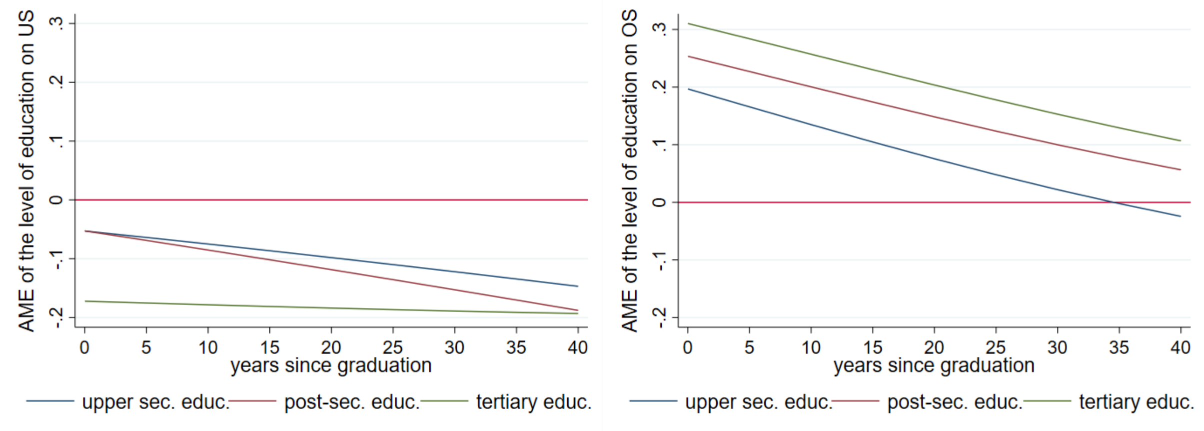
Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate average marginal effects. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background, time since graduation.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table 4 shows that individuals with a higher vocational specificity face significantly lower overskilling risks. The average probability of being overskilled decreases with a one-point higher vocational specificity by 8.8 percentage points (Model 1) resp. 8.9 percentage points (Model 3). This one-point higher vocational specificity corresponds, for example, to a hypothetical increase from the minimum of 0 to a hypothetical maximum of 1 on the vocational specificity scale, which is scaled from 0 to 0.871. These statistically significant findings are in line with the assumptions; therefore, Hypothesis 2b is not rejected. In contrast to this and contradicting the assumptions of Hypothesis 3b, higher occupational specificity is associated with a statistically significantly higher likelihood for being overskilled. A one-point higher occupational specificity is associated with a 2.6 percentage points (Model 2) resp. 2.5 percentage points (Model 3) higher risk for overskilling. Hypothesis 3b is therefore rejected.

4.2 Education and skill mismatch − the moderating role of time since graduation

The following figures present the interaction effects of educational levels, vocational specificity, and occupational specificity with time since graduation.

Figure 1 The average marginal effects of the level of education on underskilling and overskilling in relation of time since graduation

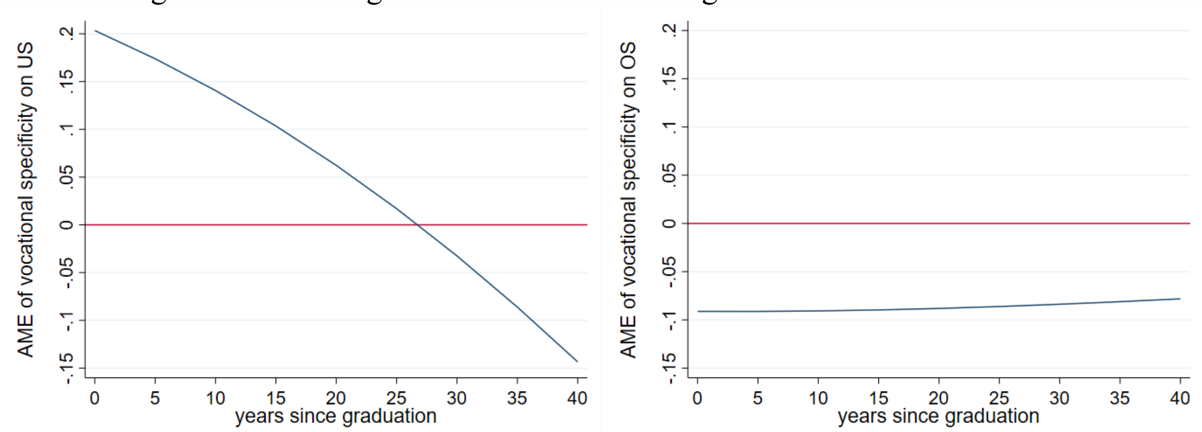


Notes: N=3,687. AME (average marginal effect), US (underskilling), OS (overskilling). Results indicate the average marginal effects of the level of education (upper secondary education, post-secondary non-tertiary education, tertiary education compared to the reference of lower secondary education) on underskilling and overskilling in relation of years passed since educational graduation. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Figure 1 indicates decreasing underskilling and overskilling risks for the higher levels of education compared to the reference level of lower secondary education, with a longer time since graduation. Directly after graduation, upper secondary and post-secondary graduates face approx. 5 percentage points lower risk of being underskilled compared to lower secondary graduates, and the underskilling risk of individuals with tertiary education is even approx. 18 percentage points lower than that of those with lower secondary education. These initially lower underskilling risks for higher levels of education compared to lower secondary education further decrease over the course of the career. In this context, the underskilling risks of upper secondary and post-secondary graduates compared to lower secondary graduates decline considerably stronger than those for tertiary education compared to lower secondary graduation. At later career stages, the underskilling-preventing influence of higher levels of education compared to lower secondary education thus approaches between the three higher levels of education. Moreover, graduates of each of the three higher educational levels demonstrate lower underskilling risks compared to lower secondary graduates throughout the entire period of up to 40 years after graduation.

This is not the case with regard to overskilling, where upper secondary, post-secondary, and tertiary graduates exhibit higher risks compared to lower secondary graduates for up to 35 resp. 40 years after graduation. At the beginning of the career, individuals with a higher level of education face considerably higher risks of being overskilled compared to lower secondary graduates (approx. 20 percentage points for upper secondary, approx. 25 percentage points for post-secondary, and approx. 30 percentage points for tertiary education graduates). However, the overskilling risks of the three higher levels of education compared to lower secondary education decrease substantially over time. There is even a trade-off in the case of overskilling risk for upper secondary education compared with lower secondary education. During the first 35 years after graduation, upper secondary graduates face higher overskilling risks than lower secondary graduates. After more than 35 years, however, individuals with upper secondary education are less likely to be overskilled than those with lower secondary education. The findings correspond to Hypothesis 4, which assumes decreasing risks of underskilling and overskilling for higher levels of education compared to lower secondary education with a longer time passed since graduation. Hypothesis 4 is therefore not rejected.

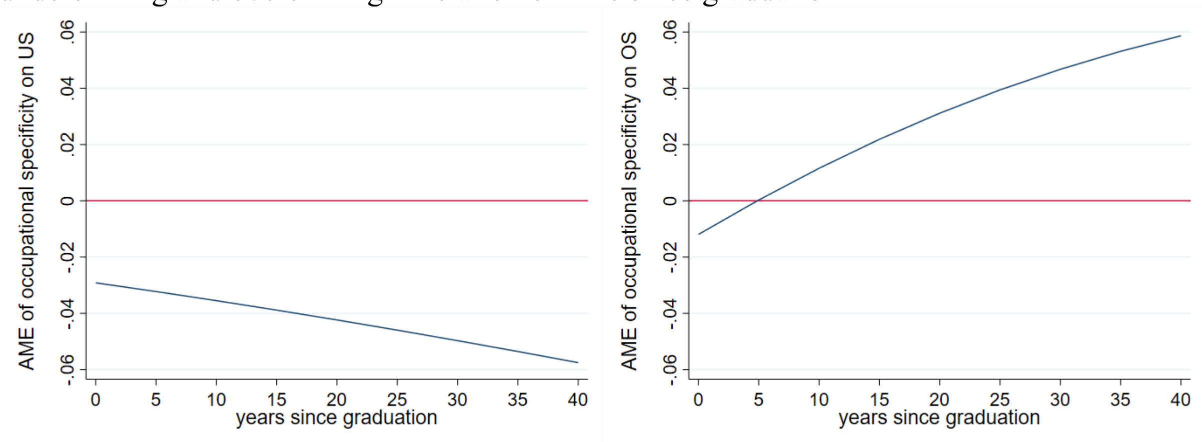
Figure 2 The average marginal effects of the vocational specificity of education on underskilling and overskilling in relation of time since graduation



Notes: N=3,687. AME (average marginal effect), US (underskilling), OS (overskilling). Results indicate the average marginal effects of the vocational specificity of education on underskilling and overskilling in relation of years passed since educational graduation. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Figure 2 shows the interaction effects of vocational specificity and time since graduation on underskilling and overskilling. In the first years after graduation, there is a positive effect (i.e. a mismatch risk-increasing influence) of vocational specificity on underskilling. A one-point higher vocational specificity translates into an approx. 20 percentage points higher likelihood of being underskilled directly after graduation. This positive effect of vocational specificity on underskilling decreases considerably over time and shows a trade-off approx. 27 years after educational graduation, even turning into a negative effect (i.e. a mismatch-preventing influence) of vocational specificity on underskilling. This means that the mismatch-preventing influence of vocational specificity on underskilling increases with time, contradicting the assumption of Hypothesis 5. Conversely, the negative effect of vocational specificity on overskilling is strongest right after graduation but slightly decreases over time, which is in line with the assumptions. However, there is a mismatch-preventing influence of vocational specificity on overskilling over the full period of up to 40 years after graduation. Nevertheless, Hypothesis 5 is rejected.

Figure 3 The average marginal effects of the occupational specificity of education on underskilling and overskilling in relation of time since graduation



Notes: N=3,687. AME (average marginal effect), US (underskilling), OS (overskilling). Results indicate the average marginal effects of the occupational specificity of education on underskilling and overskilling in relation of years passed since educational graduation. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Figure 3 shows the interaction effects of occupational specificity and time since graduation on underskilling and overskilling. There is a negative effect of occupational specificity on underskilling over the entire period up to 40 years after graduation. This negative effect of occupational specificity on underskilling increases over time, contradicting Hypothesis 6. Conversely, the mismatch-preventing influence of occupational specificity on overskilling decreases over time. In the first years after graduation, occupational specificity has a negative effect on overskilling. After more than five years, however, the mismatch-preventing influence of occupational specificity on overskilling turns into a positive effect (i.e. a mismatch risk-increasing influence). The risk of overskilling thus increases with longer time passed since graduation. This finding coincides with the assumed weaker mismatch-preventing influence of occupational specificity on overskilling over time. Corresponding to the case of vocational specificity, the findings on the interaction effect of occupational specificity and time since graduation on underskilling contradict the hypothesis that the mismatch-preventing influence of occupational specificity decreases over time. Hypothesis 6 is therefore also rejected.

Hence, the assumed mismatch-preventing influence of vocational and occupational specificity does not generally decrease with more time since graduation. The postulated decreasing mismatch-preventing influence of vocational and occupational specificity over time is only evident for overskilling, while for underskilling, an even stronger preventive influence is shown. Tables A3 to A6 in the Appendix present the corresponding logit models for the interaction effects. The findings show statistically significant interaction effects of vocational specificity and time since graduation on underskilling, and of occupational specificity and time since graduation on overskilling.

4.3 Robustness Analyses

I conduct additional robustness analyses to address some issues in more detail. For example, the associations between vocational and occupational specificity and skill mismatch might be driven by systematic differences in the extent of vocational and occupational specificity between education levels (e.g. secondary and post-secondary degrees may generally possess higher specificity and stronger workplace ties than tertiary degrees). The Appendix Table A7 shows how vocational and occupational specificity are linked to skill mismatch for the subsamples of secondary-, post-secondary-, and tertiary-educated individuals. The results for vocational specificity and skill mismatch essentially remain the same compared to the total sample, except for the subgroup of post-secondary graduates in the case of overskilling. Conversely, the associations between occupational specificity and skill mismatch in the subgroups differ significantly from the total sample results. This means that vocational and occupational specificity may have different implications within individual education subgroups.

Additionally, I rerun the main models using domain-specific skill mismatch measures to test whether the findings are driven by the multidimensional skill mismatch measure (cf. Appendix Table A8 to Table A10). The associations between educational levels and skill mismatch essentially point into the same direction, but they only show statistically significant results for underskilling in mathematics (tertiary level) and ICT (upper secondary, post-secondary, and tertiary level), as well as for overskilling in reading (tertiary level), mathematics (post-secondary and tertiary levels), and science (tertiary level). While multidimensional skill mismatches are an issue for all higher levels of education, mismatches in single skill domains are particularly relevant for tertiary graduates.

The associations between vocational specificity and domain-specific overskilling remain essentially consistent for underskilling in mathematics, ICT, and science, but contradictory for underskilling in reading and reasoning. The results of domain-specific mismatches for occupational specificity and underskilling correspond to multidimensional underskilling (statistically significant for reading, science, and reasoning) and to multidimensional overskilling, with the exception of ICT. Accordingly, the associations between education and skill mismatch partially differ between multidimensional and domain-specific mismatches, also showing some variation between different skill domains.

5 Discussion and conclusion

This study indicates how education is linked to skill mismatch by considering the role of educational levels, vocational specificity, and occupational specificity from a career perspective. Drawing on the 2016 wave of the German NEPS Adult Cohort, it demonstrates that individuals with a higher level of education and individuals with a higher occupational specificity of education are statistically significantly less likely to be underskilled but more likely to be overskilled. By contrast, skill mismatching is less likely for individuals with a higher vocational specificity of education, but there are only statistically significant associations in the case of overskilling. This means ambiguous findings for higher educational levels and higher occupational specificity of education, since both prevent underskilling while increasing the risk for overskilling.

The associations between educational levels and skill mismatch suggest a strong link between individuals' educational levels and their skill levels. Surprisingly, upper secondary graduates are not statistically significantly more likely to be overskilled in comparison to lower secondary graduates. This might be explained, for example, by their better matching processes compared to post-secondary or tertiary education graduates, or by the fact that lower and upper secondary graduates hardly differ in skill levels. The unexpected association between higher occupational specificity and higher overskilling risks may suggest that individuals with a high occupational specificity may have limited opportunities for upward mobility, making them more susceptible to overskilling. A higher vocational specificity of education is associated with lower risks for skill mismatch. This is generally in line with theoretical assumptions claiming that graduates of more vocational-specific programmes are better matched to their jobs and preferred by employers for jobs which match their specific skills.

Additionally, this study highlights the significant role of time since graduation in the association between education and skill mismatch. In line with career mobility theory, overskilling risks substantially decrease for higher-educated individuals compared to lower secondary graduates in the course of the career. The underskilling risks of individuals with upper secondary, post-secondary, or tertiary education compared to those with lower secondary education also decline with a longer time since graduation. Moreover, the higher-educated individuals face lower underskilling risks than lower secondary graduates over the entire career course. The reasons for this may be, for example, their comparatively higher ability to compensate for initial skill gaps, or the fact that they are comparatively less affected by skill depreciation over time.

Contradicting the vocational-decline hypothesis, the mismatch-preventing influence of vocational specificity on underskilling is stronger at later points in the career. Interestingly, there is even a mismatch risk-increasing influence of vocational specificity on underskilling in the first years after graduation, which turns into a mismatch-preventing influence from approx. 27 years after graduation onwards. In contrast, the mismatch-preventing influence of occupational specificity on underskilling holds for the entire career course and even increases over time. With regard to overskilling, both the mismatch-preventing influence of vocational specificity and occupational specificity on overskilling decrease over the course of the career. In the case of vocational specificity, there is a mismatch-preventing influence on overskilling over the entire career course, while in the case of occupational specificity, an initially overskilling-preventing influence turns into an overskilling risk-increasing influence from approx. five years after graduation.

I derive three main conclusions from these results. First, higher levels of education as well as higher vocational and occupational specificity minimise underskilling risks. Second, the evidence is less consistent for overskilling, as individuals with higher levels of education and a higher occupational specificity are more likely to be overskilled, whereas individuals with a higher vocational specificity are less likely to be overskilled. And third, the role of education may substantially change over the course of the career.

This study has certain limitations. While the analyses account for confounding variables that affect both individuals' education and skill mismatch, they might be subject to bias due to unobserved confounding variables. Such variables may include, for example, unverifiable interests and motivations on the side of employers such as unclear selection criteria in personnel recruitment, or employees' preferences on job selection. Furthermore, this study uses skill mismatch measures based on rather general skills primarily taught in general education, which may be less relevant in specific vocational training or studies. The classification of individuals as skill-(mis)matched might thus be subject to errors, which is why conclusions should be interpreted with caution. The varying patterns of skill mismatch over the course of the career also require cautious interpretation due to the cross-sectional design of the study, and given the fact that these individuals graduated in different educational contexts and entered the labour market at different times. Moreover, the present study does not provide evidence for young labour market entrants under the age of 30 due to the sample composition.

This research provides some valuable policy implications. Given their mismatch-preventing influence, policymaking should further strengthen the role of vocational-specific skills in education programmes. Considering that one and the same education may have different implications for skill matching in the course of the career, education programmes should place a stronger emphasis on the adaptability to new or changing tasks and demands. Moreover, policymakers could encourage and subsidise individuals' regular participation in further training and upskilling measures to ensure their long-term fitting. The expansion of higher educational attainment may be beneficial in this context, given the long-term benefits of higher education for skill matching.

Subsequent research can build on these findings, e.g. to analyse whether the associations between education and skill mismatch also apply to other countries with different education systems and educational certificates, and whether they still hold for countries with lower vocational orientation and linkage strength than Germany. Moreover, future research could take into account further facets of horizontal education and their relation to skill mismatch, for example, by considering the technological specificity of educational qualifications.

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7 Appendix

Table A1 Vocational specificity of education (by levels and fields)

Field of education (KldB-2010 2-digits)	Sec. level	Post. level	Tert. level
General education (no field)	0	.	.
Armed forces	.	.	.
Agriculture, forestry, and farming	0.7363	0.6134	0.6193
Horticulture and floristry	0.7487	0.6309	0.5239
Production and processing of raw materials	0.6706	.	.
Plastic-/ wood-making and -processing	0.7510	0.4549	.
Paper- /printing-making, techn. media design	0.7576	0.6816	0.4643
Metal-making and metal construction	0.5925	0.4711	0.3806
Machine-building and automotive industry	0.5251	0.4733	0.4527
Mechatronics and electrical engineering	0.5998	0.5693	0.5369
Techn. research and developm., construction	0.6538	0.4687	0.4976
Textile- and leather-making and -processing	0.8710	0.7446	.
Food-production and -processing	0.8586	0.5791	.
Construction scheduling, architect. and surveying	0.8304	0.5218	0.6146
Building construction above and below ground	0.7490	0.5523	.
Interior construction	0.7356	.	.
Building services engin., technical building services	0.6349	0.5247	0.4286
Mathematics, biology, chemistry and physics	0.8122	0.6323	0.5648
Geology, geography and environmental protection	.	.	0.5556
Computer science, inform. and comm. technology	0.4872	0.4137	0.4346
Traffic and logistics (without vehicle driving)	0.6634	0.4245	.
Drivers of vehicles and transport equipment	0.4789	0.2517	.
Safety and health protect., security and surveillance	0.3908	0.2699	.
Cleaning services	.	.	.
Purchasing, sales and trading	0.5786	0.5559	.
Sales occupations in retail trade	0.7183	0.5078	.
Tourism, hotels and restaurants	0.6905	0.5614	.
Business management and organisation	0.5641	0.4755	0.4375
Financial services, accounting and tax consultancy	0.5058	0.5009	0.2368
Law and public administration	0.5694	0.4608	0.4063
Medical and health care	0.6387	0.4620	0.4896
Non-medical healthcare, body care, wellness	0.8199	0.5622	0.6107
Education, social work, housekeeping, theology	0.7157	0.5779	0.4283
Teaching and training	0.3847	0.4260	0.4808
Philology, lit., humanities, social sciences, economics	.	.	0.5019
Advertising and marketing	.	0.4057	0.4672
Product design, artisan craftwork, fine arts	0.7579	0.8000	0.3334
Performing arts and entertainment	.	.	0.5642

Notes: Fields of education represent the KldB-2010 2-digits occupational main group of education. Missing values for educational qualification groups not having at least 20 observations.

Sources: BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2006, 2012, and 2018, own calculations.

Table A2 Occupational specificity of education (by levels and fields)

Field of education (ISCED-F 2013)	0/1	2	3	4/5B	5A/6
General education (no field)	0.84	0.34	0.27	.	.
Education	.	.	2.16	1.77	1.65
Arts	.	.	1.07	1.44	2.00
Humanities	.	.	1.21	1.20	1.36
Languages	.	.	1.21	1.20	1.36
Social and behavioural sciences	.	.	.	0.68	1.09
Journalism and information	.	.	.	.	2.89
Business and administration	.	.	0.58	0.80	0.95
Law	.	.	.	.	3.16
Biological and related sciences	.	.	.	.	1.98
Environment	.	.	.	.	.
Physical sciences	.	.	1.47	.	1.57
Mathematics and statistics	.	.	1.47	1.96	2.07
Information and comm. technologies	.	.	0.86	1.74	2.06
Engineering and engineering trades	.	.	0.68	0.76	1.46
Manufacturing and processing	.	.	0.70	1.14	0.76
Architecture and construction	.	.	0.94	1.07	1.98
Agriculture	.	.	1.50	1.80	1.29
Forestry	.	.	1.50	1.80	1.29
Fisheries	.	.	1.50	1.80	1.29
Veterinary	.	.	.	.	2.71
Health	.	.	1.49	1.86	3.42
Welfare	.	.	1.32	1.62	2.50
Personal services	.	.	0.89	1.32	1.21
Security services	.	.	3.01	2.79	2.50
Transport services	.	.	1.02	1.26	1.73

Notes: Fields of education represent the ISCED-F 2013 2-digits narrow fields of education. Educational levels based on ISCED-1997 categorisations. 0 pre-primary education, 1 primary education, 2 lower secondary education, 3 upper secondary education, 4 post-secondary non-tertiary education, 5A first stage of tertiary education (universities, universities of applied sciences), 5B first stage of tertiary education (trade and technical schools, vocational academies, vocational schools), 6 second stage of tertiary education.
Sources: DiPrete et al. (2017), based on the German Microcensus 2006.

Table A3 The associations between educational levels and underskilling and the moderating role of time since graduation, logistic regressions (logit models)

	Underskilling			
	Model 1		Model 2	
	Coef.	SE	Coef.	SE
Educational level				
(ref. lower sec. education)				
upper sec. education	−0.88***	0.25	−0.40	1.10
post-sec. non-tert. education	−1.09***	0.26	−0.40	1.10
tertiary education	−1.52***	0.26	−1.47	1.10
Educ. level * time since graduation				
*(ref. lower sec. educ. * time s. grad.)*				
upper sec. educ. * time s. grad.			−0.02	0.03
post-sec. educ. * time s. grad.			−0.02	0.03
tertiary educ. * time s. grad.			0.00	0.03
Time since graduation	0.01	0.01	0.02	0.03

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate logit coefficients. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A4 The associations between educational levels and overskilling and the moderating role of time since graduation, logistic regressions (logit models)

	Overskilling			
	Model 1		Model 2	
	Coef.	SE	Coef.	SE
Educational level				
(ref. lower sec. education)				
upper sec. education	0.24	0.39	1.19	1.33
post-sec. non-tert. education	0.70	0.40	1.48	1.32
tertiary education	1.00*	0.40	1.76	1.32
Educ. level * time since graduation				
*(ref. lower sec. educ. * time s. grad.)*				
upper sec. * time s. grad.			−0.03	0.04
post-sec. * time s. grad.			−0.03	0.04
tertiary * time s. grad.			−0.03	0.04
Time since graduation	−0.01	0.01	0.02	0.04

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate logit coefficients. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A5 The associations between vocational specificity, occupational specificity, and underskilling and the moderating role of time since graduation, logistic regressions (logit models)

	Underskilling											
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Voc. specificity	−0.16	0.27	1.67	0.91					−0.11	0.27	1.31	0.90
Occ. specificity					−0.30***	0.08	−0.22	0.18	−0.30***	0.08	−0.21	0.19
Voc. sp. * time. s. grad.			−0.06*	0.03							−0.05	0.03
Occ. sp. * time s. grad.							−0.00	0.01			−0.00	0.01
Time s. graduation	0.02**	0.01	0.05**	0.02	0.01*	0.01	0.01	0.01	0.01*	0.01	0.04*	0.02

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate logit coefficients. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A6 The associations between vocational specificity, occupational specificity, and overskilling and the moderating role of time since graduation, logistic regressions (logit models)

	Overskilling											
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Voc. specificity	−0.60*	0.30	−0.49	0.74					−0.61*	0.30	−0.37	0.75
Occ. specificity					0.18*	0.07	−0.07	0.13	0.17*	0.07	−0.08	0.13
Voc. sp. * time s. grad.			−0.00	0.03							−0.01	0.03
Occ. sp. * time. s. grad.							0.01*	0.01			0.01*	0.01
Time s. graduation	−0.02***	0.01	−0.02	0.02	−0.02**	0.01	−0.04***	0.01	−0.02**	0.01	−0.03	0.02

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate logit coefficients. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A7 The associations between vocational specificity, occupational specificity, and skill mismatches, logistic regressions (heterogeneity analyses)

	Underskilling					
	Model 1		Model 2		Model 3	
	AME	SE	AME	SE	AME	SE
Subsample secondary education						
Vocational specificity	−0.064	0.052			−0.044	0.058
Occupational specificity			−0.037	0.032	−0.027	0.035
Subsample post-sec. education						
Vocational specificity	−0.131	0.177			−0.140	0.181
Occupational specificity			−0.003	0.026	−0.006	0.027
Subsample tertiary education						
Vocational specificity	−0.162	0.150			−0.165	0.150
Occupational specificity			0.009	0.015	0.009	0.015
	Overskilling					
	Model 1		Model 2		Model 3	
	AME	SE	AME	SE	AME	SE
Subsample secondary education						
Vocational specificity	−0.051	0.039			−0.019	0.044
Occupational specificity			−0.052*	0.025	−0.046	0.028
Subsample post-sec. education						
Vocational specificity	0.355*	0.173			0.427*	0.172
Occupational specificity			0.032	0.024	0.048	0.025
Subsample tertiary education						
Vocational specificity	−0.114	0.195			−0.104	0.195
Occupational specificity			−0.028	0.019	−0.028	0.019

Notes: N=1,382 (subsample secondary education), N=1,078 (subsample post-secondary non-tertiary education), N=1,227 (subsample tertiary education). * p <0.05, ** p <0.01, *** p <0.001. Results indicate average marginal effects. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background, time since graduation.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A8 The associations between education levels and skill mismatches in single skill domains, logistic regressions

	Underskilling									
	Reading		**Mathematics**		**ICT**		**Science**		**Reasoning**	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Educational level										
(ref. lower sec. education)										
upper sec. education	0.019	0.042	−0.069	0.043	−0.116*	0.047	−0.046	0.040	0.003	0.044
post-sec. non-tertiary educ.	−0.026	0.043	−0.077	0.044	−0.135**	0.048	−0.052	0.041	−0.049	0.044
tertiary education	−0.053	0.043	−0.090*	0.044	−0.154**	0.048	−0.072	0.041	−0.062	0.044
	Overskilling									
	Reading		**Mathematics**		**ICT**		**Science**		**Reasoning**	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Educational level										
(ref. lower sec. education)										
upper sec. education	0.016	0.031	0.030	0.025	−0.012	0.035	−0.004	0.033	−0.029	0.041
post-sec. non-tertiary educ.	0.043	0.032	0.063*	0.026	0.021	0.036	0.023	0.034	0.001	0.042
tertiary education	0.080*	0.033	0.112***	0.026	0.049	0.036	0.070*	0.035	0.034	0.042

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate average marginal effects. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background, time since graduation.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A9 The associations between vocational specificity of education and skill mismatches in single skill domains, logistic regressions

	Underskilling									
	Reading		**Mathematics**		**ICT**		**Science**		**Reasoning**	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Vocational specificity	0.161***	0.040	−0.031	0.032	−0.005	0.032	−0.026	0.031	0.097*	0.040
	Overskilling									
	Reading		**Mathematics**		**ICT**		**Science**		**Reasoning**	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Vocational specificity	−0.061	0.035	−0.035	0.035	−0.138***	0.033	−0.036	0.035	−0.028	0.040

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate average marginal effects. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background, time since graduation.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A10 The associations between occupational specificity of education and skill mismatches in single skill domains, logistic regressions

	Underskilling									
	Reading		**Mathematics**		**ICT**		**Science**		**Reasoning**	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Occupational specificity	−0.025*	0.010	−0.007	0.008	−0.010	0.009	−0.031**	0.009	−0.024*	0.010
	Overskilling									
	Reading		**Mathematics**		**ICT**		**Science**		**Reasoning**	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Occupational specificity	0.010	0.008	0.025**	0.008	−0.005	0.008	0.021**	0.008	0.023*	0.009

Notes: N=3,687. * p <0.05, ** p <0.01, *** p <0.001. Results indicate average marginal effects. Control variables included in the regression models: male, birth cohorts, immigration background, educational qualification in former GDR, high social background, time since graduation.
Sources: NEPS Adult Cohort; doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Article 3:

Which skills pay the bills? How mismatches in different skill domains affect wages and the special relevance of ICT

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Abstract

Research has shown that skill mismatches affect wages, but to date, it is unclear in which domains skill mismatches have the strongest relevance and whether mismatches in one domain can compensate for opposing mismatches in another domain. Drawing on the 2016 wave of the German National Educational Panel Study (NEPS) Adult Cohort, we provide initial evidence for how skill mismatches in five different domains (ICT, reading, mathematics, science, and reasoning) affect individuals' wages and whether ICT mismatches compensate or eliminate wage effects due to skill mismatches in other domains. We find that being underskilled is always associated with lower wages, but being overskilled does not always pay off. Moreover, the strongest wage penalties and wage benefits are evident for skill mismatches in ICT. Additionally, our research shows that ICT overskilling is likely to compensate for wage penalties due to being underskilled in another domain, and that ICT underskilling eliminates the wage benefits of being overskilled in the other domains. Our results illustrate the special relevance of ICT skills in today's world of work.

1 Introduction

In todays' labour market shaped by automation, technology, and increasing task complexity, cognitive skills such as reading, mathematics, ICT, science, and reasoning are crucially relevant (Eurofound, 2016; OECD, 2019) and required in almost all professions across any occupational sector (Cedefop, 2018). As previous research has shown, skill mismatches both affect individuals' wages (Allen et al., 2013; Desjardins & Rubenson, 2011; Mateos-Romero & Salinas-Jiménez, 2018; McGuinness et al., 2018; Perry et al., 2014) and increase wage inequalities in the labour market (Santos & Sequeira, 2013). This implies that being underskilled or overskilled in these essential cognitive skills might have significant consequences for individuals' productivity and performance on the job.

Previous research on the association between skill mismatches and wages has mainly focused on domains such as literacy and numeracy (e.g. Allen et al., 2013; Perry et al., 2014). With regard to other domains such as ICT, science, or reasoning, the implications of skills mismatches are less clear. Moreover, most research so far has focused on the effects of skill mismatches in only one domain, thus ignoring the possibility that mismatches in some domains might be more important than mismatches in other domains, and that being overskilled in one domain might compensate for being underskilled in another domain.

The exceptional impact of digital technology has fundamentally changed the nature of work in recent decades (Cedefop, 2022). Therefore, in today's world of work, ICT mismatches can be expected to be particularly relevant for workers' productivity, and, consequently, for their wages. ICT surpluses might, moreover, compensate for productivity losses due to deficits in other skills by facilitating more efficient and productive work processes, whereas ICT deficits might eliminate productivity gains due to surpluses in other skills by hampering more efficient working methods. This raises questions about how mismatches in different cognitive skill domains affect individuals' wages, whether ICT mismatches are more significant than others, and whether wage effects associated with ICT mismatches compensate wage benefits or penalties linked to overskilling or underskilling in other skill domains.

This study provides detailed analyses on the associations between skill mismatches and wages, thus contributing to the existing literature in manifold ways. First, this study pioneers in analysing the link between skill mismatches and wages by considering five different skill domains (ICT, reading, mathematics, science, and reasoning) at the same time. Most previous studies have exclusively investigated mismatches in literacy or numeracy, using the

International Adult Literacy Survey (IALS) and the Programme for the International Assessment of Adult Competencies (PIAAC). In contrast, we draw on the German National Educational Panel Study (NEPS) Adult Cohort which provides test-based information on individuals' skill levels in five conceptually different skill domains. This allows us to identify the domain in which skill deficits or surpluses are most significant for people's wages.

Second, in focusing on these five skill domains, we provide first-time evidence on wage differences due to mismatches in ICT, science, and reasoning, all of which are of critical importance to working in a modern economy and are assumed to be highly relevant for individuals' labour market success and wages (Bol & Heisig, 2021; Falck et al., 2021; Heineck & Anger, 2010; Light & Rama, 2019). Based on PIAAC data, Fregin et al. (2019) have provided initial insights into wage effects resulting from skill mismatches in digital problem-solving skills, showing wage penalties for underskilled workers and wage benefits for overskilled workers in comparison to matched workers with the same occupational requirements. However, the PIAAC measurement of problem-solving in technology-rich environments comes with limitations (Flisi et al., 2017) and the definition is conceptually ambiguous, as it neither provides a clear-cut ICT skill nor a test of problem-solving (OECD, 2012). Therefore, the wage effects cannot be unambiguously assigned to ICT; our measurement of ICT skills, by comparison, is much more straightforward.

Third, given the variety of skill-specific skill mismatch measures, we are the first to analyse whether wage penalties or wage benefits due to skill mismatches in one domain can be compensated or eliminated by wage effects due to opposing mismatches in other domains. Given the special relevance of ICT mismatches, we analyse both whether wage benefits due to ICT overskilling compensate for wage penalties due to underskilling in another skill domain, and whether wage penalties associated with ICT underskilling eliminate wage benefits due to overskilling in another skill domain.

We draw our analyses on the 2016 wave of the NEPS Adult Cohort, focusing on employees aged 30 and above. Based on the so-called Overeducation-Required education-Undereducation (ORU) model (Duncan & Hoffman, 1981), modified for skill mismatches, we estimate for each of the five skill domains how the gross hourly wages of underskilled or overskilled workers differ from matched workers with the same occupational skill requirements, in order to identify which skill domains are most relevant for wages. Additionally, we test whether ICT mismatches offset wage differences due to opposing mismatches in other skill domains.

2 Theoretical background and hypotheses

Within jobs on the same level of occupational skill requirements, underskilled and overskilled workers differ from matched workers in their level of skills, but not in skill requirements. While underskilled workers have skill deficits and might be less productive, overskilled workers have skill surpluses and might put these into productive use, thus being more productive than matched workers. Following the assumptions of the human capital theory (Becker, 1964) which states that workers are paid according to their productivity, we expect underskilled workers to earn lower wages and overskilled workers to earn higher wages than workers in the same job with matching skill levels.

Due to differences in the relevance of skills for the labour market and for worker productivity, the strength of wage effects resulting from mismatches may vary between skill domains (Quintini, 2014). In recent decades, the impact of ICT skills on individuals' employability has increased; this is a result of the considerable changes engendered by technological advancements (Humburg et al., 2013; Humburg & van der Velden, 2017; OECD, 2019). According to the skill-biased technological change theory, technological changes have raised both the relative demand for digital skills and the relative productivity of digitally skilled workers (Acemoglu & Autor, 2011; Card & DiNardo, 2002). Due to the automation and digitalisation of work processes, digital skills are currently a basic precondition for successful participation and productivity across all occupations and sectors (Cedefop, 2018). Therefore, ICT skills might hold more relevance for worker productivity in today's work environment than other skills. For example, individuals with significant ICT deficits might be overburdened by basic requirements and tasks. This may strongly affect their overall work performance, making them less efficient and productive in manifold aspects of their job, and thus result in less efficient working time (van Deursen & van Dijk, 2014). By contrast, employees with significant ICT surpluses might show a stronger likelihood to use more efficient working methods, thereby raising their productivity and optimizing working time (Palvalin et al., 2013), e.g. through the use of digital devices, scaling effects, and the streamlining of work tasks (Singh Lota et al., 2022). Following the assumptions that mismatches in ICT affect workers' productivity most strongly and that workers are paid according to their productivity, we assume the strongest wage effects for mismatches in ICT.

H1a. *Individuals underskilled in ICT suffer stronger wage penalties than individuals underskilled in other skill domains.*

H1b. *Individuals overskilled in ICT receive stronger wage benefits than individuals overskilled in other skill domains.*

Deficits and surpluses in ICT might eliminate or compensate the effects of surpluses and deficits in other skill domains. On the one hand, ICT deficits might eliminate benefits due to surpluses in other skills as they reduce workers' overall efficiency and productivity; for example, due to the insufficient handling of digital tools and work processes (van Deursen & van Dijk, 2014). Workers underskilled in ICT may thus experience considerable difficulties in efficiently coping with relevant digital devices, software, and computer programmes that are used, for example, for email communication, mathematical calculations, digitally based measurements, or to solve complex problems and derive correct conclusions. This might seriously limit workers' productivity, even if these workers possess other skills such as excellent reading comprehension, strong mathematical skills (e.g. mental arithmetic), deep scientific knowledge of physical properties and materials, or outstanding analytical and reasoning skills.

On the other hand, ICT surpluses might compensate for deficits in other skill domains by enabling more efficient and time-saving use of digital tools and devices (Cedefop, 2022) that facilitate work processes and minimise errors, irrespective of deficits in other skills. For example, workers overskilled in ICT might use text comprehension tools to compensate for reading deficits; they may make use of digital calculation programmes to run mathematical operations even if they show deficits in conducting mathematical calculations on their own; or they may be capable of operating high-tech machines (for example, in automotive production), irrespective of a lack of specific know-how of the physical composition of engines. Furthermore, ICT surpluses may simplify individuals' work processes, for instance, by assisting them in the solution of problems or in drawing appropriate conclusions even with poor analytical and reasoning skills. Given that ICT deficits substantially reduce productivity gains due to surpluses in other skills, and that ICT surpluses enable workers to compensate for deficits in other skills, this might also be reflected in individuals' wages. We derive the following hypotheses from this:

H2a. *Wage penalties due to ICT underskilling eliminate wage benefits due to overskilling in other skills.*

H2b. *Wage benefits due to ICT overskilling compensate for wage penalties due to underskilling in other skills.*

3 Data and Methods

3.1 Data and sampling

This study uses the NEPS Adult Cohort Version 9.0.1 (NEPS Network, 2022). The first survey of the NEPS Adult Cohort named Working and Learning in a Changing World (ALWA) started in 2007 and consisted of adults living in Germany (Blossfeld & Roßbach, 2019). The NEPS Adult Cohort comprises extensive sociodemographic data as well as rich information on the educational and employment biography of the respondents from several waves. This data provides important advantages when analysing the association between domain-specific skill mismatches and wages by including objective test-based information on the skill levels of employed adults in five different skill domains and on individuals' wages.

Our analyses draw on a cross-section of the 2016 wave, the 9th wave of the NEPS Adult Cohort, since the latest skill tests were carried out in this wave. It comprises adults born between 1944 and 1986 of three subsamples with a gross sample of 10,078 individuals (4,427 of the ALWA sample; 2,641 of the NEPS wave 2 enhancement and refreshment sample; 3,010 of the NEPS wave 4 refreshment sample), cf. Landrock (2022). We restrict our analytical sample to individuals who participated in the 2016 wave, aged between 30 and 65 years,[1] being employed for at least 15 hours per week, excluding self-employed, persons in pre-professional employment (e.g. internship, student assistant, etc.), freelancers, family workers, and people employed in active labour market programmes or seasonal work. Furthermore, we exclude respondents with missing values in any of the required variables, resulting in a final sample of 3,680 respondents. Table A1 in the Appendix provides an overview of the sample sizes and the stepwise restrictions resulting in the final analytical sample.

3.2 Measurements

The dependent variable *gross hourly wages* is measured by respondents' self-reported amount of gross income received from their main occupation in the last month before the interview, and before deduction of taxes and social security contributions, but excluding special payments such as holiday pay or back payments. This sum is then divided by their contractual monthly working

[1] The minimum age of 30 years is due to the sample composition of the NEPS Adult Cohort in the 2016 wave. Following Altonji and Pierret (2001), we believe this does not pose a problem for this study because the wages of young workers under 30 might be based on their educational certificates rather than skill levels, whereas workers over 30 are primarily paid according to their skill levels. We decided to restrict the maximum age on 65 years to exclude individuals of retirement age who are still in employment.

hours.[2] We omit individuals without regular working hours or with contractual working hours of more than 50 hours per week and trim the gross monthly income by dropping the 1st and the 99th percentile to ensure that results are not biased by outliers.

The analyses include five independent variables of *test-based skill mismatches*, indicating mismatches in the skill domains *reading, mathematics, ICT, science,* and *reasoning*. These skill mismatch measures are based on information about individuals' proficiency in skill tests in each of the five skill domains and the occupational skill requirements. The skill tests were conducted in different waves depending on the skill domain (ICT and science in wave 2012; reasoning in wave 2014; reading and mathematics in wave 2016), but we assume adults' skill levels to remain constant over these short time periods (cf. Lechner et al., 2021). However, not all individuals were tested in each skill domain, since some individuals did not participate in all waves or refused to be interviewed in person (FDZ-LIfBi, 2022).[3] Moreover, all participants of the NEPS wave 4 refreshment sample were only tested in reading and reasoning, but not in mathematics, ICT, and science. For this reason, we imputed an individual's skill level if the individual has not previously been tested in the respective skill domain, following the multivariate imputation by chained equations approach (van Buuren & Groothuis-Oudshoorn, 2011).[4] Table A2 in the Appendix provides an overview of the proportions of individuals with imputed test scores for the different skill domains and subsamples.

The correlations between individuals' skill levels in the five different domains are high with a maximum of 0.66 (cf. Table A3 in the Appendix), but considerably lower than the IALS or PIAAC that have correlations exceeding 0.90 (Levels et al., 2014). The fact that the correlations

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[2] The NEPS Starting Cohort Adult offers the opportunity to add administrative income data for parts of the respondents, indicating their daily income within one year, cf. Bachbauer and Wolf (2022). However, this information is not necessarily matched to one particular job. Thus, the income data might not directly match the income of the specific job for which the link between skill mismatches and wages is to be analysed, e.g. if individuals changed jobs within the year or moved to a different professional position within the same occupation. In order to analyse the relationship between skill mismatches and wages, both the information on skill mismatches and on wages needs to refer to the same specific job, which is why the administrative data might provide biased information. Given the need for valid information on the occupation to which the income data refer, we use the respondents' self-reported information on their monthly gross income in the occupation to which their skill mismatch information also refers.

[3] The interviews in waves that included skill tests were conducted in computer-assisted personal interview (CAPI) mode as standard, since skill tests could only be carried out in personal interviews. Participants that could not be interviewed in person or those who insisted on telephone interviews in the respective wave, i.e. the computer-assisted telephone interviews (CATI), could not participate in the tests.

[4] Due to methodological reasons, we had to use different numbers of imputations for the different skill domains (19 for reading, 20 for mathematics, 45 for ICT, 39 for science, 10 for reasoning). In order to ensure that only one test score is assigned to each individual in the respective skill, we defined the average of the imputed scores per individual and per skill domain as the relevant test score in the respective skill, following the approach of the OECD (2013).

are not overwhelmingly high suggests that the NEPS Adult Cohort provides information on five conceptually different skill domains and that imputations are not an issue.

The five test-based skill mismatch indicators are calculated on the basis of comparing an individual's skill level in a particular domain with the level of skills required in their occupation for this domain. The procedure follows Pellizzari and Fichen (2017). In a first step, the occupational skill requirements are defined for the reference group of employees with a maximum age of 65 and a minimum of 15 working hours a week, who subjectively assess that their skills match the requirements of their job.[5] Next, for each skill domain, the required levels of skills are defined as the average skill level of these subjectively matched workers in the same ISCO-08 three-digit occupational minor group based on a minimum of 20 observations.[6] In a second step, employees are classified as being underskilled, matched, or overskilled in each of the skill domains, depending on whether their skill level in the respective domain lies more than one standard deviation below (underskilled) or above (overskilled) the average skill level in their occupational group, and regardless of how they subjectively defined their match situation. All others are classified as being matched. This results in five independent variables of skill mismatches, each differentiating between underskilling, match, and overskilling.

In line with previous studies, we use control variables on relevant sociodemographic, educational, and occupational characteristics of the individuals. These variables include gender (female as opposed to male); individuals' age in years resp. age squared; immigration background (as opposed to no immigration background) where only individuals of the first and second generation are defined as having an immigration background; individuals' last completed educational qualification (dummies for level and field of education); working part-time (as opposed to full-time); working in the public (as opposed to private sector); and number of years in the current job. Additionally, we control for the *level of occupational skill requirements* per skill domain, defined above as the average skill level in the respective skill domain of individuals who assess their skill level as matched working in the same ISCO-08 three-digit occupational minor group. Table 1 provides an overview of the descriptive sample statistics including all variables used in the main models of this study.

[5] This subjective assessment refers to people's general skill mismatch. Workers who "rather agree" or "completely agree" with the statement "The requirements of the job match my skills" are considered to be subjectively matched and therefore used as reference group for calculating the occupational skill requirements.
[6] We use the respective ISCO-08 two-digit sub-major group as a reference, if there are not at least 20 observations for a three-digit minor group.

Table 1 Descriptive sample statistics

Variables	Mean	SD	Min	Max
Dependent variable				
ln gross hourly wages	4.490	0.449	2.120	6.052
Variables of interest				
skill mismatch reading				
underskilled	0.133	0.340	0	1
matched	0.748	0.434	0	1
overskilled	0.119	0.324	0	1
skill mismatch mathematics				
underskilled	0.111	0.314	0	1
matched	0.784	0.412	0	1
overskilled	0.105	0.306	0	1
skill mismatch ICT				
underskilled	0.108	0.310	0	1
matched	0.786	0.410	0	1
overskilled	0.106	0.308	0	1
skill mismatch science				
underskilled	0.106	0.308	0	1
matched	0.790	0.408	0	1
overskilled	0.104	0.305	0	1
skill mismatch reasoning				
underskilled	0.164	0.370	0	1
matched	0.684	0.465	0	1
overskilled	0.152	0.359	0	1
occup. skill requirements reading	44.106	5.405	29.860	56.140
occup. skill requirements mathematics	52.859	6.142	40.200	65.130
occup. skill requirements ICT	43.256	6.269	30.740	56.700
occup. skill requirements science	53.260	6.604	38.240	68.370
occup. skill requirements reasoning	69.652	5.800	53.830	80.150
Control variables				
female	0.484	0.500	0	1
age	49.559	8.810	30	65
age squared	2533.692	836.915	900	4225
immigration background	0.156	0.363	0	1
educational level				
secondary education	0.396	0.489	0	1
post-sec. non-tert. education	0.290	0.454	0	1
tertiary education	0.313	0.464	0	1
field of education				
general education	0.043	0.203	0	1
STEM	0.361	0.480	0	1
humanities and social sciences	0.088	0.284	0	1
business, admin., law, services	0.296	0.457	0	1
education	0.052	0.223	0	1
health and welfare	0.095	0.294	0	1
field unknown	0.064	0.244	0	1
part-time work	0.300	0.458	0	1
public sector	0.329	0.470	0	1
duration in current job	12.549	10.501	0	46

Note: N=3,680.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

3.3 Analytical Strategy

The following analyses address the link between skill mismatches in reading, mathematics, ICT, science, and reasoning and individuals' earnings, using the natural logarithm (ln) of gross hourly wages. In a first step, we run OLS regressions for each of the five skill domains, using modified ORU models (cf. Equation 1) that account for individuals' occupational skill requirements in the respective domain in order to investigate wage differences of underskilled resp. overskilled workers when compared to matched workers with the same occupational requirements.[7] We compare the respective wage differences due to skill mismatches in different skill domains to identify in which skill domains the mismatches are most relevant for individuals' wages.

Equation 1 Specification of the ORU model modified for skill mismatches

$$W_i = \alpha + \beta_1 RS_{i\ skill\ j} + \beta_2 US_{i\ skill\ j} + \beta_3 OS_{i\ skill\ j} + \beta_4 C_i + \varepsilon$$

W_i = ln gross hourly wages of individual i
α = intercept
β_n = coefficient n
$RS_{i\ skill\ j}$ = occupational skill requirements in the occupational minor group of individual i's profession in skill j
$US_{i\ skill\ j}$ = underskilling of individual i in skill j
$OS_{i\ skill\ j}$ = overskilling of individual i in skill j
C_i = vector of control variables for individual i
ε = error term

Subsequently, we consistently run pairwise analyses for two skill domains simultaneously, investigating underskilling resp. overskilling in ICT and the opposing mismatch in one of the other skill domains. On this basis, we determine whether wage penalties related to ICT underskilling eliminate wage benefits due to overskilling in another skill domain, and whether wage benefits associated with ICT overskilling compensate for wage penalties related to underskilling in other skill domains. Finally, we conduct a series of robustness checks and additional analyses.

4 Findings

4.1 Wage effects of skill mismatches

Table 2 presents the wage effects due to skill mismatches in the five single skill domains.

[7] In their original ORU model, Duncan and Hoffman (1981) analyse wage differences due to educational mismatches. In contrast, we analyse wage differences due to skill mismatches based on modified ORU models using dummies for underskilling and overskilling in the respective skill domain, and controlling for the occupational skill requirements in the respective skill domain.

Table 2 The associations between skill mismatches and ln gross hourly wages (OLS regressions)

	Ln gross hourly wages				
	reading	**mathematics**	**ICT**	**science**	**reasoning**
Skill mismatch *(ref. matched)*					
underskilled	−0.075***	−0.087***	−0.110***	−0.094***	−0.074***
	(0.017)	(0.018)	(0.019)	(0.019)	(0.016)
overskilled	0.039*	0.032$^{\times}$	0.080***	0.020	0.006
	(0.018)	(0.019)	(0.019)	(0.019)	(0.016)
Occ. skill requirem.	0.033***	0.030***	0.029***	0.028***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: N=3,680. $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

In line with our assumptions, underskilled individuals earn statistically significantly lower wages than matched individuals in each skill domain. The strongest wage penalty is demonstrated for underskilling in ICT. Individuals who are underskilled in ICT earn approx. 11.0 percent lower wages when compared to individuals with matching ICT skills. The wage penalties for being underskilled compared to being matched in the remaining skill domains are also statistically significant but comparatively lower (reading approx. 7.5 percent, mathematics approx. 8.7 percent, science approx. 9.4 percent, and reasoning approx. 7.4 percent of gross hourly wages).[8] In contrast, we only find statistically significant wage benefits for overskilling in reading, mathematics, and ICT, but not for science and reasoning. Again, the strongest wage effect is evident for ICT, indicating a wage benefit of approx. 8.0 percent higher wages for individuals overskilled in ICT when compared to individuals with matching ICT skills. The wage effects are lower for reading and mathematics (approx. 3.9 percent and approx. 3.2 percent respectively), and they are only significant at the 0.05 resp. 0.10 level. We therefore conclude that while underskilling always has a negative impact on wages, overskilling only pays off in reading, mathematics, and ICT, but not in science and reasoning. We also note that working in a job with higher occupational skill requirements is financially advantageous.

[8] In the case of a natural logarithm transformed dependent variable (ln wages), the coefficients β of the independent variables (underskilling resp. overskilling) can be interpreted approximately as percentages. However, this is only a good rule of thumb for small coefficients β. According to Benoit (2011), the exact percentages are derived based on the following formula: $\left(e^{(\beta)} - 1\right) * 100$
The exact percentages for underskilling are therefore −7.2 for reading, −8.3 for mathematics, −10.4 for ICT, −9.0 for science, and −7.1 for reasoning, resp. with regard to overskilling, 4.0 for reading, 3.3 for mathematics, 8.3 for ICT, 2.0 for science, and 0.6 for reasoning.

To test the hypotheses on the strength of wage differences, we compare the wage differences for underskilling resp. overskilling between the skill domains. We consider wage effects to be significantly different from each other if they do not overlap when taking into account the range of plus and minus one standard error of the estimates. We note that the wage penalty for underskilling in ICT is stronger than the wage penalties in other skill domains. Considering the ranges of plus and minus one standard error, the wage penalty for ICT underskilling −0.110 (± 0.019) is significantly stronger than the wage penalty for being underskilled in reasoning −0.074 (± 0.016). Furthermore, the wage premium for ICT overskilling 0.080 (± 0.019) is significantly stronger than the wage benefits due to overskilling in any of the other skill domains (0.039 (± 0.018) for reading; 0.032 (± 0.019) for mathematics; 0.020 (± 0.019) for science; 0.006 (± 0.016) for reasoning).[9] This is in line with hypotheses 1a and 1b, which assume stronger wage differences for mismatches in ICT than for mismatches in other skill domains. Both hypotheses 1a and 1b are therefore not rejected.

4.2 Compensation of wage effects

Next, we analyse whether wage penalties related to ICT underskilling resp. wage benefits due to ICT overskilling eliminate or compensate wage differences associated with mismatches in other skill domains (cf. Table 3). Therefore, we run three regression models for each skill combination between ICT and one of the four other skills. Model 1 provides the separate wage effects of underskilling resp. overskilling in one of the other skill domains, and model 2 for overskilling resp. underskilling in ICT. In model 3, the two opposing mismatches are taken into account simultaneously.

[9] This approach to comparing the strength of wage differences is an approximate method. Additionally, we statistically tested the equality of underskilling coefficients resp. overskilling coefficients across models, i.e. comparing the underskilling coefficients in the different skills and the overskilling coefficients in the different skills across the models. We find a statistically significant difference between the overskilling ICT coefficient and the overskilling science coefficient, and also between the overskilling ICT coefficient and the overskilling reasoning coefficient.

Table 3 The associations between skill mismatches and ln gross hourly wages depending on the opposing mismatch in ICT (OLS regressions)

	OS reading and US ICT			**OS mathematics and US ICT**			**OS science and US ICT**			**OS reasoning and US ICT**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
OS reading	0.050**		0.044*									
(ref. MA/US)	(0.018)		(0.017)									
OS mathematics				0.030		0.025						
(ref. MA/US)				(0.019)		(0.019)						
OS science							0.025		0.019			
(ref. MA/US)							(0.019)		(0.019)			
OS reasoning										0.014		0.010
(ref. MA/US)										(0.016)		(0.016)
US ICT		-0.115***	-0.112***		-0.117***	-0.116***		-0.114***	-0.113***		-0.113***	-0.112***
(ref. MA/OS)		(0.019)	(0.019)		(0.019)	(0.019)		(0.019)	(0.019)		(0.019)	(0.019)
	US reading and OS ICT			**US mathematics and OS ICT**			**US science and OS ICT**			**US reasoning and OS ICT**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
US reading	-0.077***		-0.072***									
(ref. MA/OS)	(0.017)		(0.017)									
US mathematics				-0.084***		-0.079***						
(ref. MA/OS)				(0.018)		(0.018)						
US science							-0.098***		-0.093***			
(ref. MA/OS)							(0.018)		(0.018)			
US reasoning										-0.075***		-0.070***
(ref. MA/OS)										(0.016)		(0.016)
OS ICT		0.086***	0.080***		0.092***	0.087***		0.089***	0.083***		0.085***	0.079***
(ref. MA/US)		(0.019)	(0.019)		(0.019)	(0.019)		(0.019)	(0.019)		(0.019)	(0.019)

Notes: N=3,680. ^{x} $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. US (underskilled), MA (matched), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

First of all, we check for each pair of skills whether wage benefits resulting from overskilling resp. wage penalties resulting from underskilling are mitigated when controlling for underskilling resp. overskilling in ICT. In the upper section of Table 3, we compare the overskilling wage benefits in models 1 with the overskilling wage benefits in models 3 when including ICT underskilling. We observe some reduction in the wage benefits due to overskilling in models 3 when including underskilling ICT, but the difference is not significant. For example, the wage benefit due to overskilling in reading of approx. 5.0 percent in model 1 turns into a wage benefit of approx. 4.4 percent in model 3, signifying a small mitigation of a 0.6 percent points lower wage premium. The decrease in the wage benefit is roughly the same for all four skills domains and also comparable to the decrease in wage benefit for overskilling in ICT when introducing underskilling in the other domains (compare models 1 and models 3 in the bottom section of the table).

We also investigate how wage penalties due to underskilling differ between models 1 and models 3 when introducing overskilling in ICT (bottom section of the table). For each skill combination, we find a wage penalty that is 0.5 percent points lower when including ICT overskilling. For underskilling in ICT, however, the reduction is only 0.1 percent points when introducing overskilling in the other domains (see upper section), with the exception of overskilling in reading which induces a decrease of 0.3 percent points. We therefore conclude that both underskilling and overskilling effects are not substantially affected when controlling for mismatches in ICT and vice versa, and that wage effects of mismatches in ICT are only marginally affected by incorporating wage effects of mismatches in other skill domains.

Subsequently, we test whether wage benefits or penalties due to mismatches in reading, mathematics, science, and reasoning are eliminated or compensated by the opposing mismatch in ICT. Based on models 3, we compare the effect sizes of the underskilling wage penalty with the overskilling wage benefit for each skill pair, both including the range of the respective standard error. For example, we compare the overskilling reading wage benefit of 0.044 (± 0.017) with the underskilling ICT wage penalty of −0.112 (± 0.019) and test whether the ICT underskilling wage penalty eliminates the overskilling wage premium of reading. We notice that the ICT underskilling penalty is considerably higher than the overskilling benefits in the other skills. Hence, wage penalties due to ICT underskilling fully eliminate wage benefits due to any other overskilling. We can also consider this from the perspective of compensating underskilling wage penalties, detecting somewhat stronger wage benefits due to ICT overskilling compared to wage penalties associated with underskilling in reading, mathematics, or reasoning. The only exception is science, where the wage benefit due to ICT overskilling of 0.083 (± 0.019) is somewhat lower than the wage penalty due to science underskilling of −0.093 (± 0.018). However, this difference is not significant.

We conclude that ICT overskilling is likely to fully compensate for underskilling in reading, mathematics, and reasoning, and in large part for underskilling in science. Moreover, ICT underskilling more than eliminates the wage benefits of overskilling in the other domains. Therefore, hypotheses 2a and 2b cannot be rejected.

4.3 Robustness checks and additional analyses

We conduct robustness checks by additionally controlling for job characteristics (company size, sector, and place of work), but the results remain essentially the same when compared to the main models (cf. Table A4 in the Appendix). Additionally, we replicate the main models excluding individuals with imputed test scores (cf. Table A5 and Table A6 in the Appendix), detecting somewhat stronger wage penalties for underskilling except in the case of science and no longer statistically significant wage benefits for overskilling in mathematics. Moreover, the ICT overskilling compensations are somewhat weaker due to stronger underskilling wage penalties in the other domains.

Moreover, we run additional analyses to test whether heterogeneous wage differences exist between individual subgroups (part-time as opposed to full-time workers, public as opposed to private sector workers, female as opposed to male workers) facing specific circumstances and challenges in the labour market (Hanushek et al., 2015), cf. Tables A7 to A9 in the Appendix. We find a statistically significant difference in wage penalty for underskilling in mathematics of approx. 2.5 percent for part-time workers compared to approx. 12.4 percent for full-time workers. The reason for this may be that part-time workers are more likely to work in job positions with lower demands for mathematical skills, which is why being underskilled might be less relevant and therefore less significant for their wages compared to full-time job wages. Furthermore, our research shows both statistically significantly lower underskilling wage penalties for workers in the public compared to the private sector (mathematics approx. 2.4 vs. 13.4 percent, ICT approx. 4.8 vs. 14.6 percent, science approx. 4.4 vs. 12.4 percent, reasoning approx. 1.3 vs. 10.9 percent), and statistically significantly lower wage benefits for ICT overskilling (approx. 2.6 vs. 10.3 percent). We also find a wage penalty of approx. 8.5 percent for overskilling in science in the public sector, but a wage benefit of approx. 7.1 percent in private sector, corresponding to a wage difference of 15.6 percent points. These findings might reflect the more skill-based payment in the private sector, whereas skill deficits and surpluses are not equally relevant in the public sector in which wages are based on credentials rather than skills.

Regarding gender differences, both wage penalties and wage benefits tend to be stronger for women than for men. In particular, we find a statistically significantly stronger wage penalty for ICT underskilling for women (approx. 15.5 percent) when compared to men (approx. 5.4 percent). This difference in wage penalty of 10.1 percent points might be caused by the fact that women, on average, possess lower ICT skills than men, which is why women underskilled in ICT have stronger ICT deficits than men underskilled in ICT. As these differences in the extent of mismatches have not been taken into account by using dummies so far, we run additional analyses using linear measures for underskilling and overskilling that reflect the strength of the respective mismatch (cf. Table A10 in the Appendix). However, the statistically significant stronger wage penalty for women still remains. Consequently, women's stronger wage penalty for being underskilled in ICT cannot be attributed to their relatively lower ICT skills as such. This puzzling finding might indicate statistical discrimination and gender stereotyping (Christensen, 2023; Quadlin et al., 2023) with regard to ICT skills, where women might be perceived to possess lower ICT skills than men and therefore suffer stronger monetary penalties from ICT underskilling.

We also test whether mismatches in reading, mathematics, science, and reasoning offset wage differences due to opposing mismatches in other skills (cf. Tables A11 to A14 in the Appendix). Being underskilled in one of these skills fully eliminates wage benefits due to being overskilled in another skill, except in the case of being overskilled in ICT. On the other hand, as demonstrated earlier, the only possibility to compensate for an underskilling wage penalty is through ICT overskilling. This underlines the significance of ICT mismatches for individuals' wages.

5 Discussion and conclusion

Drawing on the 2016 wave of the German NEPS Adult Cohort, we provide first evidence for the wage effects due to skill mismatches in five different skill domains. We also investigate whether ICT mismatches compensate for wage penalties or eliminate wage benefits associated with mismatches in another skill domain. We detect statistically significant wage penalties for underskilled workers when comparing them to matched workers with the same occupational requirements in each of the five skills, and statistically significant wage benefits for overskilling in reading, mathematics, and ICT, but not for science and reasoning. Both the wage penalties and the wage benefits are strongest for ICT mismatches. These findings illustrate that while deficits resp. surpluses in specific skills are reflected in individuals' wages, some skills are more relevant than others. For example, workers overskilled in science or reasoning earn no wage benefits. This may be due to the fact that, on the one hand, science surpluses only have a beneficial effect in the private sector and, on the other hand, reasoning is a rather general cognitive skill where surpluses might not be very significant for productivity or less highly in-demand. Moreover, our results highlight that ICT skills are most relevant for worker's wages in today's world of work. This may suggest that employees with ICT surpluses are considerably more productive and efficient, whereas ICT deficits may be associated with substantial productivity losses.

Our research also provides first evidence for the elimination of overskilling wage benefits through ICT underskilling and the compensation of underskilling wage penalties through ICT overskilling. On the one hand, individuals who are overskilled in ICT can compensate for wage deficits associated with underskilling (partial compensation in the case of science underskilling, full compensation in the case of reading, mathematics, or reasoning underskilling). Hence, ICT surpluses may facilitate a more efficient way of working, enabling workers to compensate for productivity deficits in other skill domains. On the other hand, being underskilled in ICT fully eliminates the wage benefits associated with being overskilled in any of the other skills. This suggests that ICT deficits substantially reduce workers' overall productivity, despite of surpluses in other skills, hence underlining the special relevance of ICT mismatches for individuals' productivity and wages in today's world of work.

Moreover, wage penalties due to underskilling are considerably stronger than wage benefits associated with overskilling, possibly indicating that underskilling is more relevant to worker productivity than overskilling. Given a certain level of occupational requirements, skill surpluses raise workers' productivity; however, even overskilled workers cannot perform their job tasks more than perfectly, signifying a productivity ceiling and thus a wage ceiling for overskilling. By contrast, underskilling might significantly increase the risk of errors and substantially reduce workers' productivity, both of which may seriously threaten an organisation's market value (Humburg et al., 2013). Hence, underskilling may result in comparatively higher wage penalties, as skill deficits may weaken worker productivity more than skill surpluses may strengthen it.

We draw a series of conclusions from this study. Given a certain level of occupational requirements, skill surpluses usually pay off, whereas skill deficits always result in substantial wage penalties. Furthermore, the dimension of skill plays a central role in the association between skill mismatches and wages, since some skills are more beneficial than others; for instance, e.g. overskilling in science or reasoning does not translate into significantly higher wages. This study also highlights the fact that skill mismatches in ICT are most significant for individuals' wages. In this context, both ICT underskilling and ICT overskilling are associated with the strongest wage effects, but they also eliminate wage benefits resp. compensate for wage penalties due to mismatches in other skill domains. Conversely, employees cannot compensate for underskilling ICT wage penalties, and underskilling in science is the only way to eliminate overskilling ICT wage benefits. Additionally, our research demonstrates that wage differences due to skill mismatches may vary between different subgroups. For example, both wage benefits and penalties tend to be stronger for private sector workers (especially in science) and for women (especially in ICT).

This study provides some valuable implications. Having strong ICT skills pays off, both by increasing workers' productivity and by being valued most by employers. To raise their wages and increase their earnings potential, individuals should thus invest continuously in further developing their ICT skills. In the face of quite substantial wage penalties associated with underskilling in any skill domain, workers should also address and counteract skill deficits in all domains, e.g. through participation in further training and upskilling measures. For example, policymakers should promote individuals' further training and participation in in-company measures. Moreover, policymakers should implement specific training and upskilling measures which target individuals with skill deficits, in order to address underskilling as a key issue affecting wage inequalities. With regard to the special relevance of ICT skills for worker productivity in the German labour market, policymakers should place a major focus on learning ICT skills in the education and training programmes.

Some limitations, however, arise from this study. For instance, the analyses on the link between skill mismatches and wages might be subject to bias due to unobserved confounding variables, such as the payment policy and capacity of the respective employers, negotiating skills of employees, or contractual benefits exceeding the wages, all of which we could not account for. Furthermore, the actual ICT requirements in the German labour market might be somewhat underestimated by referring to the average ICT skills of the currently working population over the age of 30, for the majority of whom ICT skills have presumably not been a substantial part of their education. Accordingly, workers with average ICT skills might not necessarily be well-matched in reality, instead also being underskilled, meaning that the true extent of ICT underskilling might even be somewhat higher. Moreover, this study does not address how skill mismatches affect wages of employees under the age of 30.

Subsequent research might therefore address this issue and analyse, for example, which skill mismatches are most significant for the wages of young professionals at the beginning of their careers. Future research could build on the findings of this study, e.g. to explore why women suffer statistically significant stronger wage penalties due to ICT underskilling when compared to men and why this is only the case for ICT, but not for other skills. This might provide new insights and explanations for both the gender digital gap and the gender wage gap discussions. Moreover, future research could address the link between mismatches in 'soft' skills, such as social skills or communication skills, and individuals' wages. Cross-country analyses might also clarify whether the special relevance of ICT mismatches is specific to the German labour market or whether this also applies to other countries.

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7 Appendix

Table A1 Composition of the final analytical sample

	Sample size
Full sample	17,140
Gross sample wave 2016	10,078
Sample participants wave 2016	8,662
Individuals with skill score information in each skill	7,309
Regular dependent workers (min. 15 h per week)	4,489
Individuals aged up to 65 years	4,424
Individuals with skill mismatch information	4,388
Individuals with valid wage information	3,728
Individuals with information in any of the required variables	3,680
Final analytical sample	3,680

Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A2 Real test scores vs. imputed test scores per skill domain and subsample

Skill domain	ALWA	NEPS w2	NEPS w4	N (real test scores)	N (imputed test scores)
Reading	× (2016)	× (2016)	× (2016)	2,984 (81.09 %)	696 (18.91 %)
Mathematics	× (2016)	× (2016)	–	2,141 (58.18 %)	1,539 (41.82 %)
ICT	× (2012)	× (2012)	–	2,402 (65.27 %)	1,278 (34.73 %)
Science	× (2012)	× (2012)	–	2,470 (67.12 %)	1,210 (32.88 %)
Reasoning	× (2014)	× (2014)	× (2014)	3,492 (94.89 %)	188 (5.11 %)

Notes: × for real test scores and year of last skill test, – for no skill testing in the skill domain.
Sources: FDZ-LIfBi (2022), NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A3 Correlations between individuals' skill levels in the different skill domains

	(1)	(2)	(3)	(4)	(5)
(1) Skill level reading	1				
(2) Skill level mathematics	0.485***	1			
(3) Skill level ICT	0.537***	0.623***	1		
(4) Skill level science	0.518***	0.620***	0.660***	1	
(5) Skill level reasoning	0.416***	0.458***	0.488***	0.427***	1

Notes: N=3,680. $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A4 The associations between skill mismatches and ln gross hourly wages (OLS regressions), robustness models including company size, sector, and place of work

	Ln gross hourly wages				
	reading	**mathematics**	**ICT**	**science**	**reasoning**
Skill mismatch					
(ref. matched)					
underskilled	−0.047**	−0.065***	−0.077***	−0.064***	−0.056***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.015)
overskilled	0.036*	0.022	0.065***	0.019	0.002
	(0.018)	(0.018)	(0.017)	(0.017)	(0.015)
Occ. skill requirem.	0.030***	0.026***	0.025***	0.024***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: N=3,680. ˣ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job, company size (micro company, small company, medium company, big company, unknown company size), sector (agriculture and industry, services, information sector, public administration, sector unknown), place of work (East Germany, West Germany incl. Berlin, unknown place of work).
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A5 The associations between skill mismatches and ln gross hourly wages (OLS regressions), robustness models only based on real test scores

	Ln gross hourly wages				
	reading	**mathematics**	**ICT**	**science**	**reasoning**
Skill mismatch					
(ref. matched)					
underskilled	−0.083***	−0.102***	−0.118***	−0.087***	−0.075***
	(0.018)	(0.020)	(0.021)	(0.020)	(0.016)
overskilled	0.032ˣ	0.020	0.083***	0.018	0.008
	(0.018)	(0.021)	(0.021)	(0.020)	(0.016)
Occ. skill requirem.	0.032***	0.031***	0.027***	0.027***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
N	2,984	2,141	2,402	2,470	3,492

Notes: ˣ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A6 The associations between skill mismatches and ln gross hourly wages depending on the opposing mismatch in ICT (OLS regressions), robustness models only based on real test scores

	OS reading and US ICT			**OS mathematics and US ICT**			**OS science and US ICT**			**OS reasoning and US ICT**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
OS reading	0.034		0.022									
(ref. MA/US)	(0.022)		(0.022)									
OS mathematics				0.023		0.010						
(ref. MA/US)				(0.022)		(0.022)						
OS science							0.025		0.012			
(ref. MA/US)							(0.020)		(0.020)			
OS reasoning										0.019		0.012
(ref. MA/US)										(0.020)		(0.020)
US ICT		-0.134***	-0.132***		-0.142***	-0.141***		-0.128***	-0.126***		-0.123***	-0.122***
(ref. MA/OS)		(0.024)	(0.024)		(0.024)	(0.024)		(0.021)	(0.021)		(0.022)	(0.022)
N		1,923			1,925			2,385			2,276	
	US reading and OS ICT			**US mathematics and OS ICT**			**US science and OS ICT**			**US reasoning and OS ICT**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
US reading	-0.089***		-0.081***									
(ref. MA/OS)	(0.022)		(0.022)									
US mathematics				-0.101***		-0.093***						
(ref. MA/OS)				(0.021)		(0.021)						
US science							-0.087***		-0.078***			
(ref. MA/OS)							(0.021)		(0.021)			
US reasoning										-0.096***		-0.089***
(ref. MA/OS)										(0.021)		(0.021)
OS ICT		0.091***	0.082***		0.097***	0.086***		0.096***	0.088***		0.095***	0.086***
(ref. MA/US)		(0.023)	(0.023)		(0.023)	(0.023)		(0.021)	(0.021)		(0.021)	(0.021)
N		1,923			1,925			2,385			2,276	

Notes: ˣ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. US (underskilled), MA (matched), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A7 The associations between skill mismatches and ln gross hourly wages (OLS regressions), additional models including interaction effects for skill mismatches and part-time work

	Ln gross hourly wages				
	reading	**mathematics**	**ICT**	**science**	**reasoning**
Skill mismatch					
(ref. matched)					
underskilled	−0.090***	−0.124***	−0.107***	−0.089***	−0.066***
	(0.020)	(0.023)	(0.022)	(0.022)	(0.019)
overskilled	0.027	0.037ˣ	0.070**	0.014	0.010
	(0.022)	(0.021)	(0.022)	(0.022)	(0.019)
US * part-time	0.054	0.099**	−0.009	−0.019	−0.026
	(0.037)	(0.037)	(0.039)	(0.040)	(0.034)
OS * part-time	0.035	−0.022	0.037	0.026	−0.014
	(0.037)	(0.044)	(0.041)	(0.042)	(0.035)
Occ. skill requirem.	0.033***	0.030***	0.029***	0.028***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: N=3,680. ˣ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. US (underskilled), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A8 The associations between skill mismatches and ln gross hourly wages (OLS regressions), additional models including interaction effects for skill mismatches and public sector

	Ln gross hourly wages				
	reading	**mathematics**	**ICT**	**science**	**reasoning**
Skill mismatch					
(ref. matched)					
underskilled	−0.093***	−0.134***	−0.146***	−0.124***	−0.109***
	(0.021)	(0.024)	(0.023)	(0.023)	(0.020)
overskilled	0.050*	0.051*	0.103***	0.071**	0.004
	(0.021)	(0.023)	(0.022)	(0.023)	(0.019)
US * public sector	0.046	0.110**	0.098**	0.080*	0.096**
	(0.034)	(0.036)	(0.037)	(0.038)	(0.032)
OS * public sector	−0.040	−0.059	−0.077ˣ	−0.156***	0.002
	(0.039)	(0.039)	(0.039)	(0.039)	(0.035)
Occ. skill requirem.	0.033***	0.030***	0.029***	0.028***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: N=3,680. ˣ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. US (underskilled), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A9 The associations between skill mismatches and ln gross hourly wages (OLS regressions), additional models including interaction effects for skill mismatches and female

	Ln gross hourly wages				
	reading	**mathematics**	**ICT**	**science**	**reasoning**
Skill mismatch					
(ref. matched)					
underskilled	−0.072**	−0.096**	−0.054*	−0.060*	−0.061**
	(0.024)	(0.032)	(0.027)	(0.028)	(0.023)
overskilled	0.035	0.024	0.069**	0.021	−0.005
	(0.025)	(0.022)	(0.024)	(0.022)	(0.021)
US * female	−0.007	0.015	−0.101**	−0.059	−0.024
	(0.033)	(0.039)	(0.036)	(0.037)	(0.031)
OS * female	0.008	0.026	0.032	0.000	0.025
	(0.035)	(0.040)	(0.037)	(0.040)	(0.032)
Occ. skill requirem.	0.033***	0.030***	0.029***	0.028***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: N=3,680. ˣ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. US (underskilled), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A10 The associations between skill mismatches and ln gross hourly wages (OLS regressions), additional models including interaction effects for skill mismatches (linear) and female

	Ln gross hourly wages				
	reading	**mathematics**	**ICT**	**science**	**reasoning**
Skill mismatch					
(ref. matched)					
US linear	−0.008**	−0.013**	−0.006	−0.009**	−0.004**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)
OS linear	0.002	0.001	0.005ˣ	−0.001	0.002
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
US linear * female	−0.001	0.003	−0.012*	−0.007	−0.003
	(0.004)	(0.005)	(0.05)	(0.005)	(0.003)
OS linear * female	−0.000	0.004	0.005	0.002	−0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
Occ. skill requirem.	0.033***	0.030***	0.028***	0.027***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: N=3,680. ˣ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. US (underskilled), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A11 The associations between skill mismatches and ln gross hourly wages depending on the opposing mismatch in reading (OLS regressions)

	OS mathematics and US reading			**OS ICT and US reading**			**OS science and US reading**			**OS reasoning and US reading**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
OS mathematics	0.030		0.025									
(ref. MA/US)	(0.019)		(0.019)									
OS ICT				0.086***		0.080***						
(ref. MA/US)				(0.019)		(0.019)						
OS science							0.026		0.020			
(ref. MA/US)							(0.019)		(0.019)			
OS reasoning										0.015		0.010
(ref. MA/US)										(0.016)		(0.016)
US reading		-0.077***	-0.076***		-0.077***	-0.072***		-0.078***	-0.077***		-0.078***	-0.077***
(ref. MA/OS)		(0.017)	(0.017)		(0.017)	(0.017)		(0.017)	(0.017)		(0.017)	(0.017)
	US mathematics and OS reading			**US ICT and OS reading**			**US science and OS reading**			**US reasoning and OS reading**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
US mathematics	-0.083***		-0.080***									
(ref. MA/OS)	(0.018)		(0.018)									
US ICT				-0.115***		-0.112***						
(ref. MA/OS)				(0.019)		(0.019)						
US science							-0.096***		-0.092***			
(ref. MA/OS)							(0.018)		(0.018)			
US reasoning										-0.073***		-0.070***
(ref. MA/OS)										(0.016)		(0.016)
OS reading		0.049**	0.043*		0.050**	0.044*		0.050**	0.043*		0.046**	0.038*
(ref. MA/US)		(0.017)	(0.017)		(0.018)	(0.017)		(0.018)	(0.018)		(0.018)	(0.018)

Notes: N=3,680. ^{x} p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. US (underskilled), MA (matched), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A12 The associations between skill mismatches and ln gross hourly wages depending on the opposing mismatch in mathematics (OLS regressions)

	OS reading and US mathematics			**OS ICT and US mathematics**			**OS science and US mathematics**			**OS reasoning and US mathem.**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
OS reading	0.049**		0.043*									
(ref. MA/US)	(0.017)		(0.017)									
OS ICT				0.092***		0.087***						
(ref. MA/US)				(0.019)		(0.019)						
OS science							$0.031^{\times}$		0.027			
(ref. MA/US)							(0.019)		(0.019)			
OS reasoning										0.019		0.015
(ref. MA/US)										(0.016)		(0.016)
US mathematics		-0.083***	-0.080***		-0.084***	-0.079***		-0.085***	-0.083***		-0.084***	-0.083***
(ref. MA/OS)		(0.018)	(0.018)		(0.018)	(0.018)		(0.018)	(0.018)		(0.018)	(0.018)
	US reading and OS mathematics			**US ICT and OS mathematics**			**US science and OS mathematics**			**US reasoning and OS mathem.**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
US reading	-0.077***		-0.076***									
(ref. MA/OS)	(0.017)		(0.017)									
US ICT				-0.117***		-0.116***						
(ref. MA/OS)				(0.019)		(0.019)						
US science							-0.097***		-0.096***			
(ref. MA/OS)							(0.018)		(0.018)			
US reasoning										-0.097***		-0.094***
(ref. MA/OS)										(0.022)		(0.022)
OS mathematics		0.030	0.025		0.030	0.025		$0.035^{\times}$	0.031		$0.039^{\times}$	0.029
(ref. MA/US)		(0.019)	(0.019)		(0.019)	(0.019)		(0.019)	(0.019)		(0.022)	(0.022)

Notes: N=3,680. $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. US (underskilled), MA (matched), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A13 The associations between skill mismatches and ln gross hourly wages depending on the opposing mismatch in science (OLS regressions)

	OS reading and US science			**OS mathematics and US science**			**OS ICT and US science**			**OS reasoning and US science**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
OS reading	0.050**		0.043*									
(ref. MA/US)	(0.018)		(0.018)									
OS mathematics				0.035$^{\times}$		0.031						
(ref. MA/US)				(0.019)		(0.019)						
OS ICT							0.089***		0.083***			
(ref. MA/US)							(0.019)		(0.019)			
OS reasoning										0.014		0.008
(ref. MA/US)										(0.016)		(0.016)
US science		-0.096***	-0.092***		-0.097***	-0.096***		-0.098***	-0.093***		-0.095***	-0.095***
(ref. MA/OS)		(0.018)	(0.018)		(0.018)	(0.018)		(0.018)	(0.018)		(0.018)	(0.019)
	US reading and OS science			**US mathematics and OS science**			**US ICT and OS science**			**US reasoning and OS science**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
US reading	-0.078***		-0.077***									
(ref. MA/OS)	(0.017)		(0.017)									
US mathematics				-0.085***		-0.083***						
(ref. MA/OS)				(0.018)		(0.018)						
US ICT							-0.114***		-0.113***			
(ref. MA/OS)							(0.019)		(0.019)			
US reasoning										-0.072***		-0.071***
(ref. MA/OS)										(0.016)		(0.016)
OS science		0.026	0.020		0.031$^{\times}$	0.027		0.025	0.019		0.028	0.021
(ref. MA/US)		(0.019)	(0.019)		(0.019)	(0.019)		(0.019)	(0.019)		(0.019)	(0.019)

Notes: N=3,680. $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. US (underskilled), MA (matched), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.

Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table A14 The associations between skill mismatches and ln gross hourly wages depending on the opposing mismatch in reasoning (OLS regressions)

	OS reading and US reasoning			OS mathem. and US reasoning			OS ICT and US reasoning			OS science and US reasoning		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
OS reading	0.046**		0.038*									
(ref. MA/US)	(0.018)		(0.018)									
OS mathematics				0.032$^{\times}$		0.026						
(ref. MA/US)				(0.019)		(0.019)						
OS ICT							0.085**		0.079***			
(ref. MA/US)							(0.019)		(0.019)			
OS science										0.028		0.021
(ref. MA/US)										(0.019)		(0.019)
US reasoning		-0.073***	-0.070***		-0.076***	-0.075***		-0.075***	-0.070***		-0.072***	-0.071***
(ref. MA/OS)		(0.016)	(0.016)		(0.016)	(0.016)		(0.016)	(0.016)		(0.016)	(0.016)

	US reading and OS reasoning			US mathem. and OS reasoning			US ICT and OS reasoning			US science and OS reasoning		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
US reading	-0.078***		-0.077***									
(ref. MA/OS)	(0.017)		(0.017)									
US mathematics				-0.084***		-0.083***						
(ref. MA/OS)				(0.018)		(0.018)						
US ICT							-0.113***		-0.112***			
(ref. MA/OS)							(0.019)		(0.019)			
US science										-0.095***		-0.095***
(ref. MA/OS)										(0.018)		(0.019)
OS reasoning		0.015	0.010		0.019	0.015		0.014	0.010		0.014	0.008
(ref. MA/US)		(0.016)	(0.016)		(0.016)	(0.016)		(0.016)	(0.016)		(0.016)	(0.016)

Notes: N=3,680. $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. US (underskilled), MA (matched), OS (overskilled). Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

8 Supplementary Material

The following additional models consider various aspects that have not been addressed in the study so far. Previously, we estimated separate models for skill mismatches in the single skill domains to analyse how being underskilled resp. being overskilled in one of the domains affects individuals' wages. However, this does not provide evidence on how a mismatch in one skill domain affects wages under the control of mismatches in other skill domains. Therefore, I calculate an additional model in which the skill mismatches and occupational skill requirements of all five skill domains are simultaneously included (cf. Table S1).

Table S1 The association between skill mismatches and ln gross hourly wages (simultaneously including skill mismatches in all domains), OLS regressions

	Ln gross hourly wages	
	Coeff.	SE
Skill mismatch reading *(ref. matched)*		
underskilled reading	−0.035*	0.017
overskilled reading	0.022	0.018
Skill mismatch mathematics *(ref. matched)*		
underskilled mathematics	−0.032[×]	0.019
overskilled mathematics	−0.007	0.020
Skill mismatch ICT *(ref. matched)*		
underskilled ICT	−0.076***	0.020
overskilled ICT	0.078***	0.020
Skill mismatch science *(ref. matched)*		
underskilled science	−0.054**	0.019
overskilled science	−0.011	0.020
Skill mismatch reasoning *(ref. matched)*		
underskilled reasoning	−0.048**	0.016
overskilled reasoning	−0.009	0.016
Occupational skill requirements reading	0.010**	0.003
Occupational skill requirements mathematics	0.015***	0.003
Occupational skill requirements ICT	0.009**	0.004
Occupational skill requirements science	−0.001	0.004
Occupational skill requirements reasoning	0.002	0.002

Notes: N=3,680. [×] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included in all regression models: female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

There are still considerable wage penalties for being underskilled in each of the single skill domains. This holds even under the control of mismatches in the other domains (approx. 3.5 percent lower wages for reading, approx. 3.2 percent for mathematics, approx. 7.6 percent for ICT, approx. 5.4 percent for science, approx. 4.8 percent for reasoning). Regarding overskilling, however, there are strong and statistically significant wage benefits for ICT (approx. 7.8 percent), but only minor benefits for reading (approx. 2.2 percent). Moreover, even slight wage penalties exist due to overskilling in mathematics (approx. 0.7 percent), science (approx. 1.1 percent), and reasoning (approx. 0.9 percent). Therefore, when controlling for mismatches in other skill domains, being underskilled is negative for wages in each skill domain. However, in this case, being overskilled only pays off in ICT. Moreover, both the strongest wage penalties and benefits are evident for ICT mismatches.

The study also addressed how wage penalties related to ICT underskilling eliminate wage benefits due to overskilling in another skill domain, and how wage benefits associated with ICT overskilling compensate for wage penalties related to underskilling in other skill domains. These calculations are based on pairwise analyses, simultaneously considering underskilling resp. overskilling in ICT and the opposing mismatch in one of the other domains. However, the theoretical assumptions may also suggest interaction effects between opposing skill mismatches. In the main models of the study, we avoided interaction models due to the very small number of intra-individual overlaps between underskilling in ICT and overskilling in another skill domain, or overskilling in ICT and underskilling in another skill domain. For example, only 4 to 18 of all workers underskilled in ICT are simultaneously overskilled in another domain. Conversely, only 3 to 6 of all workers overskilled in ICT are also underskilled in one of the other domains (cf. Table S2).

Table S2 Correspondence between skill mismatches in ICT and skill mismatches in reading, mathematics, science, and reasoning

	reading			mathematics		
ICT	US	MA	OS	US	MA	OS
US	38.64 % (N=153)	59.60 % (N=236)	1.77 % (N=7)	35.86 % (N=142)	63.13 % (N=250)	1.01 % (N=4)
MA	11.47 % (N=332)	77.78 % (N=2,251)	10.75 % (N=311)	9.12 % (N=264)	82.69 % (N=2,395)	8.19 % (N=237)
OS	1.28 % (N=5)	67.95 % (N=265)	30.77 % (N=120)	0.77 % (N=3)	62.05 % (N=242)	37.18 % (N=145)
	science			**reasoning**		
ICT	US	MA	OS	US	MA	OS
US	38.13 % (N=151)	60.86 % (N=241)	1.01 % (N=4)	37.12 % (N=147)	58.33 % (N=231)	4.55 % (N=18)
MA	8.15 % (N=236	83.86 % (N=2,427)	7.98 % (N=231)	15.55 % (N=450)	70.39 % (N=2,037)	14.06 % (N=407)
OS	0.77 % (N=3)	61.28 % (N=239)	37.95 % (N=148)	1.54 % (N=6)	64.10 % (N=250)	34.36 % (N=134)

Notes: N=3,680. US (underskilled), MA (matched), OS (overskilled).
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Despite the small number of individuals with opposing mismatches, I provide additional models for the interactions between domain-specific overskilling and ICT underskilling (see Table S3) as well as between domain-specific underskilling and ICT overskilling (see Table S4).

Table S3 The association between skill mismatches and ln gross hourly wages (OLS regressions), interaction effects for overskilling in reading, mathematics, science, reasoning, and underskilling in ICT

	Ln gross hourly wages							
	reading		**mathematics**		**science**		**reasoning**	
	M1	M2	M1	M2	M1	M2	M1	M2
Overskilled *(ref. MA/ US)*	0.044*	0.044*	0.025	0.026	0.019	0.022	0.010	0.011
	(0.017)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.016)	(0.016)
Underskilled ICT *(ref. MA/ OS)*	−0.112***	−0.111***	−0.116***	−0.115***	−0.113***	−0.111***	−0.112***	−0.110***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
overskilled * underskilled ICT		−0.037		−0.151		−0.233		−0.034
		(0.129)		(0.169)		(0.169)		(0.083)

Notes: N=3,680. $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in ICT and the respective other skill domain, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job. US (underskilled), MA (matched), OS (overskilled).
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S4 The association between skill mismatches and ln gross hourly wages (OLS regressions), interaction effects for underskilling in reading, mathematics, science, reasoning, and overskilling in ICT

	Ln gross hourly wages							
	reading		**mathematics**		**science**		**reasoning**	
	M1	M2	M1	M2	M1	M2	M1	M2
Underskilled *(ref. MA/ OS)*	−0.072***	−0.072***	−0.079***	−0.081***	−0.093***	−0.092***	−0.070***	−0.073***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)	(0.016)
Overskilled ICT *(ref. MA/ US)*	0.080***	0.080***	0.087***	0.085***	0.083***	0.083***	0.079***	0.075***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
underskilled * overskilled ICT		0.013		0.245		−0.081		0.219
		(0.152)		(0.195)		(0.195)		(0.139)

Notes: N=3,680, $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in ICT and the respective other skill domain, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job. US (underskilled), MA (matched), OS (overskilled).
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S3 shows that overskilling wage benefits are stronger for those who are not underskilled in ICT than for those who are underskilled in ICT in each of the four skill domains. This means that the wage benefits from being overskilled in another domain are reduced if a worker is simultaneously underskilled in ICT. These differences in wage losses due to ICT underskilling range from approx. 3.4 percent points (reasoning) and approx. 3.7 percent points (reading) to approx. 15.1 percent points in mathematics, and even approx. 23.3 percent points in science. Thus, wage benefits can be substantially reduced by simultaneous ICT underskilling, especially in the case of overskilling in mathematics or science.

Table S4 indicates that wage penalties due to underskilling in reading, mathematics, and reasoning are stronger for those who are not overskilled in ICT. For those who are simultaneously overskilled in ICT, the wage penalties due to underskilling in reading are approx. 1.3 percent points lower when compared to those who are not overskilled in ICT. Moreover, the wage penalties are up to 21.9 percent points lower in the case of underskilling in reasoning resp. 24.5 percent points lower in the case of underskilling in mathematics. However, workers who are underskilled in science and simultaneously overskilled in ICT earn approx. 8.1 percent points lower wages than workers underskilled in science but not overskilled in ICT. This puzzling finding might be, for example, explained by the very small number of merely 3 workers who are affected by this simultaneous mismatch combination, or by unobserved characteristics of these workers. Overall, the interactions show partially strong influences on the one hand, but no statistically significant interaction on the other. Given the very small number of individuals affected by these interactions (i.e. workers who empirically possess opposing skill mismatches), both might be ascribed to limited statistical power.

In the main analyses of this study, we included a set of control variables which are usually used when estimating the association between skill mismatches and wages. These control variables cover relevant sociodemographic, educational, and occupational characteristics of the workers. However, the previous set of control variables did not sufficiently address confounding bias. This is because not all observable confounders which are a common cause for the respective independent variable (skill mismatch in the respective skill domain) and the dependent variable (wages) were controlled for. Therefore, I provide additional models that condition on all observable common causes of skill mismatches and wages to prevent confounding bias (Elwert & Winship, 2014). In addition to the control variables already included in the main models, this includes individuals' social background, personality traits (Big Five), marital status, number of children in the household, company size, economic sector, place of work, recession at the start of their current job, and long-term unemployment before their current job. Nonetheless, this does not rule out the possibility of further potential confounders that might cause both skill mismatches and wages, which cannot be controlled for because they are unobserved.

Furthermore, I estimate additional models in which I include educational mismatches (undereducation, overeducation) and field-of-education mismatch. This is to analyse whether the link between skill mismatches and wages persists if conceptually similar mismatches are also controlled for. I also run models in which I additionally control for individuals' skill levels in the respective skill domain. This control variable is not included in the former models because the worker's skill level might be a cause for being (mis)matched, but vice versa, being (mis)matched might also be a cause for a worker's level of skills. On the one hand, individuals' skill level might affect the likelihood of being skill-(mis)matched, as higher skill levels might, for instance, raise the likelihood of being matched or overskilled while decreasing the risk of underskilling. On the other hand, underskilled workers potentially face more challenges, which may lead to an increased skill gain (intellectual challenge hypothesis), while overskilled workers might face skill depreciation because they may not fully apply their skills (use-it-or-lose-it theory) (De Grip et al., 2008). For example, van der Velden and Verhaest (2017) showed that both skill growth and skill decline differ between underskilled, matched, and overskilled individuals. If individuals' skill level is a post-treatment variable resp. a variable on a causal path between treatment (skill mismatch) and outcome (wage), conditioning on it would result in overcontrol bias (Elwert & Winship, 2014). Therefore, this potentially critical control variable is only included in separate models in order to avoid overcontrol bias in the former.

Table S5 presents each four different models for the link between skill mismatches and wages separately for each of the five different skill domains. Models 1 include the same control variables that were used for the main analyses of the paper. In models 2, I additionally control for further observable common causes of skill mismatches and wages. In models 3, I further control for conceptually similar mismatches (educational mismatches and field-of-education mismatch). Models 4 additionally include individuals' skill level in the respective domain.

Table S5 The associations between skill mismatches and ln gross hourly wages (OLS regressions)

	Models 1	**Models 2**	**Models 3**	**Models 4**
SM reading *(ref. matched)*				
underskilled	−0.072***	−0.050**	−0.054**	−0.015
	(0.018)	(0.016)	(0.016)	(0.022)
overskilled	0.036$^{\times}$	0.039*	0.040*	−0.003
	(0.018)	(0.017)	(0.016)	(0.023)
SM mathematics *(ref. matched)*				
underskilled	−0.083***	−0.061**	−0.060**	0.003
	(0.019)	(0.017)	(0.017)	(0.023)
overskilled	0.035$^{\times}$	0.031$^{\times}$	0.031$^{\times}$	−0.043$^{\times}$
	(0.019)	(0.018)	(0.018)	(0.024)
SM ICT *(ref. matched)*				
underskilled	−0.106***	−0.084***	−0.088***	−0.037$^{\times}$
	(0.019)	(0.018)	(0.018)	(0.022)
overskilled	0.082***	0.070***	0.074***	0.016
	(0.019)	(0.018)	(0.018)	(0.023)
SM science *(ref. matched)*				
underskilled	−0.097***	−0.069***	−0.071***	−0.013
	(0.019)	(0.018)	(0.018)	(0.022)
overskilled	0.013	0.023	0.025	−0.045$^{\times}$
	(0.019)	(0.018)	(0.018)	(0.024)
SM reasoning *(ref. matched)*				
underskilled	−0.067***	−0.058***	−0.058***	−0.010
	(0.017)	(0.015)	(0.015)	(0.022)
overskilled	0.004	0.005	0.004	−0.047*
	(0.017)	(0.015)	(0.015)	(0.023)
Controlling for additional common causes		×	×	×
Controlling for education mismatches (level, field)			×	×
Controlling for skill level in respective skill domain				×

Notes: N=3,464. $^{\times}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the respective skill domain, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job. Models 2, 3, and 4 additionally control for further common causes of skill mismatches and wages: social background, openness, conscientiousness, extraversion, agreeableness, neuroticism, marital status, children under 14 years in household, company size, economic sector, place of work, recession at start of current job, and long-term unemployment. Models 3 and 4 moreover control for educational mismatches and field-of-education mismatch and Models 4 for individuals' skill level in the respective skill domain.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

The underskilling wage penalties are strongest in models 1 across each skill domain. In comparison, the wage penalties under control for additional common causes in models 2 are considerably lower across each skill domain. This extends from approx. 0.9 percent points lower wage penalties for reasoning to approx. 3.1 percent points lower wage penalties in science. Wage penalties do not substantially differ between models 2 and 3 when additionally controlling for mismatches in educational level or field. However, the picture substantially changes in models 4 under the control of individuals' skill levels in the relevant skill domain. There is still a considerable wage penalty for ICT underskilling of approx. 3.7 percent, which is statistically significant at the 0.10 level. However, only slight and not statistically significant wage penalties remain for reading (approx. 1.5 percent), science (approx. 1.3 percent), and reasoning (approx. 1.0 percent). Conversely, there is even a minor wage benefit of approx. 0.3 percent for mathematics.

Regarding overskilling, I detect strong wage benefits for ICT (approx. 8.2 percent) and considerable wage benefits in reading (approx. 3.6 percent) and mathematics (approx. 3.5 percent) in models 1. In comparison, in models 2, somewhat stronger wage benefits are evident in reading, science, and reasoning. The wage benefits in mathematics are somewhat smaller and there is even a substantially smaller wage benefit of approx. 1.2 percent points for ICT. The results change only slightly under the additional control for education mismatches in models 3. Again, the findings change substantially when controlling for individuals' skill levels. This indicates a small and not statistically significant wage benefit for ICT, and even wage penalties in the other skill domains. Particularly strong and statistically significant wage losses are evident in models 4 in mathematics (approx. 4.3 percent), science (approx. 4.5 percent), and reasoning (approx. 4.7 percent).

In general, the findings for both underskilling and overskilling in models 4 show that including the critical control variable skill level fundamentally changes the results. Underskilling wage penalties are considerably lower, or even turn into wage benefits, and former overskilling wage benefits turn into considerable wage penalties. The exception is ICT, where I find strong wage penalties for underskilling and considerable wage benefits for overskilling, even in the models 4. Thus, hypotheses 1a and 1b are still not rejected, because both the strongest underskilling wage penalty and the strongest overskilling wage benefit are evident for ICT across each model. However, given the potential reverse causality due to the critical control variable skill level, the findings of models 1 to 3 are considered to be most valid.

Finally, I estimate the compensation models (cf. Table S6 and Table S7), once basing them on the original set of control variables used in the main models of the study (models 1) and once additionally controlling for additional common causes (models 2). The findings in Table S6 indicate that the wage penalties due to ICT underskilling in models 2 are substantially lower than those in models 1. Yet, the overskilling wage benefits in reading, mathematics, science, and reasoning are quite similar to those in models 1. Nevertheless, even in models 2, the ICT underskilling penalty is considerably higher than the overskilling benefits in the other skills. This is why ICT underskilling wage penalties fully eliminate wage benefits due to any other overskilling both in models 1 and 2. Table S7 shows that the overskilling ICT wage benefits in models 2 are also considerably lower than those in models 1, but the same is true for the underskilling wage penalties in reading, mathematics, reasoning, and especially science. Consequently, despite the lower wage benefits due to ICT overskilling in models 2, being overskilled in ICT is likely to fully compensate for any underskilling wage penalty. This compensation holds for underskilling wage penalties in science, which is not the case in models 1. Under the control of additional observable common causes, ICT overskilling is therefore likely to fully compensate underskilling wage penalties in each skill domain. Moreover, wage penalties due to ICT underskilling fully eliminate any of the overskilling wage benefits. Thus, hypotheses 2a and 2b are not rejected in models 2 either.

Table S6 The associations between overskillings and ln gross hourly wages depending on the opposing mismatch in ICT (OLS regressions)

	OS reading and US ICT						**OS mathematics and US ICT**					
	Models 1			**Models 2**			**Models 1**			**Models 2**		
	M1a	M1b	M1c	M2a	M2b	M2c	M1a	M1b	M1c	M2a	M2b	M2c
OS reading	0.047**		0.041*	0.047**		0.043*						
(ref. MA/US)	(0.018)		(0.018)	(0.016)		(0.016)						
OS mathematics							0.033$^{\times}$		0.027	0.029$^{\times}$		0.025
(ref. MA/US)							(0.019)		(0.019)	(0.018)		(0.018)
US ICT		-0.111***	-0.108***		-0.089***	-0.087***		-0.115***	-0.113***		-0.090***	-0.089***
(ref. MA/OS)		(0.019)	(0.019)		(0.018)	(0.018)		(0.019)	(0.019)		(0.018)	(0.018)
	OS science and US ICT						**OS reasoning and US ICT**					
	Models 1			**Models 2**			**Models 1**			**Models 2**		
	M1a	M1b	M1c	M2a	M2b	M2c	M1a	M1b	M1c	M2a	M2b	M2c
OS science	0.019***		0.012	0.026		0.021						
(ref. MA/US)	(0.019)		(0.019)	(0.018)		(0.018)						
OS reasoning							0.011		0.006	0.012		0.009
(ref. MA/US)							(0.016)		(0.016)	(0.015)		(0.015)
US ICT		-0.111***	-0.110***		-0.088***	-0.087***		-0.109***	-0.109***		-0.086***	-0.086***
(ref. MA/OS)		(0.019)	(0.019)		(0.018)	(0.018)		(0.019)	(0.019)		(0.018)	(0.018)

Notes: N=3,464. $^{\times}$ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job. Models 2 additionally control for social background, openness, conscientiousness, extraversion, agreeableness, neuroticism, marital status, children under 14 years in household, company size, economic sector, place of work, recession at start of current job, long-term unemployment. US (underskilled), MA (matched), OS (overskilled).
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Table S7 The associations between underskillings and ln gross hourly wages depending on the opposing mismatch in ICT (OLS regressions)

	US reading and OS ICT						**US mathematics and OS ICT**					
	Models 1			**Models 2**			**Models 1**			**Models 2**		
	M1a	M1b	M1c	M2a	M2b	M2c	M1a	M1b	M1c	M2a	M2b	M2c
US reading	-0.073***		-0.068***	-0.053**		-0.049**						
(ref. MA/OS)	(0.017)		(0.017)	(0.016)		(0.016)						
US mathematics							-0.081***		-0.076***	-0.059**		-0.055**
(ref. MA/OS)							(0.019)		(0.019)	(0.017)		(0.017)
OS ICT		0.088***	0.083***		0.074***	0.071***		0.093***	0.089***		0.076***	0.074***
(ref. MA/US)		(0.019)	(0.019)		(0.018)	(0.018)		(0.019)	(0.019)		(0.018)	(0.018)
	US science and OS ICT						**US reasoning and OS ICT**					
	Models 1			**Models 2**			**Models 1**			**Models 2**		
	M1a	M1b	M1c	M2a	M2b	M2c	M1a	M1b	M1c	M2a	M2b	M2c
US science	-0.100***		-0.095***	-0.073***		-0.069***						
(ref. MA/OS)	(0.019)		(0.019)	(0.018)		(0.018)						
US reasoning							-0.068***		-0.062***	-0.060***		-0.056***
(ref. MA/OS)							(0.016)		(0.016)	(0.015)		(0.015)
OS ICT		0.091***	0.085***		0.075***	0.072***		0.088***	0.082***		0.073***	0.069***
(ref. MA/US)		(0.019)	(0.019)		(0.018)	(0.018)		(0.019)	(0.019)		(0.018)	(0.015)

Notes: N=3,464. [x] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients, standard errors in parentheses. Control variables included in all regression models: occupational skill requirements in the two respective skill domains, female, age, age squared, immigration background, educational level, field of education, part-time work, public sector, duration in current job. Models 2 additionally control for social background, openness, conscientiousness, extraversion, agreeableness, neuroticism, marital status, children under 14 years in household, company size, economic sector, place of work, recession at start of current job, long-term unemployment. US (underskilled), MA (matched), OS (overskilled).

Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:9.0.1, own calculations.

Article 4:

Mismatched, but Not Aware of It? How Subjective and Objective Skill Mismatch Affects Employee Job Satisfaction

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Abstract

Several studies suggest that skill mismatch reduces job satisfaction. To date, research has primarily investigated the impact of subjective skill mismatch; the impact of objective skill mismatch has less commonly been analysed and has generally only focused on mismatches in single skills. The present study addresses the question of whether both subjective and objective skill mismatch reduces employee job satisfaction. This article contributes to previous research by disentangling the effects of objective and subjective skill mismatch on job satisfaction based on a multidimensional measure of objective skill mismatch among employees in Germany. Based on the 2018 wave of the German National Educational Panel Study (NEPS) Adult Cohort, multiple linear regression models are herein estimated in order to investigate how subjective and objective skill mismatches affect people's job satisfaction. The findings indicate that subjectively skill mismatched employees are less satisfied with their job than matched employees to a statistically significant degree, even when controlling for the objective mismatch. However, objectively skill mismatched employees do not show statistically significant lower job satisfaction compared to matched employees. Although there is considerable dissonance between objective mismatches and the subjective perception of being mismatched, the findings suggest that skill mismatch only reduces job satisfaction when employees perceive themselves to be mismatched.

1 Introduction

Skill mismatch is a challenging issue in the labour market, affecting individuals, companies and societies (Bilan et al., 2020; McGuinness et al., 2018; Nikolov et al., 2018); it is still gaining in importance given already existing and advancing megatrends such as technological innovation, globalisation, and demographic change (Comyn & Strietska-Ilina, 2019; International Labour Organization, 2015; Pauceanu et al., 2020). Especially for individuals, skill mismatch causes manifold negative consequences. To date, skill mismatch research has mainly focused on the individual monetary consequences of skill mismatch such as lower wages (e.g., Brunello & Wruuck, 2019); skill mismatch may also harm non-monetary returns such as job satisfaction (e.g., McGuinness et al., 2018). Low job satisfaction itself is also claimed to cause a range of negative consequences. For example, there is evidence that job dissatisfaction is associated with lower productivity of employees (Shobe, 2018), higher absenteeism from work (Cohen & Golan, 2007; Goldberg & Waldman, 2000; Spector, 1997) and a higher probability of quitting one's job (Clark et al., 2012; Cornelißen, 2009; Green, 2010; Kristensen & Westergard-Nielsen, 2004), and is also harmful for workplace integration of foreign employees (Cseh Papp et al., 2018). To counter job dissatisfaction and its potential consequences, it is important to take a closer look at the association between job satisfaction and a possible determinant, skill mismatch.

Skill mismatch describes a situation in the labour market in which the actual skills of employees do not match the skills required for their job (International Labour Office, 2018). This distinguishes the skill mismatch concept from other mismatch concepts such as qualification mismatch or educational mismatch that are often used synonymously in the literature, which define mismatch in terms of formal education levels instead of the level of skills. Skill mismatch is typically investigated as either a vertical or horizontal phenomenon. Vertical skill mismatch differentiates in terms of levels of skills, and occurs when an individual's level of skills is lower or higher than the level of skills required to perform their job (Cedefop, 2010), distinguishing between underskilled and overskilled among the skill mismatched individuals. By contrast, horizontal skill mismatch differentiates in terms of the type of skills, and occurs when an individual's type of skills does not match the type of skills required to perform their job (Cedefop, 2010), merely distinguishing between skill matched and skill mismatched individuals without indicating the direction of mismatch.

The skill mismatch literature also distinguishes between subjective and objective measures. Measures of subjective skill mismatch are based on self-assessments by employees, whereas measures of objective skill mismatch build on objective information, typically competency tests or job analyses (Cedefop, 2010). This study uses a measure of subjective skill mismatch, combining characteristics of both vertical and horizontal skill mismatch while not allowing a distinction regarding the direction of mismatch, only distinguishing between employees whose skills match or do not match the requirements of their job, as well as a measure of objective skill mismatch covering the vertical dimension of skill mismatch, distinguishing between underskilled, matched, or overskilled employees.

Research to date has mainly focused on the vertical dimension of skill mismatch, addressing the relation of skill mismatch and job satisfaction in the manner of subjective, self-reported measures of mismatch. Several cross-sectional studies show that any type of subjective skill mismatch is associated with reduced job satisfaction (e.g., Allen and van der Velden (2001) for tertiary education graduates in the Netherlands; Béduwé and Giret (2011) for young professionals in France; Mateos-Romero and del Mar Mateos-Romero and Salinas-Jiménez (2018) for 17 OECD countries; Shevchuk et al. (2019) for Britain). Garciá-Aracil and van der Velden (2008) confirm these findings merely for overskilled employees, whereas being underskilled is associated with increased job satisfaction. Moreover, Van der Velden and Verhaest (2017) show that being overskilled at the start of the job is associated with less job satisfaction. However, in the case of being underskilled, this only applies to those who are highly underskilled at the start of their job. Some panel studies, differentiating merely between being overskilled and skill matched, show that subjective overskilling harms employee job satisfaction (Vieira (2005) for Portugal; Congregado et al. (2016) for the EU-15 countries). Other studies show that subjective skill mismatch has negative consequences for job satisfaction and that skill mismatches are much better predictors of job satisfaction than educational mismatches (e.g., Green and Zhu (2010) cross-sectional study for Great Britain; Badillo-Amador et al. (2012) panel study for Spain; Mavromaras et al. (2012) panel study for Australia; Mavromaras et al. (2013) panel study for Australia). In sum, empirical evidence about the consequences of subjective skill mismatch shows a fairly consistent picture, whereby subjective skill mismatch and especially subjective overskilling seem to reduce employee job satisfaction.

Surprisingly, only a few studies to date have analysed the impact of objective skill mismatch on job satisfaction. The first cross-sectional studies provide very important insights. For example, Allen et al. (2013) analyse the impact of objective skill mismatch in literacy and numeracy, using the first wave of PIAAC among 22 countries. For literacy, they show that being overskilled reduces job satisfaction, while being underskilled increases it. However, they find no significant relation between being mismatched in numeracy and job satisfaction. Bönisch et al. (2019) also use data from the first wave of PIAAC, focusing on Austria, Germany, Spain, Flanders, England and Northern Ireland. They show that being overskilled in literacy significantly reduces job satisfaction in Flanders, but not in other countries. Further, there are no significant results for skill mismatch in numeracy in any country. Fregin et al. (2018) are the first to compare subjective and objective measures of skill mismatch and their relation to job satisfaction. Using the first wave of PIAAC among 22 countries and focusing on male employees in full-time jobs, they show that only subjectively perceived skill mismatch (overskilled and underskilled) harms job satisfaction. Since there is no significant relation between objective skill mismatch in numeracy and job satisfaction, the authors conclude that the negative correlation between skill mismatch and job satisfaction is an artefact caused by subjective measures that does not hold for the more reliable objective measures (Fregin et al., 2018).

In sum, previous research about objective skill mismatch and job satisfaction shows different results for mismatches in different skills. However, all of these studies operationalise objective skill mismatch based on single skill dimensions, like literacy or numeracy. This is associated with the methodological problem that people are already classified as skill mismatched if they do not match the required skill level in a single skill (e.g., literacy or numeracy). Moreover, one-dimensional skill mismatch measures only refer to mismatches in a single skill domain, whereas people might rather consider a whole bundle of skills instead of a single skill domain in their subjective self-assessment. This complicates the comparability between subjective and objective skill mismatch measures, since subjective measures refer to multiple skill dimensions while previously-used objective measures are only one-dimensional. Multidimensional measurement of skill mismatch might address this methodological problem due to its coverage of a range of skills domains. The present study therefore tackles the research question of whether both subjective skill mismatch and multidimensional objective skill mismatch reduce employee job satisfaction.

Following the idea of Fregin et al. (2018), this article aims to offer further insights into the relationship between subjective and objective skill mismatch and job satisfaction, adding to the previous literature in four ways. First, a multidimensional measure of objective skill mismatch is introduced based on mismatches in five skill domains (reading, mathematical, ICT, scientific and cognitive basic literacy). The multidimensional measure of skill mismatch covers domains of basic skills that are relevant across a variety of occupations and hold strong relevance in the modern information society's world of work (Cedefop, 2018; Cedefop & Eurofound, 2018; OECD, 2019; Weinert et al., 2019). By using a multidimensional mismatch measure, it is intended to place the concept of objective skill mismatch on a broader foundation and tackle its susceptibility to erroneous classifications based on individual skills. Second, this study analyses for the first time whether multidimensional objective skill mismatch is associated with employee job satisfaction. In this context, the multidimensional skill mismatch measure may provide new evidence concerning whether the previously postulated results on the relationship between objective skill mismatch and job satisfaction are merely artefacts due to the one-dimensional measures that are only valid for individual skill domains. Third, this article investigates the association between objective skill mismatch and subjective skill mismatch. In order to meaningfully interpret the potential impact of subjective and objective skill mismatch on affective perceptions such as job satisfaction, it is necessary to analyse whether and to what extent people's subjective assessments correspond to objective circumstances. Finally, by disentangling the separate impact directly caused by the two types of skill mismatch on people's job satisfaction, this article aims to clarify whether both objective and subjective skill mismatch are directly related to workers' job satisfaction.

2 Theory and Hypotheses

2.1 The Impact of Skill Mismatch on Job Satisfaction

There are various theories assuming a negative impact of skill mismatches on people's job satisfaction. According to the theory of person-environment fit (Edwards, 1991, 1996; French et al., 1982), people's attitudes toward jobs depend on the fit between themselves and their job, e.g., concerning how their skills match the job demands. Jobs that do not fit workers since they are too complex or too simple compared to their skills can be expected to cause negative job attitudes such as lower job satisfaction (French et al., 1982). Therefore, both underskilled and overskilled employees might be less satisfied with their jobs compared to employees who fit well to their jobs. The flow theory (Csikszentmihalyi, 1975, 1990) assumes that people enjoy activities if their requirements are neither too high nor too low for them. If the challenges of an activity are just balanced with their skills, people enter into a state of flow (Csikszentmihalyi, 1990). However, challenges that are understraining or overstraining for people's skills do not cause a state of flow. Transferred to the world of work, matched employees might enter into a state of flow since the challenges of their jobs match their skills, which makes them more likely to enjoy their jobs. By contrast, underskilled employees might assess their jobs as too complex, which might lead to worries or even anxiety, and overskilled employees might be bored as they may not make use of all their skills and may perceive their jobs as less challenging (Csikszentmihalyi, 1975). Therefore, underskilled or overskilled employees might be less likely to enjoy their jobs compared to matched employees. People's level of satisfaction might also be affected by unrealised expectations or a strong discrepancy between their aspirations and reality (Campbell et al., 1976). The more strongly their achievements deviate from their aspirations, the lower their level of satisfaction. This might also be true for aspirations in working life; particularly, working in a job with a level of demand below one's level of proficiency can be expected to cause unrealised expectations for individuals (World Economic Forum, 2014), since overskilled employees might expect to perform more challenging and interesting work (Congregado et al., 2016). Conversely, underskilling might reduce people's job satisfaction by causing strain or being a hindrance in their job, which might harm their job satisfaction (van Oortmerssen et al., 2020). Thus, skill mismatch is expected to reduce job satisfaction, regardless of whether individuals are underskilled or overskilled.

However, the impact of skill mismatch on people's job satisfaction might differ depending on whether it is an objective skill mismatch or a subjectively perceived skill mismatch. On the one hand, an objective match or mismatch might not necessarily be subjectively perceived as such. For example, French et al. (1982) show that while there might be both subjective and objective mismatches between jobs and people, it is mainly the subjective mismatches which cause strain. Accordingly, employees might be objectively mismatched for their job but might not be aware of it, or their skills might match their job requirements but they might perceive themselves as mismatched. On the other hand, subjective and objective mismatch might also be considered as overlapping constructs (Maltarich et al., 2011), assuming that subjective mismatches are caused by objective mismatches (Feldman et al., 2002; García-Mainar & Montuenga-Gómez, 2020; Liu & Wang, 2012; Maltarich et al., 2011; McKee-Ryan et al., 2009).

This article follows the assumption that objectively mismatched individuals tend to perceive themselves subjectively as mismatched, and vice versa. Moreover, the theoretical explanations suggest that skill mismatch is associated with lower job satisfaction. In line with the assumption of a link between objective and subjective skill mismatch, it is assumed that both objective and subjective mismatch harm people's job satisfaction. The following two hypotheses are derived:

Hypothesis 1 (H1). *Subjectively skill mismatched employees show less job satisfaction compared to subjectively skill matched employees.*

Hypothesis 2 (H2). *Objectively skill mismatched (underskilled or overskilled) employees show less job satisfaction compared to objectively skill matched employees.*

2.2 The Direct Impact of Subjective Skill Mismatch on Job Satisfaction

How people evaluate situations and the emotional reactions they show concerning a given situation primarily depend on how the situation is subjectively evaluated (Smith & Lazarus, 1990). Therefore, the individual evaluation or emotional reaction to one's work situation might also primarily depend on how this situation is subjectively perceived. Csikszentmihalyi (1990) assumes that it is not only the actual mismatch between individuals and their jobs as such that determines how people feel and judge their situation, but rather whether they are aware of it. Thus, workers might feel, for example, overworked, bored, or complain about unrealized expectations due to subjective perceptions of being mismatched for their job, which might, in turn, harm their job satisfaction. The subjective perception of being mismatched might thus have a direct negative impact on people's job satisfaction, regardless of whether this individual is objectively mismatched or not. Hence, the third hypothesis is derived:

Hypothesis 3 (H3). *Subjectively skill mismatched employees show less job satisfaction compared to subjectively skill matched employees even when controlling for objective skill mismatch.*

2.3 The Direct Impact of Objective Skill Mismatch on Job Satisfaction

Given the assumption that objective skill mismatches are likely to affect the people concerned in the performance of their jobs, objective mismatches might have a direct impact on people's job satisfaction. Regardless of whether or not people perceive that they are mismatched, objectively skill mismatched employees might be more likely to have complications in their daily work routine compared to objectively skill matched employees, since they are either unable to deal with the requirements of their jobs (underskilled) or they cannot make use of all their skills (overskilled) in their jobs. By contrast, objectively skill matched employees might be more likely to cope with the demands of their jobs and deploy their skills on the job. Matched employees are therefore more likely to be saved from inconveniences at work and provided with a feeling of success associated with their jobs, which in turn might have a positive impact on their job satisfaction. These circumstances do not depend on subjective perceptions of mismatch, but they might be directly caused by the unfavourable working conditions of skill mismatched workers. Objective mismatches might therefore constitute objective stressors for the persons concerned, which might have a negative impact on the evaluation of the job situation, irrespective of whether a mismatch is subjectively perceived or not. For this reason, objective mismatches are assumed to harm job satisfaction irrespective of whether or not people perceive themselves as mismatched. Therefore, the fourth hypothesis is derived as follows:

Hypothesis 4 (H4). *Objectively skill mismatched (underskilled or overskilled) employees show less job satisfaction compared to objectively skill matched employees even when controlling for subjective skill mismatch.*

3 Data and Methods

3.1 Data

The following analyses are based on the German National Educational Panel Study (NEPS) Adult Cohort Version 11.1.0, Blossfeld et al. (2011). The total sample of respondents in the NEPS Adult Cohort, starting in 2007 (wave 1), consisted of adults living in Germany born between 1944 and 1986 (Blossfeld & Roßbach, 2019). The NEPS Adult Cohort provides extensive socio-demographic data and rich information on the educational and employment biography of the respondents from different waves. This paper draws on a cross-section design of the 2018 wave, the 11th wave of the NEPS Adult Cohort, since panel observations were not available for the treatment variables used. In addition to the cross-section information from wave 11, variables from previous waves of the panel data were also used if the relevant information was not collected in wave 2018 but in one of the previous waves; this primarily concerns the competency tests in the five different skills of the objective skill mismatch indicator and two personality traits, conscientiousness and neuroticism, which were assumed to remain constant over time.[1]

The NEPS Adult Cohort provided some important advantages for the sake of analysing the impact of subjective and objective skill mismatch on people's job satisfaction. By covering objective information on the competencies of employed adults in five different skill domains relevant for labour market success, it offered the opportunity to construct a multidimensional skill mismatch measure reflecting the coverage of a broader range of skill domains relevant to the labour market among adults compared to other studies, such as the PIAAC. In addition, the NEPS Adult Cohort provided subjective assessments of how employed people subjectively

[1] The competency tests were collected at different points in time before the 2018 wave (reading literacy: 2010 wave, 2012 wave, 2016 wave; mathematical literacy: 2010 wave, 2016 wave; ICT literacy: 2012 wave; scientific literacy: 2012 wave; cognitive basic literacy: 2014 wave). In each skill domain, the most recent score was used as a proxy for the proficiency level of people who took part in several tests in one skill domain. The two personality traits, conscientiousness and neuroticism, were collected in the 2015 wave.

assess their own fit in their job. Thus, the NEPS Adult Cohort provided the opportunity to compare objective multidimensional skill mismatches with subjective skill mismatches and analyse the consequences among employed adults.

3.2 Sample

The analysis sample was based on people who participated in the 2018 wave of the NEPS Adult Cohort. In order to construct a multidimensional skill mismatch measure, all people who were missing values in any of the five skills of the objective skill mismatch indicator were excluded from the sample. Employees whose occupational groups could not be assigned to the ISCO-08 were also excluded, since the information about people's occupational group membership was necessary in order to operationalise the objective skill mismatch indicator. Further, the sample was restricted to adults with a maximum age of 65 years who at the time of their interview in the 2018 wave were employed for at least 15 h per week, excluding the self-employed, persons with pre-employment activities, freelancers, family workers, people employed in the secondary labour market or seasonal work, and people with missing values in any of the required variables. The final sample was unweighted and relied on 3116 respondents.

3.3 Measurements

The dependent variable of *job satisfaction* was based on an 11-point scale asking respondents how satisfied they are with their work, ranging from "completely dissatisfied" to "completely satisfied".

The first independent variable of *subjective skill mismatch* was based on the statement that "The requirements of the job match my skills", offering a five-point scale to respondents ranging from "completely disagree" to "completely agree". This indicator might capture both mismatches in the type of skills or mismatches in the level of skills, but does not allow for differentiation among mismatched employees as underskilled or overskilled, merely between skill matched and skill mismatched employees. Therefore, this study used a dichotomised subjective skill mismatch indicator (skill match as opposed to skill mismatch) where those who completely or somewhat agreed with the statement were predicted as subjectively skill matched, and those who partly agreed, somewhat disagreed, or completely disagreed were predicted as subjectively skill mismatched.

The second independent variable of *objective skill mismatch* was operationalised based on a multidimensional concept taking into account mismatches in five different skills. For this reason, five single objective skill mismatch indicators were calculated for each individual in reading, mathematical, ICT, scientific and cognitive basic literacy. Each of the five objective skill mismatch indicators were based on a comparison of the level of skills required per occupational group and the level of skills of the individuals. The reference group for the calculation of skill requirements was based on persons up to the age of 65 who were employed for at least 15 h per week, excluding the self-employed, persons with pre-employment activities, freelancers, and family workers who subjectively evaluated that the requirements of their job matched their skills.[2] For each skill domain, the required levels of skills were defined as the average proficiency level of people working in the same ISCO-08 two-digit occupational sub-major group, plus and minus one standard deviation.[3] Employees were classified as underskilled or overskilled in the specific skills if their proficiency level was more than one standard deviation below or above the required level in their occupational group. If the skill level of an employee was in between the range of averaged skill levels plus and minus one standard deviation, the person was classified as matched. Thus, every person in the sample was classified as underskilled, matched or overskilled in all of the five skills. The multidimensional skill mismatch measure was generated based on the five different skill mismatch indicators. If employees were rated as underskilled in the majority, i.e., at least three out of five of the single skill mismatch indicators, they were classified as underskilled in the multidimensional measure. Employees were rated as overskilled in the multidimensional measure if they were overskilled in the majority of the five skill mismatch indicators. People who were matched in the majority of the skills or who were not underskilled in at least three out of five skills or not overskilled in at least three out of five skills were considered matched.

Further, the analyses herein draw on control variables that are likely to condition both the independent variables of subjective skill mismatch and objective skill mismatch and the dependent variable of job satisfaction. Table 1 provides an overview of the descriptive sample statistics, including all variables used in the study.

[2] People who "rather agree" or "completely agree" with the statement "The requirements of the job match my skills" were considered as the reference group for calculating skill requirements.

[3] If an ISCO-08 two-digit occupational sub-major group had fewer than 20 observations, the skill requirements were calculated using the ISCO-08 one-digit occupational major group. If the minimum value of 20 observations was not reached even at the ISCO-08 one-digit level, no skill requirements could be set for the occupational groups concerned.

Table 1 Descriptive sample statistics

Variables	Mean	SD	Min	Max
Dependent variable				
job satisfaction	7.23	1.67	0	10
Independent variables				
subjective skill mismatch	0.20	0.40	0	1
objective skill mismatch				
underskilled	0.09	0.28	0	1
matched	0.83	0.37	0	1
overskilled	0.08	0.27	0	1
Control variables				
male	0.50	0.50	0	1
age	51.37	8.27	32	65
immigration background	0.15	0.35	0	1
highest educational attainment				
unskilled/no apprenticeship	0.02	0.15	0	1
Hauptschule w. apprenticeship	0.11	0.32	0	1
sec. school w. apprenticeship	0.32	0.47	0	1
A level without tertiary degree	0.19	0.39	0	1
tertiary degree	0.35	0.48	0	1
duration in the job	156.02	127.15	0	553
occupational area				
agriculture, forestry, etc.	0.00	0.06	0	1
production of raw materials, etc.	0.16	0.37	0	1
construction, architecture, etc.	0.05	0.21	0	1
natural sciences, informatics, etc.	0.06	0.24	0	1
traffic, logistics, etc.	0.08	0.26	0	1
commercial services, sales, etc.	0.09	0.28	0	1
business organisation, law, etc.	0.27	0.44	0	1
social sector, teaching, etc.	0.26	0.44	0	1
humanities, economics, etc.	0.03	0.18	0	1
occupational requirement level				
unskilled or semi-skilled	0.05	0.22	0	1
specialist	0.47	0.50	0	1
complex specialist	0.17	0.37	0	1
highly complex	0.32	0.47	0	1
part-time job	0.33	0.47	0	1
workplace in East Germany	0.19	0.39	0	1
educational mismatch				
undereducated	0.23	0.42	0	1
matched	0.55	0.50	0	1
overeducated	0.22	0.42	0	1
conscientiousness	3.95	0.67	1.5	5
neuroticism	2.62	0.75	1	5

N = 3116.

3.4 Analytical Strategy

The analysis began by examining the extent to which subjective and objective skill mismatches were related, drawing on bivariate distributions.

Subsequently, the hypotheses of whether and how subjective and objective skill mismatch affect people's job satisfaction were tested using multivariate linear regression models. Given the cross-sectional design, this paper draws on OLS regressions. Three models were estimated to test the hypotheses. The first two models analysed the impact of subjective to objective skill mismatch, respectively, on people's job satisfaction. Both models drew on controls that conditioned both the respective independent variable (subjective skill mismatch in model 1; objective skill mismatch in model 2) and the dependent variable (job satisfaction) in order to prevent confounding bias in the effect of skill mismatch (Elwert & Winship, 2014). The third model tested the separate effects of subjective skill mismatch and objective skill mismatch on job satisfaction. This model included subjective skill mismatch and objective skill mismatch in addition to the control variables, in order to determine the separate effects of both types of skill mismatch while controlling for the other one.

4 Findings

4.1 Bivariate Findings

The descriptive sample statistics show a discrepancy between the proportion of workers who subjectively perceive themselves as mismatched and the proportion of objectively mismatched employees (Table 1). Around 20 per cent of employees subjectively assess themselves as skill mismatched, whereas only around 17 per cent of employees are objectively considered to be mismatched (around nine per cent underskilled; around eight percent overskilled). Table 2 shows how people with an objective skill match or skill mismatch classify themselves subjectively.

Table 2 Bivariate relation between objective and subjective skill mismatch

Objective Skill Mismatch	**Subjective Skill Mismatch**	
	Matched	Mismatched
matched	80.02%	19.98%
mismatched	78.01%	21.99%
underskilled	75.65%	24.35%
overskilled	80.56%	19.44%

N = 3116.

As can be seen, 80.02 per cent out of all workers who objectively possess the required level of skills classify themselves subjectively as matched, whereas 19.98 per cent of them perceive themselves to be mismatched. However, out of all workers who are objectively skill mismatched, only 21.99 per cent subjectively classify themselves as mismatched. By contrast, 78.01 per cent out of all objectively skill mismatched workers do not subjectively classify themselves as mismatched but rather as matched. This means that the vast majority of objectively mismatched employees are either not aware of their mismatched situation or they irrespectively assume that their skills match the requirements of their job. These dissonances between objective mismatch and subjective perception of mismatch are slightly more common among objectively overskilled workers — where 80.56 per cent assess themselves as matched — compared to objectively underskilled workers, where 75.65 per cent assess themselves as matched. Table 3 provides an overview of how people who assess themselves as mismatched or matched are classified in terms of objective skill mismatch.

Out of all workers who subjectively classify themselves as matched, 83.57 per cent are objectively matched. However, of all those who subjectively classify themselves as mismatched, 81.83 per cent objectively do have the required level of skills for their job. Thus, the vast majority of employees who subjectively classify themselves as skill mismatched actually objectively possess the required skills.

Table 3 Bivariate relation between subjective and objective skill mismatch

Subjective Skill Mismatch	**Objective Skill Mismatch**			
	Matched	Mismatched	Underskilled	Overskilled
matched	83.57%	16.43%	8.26%	8.18%
mismatched	81.83%	18.17%	10.43%	7.74%

N = 3116.

These findings indicate considerable differences between the objective circumstances and the subjective self-assessments of workers and contradict the assumption of a strong correlation between objective mismatch and subjective mismatch perception. The majority of those who are objectively mismatched perceive themselves to be matched, and the majority of those who subjectively perceive themselves to be mismatched objectively in fact possess the required level of skills. Whether one's skills actually match the requirements of the job or not therefore seems to hold only minor relevance to people's subjective perception of being matched or mismatched.

4.2 Regression Analyses

Table 4 presents the findings of the three models estimated in order to test the hypotheses.

Table 4 Multiple linear regression analyses regarding skill mismatch and job satisfaction

	Model 1		**Model 2**		**Model 3**	
	Coef.	SE	Coef.	SE	Coef.	SE
Subjective skill mismatch	−1.01***	0.07			−1.00***	0.07
(ref. matched)						
Objective skill mismatch						
(ref. matched)						
underskilled			−0.19	0.11	−0.13	0.11
overskilled			−0.01	0.11	−0.03	0.11
Male	−0.13	0.08	−0.13	0.08	−0.14	0.08
(ref. female)						
Age	−0.00	0.00	−0.00	0.00	−0.00	0.00
Immigration background	−0.02	0.08	−0.05	0.08	−0.01	0.08
(ref. no immigration background)						
Educational attainment						
(ref. sec. school w. appr.)						
unskilled/no appr.	0.38	0.22	0.52*	0.23	0.39	0.22
Hauptschule w. appr.	0.08	0.14	0.17	0.14	0.08	0.14
A level without tertiary degree	−0.16	0.12	−0.22	0.12	−0.17	0.12
tertiary degree	−0.19	0.13	−0.33*	0.13	−0.20	0.13
Duration in the job	−0.00***	0.00	−0.00**	0.00	−0.00***	0.00
Occupational area						
(ref. social sector, teaching., etc.)						
agriculture, forestry, etc.	−0.71	0.51	−0.75	0.52	−0.71	0.51
prod. of raw materials, etc.	−0.17	0.10	−0.27**	0.10	−0.17	0.10
construction, architecture, etc.	0.12	0.15	0.00	0.16	0.12	0.15
natural sciences, etc.	−0.08	0.13	−0.10	0.14	−0.08	0.13
traffic, logistics, etc.	−0.26	0.13	−0.50***	0.13	−0.26*	0.13
commercial services, etc.	−0.05	0.12	−0.14	0.12	−0.06	0.12
business organisation, etc.	−0.06	0.08	−0.10	0.08	−0.06	0.08
humanities, economics, etc.	−0.18	0.17	−0.26	0.18	−0.18	0.17
Occupational requirement level						
(ref. unskilled or semi-skilled)						
specialist	−0.05	0.14	0.05	0.15	−0.04	0.14
complex specialist	−0.16	0.16	0.04	0.16	−0.14	0.16
highly complex	0.18	0.18	0.50**	0.19	0.20	0.18
Part-time job	0.02	0.07	−0.01	0.08	0.02	0.07
(ref. full-time job)						
Workplace in East Germany	0.06	0.07	0.04	0.08	0.07	0.08
(ref. workplace in West Germany)						
Educational mismatch						
(ref. matched)						
undereducated	−0.06	0.11	−0.14	0.12	−0.05	0.11
overeducated	0.31**	0.12	0.39**	0.12	0.33**	0.12
Conscientiousness	0.18***	0.04	0.21***	0.04	0.19***	0.04
Neuroticism	−0.34***	0.04	−0.37***	0.04	−0.34***	0.04
R-squared	0.11		0.06		0.11	

N = 3116; * p < 0.05; ** p < 0.01; *** p < 0.001. Data: NEPS Adult Cohort, Version 11.1.0.

Model 1 investigated the effect on job satisfaction of being subjectively skill mismatched. In line with Hypothesis 1, employees who perceive themselves as skill mismatched report statistically significant lower job satisfaction compared to those who are subjectively skill matched. The job satisfaction of employees assessing themselves as subjectively skill mismatched is 1.01 points lower compared to that of employees assessing themselves as skill matched.

Model 2 refers to the association between objective skill mismatch and employee job satisfaction. Compared to objectively skill matched employees, both underskilled and overskilled individuals tend to be less satisfied with their job. However, these results are not statistically significant, and Hypothesis 2 is therefore falsified. Regarding the first two hypotheses, the findings indicate that job satisfaction is only lower to a statistically significant degree for subjectively skill mismatched people, not for objectively skill mismatched people.

Model 3 investigated whether objective and subjective skill mismatch have a direct effect on employees' job satisfaction. Therefore, the separate effect of subjective mismatch on job satisfaction was analysed while controlling for objective mismatch, and the separate effect of objective mismatch on job satisfaction was analysed under the control of subjective mismatch. In accordance with Hypothesis 3, subjectively skill mismatched employees were statistically significantly less satisfied with their job compared to subjectively skill matched employees even when controlling for objective skill mismatch. Compared to Model 1, where subjectively skill mismatched employees had lower job satisfaction by 1.01 points compared to subjectively matched employees, the job satisfaction of subjectively skill mismatched employees was still 1.00 points lower compared to subjectively matched employees in Model 3 when controlling for objective skill mismatch. Thus, even when controlling for objective skill mismatch, the perception of being subjectively skill mismatched has an almost identical negative effect on people's job satisfaction. By contrast, Hypothesis 4 is falsified, since objectively underskilled or overskilled employees do not show statistically significant lower job satisfaction compared to objectively skill matched employees even when controlling for subjective skill mismatch. Thus, there is no direct negative effect of objective skill mismatch on people's job satisfaction.

Overall, the findings indicate that subjectively perceived skill mismatch is relevant for people's job satisfaction, irrespective of whether such a mismatch objectively exists or not, although there is no direct statistically significant association between objective skill mismatch and people's job satisfaction. These results are essentially in line with the findings of Fregin et al. (2018), who also showed lower job satisfaction only for subjectively perceived skill mismatch, not for objective skill mismatch in numeracy. The present results also confirm these findings for multidimensional objective skill mismatch considering more than one skill dimension.

Moreover, the findings show that objective mismatch does not contribute either directly or indirectly to statistically significant lower job satisfaction. The findings on subjective skill mismatch are also in line with previous research postulating a negative relation between subjective skill mismatch and job satisfaction. In addition to previous research, these results also show that the subjective perception of being skill mismatched reduces employee job satisfaction regardless of whether the skill mismatch objectively exists.

One reason for the differing effects of objective and subjective skill mismatches on workers' job satisfaction might be due to the fact that the majority of objectively mismatched people do not subjectively perceive themselves as mismatched. Hence, interaction effects were added to the previous models to test whether objectively and subjectively mismatched employees are less satisfied with their jobs than objectively matched but subjectively mismatched employees (Table A1 in Appendix). Nonetheless, people who are both objectively mismatched (underskilled or overskilled) and subjectively mismatched do not show statistically significant lower job satisfaction compared to people who are objectively matched and subjectively mismatched. This is another hint that people's job satisfaction is only reduced by skill mismatch if people perceive themselves to be skill mismatched. Whether or not the self-assessment of a skill mismatch corresponds to the objective facts does not seem to have any additional relevance. Thus, subjective feelings rather than objective conditions seem to be most relevant to employee job satisfaction.

4.3 Robustness Checks

In order to rule out the possibility that these results are due to the multidimensional measure of objective skill mismatch, the main models were additionally calculated using unidimensional objective skill mismatch measures, defining objective skill mismatch in terms of the mismatch in the individual skills in reading, mathematics, ICT, scientific literacy and basic cognitive literacy. However, across all five different unidimensional objective skill mismatch measures the results remained essentially the same compared to the results of the models for the multidimensional objective skill mismatch measure (Table A2 in the Appendix).

Further, to determine whether there are differences between objectively skill matched and objectively skill mismatched employees in general, the models including objective skill mismatch were estimated again, distinguishing only skill matched from skill mismatched (either underskilled or overskilled) employees (Table A3 in the Appendix). There were also no statistically significant differences between objectively matched and mismatched employees.

Accordingly, neither a general objective skill mismatch nor individual manifestations of this mismatch (underskilled or overskilled) have a statistically significant negative effect on job satisfaction.

Moreover, the main models were calculated again without using the control variable of educational mismatch, considered problematic for causal analytical considerations (Table A4 in the Appendix). Again, there were no statistically significant changes regarding the relevant associations.[4]

5 Discussion and Conclusions

The present study has investigated whether and how subjective and objective skill mismatch affects the job satisfaction of employees in Germany. Using cross-section data from the 2018 wave of the NEPS Adult Cohort, this article shows that subjectively perceived skill mismatch reduces people's job satisfaction to a statistically significant degree, including when controlling for objective mismatches. However, objectively skill mismatched employees are not less satisfied with their jobs to a statistically significant degree compared to matched employees, neither in general nor when controlling for subjective mismatch. Therefore, job satisfaction is only harmed by skill mismatch if people subjectively perceive it, regardless of whether this skill mismatch actually exists or not. In addition, for people's job satisfaction it holds no additional importance whether the subjective perception of a skill mismatch corresponds to objective reality or not.

The main findings are essentially in line with previous studies suggesting job satisfaction penalties for subjectively skill mismatched employees (e.g., Allen & van der Velden, 2001; Mateos-Romero & Salinas-Jiménez, 2018) and with the findings of Fregin et al. (2018), which indicated statistically significant lower job satisfaction only for subjectively perceived skill mismatch, not for objective skill mismatch in numeracy. The present study is the first to confirm these findings for a multidimensional measure of objective skill mismatch. This study also highlights that objective findings of skill mismatch do not coincide with people's subjective perceptions. The majority of objectively skill mismatched employees are not aware of it. Moreover, the majority of subjectively skill mismatched employees are not aware of objectively

[4] The control variable of objective educational mismatch is considered problematic for causal analytical considerations due to doubts of being a temporally preceding cause of objective skill mismatch. In the sensitivity analysis models without taking the control variable objective educational mismatch into account, there was a positive correlation between being objectively overskilled and job satisfaction. In the main models, taking into account the control variable objective educational mismatch, a negative correlation between being objectively overskilled and job satisfaction was found. However, in both cases the results were not significant.

possessing the required level of skills. These discrepancies between objective circumstances and subjective self-assessment might explain why objective mismatch does not have a statistically significant effect on job satisfaction, since the majority of objectively mismatched employees might not evaluate their job situation as being burdening.

However, this gap between objective circumstances and subjective self-assessments is not necessarily based on misperceptions by workers; it might also be explained by the limitations of objective skill mismatch measures. For example, workers might mismatch the required skill levels in the objectively assessed skill domains but define themselves as matched due to their level of skills in other skill domains such as communication, planning and organisation, problem-solving, or physical skills, or vice versa. Such limitations of objective skill mismatch measures cannot be completely prevented even by a multidimensional skill mismatch measure. The present study comes with further limitations. To analyse the differences between subjective and objective skill mismatch in further detail, subjective skill mismatch should not only be measured based on the horizontal but also the vertical dimension, differentiating between subjectively underskilled and subjectively overskilled employees. Moreover, the analyses herein may be subject to bias due to unobserved confounding variables such as, for example, people's capacity for self-reflection, feedback from their superiors, or workplace atmosphere. Further, the present study does not allow for drawing any conclusions on the relationship between skill mismatch and job satisfaction for younger labour market entrants, due to sample composition in terms of age.

To sum up, the present article derives three main conclusions. First, subjective skill mismatch has a negative effect on workers' job satisfaction even if this mismatch does not objectively exist. Second, objective skill mismatches do not have a statistically significant effect on job satisfaction. Third, there is a considerable discrepancy between objective skill mismatches and subjective feelings of being skill mismatched, and vice versa.

These findings might enable the drawing of valuable conclusions; for example, allowing companies to optimise the job satisfaction of their workforce. Thus, employers who want to increase the job satisfaction of their staff or aim to prevent negative consequences caused by a lack of job satisfaction, such as employee-intended job changes or absenteeism, might consider the subjective perceptions of their staff and take targeted countermeasures in cases of perceived mismatch. However, for policy-making, the findings primarily mean some sobering conclusions, since targeted policy measures that, for example, aim to increase and ensure matching between jobs and individuals do not necessarily improve people's level of job satisfaction.

Subsequent research might build on these findings addressing, for example, the gap between objective and subjective skill mismatch in further detail. Future research might address the causes of discrepancies between subjective perceptions of skill mismatch and the objectively existing skill mismatch, showing how subjectively skill mismatched people differ from objectively skill mismatched people. Moreover, additional research might investigate whether these contrasts in consequence of subjective and objective skill mismatch are confirmed for other affective work-related outcomes, such as feelings of overload, pressure or work-life conflict, as well as non-affective outcomes like individuals' education and training behaviour. The limitations might also offer opportunities for future research. For example, subsequent research might target young labour market entrants, investigating whether objective mismatches in this group matter for their job satisfaction. The findings of the present study also hint that mismatches between education levels and the level required for their job might affect their job satisfaction. Therefore, future research might also refocus on the facets of educational mismatch and skill mismatch, and their significance for job satisfaction.

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7 Appendix

Table A1 Multiple linear regression analyses regarding skill mismatch and job satisfaction including interaction effects between subjective and objective skill mismatch

	Model	
	Coef.	SE
Subjective skill mismatch	−1.00***	0.08
(ref. matched)		
Objective skill mismatch		
(ref. matched)		
underskilled	−0.09	0.12
overskilled	−0.04	0.12
Subj. skill mismatch * obj. skill mismatch		
*(ref. subj. mismatch * obj. matched)*		
subj. mismatched * obj. underskilled	−0.15	0.24
subj. mismatched * obj. overskilled	0.10	0.27
Male	−0.14	0.08
(ref. female)		
Age	−0.00	0.00
Immigration background	−0.02	0.08
(ref. no immigration background)		
Educational attainment		
(ref. sec. school w. appr.)		
unskilled/no appr.	0.40	0.22
Hauptschule w. appr.	0.08	0.14
A level without tertiary degree	−0.17	0.12
tertiary degree	−0.21	0.13
Duration in the job	−0.00***	0.00
Occupational area		
(ref. social sector, teaching, etc.)		
agriculture, forestry, etc.	−0.71	0.51
prod. of raw materials, etc.	−0.17	0.10
construction, architecture, etc.	0.12	0.15
natural sciences, etc.	−0.08	0.13
traffic, logistics, etc.	−0.26*	0.13
commercial services, etc.	−0.06	0.12
business organisation, etc.	−0.06	0.08
humanities, economics, etc.	−0.18	0.17
Occupational requirement level		
(ref. unskilled or semi-skilled)		
specialist	−0.04	0.14
complex specialist	−0.14	0.16
highly complex	0.21	0.18
Part-time job	0.02	0.07
(ref. full-time job)		
Workplace in East Germany	0.07	0.08
(ref. workplace in West Germany)		
Educational mismatch		
(ref. matched)		
undereducated	−0.06	0.11
overeducated	0.32**	0.12
Conscientiousness	0.19***	0.04
Neuroticism	−0.34***	0.04
R-squared	0.11	

N = 3116; * p < 0.05; ** p < 0.01; *** p < 0.001. Data: NEPS Adult Cohort, Version 11.1.0.

Table A2 Multiple linear regression analyses regarding skill mismatch and job satisfaction using unidimensional measures for objective skill mismatch

	Reading Literacy		**Mathematical Literacy**		**ICT Literacy**		**Scientific Literacy**		**Cog. Basic Literacy**	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Subjective skill mismatch	−1.01***	0.07	−1.01***	0.07	−1.00***	0.07	−1.01***	0.07	−1.01***	0.07
(ref. matched)										
Objective skill mismatch										
(ref. matched)										
underskilled	0.06	0.08	0.04	0.09	−0.11	0.08	−0.09	0.09	−0.06	0.08
overskilled	0.05	0.08	0.07	0.09	−0.09	0.09	−0.15	0.09	0.05	0.08
Male	−0.13	0.08	−0.13	0.08	−0.13	0.08	−0.12	0.08	−0.13	0.08
(ref. female)										
Age	−0.00	0.00	−0.00	0.00	−0.00	0.00	−0.00	0.00	−0.00	0.00
Immigration background	−0.02	0.08	−0.02	0.08	−0.02	0.08	−0.02	0.08	−0.01	0.08
(ref. no immigration background)										
Educational attainment										
(ref. sec. school w. appr.)										
unskilled/no appr.	0.38	0.22	0.38	0.22	0.38	0.22	0.38	0.22	0.38	0.22
Hauptschule w. appr.	0.08	0.14	0.08	0.14	0.07	0.14	0.07	0.14	0.08	0.14
A level without tertiary degree	−0.15	0.12	−0.15	0.12	−0.17	0.12	−0.16	0.12	−0.16	0.12
tertiary degree	−0.19	0.13	−0.19	0.13	−0.19	0.13	−0.18	0.13	−0.20	0.13
Duration in the job	−0.00***	0.00	−0.00***	0.00	−0.00***	0.00	−0.00***	0.00	−0.00***	0.00
Occupational area										
(ref. social sector, teaching, etc.)										
agriculture, forestry, etc.	−0.71	0.51	−0.70	0.51	−0.71	0.51	−0.73	0.51	−0.71	0.51
prod. of raw materials, etc.	−0.16	0.10	−0.16	0.10	−0.17	0.10	−0.17	0.10	−0.17	0.10
construction, architecture, etc.	0.12	0.15	0.12	0.15	0.13	0.15	0.11	0.15	0.12	0.15
natural sciences, etc.	−0.07	0.13	−0.08	0.13	−0.08	0.13	−0.07	0.13	−0.08	0.13
traffic, logistics, etc.	−0.26*	0.13	−0.25	0.13	−0.26*	0.13	−0.27*	0.13	−0.26*	0.13
commercial services, etc.	−0.05	0.12	−0.05	0.12	−0.05	0.12	−0.05	0.12	−0.05	0.12
business organisation, etc.	−0.06	0.08	−0.06	0.08	−0.06	0.08	−0.06	0.08	−0.06	0.08
humanities, economics, etc.	−0.18	0.17	−0.18	0.17	−0.18	0.17	−0.17	0.17	−0.18	0.17

Occupational requirement level										
(ref. unskilled or semi-skilled)										
specialist	−0.04	0.14	−0.05	0.14	−0.04	0.14	−0.05	0.14	−0.04	0.14
complex specialist	−0.15	0.16	−0.15	0.16	−0.15	0.16	−0.16	0.16	−0.15	0.16
highly complex	0.18	0.18	0.18	0.18	0.19	0.18	0.18	0.18	0.19	0.18
Part-time job	0.01	0.07	0.01	0.07	0.02	0.07	0.02	0.07	0.01	0.07
(ref. full-time job)										
Workplace in East Germany	0.06	0.08	0.06	0.08	0.06	0.08	0.06	0.08	0.06	0.08
(ref. workpl. in West Germany)										
Educational mismatch										
(ref. matched)										
undereducated	−0.07	0.11	−0.07	0.11	−0.05	0.11	−0.06	0.11	−0.06	0.11
overeducated	0.31**	0.12	0.31**	0.12	0.33**	0.12	0.33**	0.12	0.31**	0.12
Conscientiousness	0.18***	0.04	0.18***	0.04	0.18***	0.04	0.18***	0.04	0.19***	0.04
Neuroticism	−0.34***	0.04	−0.34***	0.04	−0.34***	0.04	−0.34***	0.04	−0.34***	0.04
R-squared	0.11		0.11		0.11		0.11		0.11	

N = 3116; * p < 0.05; ** p < 0.01; *** p < 0.001. Data: NEPS Adult Cohort, Version 11.1.0.

Table A3 Multiple linear regression analyses regarding objective skill mismatch and job satisfaction

	Model 1		Model 2	
	Coef.	SE	Coef.	SE
Objective skill mismatch	−0.10	0.08	−0.08	0.08
(ref. matched)				
Subjective skill mismatch			−1.01***	0.07
(ref. matched)				
Male	−0.11	0.08	−0.13	0.08
(ref. female)				
Age	−0.00	0.00	−0.00	0.00
Immigration background	−0.05	0.08	−0.02	0.08
(ref. no immigration background)				
Educational attainment				
(ref. sec. school w. appr.)				
unskilled/no appr.	0.51*	0.23	0.39	0.22
Hauptschule w. appr.	0.16	0.14	0.08	0.14
A level without tert. d.	−0.21	0.12	−0.17	0.12
tertiary degree	−0.31*	0.13	−0.19	0.13
Duration in the job	−0.00***	0.00	−0.00***	0.00
Occupational area				
(ref. social sector, teaching, etc.)				
agriculture, forestry, etc.	−0.77	0.52	−0.72	0.51
prod. of raw materials, etc.	−0.27**	0.10	−0.17	0.10
construction, architecture, etc.	0.00	0.16	0.12	0.15
natural sciences, etc.	−0.10	0.14	−0.08	0.13
traffic, logistics, etc.	−0.50***	0.13	−0.26*	0.13
commercial services, etc.	−0.14	0.12	−0.06	0.12
business organisation, etc.	−0.10	0.08	−0.06	0.08
humanities, economics, etc.	−0.25	0.18	−0.18	0.17
Occupational requirement level				
(ref. unskilled or semi-skilled)				
specialist	0.04	0.15	−0.04	0.14
complex specialist	0.03	0.16	−0.15	0.16
highly complex	0.48**	0.18	0.19	0.18
Part-time job	−0.01	0.08	0.02	0.07
(ref. full-time job)				
Workplace in East Germany	0.03	0.08	0.06	0.07
(ref. workplace in West Germany)				
Educational mismatch				
(ref. matched)				
undereducated	−0.14	0.12	−0.06	0.11
overeducated	0.39**	0.12	0.33**	0.12
Conscientiousness	0.21***	0.04	0.18***	0.04
Neuroticism	−0.37***	0.04	−0.34***	0.04
R-squared	0.06		0.11	

N = 3116; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Data: NEPS Adult Cohort, Version 11.1.0.

Table A4 Multiple linear regression analyses regarding skill mismatch and job satisfaction excluding objective educational mismatch

	Model 1		Model 2		Model 3	
	Coef.	SE	Coef.	SE	Coef.	SE
Subjective skill mismatch	−1.02***	0.07			−1.01***	0.07
(ref. matched)						
Objective skill mismatch						
(ref. matched)						
underskilled			−0.18	0.11	−0.12	0.11
overskilled			0.03	0.11	0.01	0.11
Male	−0.13	0.08	−0.13	0.08	−0.14	0.08
(ref. female)						
Age	−0.00	0.00	−0.00	0.00	−0.00	0.00
Immigration background	−0.01	0.08	−0.04	0.08	−0.00	0.08
(ref. no immigration background)						
Educational attainment						
(ref. sec. school w. appr.)						
unskilled/no appr.	0.30	0.20	0.36	0.21	0.31	0.20
Hauptschule w. appr.	0.01	0.10	0.04	0.11	0.02	0.10
A level without tertiary degree	0.07	0.09	0.05	0.09	0.06	0.09
tertiary degree	0.04	0.09	−0.03	0.09	0.02	0.09
Duration in the job	−0.00***	0.00	−0.00**	0.00	−0.00***	0.00
Occupational area						
(ref. social sector, teaching, etc.)						
agriculture, forestry, etc.	−0.69	0.51	−0.72	0.52	−0.69	0.51
prod. of raw materials, etc.	−0.15	0.10	−0.25**	0.10	−0.15	0.10
construction, architecture, etc.	0.14	0.15	0.03	0.16	0.14	0.15
natural sciences, etc.	−0.12	0.13	−0.17	0.14	−0.13	0.13
traffic, logistics, etc.	−0.21	0.13	−0.43**	0.13	−0.21	0.13
commercial services, etc.	−0.02	0.12	−0.11	0.12	−0.03	0.12
business organisation, etc.	−0.03	0.08	−0.07	0.08	−0.04	0.08
humanities, economics, etc.	−0.23	0.17	−0.33	0.17	−0.23	0.17
Occupational requirement level						
(ref. unskilled or semi-skilled)						
specialist	−0.04	0.14	0.07	0.15	−0.03	0.14
complex specialist	−0.18	0.16	0.02	0.16	−0.16	0.16
highly complex	−0.03	0.16	0.23	0.17	−0.01	0.16
Part-time job	0.01	0.07	−0.01	0.08	0.01	0.07
(ref. full-time job)						
Workplace in East Germany	0.07	0.07	0.06	0.08	0.08	0.08
(ref. workplace in West Germany)						
Conscientiousness	0.19***	0.04	0.22***	0.04	0.19***	0.04
Neuroticism	−0.33***	0.04	−0.37***	0.04	−0.33***	0.04
R-squared	0.11		0.06		0.11	

N = 3116; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Data: NEPS Adult Cohort, Version 11.1.0.

8 Supplementary Material

This study uses a multidimensional measure of objective skill mismatch based on the mixed approach, with plus and minus one standard deviation defining the thresholds in each skill domain. This one standard deviation method is more restrictive in defining individuals as mismatched than the one-half of a standard deviation method which I use for the multidimensional measures of test-based skill mismatch in Articles 1 and 2. I replicate the main models of the study using a one-half of a standard deviation measure of multidimensional skill mismatch to test whether the results also hold for this less restrictive method.

Table S1 Multiple linear regression analyses regarding skill mismatch and job satisfaction, objective skill mismatch based on the ± 0.50 standard deviation approach

	Model 1		**Model 2**		**Model 3**	
	Coef.	SE	Coef.	SE	Coef.	SE
Subjective skill mismatch	−1.01***	0.07			−1.01***	0.07
(ref. matched)						
Objective skill mismatch						
(ref. matched)						
underskilled			0.01	0.08	0.05	0.08
overskilled			−0.01	0.08	−0.01	0.08

Notes: N=3,116. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results indicate OLS regression coefficients. Control variables included in all regression models: male, age, immigration background, educational attainment, duration in the job, occupational area, occupational requirement level, part-time job, workplace in East Germany, educational mismatch, conscientiousness, neuroticism.
Sources: NEPS Adult Cohort, doi:10.5157/NEPS:SC6:11.1.0, own calculations.

Table S1 shows that the results are almost identical with regard to subjective skill mismatch and objective overskilling. In contrast to the main models in Table 4, the findings based on the one-half standard deviation measure indicate that objectively underskilled workers show a slightly higher job satisfaction than objectively matched workers. The associations between objective skill mismatches and job satisfaction, however, are not statistically significant. This means that the findings based on the less restrictive one-half of a standard deviation measure of objective skill mismatch suggest the same conclusion: subjective skill mismatch, but not objective skill mismatch, significantly affects workers' job satisfaction.