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KÄTLIN ANNI

Intelligence, personality, and socioeconomic outcomes in Estonia

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LIST OF ORIGINAL PUBLICATIONS

This dissertation is based on the following original studies, which are referred to in the text by their respective Roman numerals:

I. **Anni, K.**, & Mõttus, R. (2019). Intelligence as a predictor of social mobility in Estonia. *Scandinavian Journal of Psychology, 60*(3), 195–202. https://doi.org/10.1111/sjop.12528

II. **Anni, K.**, Käärik, M., & Mõttus, R. (2021). WAIS-III measurement invariance: Data from Estonian standardization. *The Clinical Neuropsychologist, 35*(S1)*,* s1–s20. https://doi.org/10.1080/13854046.2020.1812723

III. **Anni, K.**, Vainik, U., & Mõttus, R. (2024). Personality Profiles of 263 Occupations*. Journal of Applied Psychology.* Advance online publication. https://doi.org/10.1037/apl0001249

The author of the current dissertation contributed to the publications as follows:

In **Study I**, conducted and participated in data collection, participated in conceptualization and data analyses, interpreted the results, and wrote the manuscript as the first author.

In **Study II**, conducted and participated in data collection, formulated the research questions, carried out the data analyses, and wrote the manuscript as the first author.

In **Study III**, participated in the conceptualization of the study and data analyses, interpreted the results, and wrote the manuscript as the first author.

1. INTRODUCTION

Socioeconomic (SE) outcomes, such as educational attainment, occupational status or income, are shaped by many factors that have attracted the interest of researchers across various disciplines. Prior scientific work has clearly indicated that there is no single most important factor determining individual life outcomes; rather, understanding the complexity of these influences is crucial (Soto et al., 2022).

Disentangling the predictors of SE outcomes has become central to several fields of study because it is important for understanding both individual well-being and the fundamental nature of society. One of the main topics of status attainment research over the decades is the debate over whether SE outcomes are more significantly influenced by social class of origin such as parental SE status, or by individual psychological variables such as intelligence and personality (Betthäuser et al., 2020, 2021; Herrnstein & Murray, 1994; Marks, 2020; Saunders, 1997). Most modern societies strive for a meritocratic ideal, meaning that an individual's SE outcomes should not be determined by their social status of origin but rather by their own abilities and effort (Erola & Kilpi-Jakonen, 2017; Young, 1958). The meritocracy also reflects a concept of talent allocation (Murphy et al., 1991), an idea that individuals have opportunities to position themselves in environments, particularly jobs, that match their individual characteristics. There is evidence that if the merit allocation is effective, then societies are, in general, more successful (Murphy et al., 1991). However, critics like Markovits (2019) argue that meritocracy often perpetuates inequality, creating a "trap" where the advantages of the elite are maintained, rather than promoting equal opportunities. This highlights the complexity of the meritocratic ideal.

Furthermore, understanding the individual differences associated with SE outcomes is important on an individual level as well, often conceptualized as the environment-person fit. Most people tend to devote much of their adult life to work, and deciding the educational and professional paths to pursue are the socially and economically most significant choices individuals make in their lifetime (Buser et al., 2023; Kristof-Brown et al., 2005). The match between individual characteristics and SE environment, such as educational or occupational attainment is associated with higher satisfaction and job performance (Kristof-Brown et al., 2005). Therefore, strengthening the understanding of the predictors of SE success and their interplay can have implications at the societal and individual levels.

The main objective of this dissertation is to explore the relationships between individual differences, specifically intelligence and personality traits, and SE outcomes, such as educational attainment and occupational status. The following sections will summarize prior research on predictors of SE outcomes. Initially, I will focus on intelligence and personality, emphasizing the importance of measurement issues related to these variables, which may influence overall conclusions. Following this, I will provide an overview of how social origin interacts with these psychological factors. Lastly, I will discuss the significance of societal and country-level differences on these interactions.

1.1 Intelligence

1.1.1 Definition and measurement

Throughout history, numerous theories and conceptualizations have attempted to describe human intelligence. While definitions vary, a widely accepted one characterizes intelligence as "the capacity to learn, reason, and solve problems" (Gottfredson, 1997; Plomin & von Stumm, 2018). As a psychological construct, intelligence is not directly observable but measured through performance on tasks requiring mental effort. The evolution of intelligence testing reflects the diverse conceptual frameworks, but most professionally developed contemporary intelligence measures involve many different types of tasks to capture a variety of cognitive abilities (Warne, 2020). The correlation observed between different cognitive tests has led to the identification of a shared component, often referred to as general cognitive ability, denoted as *g* (Spearman, 1904). This concept is further integrated into the factor-analytic frameworks, such as the Cattell-Horn-Carroll (CHC) model, which is probably the most recognized contemporary intelligence model (Carroll, 1993; Deary et al., 2022). Structure of the CHC approach integrates prior theoretical contributions into a comprehensive model, distinguishing between *g* and more specific cognitive abilities across construct levels (Schneider & McGrew, 2018). At the bottom of the hierarchy are specific abilities that can be described by tasks such as defining words, solving visual puzzles, and processing information quickly, among many others. Specific abilities are the only constructs that can be directly measured. The next level involves narrow abilities, clusters of highly correlated specific abilities. For example, tests that require defining words and finding similarities between words correlate, clustering under the narrow ability of lexical knowledge. Narrow abilities are, in turn, clustered under broad abilities, such as fluid reasoning (Gf), working memory (Gwm), visual-spatial processing (Gv), and others. The highest level of the hierarchy captures the general intelligence (*g*). The CHC model has wide empirical support, and it is the foundation for the development of several widely used intelligence tests (Carroll, 1993; Deary et al., 2022; Schneider & McGrew, 2018).

While the CHC model provides a detailed framework of both narrow and broad cognitive domains, intelligence tests usually capture only a fraction of these abilities due to the practical limitations of psychological assessment (Schneider & McGrew, 2018; Zaboski et al., 2018). For example, one of the most popular intelligence measures, Wechsler Intelligence Scales, enables to derive results for four index-scores that are based on the broad ability level – Verbal Comprehension, Perceptual Processing, Working Memory and Processing Speed (Drozdick et al., 2018). Furthermore, the way psychological constructs are defined and assessed not only influences our understanding of their relationship with SE variables but may also affect the strength of these associations (Stankov, 2023). Therefore, the link between cognitive abilities and SE outcomes can be influenced by the reliability and validity of the measurement method and the variety of abilities measured with it.

For example, differentiation hypotheses of intelligence (Spearman, 1927) assume that the relations between general intelligence and more specific abilities vary with ability and age levels, in a way that the associations between general intelligence and specific abilities become weaker with increasing general ability. The majority of the findings from a recent systematic review supported that hypothesis (Breit et al., 2022). Therefore, the structural organization between cognitive abilities may depend on the overall ability level of the individual. That is connected with SE outcomes, as more educated individuals have higher overall intelligence scores than individuals with less education (described further in section 1.1.2) – therefore, the structural organization of abilities across educational levels may also vary as schooling increases overall general ability (or IQ) scores (Brinch & Galloway, 2012; Ceci, 1991; Ritchie & Tucker-Drob, 2018). It has been shown that these IQ-score differences are not due *g* itself but because of the specific knowledge and skills developed in schools, which could be measured well by intelligence tests (Colom et al., 2002; Ritchie et al., 2015). Therefore, more education may not mean that the *g* (defined as scientific construct) rises, but more likely, the *g* with specific cognitive abilities and skills are enhanced (Colom et al., 2002). The same may apply to lower-level constructs, such as verbal ability or perceptual ability, meaning that the measured scores may not reflect the differences of underlying latent constructs, but rather differences in specific skills. In sum, the structure of abilities may vary across SE levels (such as educational attainment). Conclusions based on cognitive assessment and applicability of the results, therefore, require a thorough assessment of the psychometric properties of the measures (Breit et al., 2022; Warne, 2023), especially when tests are modified for use in various cultural or linguistic settings (Wicherts, 2016).

1.1.2 Associations with SE outcomes

Cognitive ability greatly impacts the individual's life outcomes, with no other psychological variable predicting SE outcomes better (Plomin & von Stumm, 2018). The correlation between intelligence, as measured by standardized tests in childhood, and subsequent educational attainment and achievement is well-documented (Deary et al., 2007; Deary & Johnson, 2010; Kriegbaum et al., 2018; Roth et al., 2015; Strenze, 2007; Zaboski et al., 2018). Cognitive abilities are linked with study choices in university (Humburg, 2017), as well as occupational and economic success (Bertua et al., 2005; Ng et al., 2005; Schmidt & Hunter, 2004; Strenze, 2007). This evidences intelligence's crucial role in SE sorting, as seen in the cognitive stratification across various occupations (Wolfram, 2023). Additionally, the mean intelligence of occupational groups is strongly linked to job complexity and income (Zisman & Ganzach, 2023).

The key predictor of occupational success is education, with educational attainment and intelligence showing phenotypically and genetically strong correlations (Okbay et al., 2022; Rietveld et al., 2014; Sniekers et al., 2017). The

relationship between these two variables is likely bidirectional – higher intelligence is the prerequisite of longer education and better academic achievement, yet more education also improves performance on intelligence tests (Ritchie & Tucker-Drob, 2018). The biological underpinnings are significant too, as there is a genetic correlation between educational attainment and cognitive performance (Okbay et al., 2022). For instance, education has been used as a proxy phenotype for investigating genetic variations in intelligence (Rietveld et al., 2014), and studies have found that polygenic scores for education correlate with cognitive performance (Belsky et al., 2016; Okbay et al., 2022; Plomin & von Stumm, 2018; Selzam et al., 2017).

Research exploring the predictors of SE outcomes has mostly emphasized the predictive power of the *g*. However, Epstein and Winship (2006) suggested that studying distinct cognitive abilities may add some valuable insights to the complex relationship between intelligence and social status. Their work indicated that not all cognitive abilities contribute equally to educational and economic attainment, highlighting quantitative and verbal abilities that predict educational success and their indirect influence on economic outcomes. Subsequent studies have further explored this topic, emphasizing the importance of specific abilities, especially in the context of occupational success and performance (Lang et al., 2010; Schneider & Newman, 2015). It has been found that verbal ability is more strongly associated with school achievement (Roth et al., 2015) and work performance (Lang et al., 2010) than performance in nonverbal tests.

Furthermore, it has also been found that some components of intelligence (e.g., language skills, executive functions, and memory) may be more sensitive to the effect of parental background than others (Farah et al., 2006; Noble et al., 2005). Asbury et al. (2005) studied the genotype-environment interactions on cognitive ability and concluded that the environmental influences emerged for verbal ability but not for nonverbal ability. Therefore, there is a possibility that the different aspects of cognitive ability may contribute differently to SE outcomes and are disproportionately affected by different environmental or individual factors (Asbury et al., 2005; Farah et al., 2006). Although, based on prior work, the *g* is definitely a valuable construct and "one of the most central phenomena in all behavioral science" (Jensen, 1998), still the separate components may indicate some of the underlying complexities in relation to intelligence and life outcomes.

Several explanations exist about the mechanisms of associations between cognition and SE outcomes. One approach suggests a direct connection between intelligence and life outcomes, meaning that cognitive tests measure intelligence levels, and life itself can be seen as an intelligence test (Gottfredson, 1997). Therefore, cognitive ability influences both test results and life outcomes, explaining their association. Additionally, general ability is conceptualized as the capacity to handle complexity, which is considered a key characteristic distinguishing various levels of SE outcomes, such as different occupations (Gottfredson, 1997).

Another specific mechanism might be related to the concept of person-environment fit, which proposes that individuals seek out environments that best match their characteristics, including cognitive ability. This idea is supported by the gravitational hypothesis (McCormick et al., 1972), as evidenced by the findings of Wilk et al. (1995), which indicate that individuals gravitate toward jobs that align with their cognitive abilities. A good match between an individual and their environment, such as a job or educational path, leads to higher overall satisfaction. If this fit is lacking, individuals may pursue alternative opportunities that better suit their abilities, exploring other educational or job options (Gottfredson, 1997; Wilk et al., 1995).

1.2 Personality

1.2.1 Definition and measurement

Although intelligence has been established as the main psychological predictor of SE outcomes, in recent years, there has been an increase in research focusing on the impact of non-cognitive factors, primarily personality traits, on life outcomes (Borghans et al., 2016; Duckworth et al., 2019; Wolfram, 2023; Zisman & Ganzach, 2022).

Personality traits are often described as consistent patterns of thinking, feeling, and behaving that vary among individuals (Costa & McCrae, 1992). Likewise, with intelligence, there are a variety of definitions and conceptualizations of personality. It is not rare to study individuals' success in relation to specific traits, like grit and locus of control (Ng et al., 2006; Zisman & Ganzach, 2021). However, wide recognition has been given to the attempts to describe personality traits more comprehensively by a set of traits conceptualized as personality models (Bainbridge et al., 2022).

Similarly to intelligence, personality can also be understood through a hierarchical framework, where at the top of the hierarchy lie the broadest trait descriptors. The idea of a general personality factor, akin to the general intelligence factor, has been suggested in research (e.g., Musek, 2007; van der Linden et al., 2017). Additionally, the concept of a two-factor apex for the hierarchy has been proposed (DeYoung, 2006; Digman, 1997). Nonetheless, both the one-factor and two-factor models have faced considerable criticism (Ashton et al., 2009; Danay & Ziegler, 2011; Revelle & Wilt, 2013), and have not gained broad acceptance. At present, the Five-Factor Model (McCrae & John, 1992), or Big Five (Goldberg, 1993), is the most prevalently adopted model, along with the six-factor HEXACO model (Lee & Ashton, 2004). The top level of Five-Factor Model includes five domains: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Domains are further divided into aspects (DeYoung et al., 2007) or facets (Costa & McCrae, 1995). The finest granularity of personality traits, nuances, are typically represented by single items in personality assessments (McCrae, 2015; Mõttus, Kandler, et al., 2017).

These multiple levels of assessment can all be valuable, providing parallel findings that can be used depending on the purpose at hand (Mõttus et al., 2020). The Big Five personality domains play a valuable part in describing a significant portion of the personality spectrum, yet they do not cover everything. Research suggests that beyond these domains lie at least 70 distinct facets, along with numerous single-item traits (Irwing et al., 2023). These traits, stable and measurable in their own right, are seen as the foundational elements of trait assessment and offer valuable insights that extend beyond the scope of the Big Five (Condon et al., 2020; Mõttus et al., 2019). The facets and nuances often vary more across human groups such as age (Mõttus & Rozgonjuk, 2021), gender (Hofmann et al., 2023), and nationality (Achaa-Amankwaa et al., 2021), and typically account for more variance in life outcomes than domains (e.g., Stewart et al., 2022). With respect to SE outcomes, the differences might also be more pronounced across some of the narrower traits than in the Big Five domains. For example, prior results have shown that nuances help to differentiate higher- and lower-performing employees better than the domains (Speer et al., 2022). Therefore, it is reasonable to expect that SE differences, for example occupational variation, might be more pronounced in certain narrower traits than in the Big Five domains. However, no studies have explored item-level personality differences across SE outcomes, such as occupational attainment.

Personality assessments mostly rely on self-report measures. Although there are some other methods, like behavioural assessment (Furr, 2009) and digital records (Kosinski et al., 2013; Vazire & Gosling, 2004; Youyou et al., 2015), the easy administration of questionnaires has made it possible to study large enough data to make meaningful conclusions. However, using only self-reports is definitely a limitation since method-specific variance constitutes a large fraction of the assessed trait score variance (McCrae & Mõttus, 2019) and potentially influences observed trait differences between studied groups. For example, in industrial-organizational psychology, the people's self-reports, representing both their "true traits" and "identity", predict occupational performance worse than informants' ratings, which represent a combination of the true traits and "reputation" (Connelly et al., 2022; Connelly & Ones, 2010; McAbee & Connelly, 2016; Oh et al., 2011). Likewise, other SE outcomes, such as career progression (e.g., hiring and promotion), may be influenced by people's reputation besides their identity, suggesting that informant-reports may capture some differences in personality traits somewhat differently than self-reports. Hence, the multiple ratings sources make the personality assessment more reliable and valuable (Mõttus et al., 2020).

1.2.2 Associations with SE outcomes

Personality traits are associated with many life outcomes, including SE outcomes, sometimes even after controlling other relevant variables like social status or cognitive ability (Beck & Jackson, 2022; Roberts et al., 2007). Personality traits are associated with educational attainment and achievement (Damian et al., 2015;

Mõttus, Realo, et al., 2017; Poropat, 2009), choices of university majors (Humburg, 2017; Vedel, 2016) as well as occupational attainment (Jackson, 2006; Roberts et al., 2007). In addition, certain personality traits tend to go with higher performance in most jobs, especially those in the conscientiousness or extraversion domains but also the domains of emotional stability, openness, and agreeableness (Barrick & Mount, 1991; Judge et al., 2013; Wilmot & Ones, 2021). Personality traits have been associated with labor-market performance (Edin et al., 2022; Jokela et al., 2017). For example, a recent meta-analysis (Alderotti et al., 2023) found that higher income was linked to openness, conscientiousness, and extraversion, while lower earnings were associated with agreeableness and neuroticism.

Given that personality is highly associated with several indicators of SE success, little systematic research has been dedicated to the magnitude of personality differences across these SE outcomes. One of these outcomes can be the choice of occupation, the area most frequently associated with personality traits (Roberts et al., 2007). Several studies have focused on the personality of one or a few jobs (Booth et al., 2016; Cerasa et al., 2016; Furnham, 2017; King et al., 2011; Lan et al., 2021; Lounsbury et al., 2012, 2016; Oh et al., 2018; Slišković et al., 2022). However, to comprehensively describe the magnitude of differences, it is more useful to assess traits across a wide range of occupations, and such studies are rare. Only two published larger-scale studies have systematically mapped personality traits across a broader number of occupations. The first, by Törnroos et al. (2019), examined average differences in the Big Five personality traits across 25 occupational groups. The second, by Wolfram (2023), presented average Big Five scores for over 360 occupations. However, because larger-scale studies often require minimalist methods due to the need for extensive sample sizes, both studies used only three items to assess each of the broad and multifaceted Big Five domains, which in turn may limit the reliability and generalizability of the findings (McCrae, 2015). The Big Five are not traits *per se* but broad and multifaceted domains that summarize many traits (Bainbridge et al., 2022; Goldberg, 1995), therefore, capturing a complete and balanced representation of these domains with just three items is unachievable (McCrae & Mõttus, 2019). Hence, more comprehensive research on the associations between personality and occupations is needed.

The underlying mechanisms of the association of personality-SE outcomes are somewhat analogous, as described earlier, with intelligence. One of the main underlying topics is the person-environment fit and the gravitational processes (Wilk et al., 1995) that link personality to various outcomes. Narrowing down to occupational attainment, the main influences of personality can be generally described as selection effects and socialisation effects.

Selection effects are based on the fact that people choose jobs and are chosen on jobs based on their individual characteristics. Holland's RIASEC model (Holland, 1959, 1997), which categorizes individuals and occupations into six interest-based groups, suggests that congruence between personality and job characteristics contributes to successful career decisions. Research has consistently shown that individuals who work in occupations aligned with their traits

tend to experience higher job satisfaction, motivation, commitment, and success (Ghetta et al., 2020; Hoff et al., 2020; Kristof-Brown et al., 2005; Nye et al., 2017; Su, 2020; Van Iddekinge et al., 2011).

Personality traits also come with different social, emotional, and behavioural skills (Soto et al., 2022) that occupations may require to different degrees. Therefore, people with higher levels of certain skills and associated traits are more likely to be selected for and retained at the jobs requiring these skills. For example, many of those interested in managerial roles may not end up in these roles due to a lack of the skills typically expected of leaders. Personality trait assessments are often explicitly used in the candidate selection processes; in fact, this is a vibrant business field and one of the most direct commercial applications of personality research and psychometrics.

Socialization effects are based on the fact that sometimes jobs may change people's personality traits, and individuals may change their jobs according to their traits. Based on prior work, specific life experiences usually have minimal influence on personality traits, at least in a way that is similar across people (Bühler et al., 2023). Still, personality trait change is common (Mõttus, 2022), and job-related experiences that differ across occupations might still contribute to these changes (Holman & Hughes, 2021; Wu, 2016; Zheng et al., 2023). Perhaps most plausibly, job-related experience may accentuate the traits that contributed to people ending up in these jobs in the first place, consistently with the so-called corresponsive principle of personality development (Roberts et al., 2003; Zheng et al., 2023). For example, leadership, sales, or childcare positions may amplify the traits usually required to choose and be chosen for these positions. If so, both the selection and socialisation effect may contribute to similar average trait differences between occupations.

1.3 Social origin

Previous sections have focused on psychological differences, however, one of the central factors in social stratification studies has been the impact of parental social background. The relationship between the SE status of parents and their offspring, referred to as intergenerational social mobility, has been one of the main topics of sociology (Bukodi et al., 2020).

Earlier studies have shown that both individual characteristics, such as cognitive abilities and personality traits, and social background significantly affect SE outcomes (Strenze, 2007). However, the debate on which of those has a stronger impact on determining an individual's success remains one of the most discussed topics in that field (Marks, 2022). This ongoing debate (e.g., Betthäuser et al., 2020, 2021; Marks, 2013, 2020) likely originated with the "Bell Curve" studies (Herrnstein & Murray, 1994), which suggested intelligence as the main determinant of success, positioning the impact of parental background as secondary, particularly within the U.S. context. Subsequent research across different populations has supported this perspective. In the UK, several studies reaffirmed *g* as the principal predictor of social mobility and professional success (Nettle, 2003;

Saunders, 1997, 2002). The Scottish Mental Survey's results (Deary et al., 2005) further validate the strong link between childhood intelligence and midlife occupational status. In a comprehensive meta-analysis, Strenze (2007) found that cognitive ability had a slightly stronger link to educational and occupational success than other factors like parental education or family background. Marks (2013) argues that when IQ is considered, the relationship of social origin with SE outcomes is reduced. Recent research continues to show cognitive ability as the strongest predictor of social stratification (Marks, 2022), with some studies suggesting that parental influence primarily operates through genetically transmitted cognitive ability (Marks, 2013; Plomin & von Stumm, 2018; Saunders, 2002).

Alternatively, research across multiple disciplines emphasizes the significant influence of social background on SE outcomes (Chetty et al., 2014; Laurison & Friedman, 2016; von Stumm et al., 2009). This line of research argues that cognitive ability plays a relatively modest role, or at least far less significant than The Bell Curve studies (Murray, 2012) or Marks (2013) suggest. The significant impact of parental background is demonstrated by a direct effect of parental class on individuals' educational attainment independent of cognitive ability (Betthäuser et al., 2020; Bourne et al., 2018; Erikson, 2016; Hsin & Xie, 2017). A recent study by Betthäuser et al. (2020) found that cognitive ability mediates less than 20% of the relationship between parental class and initial labor market position after considering educational attainment. Further research supports this, showing that individuals with similar cognitive abilities but different social origins have divergent educational outcomes, emphasizing the role of social background in shaping life chances (Betthäuser et al., 2021).

The transmission of SE status from parents to offspring involves various mechanisms. Earliest works have proposed the significant role of parental social, economic, and cultural capital (Bourdieu, 1986; Coleman, 1988). Social capital, through parents' personal contacts and social relationships, can directly influence their children's occupational outcomes and secure better job opportunities. Mobilizing parental resources, such as economic capital, aids job searches and enhances mobility, significantly impacting children's SE outcomes. Cultural capital involves transmitting values, knowledge, and practices beneficial in later life (Bernardi & Ballarino, 2016). These parental capitals can make an impact through investments or endowments (G. S. Becker & Tomes, 1986). Investments refer to the direct parental effort to contribute to the offspring's success in life. These are dependent on the resources available to parents, such as money or time spent with children (Erola & Kilpi-Jakonen, 2017). Parental endowments refer to the resources of the rearing environment and can include almost anything possibly positive, such as social networks or economic assets. These mechanisms are complex because it is hard to differentiate them empirically from each other (Erola & Kilpi-Jakonen, 2017).

More recent developments in behavioural genetics have added another dimension to these phenotypic associations. Contemporary social mobility studies cannot deny that several arguably environmental features are also genetically transmitted (Lucchini et al., 2013; Plomin et al., 1997). Although not always

acknowledged by social researchers, genetic endowment is a significant form of capital that plays a crucial role in the mechanisms through which social origin influences social destination (Erola et al., 2022; Guo, 2008; Lucchini et al., 2013).

Moreover, offsprings' individual differences (such as intelligence, personality, and educational attainment) also have a largely overlapping genetic basis (Marioni et al., 2014; Mõttus, Realo, et al., 2017). This suggests that the same genetic variants might not only influence these traits but also play a role in determining SE success (pleiotropy), or that these traits could mediate the genetic impact on SE outcomes. Consequently, direct causal relationships between cognitive ability, education, and social class indicators may be less likely, as these connections are probably influenced by shared genetic factors.

Additionally, studies have identified genetic commonalities across various psychological and social domains (Marioni et al., 2014; Mõttus, Marioni, et al., 2017), pointing toward a complex interaction between genetic and environmental factors in influencing social mobility. Damian et al. (2015) emphasized the need for integrating individual and environmental influences in social mobility research, proposing several scenarios for how personal attributes and environmental conditions might interact to affect attainment. They suggested that personality and intelligence could influence success independently of parental SE status. Individual factors may be compensatory at lower SE levels or amplify advantages at higher levels. Their analysis within a large U.S. dataset revealed that intelligence could offset disadvantages stemming from a lower SE background, maintaining its influence even after accounting for personality traits. Although personality traits could partially mitigate the impact of a disadvantaged background, intelligence showed a more pronounced "catch-up" effect (Damian et al., 2015).

In conclusion, SE outcomes are shaped by a complex interplay of genetic endowments, individual characteristics, and parental social background. While cognitive abilities and personality traits significantly influence success, the impact of parental SE status remains substantial, indicating the influence of both genetic and environmental factors.

1.4 Importance of the context

Associations between previously described factors influencing SE outcomes may vary across country-specific contexts. Previous research has indicated that the economic situation (Beller & Hout, 2006), educational system (Bol & van de Werfhorst, 2013; Sorjonen et al., 2011), and other institutions, as well as stratification of income (Johnson et al., 2009) and societal openness (Breen & Luijkx, 2004) in the particular country may influence the associations between parental background, individual differences, and SE outcomes. For example, there are a series of studies showing the stronger effects of social origin on educational or occupational outcomes in the UK and the U.S. compared to Sweden (Bukodi et al., 2014; Judge et al., 2010; Sorjonen et al., 2012; Spengler et al., 2018; von Stumm et al., 2010). Additionally, social origin plays a larger role in occupational

success in Italy compared to the Netherlands (Passaretta et al., 2018), indicating how country-specific contexts may shape these relationships (Bernardi & Ballarino, 2016; Passaretta et al., 2018).

These differences may be influenced by labor market modernization, which is based on meritocratic values and ideas that modern society is open and occupational positions are filled on the basis of merit instead of social origin (Breen, 2004; Thijssen & Wolbers, 2016). Some governments have been more interested in pursuing such values, and one of the pathways is through improved access to (higher) education. Hence, an important factor that may explain the contextual variations is different educational systems across countries (M. Becker et al., 2019). Individuals' allocation to the labour market may also depend on dimensions of the educational system, such as tracking and vocational orientation (see further Allmendinger, 1989; Bol & van de Werfhorst, 2013). In sum, these kinds of policy changes and variations in educational systems, in combination with economic modernization, may give different opportunities for meritocratic mobility (Thijssen & Wolbers, 2016). Therefore, studies of different samples and locations are essential to explain further the interplay that predicts SE outcomes (Hanscombe et al., 2012) and offer possible evidence of the generalisability of these associations across different contexts.

This dissertation focuses on the context of Estonia, which is less studied and may enrich the present knowledge, as most of the studies have mainly analysed data from the UK or the U.S., although, in recent years, the contexts have also broadened (e.g., M. Becker et al., 2019; Gu et al., 2022). Estonia offers valuable insights as a former socialist society that has experienced significant structural changes over recent decades, successfully transforming into a functional market economy (Saar, 2010; Titma et al., 2010). Previous studies have mixed findings about the changes in social mobility concerning the transition from early socialist to post-socialist regimes (Gerber & Hout, 2004; Mach, 2004; Róbert & Bukodi, 2004). One of the reasons for the differences may be the transition model that governments have followed. In many post-socialist nations, state control over the economy relaxed, leading to an increase in private ownership. Most countries followed a gradual strategy for this transition, whereas Estonia was unique in its abrupt shift to low-state intervention and a liberal transition model (Saar, 2010).

To my knowledge, the personality differences across SE outcomes have not been studied in Estonia. However, intelligence was included by Strenze (2006), who conducted a comparative analysis of data from Estonia and the U.S. to identify factors contributing to SE success. The study confirmed that parental social status and cognitive abilities are positively linked to success in both countries. However, cognitive ability played a more significant role in predicting success in the U.S. than in Estonia. This disparity might be attributed to differences in environmental stability: the more stable and open social environment in the U.S. potentially offers better opportunities for individuals to leverage their cognitive skills (Herrnstein & Murray, 1994). Strenze (2006) suggested that as Estonian society becomes more stable and mature, the significance of intelligence in achieving success is likely to increase.

2. AIMS OF THE DISSERTATION

The main objective of this dissertation was to examine how key individual differences, intelligence and personality traits, relate to variations in educational and occupational outcomes in Estonia.

Initially, I examined the influence of parental SE status and an individual's cognitive abilities on educational and occupational attainment (**Study I**). To explore the role of more specific cognitive abilities further, I established the psychometric properties of the measure and studied the structure of cognitive abilities across various demographic groups (**Study II**). Additionally, I analysed differences in ability components across educational levels (**Study II**) and their role in predicting occupational attainment (**Study I**).

The second part of the dissertation focused on personality traits in relation to occupations (**Study III**). I examined how much occupations account for personality variations, including analyses of the Big Five and nuanced personality profiles. Additionally, the generalizability of these findings across different samples and assessment methods was analysed.

3. MATERIALS AND METHODS

3.1 Participants

3.1.1 Sample from the adaptation project of the Estonian Wechsler Adult Intelligence Scale, Third Edition (WAIS-III)

Participants for **Study I** and **Study II** were recruited during the adaptation process of the Estonian WAIS-III, and the data collection took place from 2012 to 2017. The data was collected by clinical psychologists or clinical psychologist trainees who had previously completed WAIS-III training.

The sample composition was based on the 2014 Estonian census data, stratified by age, sex, and educational level. The exclusion criteria set by the original WAIS-III standardization (Psychological Corporation, 2002) were used. In **Study I,** the sample size was 759, and in **Study II,** the completed standardization sample was used, including 770 participants (44% male, 56% female, age range 16–89).

3.1.2 Sample from the Estonian Biobank Personality Study

Participants in **Study III** were members of the Estonian Biobank, who took part in a Personality Study data collection (Vaht et al., 2024). The personality and occupation data were collected in an online survey between November 2021 and April 2022.

For **Study III,** we included the sample who answered in Estonian (participants who answered in English or Russian were excluded), did not have more than ten missing personality measure responses, and had occupational data. The resultant sample included 68,540 participants (sex assigned at birth: 48,231 women, 20,309 men; age: range from 18 to 102; $M = 47.9$, $Mdn = 47.0$, $SD = 14.6$), 19,989 of whom were also rated by an informant with up to 10 missing responses (sex assigned at birth: 13,616 women, 6373 men; age: range from 18 to 93; $M = 45.5$, $Mdn = 44.0$, $SD = 13.6$). The informants were usually partners or spouses (56%), children/grandchildren (14%), friends (14%), parents/grandparents (7%), or other relatives (8%).

3.2 Measures

3.2.1 Estonian version of the WAIS-III

Study I and **Study II** implemented the Estonian version of WAIS-III (Wechsler, 2011, 2021).

WAIS-III consists of 14 subtests that can be broadly divided into Verbal and Performance scales, which in turn can be divided into four index scores: Verbal Comprehension (Vocabulary, Similarities, Information subtests), Perceptual Organization (Picture Completion, Block Design, Matrix Reasoning), Working

Memory (Arithmetic, Digit Span, Letter-Number Sequencing), and Processing Speed (Digit Symbol – Coding, Symbol Search). Comprehension subtest is an optional subtest typically grouped with verbal abilities in factor analyses. Object Assembly, also optional, is part of the Performance scale and is often excluded from factor analytic studies due to its supplementary nature.

The adaptation and standardization of the Estonian version was completed in 2019. Normative data was developed using the inferential norming method, which is most suitable for smaller sample sizes (Zhu & Chen, 2011).

During the adaptation process, I analysed the psychometric properties of the scales, and the Estonian adaptation had mostly acceptable to excellent internal consistency statistics that are comparable with the original UK and U.S. versions (Psychological Corporation, 2002). The average reliability coefficients (Cronbach's alphas) across 11 age groups were .97 for Full Scale IQ, .96 for Verbal IQ, and .92 for Performance IQ. Comprehensive psychometric analyses were published in the Estonian WAIS-III Administration and Scoring Manual (Wechsler, 2021).

Due to the incompletion of norm development, it was impossible to include the IQ or index scores in the analyses of **Study I**. Therefore, we applied factor analysis to all subtests to obtain the score for *g* and combinations of subtests to obtain equivalents for index scores. The equivalent for the Verbal Comprehension (VC) Index was obtained with Vocabulary, Similarities, Information, and Comprehension subtest results. The Perceptual Organization (PO) component was calculated using scores from the Picture Completion, Matrix Reasoning, and Block Design subtests. The Working Memory (WM) Index equivalent included results of Arithmetic, Digit Span, and Letter-Number Sequencing. The Processing Speed (PS) Index component was calculated using the scores of the Symbol-Digit Coding and Symbol Search subtests. In **Study II**, the main analyses, confirmatory factor analyses (CFA) and measurement invariance (MI) analyses, included the subtests' raw scores. However, descriptive statistics were presented using the available Estonian norm data.

3.2.2 100 Nuances of Personality

In **Study III**, we used the measure of 100 Nuances of Personality (100-NP; Henry & Mõttus, 2023) to collect personality data. 100-NP is designed to cover numerous personality traits with reduced redundancy. It captures trait content associated with most facets and domains assessed in standard Big Five measures and some traits typically not covered by these (e.g., competition, envy, humor, sexuality, spirituality, and the "Dark Triad" traits). Based on the rationale described by Condon et al. (2020), the 100-NP items were iteratively selected from larger item pools for their diverse content. Items were retained if they 1) had acceptable test-retest reliability, variance, and cross-rater agreement, and 2) were not excessively redundant with other items, except some more highly correlated items to assess acquiescent responding and provide two items of apparently less reliably assessable traits (e.g., impulsiveness). Participants responded using a six-point Likert-

type scale, ranging from "Completely Inaccurate" to "Completely Accurate". A full description of the 100-NP's development can be found in Henry and Mõttus (2023), and items can be found at the Open Science Framework https://osf.io/xztkv.

We calculated participants' Big Five scores based on 60 items. We selected these by (a) averaging standardized self- and informant-ratings of 20,886 participants who had no more than ten missing responses for personality items (replacing remaining missing responses with the median); (b) dropping the item with less variance from each pair correlating above .50 and dropping items with no correlation with other items at least .30 (to avoid redundancy as well as isolated items); (c) running the principal component analysis (PCA) in the remaining 119 items, extracting five varimax-rotated components and retaining 12 highest-loading items for each component; (d) re-running PCA with the remaining 60 items and using the resulting loading matrix to calculate participants' Big Five scores in self-reports and, when available, informant-reports. This procedure ensured that Big Five scores were relatively orthogonal (absolute inter-correlations between .02 and .11, *Mdn* = .05, in self-reports and 0 and .15, *Mdn* = .04, in informant-reports), similarly calculated in self- and informant-reports, and based on sufficiently diverse item content. In the additional online material of **Study III**, we provide a comprehensive psychometric evaluation of the 100-NP Big Five scales (https://osf.io/m9sw3/).

3.2.3 Education and Occupation

The education in **Study I** and **Study II** was the self-reported highest finished educational level, which was coded into five categories: (1) primary and basic education; (2) vocational education; (3) specialized secondary education; (4) general secondary education; and (5) higher education. The parents' educational level analysed in **Study I** was reported by the participants (off-springs) and coded into the same categories. If parents' educational levels differed, a higher level was used (according to the dominance principle proposed by Erikson, 1984).

The self-reported occupations collected in **Study I** and **Study III** were coded to the International Standard Classification of Occupations (ISCO-08; International Labour Office, 2012). In **Study I**, the three-digit code of ISCO-08 was transformed into a slightly modified version of the Erikson-Goldthorpe scheme (Erikson & Goldthorpe, 1993). Some country-specific modifications were made to the original version analogously with similar sociological studies conducted in Estonia (e.g., Saar, 2010; Titma et al., 2003). These changes corresponded better with the occupational distribution and sample features, as some of the occupations in the Erikson-Goldthorpe scheme are too sparsely populated in Estonia, which also appeared in **Study I** data. The original Erikson-Goldthorpe version and the modified classification for **Study I** are shown in Table 1.

Table 1. *The Erikson-Goldthorpe Class Scheme: Original and Modified Versions*

Original version	Modified version
I: Upper service class; senior civil servants, higher managerial, higher-grade professionals (also self-employed).	I: Upper service class; senior civil servants, higher managerial, higher-grade professionals (also self-employed).
II: Lower service class; middle-level administrators and officials, lower managerial, lower-grade professionals.	II: Lower service class; middle-level administrators and officials, lower managerial, lower-grade professionals.
III: Routine non-manual employees, clerks.	III: Routine non-manual employees, clerks.
IVab: Self-employed and employers in non-agricultural businesses.	IV: Agricultural skilled workers
IVcd: Farmers and smallholders, including self-employed fishermen.	
VI: Skilled manual workers.	V: Skilled manual workers, non-agricultural
VII: Semi- and unskilled manual workers, including unqualified sales personnel.	VI: Unskilled manual workers

In **Study III**, the aim was to use four-digit (4d) ISCO-08 codes. However, additional self-generated codes based on the ISCO-08 classification were created for those not aligned precisely with the ISCO-08 groupings. These self-generated codes were used when the answers provided by participants were too generic and did not involve enough information for the exact coding. For example, the answer "analyst" broadly aligns with the ISCO-08 major level category "Professionals", marked with one-digit code "2". Yet, this answer refers to a specific group of professionals, and to separate it from other jobs at the level of "Professionals", we created the code "202x". In this code, "2" denotes its affiliation with the one-digit group of "Professionals", "02" is the sequence number indicating its order among the codes we created within the "Professionals" category, and "x" stands for our unique identifier. In total, 26 self-generated codes were created.

Of 69,351 responses, 68,540 were coded, leaving out answers indicating unemployment, retirement, or educational attainment in process. After restricting group sizes from 25 to 1000, the main analyses of **Study III** were executed across 263 occupational groups (N = 59,027) with self-reported traits and across 176 occupations (N = 18,496) with informant-reported traits.

4. RESULTS AND DISCUSSION

4.1 Intelligence in relation to SE outcomes

4.1.1 MI of WAIS-III (Study II)

Earlier studies have stated that the measurement of cognitive abilities may have an impact when combined with analyses of SE outcomes (Stankov, 2023). Therefore, psychometric properties of the Estonian version of WAIS-III were established.

MI is a crucial requirement for any psychological instrument used to compare individuals across different groups, such as gender, age, or educational level. MI ensures that the test measures the same psychological constructs consistently, regardless of the specific group to which the test-taker belongs (Wicherts, 2016). MI is essential to establish not only for testing mean differences across groups but also for comparing relations of the constructs with other variables across the groups (Putnick & Bornstein, 2016). Only after establishing the MI are the interpretations of group comparisons meaningful. Hence, MI is among the central testing concepts in psychological sciences and an obligatory feature of any psychological measure (Putnick & Bornstein, 2016).

The first aim of **Study II** was to identify the factor structure of the Estonian WAIS-III. We tested nine models that have been studied in prior research with the original scale (Psychological Corporation, 2002) and previous adaptations (Egeland et al., 2009; Grégoire, 2004; Tulsky & Price, 2003). The results of the CFA supported the correlated four-factor model with the latent factors of VC, PO, WM, and PS. The fit was further improved if the Arithmetic subtest was allowed to load both on the VC and the WM factors (Figure 1). This was chosen as the baseline model for following MI analyses as it provided the best overall fit to the data [$\chi^2(58) = 179.36$, CFI = .984, TLI = .978, RMSEA = .051].

Next, the MI analyses showed that the Estonian WAIS-III has a partial MI across gender and age groups. Latent mean comparisons showed that men had a significantly higher mean score on the PO factor than women. No significant mean differences were found between males and females in VC, WM, or PS. Comparing latent means across age groups, the older groups had significantly lower means than younger ones. The largest discrepancies were in the PS factor and the smallest in the VC factor.

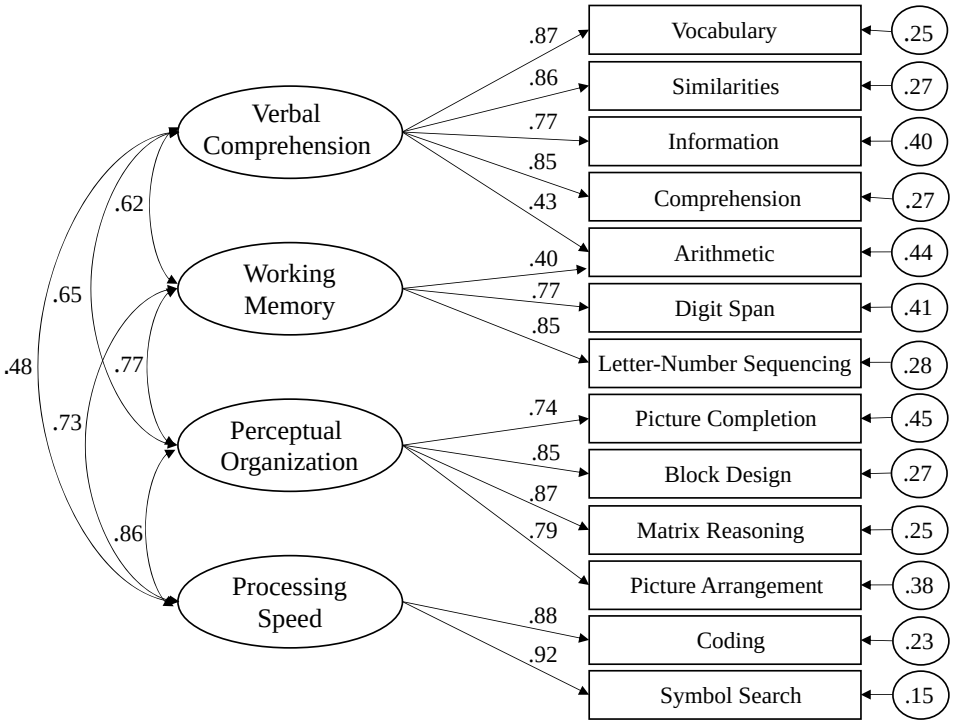

Figure 1. *Path Diagram to Present the Standardized Factor Loadings and Covariances Between Factors for the Four-Factor Model*

However, measurement invariance (MI) across age groups is also relevant to the very concept of intelligence. For instance, it has been suggested that intelligence factors such as g may develop through mutually beneficial interactions among specific skills, as proposed by the dynamic mutualism approach (Van Der Maas et al., 2006). According to this theory, the co-variances between these skills should not remain structurally invariant over time. In response, Gignac (2014) tested both the mutualism model and g models using various Wechsler scales. His findings did not support the mutualism approach, as the g factor remained consistently strong throughout development. However, the partial invariance suggests caution in interpreting these differences due to potential biases in latent mean comparisons (Immekus & Maller, 2010; Putnick & Bornstein, 2016; Steinmetz, 2013). Overall, these results provide evidence that the test functions similarly across gender and age groups.

We further established that the Estonian WAIS-III is not invariant and likely biased across educational levels. Measurement non-invariance indicates that the construct may have different structures or meanings for different groups (Putnick & Bornstein, 2016), making group mean differences in latent cognitive abilities difficult to interpret (Wicherts, 2016). Therefore, the structural organization of abilities may vary across educational levels, as proposed by differentiation hypotheses (Spearman, 1927). Although prior research with Wechsler's scales does not clearly indicate that. Tommasi et al. (2015) found MI across educational

levels with the WAIS-R, while Abad et al. (2016) studied the WAIS-IV in Spain and found it partially invariant. They noted that three subtests (Matrix Reasoning, Coding, and Letter-Number Sequencing) had lower loadings as educational levels increased. Differences between these studies and ours may arise from the different editions of the Wechsler scales, which, while similar, have structural changes across versions. Additionally, variations in language, sample composition, educational level divisions, and educational systems could influence results. Thus, studying the relationships between intelligence models, educational systems, and locations is essential for drawing further conclusions. Wicherts and Dolan (2010) have discussed other reasons for intercept differences in intelligence test CFA models, such as test-taking strategies, familiarity with testing, and abilities tapped by specific subtests that differ from the targeted latent ability.

4.1.2 The predictive effect of parental education and cognitive ability for participants' own educational level and occupational class (Study I)

The general aim of **Study I** was to analyse the associations between parental background, education, and cognitive ability in Estonia.

First, we examined the predictive effect of parental education and individual's cognitive ability on participants' educational level and occupational class, controlling for age and gender. Our findings indicated that when analysed separately, both parental education and individual's own cognitive ability were significant predictors of educational level and occupational status. Parental educational background accounted for about 13% of the variance in children's educational attainment ($F(3, 727) = 35.42$, $p < .001$; $R^2 = .13$) and 8% of the variance in occupational attainment ($F(3, 552) = 17.02$, $p < .001$; $R^2 = .09$). The regression model that included cognitive ability as a predictor showed higher explanatory power, accounting for 27% of the variance in educational level ($F(3, 747) = 92.46$, $p < .001$; $R^2 = .27$) and 22% of the variance in occupational status ($F(3, 561) = 52.29$, $p < .001$; $R^2 = .22$). Cognitive ability alone accounted for a greater proportion of the variance – 27% for education and 22% for occupation. These findings align with Erikson's (2016) study in Sweden, which found that social origin factors accounted for 16–19% of the variance in education, and cognitive ability for 25%. Our results suggest that in Estonia, the influence of parental background is slightly lower, possibly indicating a higher role of intelligence in social mobility.

The results are consistent with previous research (e.g., Strenze, 2007), showing that cognitive ability has a stronger predictive power for educational attainment than for occupational attainment. Together, parental education and individual cognitive ability explained about one-third of the variance in educational attainment and one-fifth of the variance in occupational attainment. Interestingly, it appeared that when parental education and intelligence were added simultaneously to the analysis, the predictive effect of parental education diminished

by 37–38% for both outcomes, although it did not disappear entirely. This suggests that approximately 40% of the parental background association is mediated through cognitive ability for both variables. The results of the Sobel test indicated that cognitive ability was a significant mediator between parental education and participant education ($Z = 2.440$, $SE = 0.052$, $p < .05$; standardized indirect effect $ab_{es} = .13$) as well as between parental education and participant occupational status ($Z = 5.583$, $SE = .020$, $p < .001$; $ab_{es} = .11$).

Damian et al. (2015) argued that social attainment and the likelihood of social mobility may result from more complex interactions between various factors. They proposed several scenarios for possible interplays between individual and environmental factors: (a) personality characteristics and intelligence may predict attainment independently of parental SE level (no interaction), (b) personality characteristics and intelligence are stronger predictors of attainment at lower levels of parental SE status (compensation) or (c) personality characteristics and intelligence are stronger predictors of attainment at higher levels of parental SE status (accumulated advantage). To explore these possible interplays with our data, we added an interaction between parental education and intelligence to predict educational and occupational level. This addition did not provide any remarkable predictive power to the analysis, which indicates that the level of parental education does not influence the effect of cognitive abilities on educational or occupational attainment or vice versa. In other words, we found confirmation of the independent effect hypothesis and no confirmation of the compensation or accumulated advantages hypothesis.

4.1.3 Participant's own education as a mediator between parental education/cognitive ability and occupational attainment (Study I)

To further specify how different variables contribute to the participant's occupational attainment, we expanded our analysis to include the participants' own education and specific components of cognitive ability, in addition to parental education and general intelligence. As anticipated, the predictive power for occupational level increased when the participants' own educational level was included in the model. The results showed that adding the participants' own educational level reduced the predictive effects of parental education to an insignificant level. A similar attenuating effect was observed with cognitive ability, though it remained a significant predictor of occupational attainment. This suggests that one's own education may mediate the effects of parental education and cognitive ability on social status attainment. The Sobel test confirmed this mediation, showing that participant education significantly mediated the relationship between cognitive ability and occupational status ($Z = 8.199$, $SE = .030$, $p < .001$; $ab_{es} = .25$), as well as between parental education and occupational status ($Z = 6.003$, $SE = .023$, $p < .001$; $ab_{es} = .14$). Similar results have been reported in earlier studies as well (Breen & Goldthorpe, 2001; Deary et al., 2005; Nettle,

2003). The study by Johnson et al. (2010) found that social class of origin predicted educational attainment, and educational attainment fully mediated the relationship between social class of origin and social class attainment. Moreover, cognitive ability predicted both educational and social class attainment, with educational attainment directly contributing to class mobility (Johnson et al., 2010).

4.1.4 Differences in cognitive ability domains linked with occupational and educational attainment (Study I, Study II)

With an aim to determine whether different components of cognitive ability influence social mobility in distinct ways, we analysed separate cognitive abilities as predictors of participants' occupational status in **Study I**. When analysing different intelligence components as predictors of occupational attainment, verbal ability stood out as a significant contributor (Table 2). Processing speed, perceptual organization ability, and working memory did not show a significant effect on occupational attainment in a multivariate model alongside verbal ability and other highly correlated variables. The predictive power with separate cognitive domains was comparable to the model that included the general *g*, explaining 35% of the variance ($F(8, 542) = 36.15$, $p < .001$; $R^2 = .348$).

Table 2. *Summary of Regression Analysis for Predicting Participant Occupational Status Adding Own Education and Different Components of g as Predictor Variables*

	Dependent variable: Occupational status	
Predictor variables	Model 1	Model 2
Participant age	.009***	.007*
Participant sex	.373***	.358***
Parental education	.054	.043
Participant cognitive ability *g*	.229***	
Participant education	.427***	.412***
Different components of *g*		
Verbal component		.158**
Perceptual component		.018
Working memory		.025
Processing speed		.063
N	545	543
R^2	.342 (.336)	.348 (.338)
ΔR^2		.006

Note. Unstandardized regression coefficients. *$p < .05$; **$p < .01$; ***$p < .001$

Previous research has shown that verbal abilities are among the strongest predictors of academic achievement (Roth et al., 2015), which may also influence occupational attainment. This association between verbal abilities and education was supported in **Study II**. The highest correlations with educational attainment were found with the VC index ($\rho = .53$, $p < .001$), Verbal IQ ($\rho = .51$, $p < .001$), and several verbal subtests such as Vocabulary ($\rho = .50$, $p < .001$), Similarities ($\rho = .47$, $p < .001$), and Comprehension ($\rho = .47$, $p < .001$). Other index scores had correlations in the range of .33 to .36 ($p < .001$), with Performance IQ and education correlating at $\rho = .36$ $p < .001$). The Full Scale IQ correlated with educational attainment at $\rho = .49$ ($p < .001$).

It has been proposed that a higher social position of the family leads to more stimulating and demanding resources and environments that support the development of verbal abilities (Bradley et al., 2001; Hauser & Huang, 1997). However, our correlational results did not indicate a stronger relationship between parental status and verbal abilities. In fact, other components of measured cognitive abilities had stronger correlations than the verbal component. One explanation for this pattern may be the classification system of occupations itself. Higher positions in the Erikson–Goldthorpe classification may predominantly require verbal skills. Similarly, higher educational paths may demand more verbal skills, or the education itself may focus more on developing verbal skills. Ritchie et al. (Ritchie et al., 2015) have shown that education raises specific cognitive abilities rather than general intelligence. In conclusion, differentiating between separate cognitive domains may be valuable in establishing predictors of SE success.

4.2 Personality traits in association with occupational variation

Another major aim of this dissertation was to explore the personality differences among distinct occupational groups, which was done by comprehensive multimethod assessments in a large population sample and directly comparing the results to existing similar data (**Study III**).

4.2.1 The magnitudes of occupational differences in personality traits

Systematic research of personality differences across occupations is quite limited. Several studies have described personality traits of one specific occupation or compared a couple of occupations (Booth et al., 2016; Cerasa et al., 2016; Furnham, 2017; King et al., 2011; Lan et al., 2021; Lounsbury et al., 2012, 2016; Oh et al., 2018; Slišković et al., 2022). Although that kind of studies contribute to the knowledge about which variables “significantly” differ between groups, however, the overall magnitude of occupational differences in personality traits

is also important. For instance, greater overall differences strengthen the empirical justification for incorporating personality traits into career counselling, coaching, and applicant selection. Similarly, more pronounced occupational differences offer a stronger empirical foundation for the idea that personality plays a significant role in shaping life outcomes (Roberts et al., 2007).

Earlier studies that included a wider selection of occupations have had different results regarding the magnitude of the group differences. Occupations accounted for 7% to 10% of Big Five variance in Wolfram (2023) but only 1% to 4% in Törnroos et al. (2019). Hence, the evidence about the strength of the job-trait relationship is unclear, especially measured with comprehensive personality questionnaires.

To quantify the proportion of variance in personality traits explained by jobs, we calculated the eta-squared (η^2) from a series of analyses of variance with traits as dependent variables and job groups as categorical independent variables. The occupational groups explained between 2% and 7% of the self-reported Big Five domain variance, with openness levels varying the most among jobs.

For comparison, we also calculated the proportions of trait variance explained by occupations without first controlling for age and gender, following the approach used by Wolfram (2023). These proportions were slightly higher, ranging from 2% to 8%. This suggests that age and gender differences among individuals in different occupations contributed to some of the observed personality trait differences.

We anticipated that occupations would account for somewhat more variance in personality domains than 2% to 7%, given that we assessed domains more comprehensively than previous comparable studies (Törnroos et al., 2019; Wolfram, 2023) and covered a broad range of jobs classified into the narrowest occupational groups. Differences with previous studies could stem from socio-cultural variation or different classification systems (SOC vs. ISCO). Additionally, using a minimalist measurement method (BFI-S; Lang et al., 2011) may impact the outcomes. For example, high inter-correlations (up to ~.50; Lang et al., 2011) among some domain scores in the BFI-S used by Wolfram may have inflated the estimates for individual domains, with the same variance varying between occupations under different domain labels. That is, the proportion of variance accounted for by occupational differences in all five domains combined may have been more comparable. In addition, subtraits of the Big Five domains may vary more across occupations than the broader domains themselves, as our findings and previous research supported. Wolfram's narrower domain assessments might have inflated variability by focusing on subtraits that differ more across occupations. For example, single-item nuances like "Want to be in charge" and "Try to avoid speaking in public" varied more across occupations than their associated broader domains. To conclude, the BFI-S used by Wolfram may capture the most job-related components of traits, omitting other facets. Our broader assessment of subtraits allowed for a more comprehensive understanding of domain variability across occupations, suggesting that personality facets or nuances differentiate occupations better than broad domains.

4.2.2 Occupational personality profiles

We calculated average trait scores for 263 occupations coded into the 4d (unit) ISCO job categories. For more reliable estimates, we smoothed these averages towards those of the broader (parent) occupational groups (generally, coded with three digits), inversely proportionally to the 4d groups' sizes. For example, with the smallest possible 4d group size, 25, the smoothed average was halfway between the original 4d group's average and its parent group's average; while with group sizes of 50 and 100, the original 4d group had weights of 80% and 94%. This was done because many less-represented occupational groups can have unique and, thus, practically and theoretically useful personality trait profiles. However, the traits' (domains, nuances) mean and variance estimates for these groups can also be unreliable due to sampling biases.

Jobs' rankings in the Big Five domains were generally intuitive and appeared to reflect the demands and characteristics of these professions. For instance, jobs with the highest average openness included creative roles like artists and writers, and professions generally more open to novel knowledge, like (university) teachers and research professionals (Table 3). Additionally, roles within the creative sector—such as actors, artists, designers, and writers—also tended to score high in neuroticism and low in conscientiousness (Table 4). Occupations characterized by the lowest average neuroticism included various managerial roles and pilots (Table 5). The highest conscientiousness scores were found among ship engineers, dental assistants, construction managers (Table 4), reflecting their core responsibilities that require diligence and attention to detail.

For extraversion, jobs typically considered demanding social and outgoing roles, like advertising and public relations managers, actors, and event planners, tended to score the highest. Conversely, occupations involving less social interaction, such as electronics engineers, software/multimedia developers, assemblers, and laboratory technicians, had the lowest average extraversion scores (Table 6).

In the agreeableness domain, psychologists, religious professionals, and health professionals ranked among the occupations with the highest scores. Interestingly, electronics engineers and multimedia developers also displayed high average agreeableness scores, which might challenge common perceptions of these roles. The lowest agreeableness scores were observed among sales workers, entrepreneurs, real estate agents, business services professionals, and sales managers (Table 7).

The findings described were generally consistent with earlier research concerning different occupations (Törnroos et al., 2019; Wolfram, 2023) and university majors (Vedel, 2016). The findings align well with studies focusing on specific occupations (Cerasa et al., 2016; King et al., 2011; Lounsbury et al., 2016). An interactive table available at https://apps.psych.ut.ee/JobProfiles/ shows Big Five profiles for all 263 occupations.

Table 3. *Jobs with the Highest and Lowest Mean Scores in Openness*

Highest-scoring jobs				Lowest-scoring jobs			
Job	Mean	*SD*	*N*	Job	Mean	*SD*	*N*
Visual Artists	58.52	9.53	208	Crane, Hoist & Rel. Plant Operators	43.95	8.94	48
Language Teachers	57.04	10.76	87	Plumbers & Pipe Fitters	44.72	10.15	50
Authors & Rel. Writers	56.89	8.72	41	Car, Taxi & Van Drivers	44.85	9.42	513

Note. SD = standard deviation; *N* = number of people in the group; Rel. = related.

Table 4. *Jobs With the Highest and Lowest Mean Scores in Conscientiousness*

Highest-scoring jobs				Lowest-scoring jobs			
Job	Mean	*SD*	*N*	Job	Mean	*SD*	*N*
Ships' Engineers	53.90	8.50	40	Visual Artists	45.55	9.95	208
Dental Assistants & Therapists	53.68	11.70	25	Electronics Engineers	45.92	8.57	50
Construction Managers	53.45	9.12	108	Graphic & Multimedia Designers	46.03	10.80	232

Note. SD = standard deviation; *N* = number of people in the group.

Table 5. *Jobs With the Highest and Lowest Mean Scores in Neuroticism*

Highest-scoring jobs				Lowest-scoring jobs			
Job	Mean	*SD*	*N*	Job	Mean	SD	*N*
Actors	57.94	10.97	63	Database & Network Profs N.E.C	45.19	10.09	30
Visual Artists	55.06	9.60	208	Health Services Managers	45.44	9.16	127
Graphic and Multimedia Designers	54.76	10.86	232	Aircraft Pilots & Rel. Associate Profs	46.08	8.25	42

Note. SD = standard deviation; *N* = number of people in the group; Profs = professionals; N.E.C = not elsewhere classified.

Table 6. *Jobs With the Highest and Lowest Mean Scores in Extraversion*

Highest-scoring jobs				Lowest-scoring jobs			
Job	Mean	*SD*	*N*	Job	Mean	*SD*	*N*
Advertising & Public Relations Managers	55.11	9.19	136	Electronics Engineers	42.02	12.74	50
Actors	55.01	10.13	63	Software Developers	44.90	10.60	876
Conference & Event Planners	54.83	8.71	29	Web & Multimedia Developers	44.94	10.07	38

Note. SD = standard deviation; *N* = number of people in the group.

Table 7. *Jobs With the Highest and Lowest Mean Scores in Agreeableness*

Highest-scoring jobs				Lowest-scoring jobs			
Job	Mean	*SD*	*N*	Job	Mean	*SD*	*N*
Electronics Engineers	55.71	9.81	50	Unspecified Sales Workers	46.72	9.34	36
Web & Multimedia Developers	54.63	8.91	38	Self-employed/ Entrepreneurs	47.13	9.94	610
Psychologists	54.34	9.87	245	Real Estate Agents, Property Managers	47.28	10.66	199

Note. SD = standard deviation; *N* = number of people in the group.

4.2.3 Nuanced occupational differences

Some previous studies have argued that the Big Five may be too broad to comprehensively understand or predict work-related criteria (Hough & Oswald, 2005; Paunonen et al., 1999; R. Schneider et al., 1996, p. 199; Tett & Burnett, 2003), but systematic research on mapping occupational differences with narrower traits is very limited. Therefore, a unique contribution of **Study III** was profiling personality nuances across the 263 occupations.

First, we compared the occupational groups in personality items and calculated the η^2 for every item, representing the proportion of variance accounted for by occupational groups. Next, 23 items with $\eta^2 \geq .04$ were identified, and from these, 2 items were removed that had an inter-correlation larger than $r > .50$ with another item to minimize content overlap. For these pairs, the item with the higher η^2 was retained. This left us with 21 personality nuances (see Table 8) that showed occupational differences equal to the typical association strength in psychology ($r \approx .20$, $\eta^2 = .04$), considered the threshold for medium effects with potential practical and explanatory use (Funder & Ozer, 2019). Finally, we smoothed the

items' mean scores and *SD*s of the 4d occupational groups towards those of their parent groups, like domains-based analyses.

Similarly to domains, the resulting profile patterns were usually highly intuitive. For example, the item "Want to be in charge" showed the greatest variation across jobs, with the highest scores in leadership roles and the lowest in support roles such as clerks, kitchen helpers, and teachers' aides.

Occupational groups accounted for significant proportions of variance in several nuances related to the openness domain. Yet, these nuances were not redundant, correlating less than .50, far lower than their reliability (Henry & Mõttus, 2023). Many other trends in item profiles also seem to be linked with the expected responsibilities, vocational interests, or day-to-day activities of different jobs: managers deal with problem-solving and competitive tasks; judges, pilots, and officials are decisive; pilots and air controllers adapt well to changes; researchers are science-focused; and HR, welfare managers, and psychologists are good in influencing other people. Some occupational differences reflect broader perspectives or emotional states rather than job functions, like religious professionals' conservatism versus the liberalism seen in creative fields and law. All occupations' item-score rankings are shown at https://apps.psych.ut.ee/JobProfiles/.

4.2.4 Cross-validation of the findings

To assess the findings' robustness across samples, countries, and assessment approaches, reinforcing their general applicability, we cross-validated our self-reported results against informant-reports and previous findings.

Informant-ratings were available for 18,496 individuals across 176 occupational groups. Analyses with informant-ratings showed that 4d occupational groups explained similar proportions of Big Five domain variances as in self-reports, with $\eta^2 = .07$ for openness, .04 for extraversion, and .03 for neuroticism, agreeableness, and conscientiousness. Therefore, the magnitudes of occupational differences replicated well across methods.

The correlations between self- and informant-rated smoothed personality scores were remarkably high, with ρs ranging from .63 to .90 for domains and from .67 to .92 for nuances. This supports the reliability and validity of our findings, meaning that occupational differences in personality domains and nuances did not reflect merely people's self-concepts but also their externally visible traits.

Table 8. *Variance Proportions (Eta-Squared) of the Items Accounted for by Jobs Coded Into Four-Digit to Single-Digit ISCO Categories*

Items	4d	3d	2d	1d
1. Want to be in charge	.12	.11	.10	.09
2. Try to avoid speaking in public	.09	.08	.06	.05
3. Need a creative outlet	.09	.07	.04	.01
4. Am interested in science [a]	.08	.07	.05	.04
5. Like to solve complex problems [a]	.07	.06	.05	.04
6. Have a natural talent for influencing people	.06	.06	.04	.04
7. Have a rich vocabulary [a]	.06	.06	.04	.03
8. Believe in the importance of art [a]	.06	.05	.03	.02
9. Support liberal political candidates	.06	.05	.04	.04
10. Like to stand out in a crowd	.06	.05	.04	.03
11. See myself as an average person	.05	.04	.03	.02
12. Avoid philosophical discussions [a]	.05	.04	.03	.03
13. Try to out do others	.05	.04	.03	.03
14. Am considered to be a wise person [a]	.05	.04	.03	.03
15. Become anxious in new situations	.04	.04	.03	.03
16. Believe that we should be tough on crime	.04	.04	.03	.02
17. Like to read	.04	.04	.03	.02
18. Believe in the power of fate	.04	.03	.02	.02
19. Tend to feel very hopeless	.04	.03	.03	.02
20. Adapt easily to new situations	.04	.03	.02	.02
21. Can't make up my mind [b]	.04	.03	.02	.02

Note. N = 59,027. 4d = four-digit ISCO codes (k = 263); 3d = three-digit ISCO codes (k = 125); 2d = two-digit ISCO codes (k = 43); 1d = single-digit ISCO codes (k = 10).
[a] These items were loaded onto the openness component in the PCA. [b] Item loaded onto the neuroticism component in the PCA.

As much of assessed trait scores reflect systematic but method-specific variance, being constrained to a single method, self-reports, has been an important limitation in past research. But this is also a substantive finding that reputation, better reflected in informant-reports, did not vary more with jobs than identity, better captured with self-reports. The reverse could have been possible because reputation better predicts some occupational outcomes (Connelly et al., 2022; Connelly & Ones, 2010; McAbee & Connelly, 2016; Oh et al., 2011).

Wolfram (2023) published personality profiles for 360 occupations using a considerably different method, which involved a 15-item personality measure and smoothing trait scores with small area estimation and external auxiliary information derived from the O*NET job descriptions database. Comparing the occupational rankings across the two studies for 217 occupations with overlapping data, Spearman's ρ ranged from .48 to .71. The level of overlap is notable,

especially considering the sociocultural differences (Wolfram's sample is based in the UK) and various methodological variations. Despite these differences, the strong associations between the results highlight the robustness of both our and Wolfram's findings.

4.2.5 Occupations with higher performance-related average trait scores are more selective

We also explored whether Big Five scores of occupational groups were more homogeneous at the higher (or lower, for neuroticism) end of the mean scores. This hypothesis was drawn from intelligence studies, where job groups with higher mean intelligence levels tend to have lower variance in these scores than groups with lower mean levels (Harrell & Harrell, 1945; Jensen, 1980; Wolfram, 2023). In other words, we expected more homogeneity in those personality traits that are generally linked with better job performance in jobs having higher average levels of these traits.

To explore that, we calculated the correlations between the mean scores and *SD*s of the Big Five domains of the 4d occupational groups. The associations between the smoothed means and *SD*s were statistically significant ($p < .01$) for four traits: $\rho = .29$ for neuroticism, $\rho = –.32$ for extraversion, $\rho = –.16$ for openness, and $\rho = –.42$ for conscientiousness.

The associations between informant-rated means and *SD*s ($k = 176$) were statistically significant ($p < .001$) for extraversion ($\rho = –.31$) and conscientiousness ($\rho = –.31$). For informant-rated agreeableness, the correlation was stronger ($\rho = –.24$, $p < .01$) than the correlation for self-reported agreeableness. However, the correlations for neuroticism ($\rho = .14$) and openness ($\rho = –.15$) were not statistically significant in informant-ratings ($p > .05$). Finally, because combining self- and informant-ratings may yield more reliable means and *SD*s than either method alone, we averaged the smoothed means and *SD*s based on self- and informant-ratings for the 176 occupations with available data. In these data, means and *SD*s were significantly correlated for all domains: $\rho = .23$, $–.20$, and $–.24$ ($p < .01$) for neuroticism, openness, and agreeableness, and $\rho = –.42$ ($p < .001$) for extraversion and conscientiousness. In summary, most of the results supported this hypothesis, particularly for extraversion and conscientiousness.

Wolfram (2023) results showed a partly similar pattern of correlations. Specifically, neuroticism had a substantial positive relationship between means and *SD*s, while openness and conscientiousness had negative correlations. Wolfram did not find the expected relationship for agreeableness, whereas we found it in informant-reports and combined self- and informant-reports. However, the findings noticeably differed for extraversion, as Wolfram had a positive mean-*SD* correlation, while the association was consistently negative with our data. The positive correlation was unexpected, given that previous studies have also shown that extraversion is strongly correlated with better job performance (Judge et al., 2013; Wilmot & Ones, 2021). Wolfram reported potential floor and ceiling

effects in the trait score distributions given their limited assessment, which could bias the results. However, this may not fully account for the observed discrepancy with our study. One possible explanation could be differences in how personality traits are assessed. The three extraversion items in the BFI-S used in Wolfram exclusively tap sociability (e.g., “Is talkative”; “Is outgoing”; “Is reserved”), while our findings suggest that the assertiveness component of extraversion (“Want to be in charge”) may vary more between occupations. Therefore, the content of the extraversion domain may differ between the two studies. Another probable factor could be sociocultural differences and job expectations, possibly indicating a higher selection for extraversion in Estonia compared to the UK.

5. CONCLUSIONS AND FUTURE DIRECTIONS

The general aim of this doctoral dissertation was to explore the role of key individual differences—intelligence and personality—in educational and occupational variation within the context of Estonia.

Measurement methods can influence the associations between psychological variables and SE outcomes. Therefore, it is essential to examine the factor structure and psychometric properties across different adaptations and standardization samples. The confirmatory factor analyses of the Estonian WAIS-III standardization sample in **Study II** supported a four-factor model consistent with the original WAIS-III structure (Psychological Corporation, 2002). These results align with previous findings from other standardizations as well (Egeland et al., 2009; Grégoire, 2004). Results indicated partial MI across sexes and age groups. However, our study revealed that the Estonian WAIS-III is not invariant across educational levels. Therefore, the structural organization of abilities may vary across educational levels, although the specific alignment with differentiation hypotheses (Ritchie et al., 2015; Spearman, 1927) will remain to be studied.

Study I explored the interplay between cognitive ability and parental background in predicting individual educational and occupational status in the context of Estonia. Our results demonstrated that both parental education and intelligence significantly predicted educational and occupational status. Parental education explained 8–13%, while cognitive ability accounted for 22–27% of children's educational and occupational attainment variance. These findings align with Erikson's (2016) study in Sweden, which found that social origin factors accounted for 16–19% of the variance in education and cognitive ability for 25%. Our results suggest that in Estonia, the influence of parental background is slightly lower, possibly indicating a higher role of intelligence in social mobility. Also consistent with previous studies (e.g., Strenze, 2007), cognitive ability had a stronger predictive power for educational attainment than occupational attainment. Further analyses showed that about 40% of the parental background effect is mediated through cognitive ability. Additionally, as suggested in previous studies (Breen & Goldthorpe, 2001; Deary et al., 2005; Nettle, 2003), our results confirm that a participant's own education may mediate between parental education and cognitive ability and occupational attainment. This may indicate meritocracy or genetic confounding, which could be explored in future research.

Prior studies have also indicated that some cognitive abilities are more associated with SE outcomes than others (Asbury et al., 2005; Epstein & Winship, 2006; Farah et al., 2006). Indeed, our results confirmed that compared to other ability domains, verbal ability had slightly stronger links with educational as well as occupational attainment. Specifying the differences between various abilities may be crucial for future studies aimed at disentangling the genetic foundations of social mobility and SE success.

While cognitive ability captures substantial variability in SE outcomes, the associations with personality differences is less studied. Results of **Study III** indicated that occupations account for significant variation in personality traits,

explaining between 2% and 7% of the self-reported Big Five domain variance, with openness varying the most among jobs. This explained variance was higher for personality nuances, with occupations accounting for up to 12% of variance in single items. Prior research has shown that personality traits are significantly associated with life outcomes, with stronger correlations in self-reported constructs like life satisfaction (r ≈ .10 to .30; Soto, 2019) and much smaller correlations with objective outcomes, e.g., in Beck and Jackson's (2022) mega-analysis, all associations were smaller than $r < .05$. Notably, occupational choice shows one of the strongest correlations with personality traits (e.g., $\eta^2 = .07$ means $r = .26$), clearly establishing the importance of personality in influencing SE outcomes.

This dissertation provides the most comprehensive database of occupational personality profiles, which is publicly available (https://apps.psych.ut.ee/JobProfiles/). Most occupations' average trait levels were intuitive, replicated in informant ratings, and were consistent with those previously obtained with a brief personality assessment in a different sociocultural context. However, it is essential to recognize that these data are about mean differences between occupations, while many individuals defy these mean-level trends. Therefore, while personality assessments can offer valuable insights into person–job fit, they should be used in conjunction with a comprehensive understanding of each individual's unique attributes and potential. Several other factors, such as cognitive ability and mental health (Wolfram, 2023), interests (Hoff et al., 2020), and external facilitators and constraints, among others, can influence occupational sorting—besides mere happenstance.

Lastly, the results indicated that occupations with higher average traits typically associated with better job performance tended to be more homogeneous in these traits, suggesting that jobs with higher-performing incumbents are often more selective for these traits. These results highlight that person–environment transactions may vary across trait levels, with some jobs showing increased homogeneity in traits like extraversion and conscientiousness due to selection effects. Certain occupations may attract or seek specific traits, creating homogeneity, while different factors may influence other jobs. Professions requiring high levels of performance-related traits might also foster growth in these traits, supporting the corresponsive principle of personality development (Le et al., 2014; Roberts et al., 2003).

In conclusion this dissertation advances the understanding of how intelligence and personality are related to educational and occupational outcomes in Estonia. The results of the included studies have several implications. **Study I** contributes to the broader understanding of the interplay between cognitive ability, parental background, and SE outcomes across different sociocultural contexts. It underscores the importance of analysing these dynamics in various geographical settings, especially when genetic data is available to further investigate the complexities of social mobility. The findings suggest that no single factor predicts social mobility or status attainment; rather, multiple mediators, likely interacting in different ways based on factors like geography, education systems, and societal

structures, contribute to these outcomes. **Study II** provides evidence supporting the appropriateness of the Estonian WAIS-III adaptation, while also highlighting the importance of in-depth analysis of the psychometric properties of intelligence measures. **Study III** has practical applications for career counselling, coaching, and applicant selection by showing that occupations differ significantly in Big Five traits and narrower personality nuances. Matching individuals to jobs based on these traits can improve job fit and success, particularly by focusing on openness and extraversion, which vary the most across occupations. The study's publicly available database offers a valuable resource for professionals to enhance career guidance, promoting better SE outcomes through more personalized approaches.

Future research could expand on the interplay between intelligence, personality, social origin, and context to enhance the understanding of predictors of SE outcomes. Integrating genetic data would be crucial for understanding the complex associations between parental background, psychological variables, and SE success (Buser et al., 2023; Cheesman et al., 2024; Van Hootegem et al., 2024). Additionally, personality and intelligence interact with several other variables such as physical and mental health (Jokela et al., 2009), interests (Hurtado Rúa et al., 2019; Volodina & Nagy, 2016), and broader contextual factors like educational systems, economic conditions, and access to opportunities (Damian et al., 2015; Todd & Zhang, 2020). These factors are likely to play significant roles in shaping individual SE success, and their interactions underscore the necessity of adopting a multifaceted approach in future research to better capture the complexity of these relationships.

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SUMMARY IN ESTONIAN

Intelligentsus, isiksuseomadused ja sotsiaalmajanduslikud tulemused Eestis

Sotsiaalmajanduslikke tulemusi, nagu haridustase, ametialane staatus või sissetulek, kujundavad paljud tegurid, mis on pälvinud teadlaste tähelepanu mitmetes erinevates distsipliinides. Varasemad uuringud on selgelt näidanud, et ei ole ühte kõige olulisemat faktorit, mis määraks, kui kaua inimene koolis õpib või millise karjääri valib. Oluline on hoopis see, kuidas erinevad tegurid omavahel põimuvad ja üksteist mõjutavad (Soto et al., 2022).

Sotsiaalmajanduslike tulemuste mõjutajate eristamine on muutunud keskseks suunaks mitmes valdkonnas, sest see on oluline nii individuaalse heaolu kui ka ühiskonna laiema olemuse mõistmiseks. Üks olulisemaid teemasid on olnud näiteks aastakümneid kestnud vaidlus selle üle, kas inimese sotsiaalmajanduslikku edukust mõjutavad rohkem pärituolu ehk vanemate sotsiaalne staatus (klass) või pigem inimese enda individuaalsed psühholoogilised omadused, näiteks intelligentsus ja isiksuseomadused (Betthäuser et al., 2020, 2021; Herrnstein & Murray, 1994; Marks, 2020; Saunders, 1997). Enamik kaasaegseid ühiskondi püüdleb meritokraatliku ideaali poole, mis tähendab, et inimese sotsiaalmajanduslikud tulemused ei peaks sõltuma päritolustaatusest, vaid pigem inimese enda võimetest, omadustest ja pingutusest (Erola & Kilpi-Jakonen, 2017; Young, 1958). Meritokraatia üheks osaks on ka talendi või ressursi mõistliku jaotamise idee (Murphy et al., 1991), mille kohaselt võiks inimesel olla võimalus leida endale töökoht või muu keskkond, mis sobib tema omadustega. On viiteid, et kui meritokraatlik jaotumine toimib tõhusalt, on ühiskonnad ka üldiselt edukamad (Murphy et al., 1991). Lisaks on see oluline ka individuaalsel tasandil, mida kirjeldatakse kui keskkonna ja inimese sobivust. Enamik inimesi pühendab suure osa oma täiskasvanuelust tööle ning haridus- ja karjäärivalikud on ühed olulisemad sotsiaalsed ja majanduslikud otsused, mida inimesed oma elu jooksul teevad (Buser et al., 2023; Kristof-Brown et al., 2005). Individuaalsete omaduste ja sotsiaalmajandusliku keskkonna, nagu haridus või ametialane staatus, sobivus on seotud suurema rahulolu ja tööalase sooritusvõimega (Kristof-Brown et al., 2005). Seetõttu on oluline paremini mõista sotsiaalmajandusliku edukuse ennustajaid ja nende omavahelisi seoseid, kuna see võib avaldada mõju nii ühiskondlikul kui ka individuaalsel tasandil. Selle doktoritöö peamine eesmärk oli uurida, kuidas individuaalsed erinevused, nagu intelligentsus ja isiksuseomadused, on seotud sotsiaalmajanduslike tulemustega ehk haridustaseme ja ametialase staatusega. Käesoleva töö oluline panus on selle teema kaardistamine Eestis.

Psühholoogiliste tunnuste ja sotsiaalmajanduslike tulemuste vaheliste seoste analüüsi võib oluliselt mõjutada meetod, mida kasutatakse nende tunnuste mõõtmiseks. Näiteks võivad seoste tugevused erineda olenevalt sellest, millist testi me intelligentsuse mõõtmiseks kasutame. Seetõttu uurisimegi käesoleva doktoritöö

raames põhjalikult eestindatud intelligentsustesti Wechsleri täiskasvanute intelligentsusskaala (WAIS-III) psühhomeetrilisi näitajaid, mis aitavad välja selgitada, kas saadud testitulemused on usaldusväärsed ja mida peaks nende tõlgendamisel arvesse võtma (**Uurimus II**). Analüüside tulemused kinnitasid, et eestindatud WAIS-III intelligentsustesti faktorstruktuur oli võrreldav USA-s avaldatud originaaltesti ja mitmete teiste kohandatud versioonide struktuuriga (Egeland et al., 2009; Grégoire, 2004). Lisaks uurisime selles töös mõõtmise invariantsust – kui mõõdik on erinevate gruppide võrdlemisel piisavalt sarnaste näitajatega, siis peetakse seda oluliseks testi iseloomustavaks tunnuseks ja viitab sellele, et test mõõdab erinevate gruppide kognitiivseid võimeid sarnaselt. Eestindatud WAIS-III faktorstruktuuri näitajad olid piisavalt sarnased sugude ja vanusegruppide lõikes. **Uurimus II** tulemused näitasid aga, et invariantsus ei kehtinud siis, kui analüüsisime gruppe haridustasemete lõikes. Seega, vaimsete võimete struktuur võib olla haridustasemete lõikes erinev ja seda peaks arvestama võimete ja haridusalaste tulemuste seoste tõlgendamisel.

Edasi uurisime samal andmestikul, kas inimese haridustaseme ja tööalase staatuse ennustamisel on olulisem inimese enda vaimne võimekus või pärituolu ehk vanemate haridus (**Uurimus I**). Tulemuste alusel on mõlemad olulised ennustajad, kuid inimese enda intelligentsus oli mõnevõrra parem ennustaja. See oli ootuspärane, kuna sarnaseid tulemusi on kirjeldatud ka varasemates töödes, sealhulgas ka Rootsis (Erikson, 2016). Samuti sai **Uurimuses I** kinnitust varasemalt kirjeldatud tulemus selle osas, et arvestatav osa vanemate hariduse mõjust oli vahendatud vaimsete võimete poolt.

Vaimsed võimed jagunevad erinevatesse alatahkudesse, nt sõnalised oskused, visuaal-ruumilised võimed, tähelepanuprotsessid jmt. Varasemad tööd on enamasti kasutanud üldintelligentsuse näitajad (nt IQ-skoori), aga **Uurimuses I** analüüsisime ka kitsamate võimete erinevusi sotsiaalmajanduslike tulemuste ennustamises. Analüüsid kinnitasid mõningate varasemate tööde tulemusi (Asbury et al., 2005; Epstein & Winship, 2006; Farah et al., 2006)), kus leiti, et sõnalisel võimekusel oli mõnevõrra tugevam seos haridustaseme ja tööalase staatusega kui visuaal-ruumilisel võimekusel, töömälul või töötluskiirusel.

Kuigi vaimset võimekust peetakse üheks olulisemaks psühholoogiliseks tunnuseks, mis mõjutab inimeste sotsiaalmajanduslikke tulemusi, siis viimasel ajal on aina olulisemaks muutunud ka erinevused isiksuseomadustes. Isiksuse olulisust on elusündmuste ennustamisel korduvalt näidatud, siis ei ole varasemalt põhjalikult uuritud paljude ametite erinevusi isiksuseomaduste lõikes. Kasutasime selle uurimiseks Geenivaramu Isiksuseuuringu andmeid. **Uurimuses III** ilmnes, et olenevalt isiksuseomadusest kirjeldasid ametid 2–7% Suure Viisiku isiksuseomaduste (ehk avatuse, ekstravertsuse, neurootilisuse, meelekindluse ja sotsiaalsuse) erinevustest. Sama analüüs isiksusemõõdiku üksikküsimuste lõikes näitas, et ametid kirjeldasid kuni 12% üksikküsimuste erinevustest. Võrreldes muude elusündmuste ja isiksuse vahelisi seoseid, siis võib ameti ja isiksuseomaduste seos olla üks tugevamatest.

Uurimuses III kaardistasime ka 263 ameti isiksuseprofiilid nii Suure Viisiku isiksuseomaduste kui ka ametite lõikes enim erinenud 21 üksikküsimuse osas.

Enamik ametite keskmised isiksuseprofiilid olid üsna ootuspärased. Näiteks loovvaldkondade esindajatel (kunstnikel ja kirjanikel) ning teadustöötajatel olid kõrgeimad keskmised avatused skoorid. Juhipositsioonidel olid keskmiselt kõrgeimad meelekindluse ja ekstravertsuse skoorid. Kõigi 263 ameti isiksuseprofiilid on avalikult kättesaadavad (https://apps.psych.ut.ee/JobProfiles/).

Samuti näitasime **Uurimuses III**, et ametite keskmised tulemused olid üsna sarnased nii inimese enda hinnatud isiksuse kui ka tema tuttava hinnatud isiksuseomaduste osas. Samuti olid meie saadud tulemused üle ootuste sarnased Suurbritannia andmetel (Wolfram, 2023) kuid väga lühikese isiksuseküsimustikuga hinnatud isiksuseomadustega võrreldes. Kõik need lisaanalüüsid kinnitasid meie tulemuste üldistatavust ja usaldusväärsust.

Lisaks kinnitasime **Uurimuses III** hüpoteesi, et kui ameti keskmine isiksuseomaduse tase on kõrge (või neurootilisuse puhul madal), siis on seda ametit pidavad inimesed ka selle isiksuseomaduse poolest ka sarnasemad. See sai eriti kinnitust ekstravertsuse ja meelekindlusega, see tähendab, et mida kõrgem on ameti keskmine ekstravertsus, seda sarnasema ekstravertsuse tasemega inimesed seal grupis on. See võib tähendada seda, et mõne ameti pidamiseks on vajalik kõrgem ekstravertsus. Võimalik, et mingis ametis pikemaajalisem töötamine ka muudab natuke isiksuseomadusi – nt tööülesanded, mis vajavad keskmisest kõrgemat ekstravertsust võivad muuta inimest neid tehes veel mõnevõrra ekstravertsemaks (Le et al., 2014; Roberts et al., 2003).

Kokkuvõttes võimaldab see doktoritöö paremini mõista, kuidas intelligentsus ja isiksuseomadused on seotud haridustaseme ja ametitega Eestis. Doktoritöö raames tehtud uuringutel on mitmeid rakendusi. **Uurimus I** toob esile kognitiivsete võimete ja vanemate tausta seosed sotsiaalmajanduslike tulemustega eri sotsiaal-kultuurilistes kontekstides, rõhutades geograafiliste eripärade ja geneetiliste andmete analüüsi olulisust sotsiaalse mobiilsuse uurimisel. Tulemused viitavad, et sotsiaalset mobiilsust ei määra üks tegur, vaid mitmed vahendajad, mis varieeruvad sõltuvalt piirkonnast, haridussüsteemist ja ühiskondlikest eripäradest. **Uurimus II** toetab kohandatud Eesti WAIS-III intelligentsusskaala sobivust, rõhutades samas mõõtmisvahendite psühhomeetriliste omaduste põhjaliku analüüsi olulisust. **Uurimus III** tulemused on rakendatavad karjäärinõustamises ja värbamisprotsessides, kuna ametid erinevad oluliselt Suure Viisiku omaduste ja kitsamate isiksuse nüansside poolest. Inimeste sobitamine ametikohtadele nende omaduste põhjal võib parandada töö sobivust ja edukust töö tegemisel ning eriti kasulik võib olla keskenduda avatusele ja ekstravertsusele, mis varieeruvad ametite lõikes kõige rohkem. Avalikult kättesaadav andmebaas pakub väärtuslikku vahendit täiustamaks isikustatud karjäärinõustamist, mis võib soodustada paremaid sotsiaalmajanduslikke tulemusi.

Tulevased uuringud võiksid laiendada teadmisi intelligentsuse, isiksuse, sotsiaalse päritolu ja konteksti koosmõjust, et paremini mõista sotsiaalmajanduslike tulemuste ennustajaid. Geneetiliste andmete kaasamine on oluline, et paremini mõista sotsiaalse päritolu, kognitiivsete võimete ja isiksuse keerukaid seoseid (Buser et al., 2023; Cheesman et al., 2024; Van Hootegem et al., 2024). Samuti on isiksus ja intelligentsus seotud erinevate teguritega, nagu füüsiline ja vaimne

tervis (Jokela et al., 2009; Wolfram, 2023), huvid (Hurtado Rúa et al., 2019; Volodina & Nagy, 2016) ning laiemad kontekstuaalsed erinevused, nagu haridussüsteemid ja majanduslikud tingimused (Damian et al., 2015; Todd & Zhang, 2020). Need seosed võivad mängida olulist rolli inimeste sotsiaalmajandusliku edu kujundamisel, ning need koosmõjud rõhutavad vajadust mitmetahulise lähenemisviiside järele edasistes uuringutes.

PUBLICATIONS

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Sirts, K., Anni, K., Balõtšev, R., Jakobsoo, S., Jaanson, K. L., & Haring, L. (2024). Adapting the early recognition inventory ERIraos to Estonian: A validation study. *Early Intervention in Psychiatry*, 1–11. DOI: 10.1111/eip.13519

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Anni, K., Ennok, M., & Burk, K. (2015). Intelligentsuse hindamise võimalusi: Wechsleri täiskasvanute intelligentsusskaala. *Eesti Arst, 94*(4), 217–224.

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Uurimistöö põhisuunad: individuaalsed erinevused, intelligentsus, isiksus, ametitevahelised erinevused

Publikatsioonid

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