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Exploring the influence of non-cognitive skills on academic achievement in STEM education: the case of Kazakhstan

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Introduction: This exploratory study delves into the relationships between non-cognitive skills and academic achievement within the unique context of STEM schools in Kazakhstan.

Methods: Survey data were collected from 109 teachers and 395 students at a STEM secondary school in Kazakhstan. Correlational, regression and path analyses were conducted to explore the relationship between non-cognitive skills and academic performance in Mathematics, Computer Science, Physics, and Chemistry classes.

Results: The results showed that out of the 26 skills, eight had a direct impact, 12 had an indirect impact, and six had no impact on academic achievement of students in the four STEM subjects.

Discussion: This study is the first to explicitly examine the impact of one group of non-cognitive skills on academic achievement of students in STEM subjects mediated by another group of these skills. Teachers are encouraged to integrate non-cognitive skill development into curricula, tailored to subject-specific needs. Policymakers can use findings to inform equitable skill development policies.

KEYWORDS

science, technology, engineering, and mathematics (STEM), secondary education, non-cognitive skills, academic achievement, direct effects, indirect effects, path analysis, Kazakhstan

1 Introduction

In today's constantly evolving educational landscape, understanding and improving the academic achievement of high school students in science, technology, engineering, and mathematics (STEM) subjects is an ongoing concern. In this dynamic context, the importance of non-cognitive skills has gained increasing recognition (Barrett, 2014; Stankov and Lee, 2014). Being sometimes defined as "generic competences", "key competences", "life skills/competences", "transversal skills", "transferable skills" and "21st century skills" (Cinque et al., 2021), these skills extend beyond traditional cognitive abilities, encompassing a diverse range of personal attributes, social skills, and character traits that influence an individual's ability to learn and succeed in academic settings (Farrington et al., 2012; Jones and Doolittle, 2017; Lechner et al., 2019). Unlike non-cognitive skills, cognitive skills involve conscious intellectual effort, such as thinking, reasoning, or remembering (Heckman et al., 2006). While existing research has provided a foundation for examining the influence of non-cognitive skills on academic achievement, it often focuses on a restricted set of skills at a time (e.g., Honicke and Broadbent, 2016; Alhadabi and Karpinski, 2020). Nevertheless, practical considerations necessitate a more comprehensive analysis encompassing a broad spectrum of non-cognitive skills and their impacts within specific STEM subjects (Fonteyne et al., 2017). This research is explicitly designed to address this significant gap in existing literature.

The present study delves into the multifaceted world of STEM secondary education, exploring the complex relationships between 26 non-cognitive skills and academic achievement in four pivotal subjects: Mathematics, Computer Science, Physics, and Chemistry. The study utilizes an existing framework of non-cognitive skills developed for the national STEM schools in Kazakhstan. Therefore, the justification for including this specific set of non-cognitive skills and their distribution across domains is beyond the scope of this research. It aims to comprehensively investigate and understand the direct and indirect effects of these skills on academic achievement in four subjects among students at a STEM school in Kazakhstan. The study seeks to provide actionable insights into which non-cognitive skills are positively associated with academic success in each subject, facilitating informed educational practices and interventions. The research objectives are to identify statistically significant non-cognitive skills with a positive impact, both direct and indirect, on academic achievement in these STEM subjects among secondary education students.

This paper embarks on a comprehensive journey of exploration, utilizing correlational, regression, and path analysis techniques to uncover the hidden dynamics between non-cognitive skills and academic success. Survey data were collected from 109 teachers and 395 students at one STEM secondary school. The results showed that out of the 26 skills, eight had a direct impact, 12 had an indirect impact, and six had no impact on the academic achievement of students in the four STEM subjects. The significance of this research lies in its potential to provide actionable insights for teachers, policymakers, and stakeholders in the realm of STEM education. By understanding which non-cognitive skills have a direct and positive impact on academic achievement in each subject, interventions and support mechanisms that empower students to thrive in their STEM pursuits can be tailored. Navigating the complex landscape, this study aims to illuminate pathways to educational enhancement that are not only grounded in theory but also deeply rooted in practical relevance.

1.1 The role of non-cognitive skills for long-term success

Alongside cognitive abilities, non-cognitive skills are crucial for long-term success. Research from economics, psychology, and education highlights their pivotal role in academic achievements and overall accomplishments (Farkas, 2003; Heckman et al., 2006; Lee and Shute, 2010; Richardson et al., 2012; Stankov, 2013; Duckworth and Yeager, 2015). Going beyond cognitive abilities, non-cognitive skills determine how individuals apply their knowledge in real-world scenarios (Stehle and Peters-Burton, 2019). These skills include resilience, adaptability, emotional intelligence, self-discipline, communication, teamwork, and problem-solving. They help individuals overcome challenges, handle setbacks, and maintain positive relationships.

Historically, the focus on cognitive abilities, such as logical reasoning and analytical thinking, has overshadowed the contributions of non-cognitive skills in academic contexts. Nonetheless, scholars and teachers have come to recognize that non-cognitive skills encompass a broad range of personal attributes, social skills, and character traits that profoundly influence an individual's ability to thrive academically (Heckman and Rubinstein, 2001; Durlak et al., 2011; Farrington et al., 2012; Jones et al., 2017). These skills comprise grit, perseverance, self-control, social skills, emotional intelligence, and self-efficacy.

Non-cognitive skills play a vital role in determining academic achievement, complementing, and often surpassing the importance of cognitive abilities. While cognitive skills such as intelligence and academic knowledge are crucial for learning, non-cognitive skills encompass a range of attributes like perseverance, self-control, motivation, and social–emotional competencies that significantly impact educational outcomes (Durlak et al., 2011; Farrington et al., 2012; Jones et al., 2017).

Non-cognitive skills contribute to academic achievement by facilitating a positive learning environment and enhancing students' ability to overcome challenges. For instance, perseverance and grit enable students to persist in the face of difficulties and setbacks, promoting a growth mindset that encourages continuous improvement (Durlak et al., 2011; Farrington et al., 2012; Jones et al., 2017; He et al., 2021). Self-control and impulse regulation facilitate better time management and goal-setting, essential for effective studying and task completion (Heckman and Rubinstein, 2001). Motivation fuels students' desire to learn, encouraging active engagement in the learning process and higher levels of achievement (Heckman and Rubinstein, 2001). Longitudinal studies, such as Moffitt et al. (2011), have indicated that children with higher levels of self-control achieve superior academic outcomes, even when accounting for their cognitive abilities.

Studies have shown that students with strong non-cognitive skills tend to perform better academically, achieve higher graduation rates, and are better equipped for success both in and beyond the classroom (Caprara et al., 2008; Doménech-Betoret et al., 2017; Fonteyne et al., 2017). For instance, resilience and the ability to cope with setbacks stimulate a growth mindset, enabling students to persist in the face of challenges and embrace learning opportunities (Yeager and Dweck, 2012). Non-cognitive skills also have long-term implications for students' lives, extending beyond their academic journey. These skills are associated with improved employability, higher earning potential, and overall well-being in adulthood (Poropat, 2009).

Furthermore, non-cognitive skills bolster social and emotional competencies, promoting positive relationships with peers and teachers. Effective communication, empathy, and cooperation stimulate collaborative learning, group projects, and overall classroom engagement (Durlak et al., 2011; Farrington et al., 2012). Emotional regulation and stress management enable students to cope with academic pressures, leading to better focus and overall well-being (Heckman and Rubinstein, 2001; Fonteyne et al., 2017). Moreover, non-cognitive skills contribute to improved classroom behavior, higher attendance rates, and reduced dropout rates (Durlak et al., 2011; Farrington et al., 2012). This behavior is not just about following rules, but also encompasses how students interact with teachers and peers, manage their emotions, respond to challenges, and participate in classroom activities (Khine and Areepattamannil, 2016). Additionally, these skills foster adaptability, creativity, and critical thinking, empowering students to tackle complex problems and excel in higher education and future careers (Heckman and Rubinstein, 2001).

In understanding the development of these non-cognitive skills, the role of teachers becomes crucial. Research has consistently shown that teachers significantly influence both the academic and non-cognitive skills of their students. For instance, Jackson (2012) discovered that teachers have a significant impact on various non-cognitive aspects of student performance. This impact is evident in measurable outcomes such as student absences, suspensions, grades, and timely progression through grades. Although the exact ways teachers affect these non-cognitive skills remain unclear, the impact is undeniable. Supporting this, Ruzek et al. (2014) demonstrated that teachers play a crucial role in shaping students' motivation, as seen in mastery and performance achievement goals. Similarly, Gershenson (2016) identified a significant effect of teachers on student attendance patterns. These findings collectively highlight the multifaceted influence of teachers on student development.

Effective STEM teaching should balance cognitive and non-cognitive learning goals, ensuring that both are addressed in classroom activities and standards-oriented teaching, as seen in the educational reforms in Germany and other countries (Schiepe-Tiska et al., 2021). Teachers, for instance, can promote the "3Cs" (collaboration and complex thinking, communication and compassion, curiosity), aimed to foster an inclusive environment, preparing students for both content mastery and crucial non-cognitive skills (Upadhyay et al., 2021). Given this influence of teachers, there is a growing consensus on the need for a holistic educational approach that includes non-cognitive skills (Suto, 2023).

Recognizing the significance of non-cognitive skills for long-term academic and life success, educators and policymakers should prioritize their integration into educational curricula. By nurturing and developing these skills alongside cognitive abilities, schools can cultivate well-rounded individuals who are better equipped to succeed academically and in life beyond the classroom (Heckman and Rubinstein, 2001; Durlak et al., 2011; Farrington et al., 2012). There have been attempts to promote the development of non-cognitive skills in secondary education (Doménech-Betoret et al., 2017; Boman, 2023), including schools that naturally emphasize the advancement of cognitive abilities, such as STEM schools.

Traditionally, cognitive abilities have garnered primary attention in STEM education, with an emphasis on intellectual aptitude and problem-solving proficiency. However, recent research has revealed the significant role of non-cognitive skills as crucial determinants of academic achievement in diverse disciplines, including the fields of STEM (Farkas, 2003; Heckman et al., 2006; Lee and Shute, 2010; Richardson et al., 2012; Stankov, 2013; Duckworth and Yeager, 2015). While cognitive abilities like analytical thinking and problem-solving are vital, non-cognitive skills encompass a range of attributes that contribute significantly to success in STEM disciplines (Rimm-Kaufman and Hulleman, 2015). These skills enable students to persist in the face of setbacks, maintain focus during complex problem-solving, and navigate through difficult concepts.

Non-cognitive skills are indispensable in STEM fields. Effective collaboration is integral to scientific research and engineering projects, making teamwork a key non-cognitive skill. Effective communication is crucial for knowledge sharing and innovation, while creativity boosts the generation of novel ideas and breakthroughs in STEM (Vest, 2005). Self-regulation skills, including time management and goal-setting, are essential for effective learning in STEM disciplines. By explicitly integrating non-cognitive skills instruction and support within STEM curricula, teachers can facilitate a learning environment that nurtures both cognitive and non-cognitive skills (Bybee, 2010). Implementing targeted interventions, such as incorporating project-based learning, collaborative activities, and opportunities for student voice and choice, can help cultivate non-cognitive skills while promoting deep engagement and understanding of STEM concepts (Durlak et al., 2011).

To sum up, while cognitive skills are necessary, non-cognitive skills provide the foundation for academic achievement in education in general and in secondary STEM education in particular. By promoting resilience, self-regulation, and collaboration, teachers can help students develop the non-cognitive skills necessary for success in STEM fields, enabling them to navigate challenges, overcome setbacks, and thrive in an ever-evolving technological world. Recognizing the importance of non-cognitive skills, educators should integrate strategies that promote their development alongside cognitive abilities. By nurturing these skills, teachers empower students to excel in STEM education, equipping them with the tools necessary to tackle complex challenges, innovate, and contribute meaningfully to the scientific and technological advancements of tomorrow.

1.2 Direct and indirect effects of non-cognitive skills

Non-cognitive skills have a profound impact on academic achievement, and their effects can be categorized into both direct and indirect influences, reflecting the complexity of their contribution to students' success (Doménech-Betoret et al., 2017). Direct effects of non-cognitive skills refer to their immediate influence on academic outcomes. Indirect effects of these skills on academic performance of students occur through other non-cognitive skills.

Non-cognitive skills, encompassing self-discipline, perseverance, and time management, significantly shape students' academic achievement, directly contributing to improved study habits and productivity (Gutman and Schoon, 2013). Duckworth and Seligman's research (Duckworth and Seligman, 2005) underscores the positive impact of self-regulation skills, including time management and goal-setting, on organizational competence and punctuality. Additionally, Rimm-Kaufman and Hulleman (2015) highlight a direct correlation between self-regulation skills, specifically self-control and time management, and students' performance in STEM courses. Extensive literature, including studies by Duckworth et al. (2007) and Durlak et al. (2011), emphasizes the collective impact of non-cognitive skills on academic achievement. These skills, such as self-discipline, perseverance, motivation, and self-regulation, directly influence academic success by facilitating effective goal-setting, time management, and the ability to overcome challenges (Duckworth et al., 2007; Duckworth and Yeager, 2015). Notably, self-regulation skills, particularly in time management and goal-setting, are singled out for their direct contribution to organizational competence and punctuality, positively influencing academic performance, especially in STEM courses (Duckworth and Seligman, 2005; Rimm-Kaufman and Hulleman, 2015).

Academic self-efficacy, a belief in one's academic abilities, directly impacts academic achievement and exerts an indirect effect through motivation and effort (Muenks et al., 2015). Additionally, motivation, perseverance, and self-control directly predict academic performance, including in STEM subjects (Rimfeld et al., 2016). Elevated self-control levels correlate with superior academic outcomes, highlighting the direct impact of self-regulation skills (Moffitt et al., 2011). Non-cognitive skills, such as self-discipline, perseverance, motivation, and self-regulation, directly influence academic achievement by enhancing goal-setting, time management, and the ability to overcome challenges (Duckworth et al., 2007; Duckworth and Yeager, 2015). Social and emotional skills, encompassing communication, teamwork, empathy, and conflict resolution, also contribute directly to academic success, fostering positive learning environments and relationships with peers and teachers (Durlak et al., 2011; Farrington et al., 2012). In STEM fields, collaboration and communication skills significantly and immediately influence academic achievement (Raver and Knitzer, 2002; Pellegrino and Hilton, 2012).

The concept of grit, characterized by enduring determination and unwavering commitment to long-term goals, proves to be a more robust and immediate predictor of academic performance than IQ scores (Duckworth and Seligman, 2005, 2007; He et al., 2021). Students with a resilient mindset and steadfast work ethic exhibit a greater likelihood of overcoming challenges and setbacks, maintaining focus on academic goals. Interventions promoting a growth mindset have shown significant improvements in academic performance, emphasizing the positive and direct impact of nurturing this mindset (Paunesku et al., 2015). Attributes like resilience, perseverance, and grit are instrumental in overcoming failure, staying motivated, and fostering a growth mindset, all crucial factors that directly contribute to academic success (Duckworth et al., 2007; Duckworth and Yeager, 2015). Additionally, the belief in mindset – that abilities can be developed through hard work and effort – is a strong predictor of academic achievement (Dweck et al., 2014).

While direct effects of non-cognitive skills are well-documented, their indirect effects on academic achievement are less explored. Motivation serves as a crucial mediating factor through which non-cognitive skills can indirectly influence academic success in STEM (Schunk et al., 2010; Stankov and Lee, 2014). Students with higher levels of self-efficacy and intrinsic motivation are more likely to set challenging goals, exert effort, and persist in the face of difficulties, leading to enhanced academic achievement in STEM (Watt and Richardson, 2007). Interest in the subjects has been shown to positively relate to achievement in science subjects, emphasizing the indirect impact of non-cognitive skills on academic outcomes (Hidi and Renninger, 2006). Additionally, non-cognitive skills can indirectly affect academic achievement in STEM through their influence on students' perception of their learning environments and experiences (Yusuf, 2011; Van der Kleij, 2019).

To wrap up, non-cognitive skills have both direct and indirect effects on academic achievement, making them crucial for success in STEM and other educational fields. Understanding these effects can help educators and policymakers create interventions that nurture these skills, leading to improved educational outcomes and students' holistic development.

1.3 The research question and hypothesis

The reviewed literature reveals a recognition of the significance of non-cognitive skills in enhancing academic performance; however, research focusing specifically on their impact in the field of STEM education is limited. Previous studies have predominantly concentrated on the direct effects of non-cognitive skills on academic achievement, with the identification of indirect effects being largely serendipitous. Consequently, there is currently no established and comprehensive approach for concurrently measuring both the direct and indirect effects of non-cognitive skills. Moreover, the investigation of non-cognitive skills in the specific context of STEM education in Kazakhstan is notably understudied. Given these gaps in the existing literature, the primary objective of this study is to systematically examine and quantify the direct and indirect influence of non-cognitive skills on the academic achievement of students within the unique context of STEM secondary education in Kazakhstan. This research aims to contribute to the ongoing dialogue on non-cognitive skills and academic achievement by empirically testing hypotheses and employing various analytical methods to explore the multifaceted interactions within the proposed conceptual framework.

Building on this knowledge, the present study seeks to address the following research question: To what extent do non-cognitive skills influence academic achievement in four STEM subjects among students in secondary education? Drawing from the insights gained from previous research and theoretical frameworks, we formulate the following hypothesis: Non-cognitive skills have a positive effect, both direct and indirect, on academic achievement in STEM subjects. By framing the research with this question and hypothesis, the study aims to delve deeper into the relationship between non-cognitive skills and academic achievement in STEM secondary education, contributing to the body of knowledge and providing actionable insights for educators and policymakers.

2 Methods

2.1 Conceptual framework

Recognizing the significance of non-cognitive skills in shaping students' holistic development and success, educators and policymakers have been increasingly incorporating programs and strategies to nurture these skills alongside traditional academic instruction (Durlak et al., 2011; Jones et al., 2017, 2019). Several frameworks have been developed to focus on non-cognitive skills providing essential tools for understanding and fostering these skills in secondary education.

The "Behavioral and Emotional Skills for Success Index" (BESSI) is a comprehensive framework designed to assess non-cognitive skills in students. It encompasses key components like self-management, social awareness, and responsible decision-making (Soto and Tackett, 2015). BESSI offers teachers a structured approach to cultivate these skills, facilitating supportive learning environments. The "Collaborative for Academic, Social, and Emotional Learning" (CASEL) aims to promote social and emotional competence among students. CASEL provides guidelines, practices, and resources to support the integration of SEL in schools and districts (Shriver, 2022). The "Ecological Approaches to Social Emotional Learning" (EASEL) adopts an ecological perspective, emphasizing the influence of diverse settings on social–emotional development. It recognizes the critical role of relationships, cultural responsiveness, and the integration of social–emotional learning across school, home, and community settings (Jones and Doolittle, 2017).

Kazakhstan demonstrates a strong commitment to cultivating innovation by actively advancing the development of STEM secondary education. This strategic initiative underscores the nation's recognition of the pivotal role that STEM education plays in fostering a culture of innovation. By establishing and enhancing STEM secondary schools, Kazakhstan aims to provide a specialized educational environment that nurtures critical thinking, creativity, and problem-solving skills among its students. This forward-looking approach is aligned with the broader goal of equipping the workforce with the knowledge and capabilities necessary to contribute significantly to technological advancements, scientific discoveries, and innovative solutions. Kazakhstan's eagerness to invest in STEM secondary education reflects its proactive stance in preparing the next generation of innovators, positioning the country to thrive in a rapidly evolving global landscape.

Non-cognitive skills hold paramount significance in Kazakhstan's national STEM schools, reflecting a comprehensive approach to education. These skills are cherished for their role in fostering holistic student development, emphasizing attributes like teamwork, adaptability, and effective communication. Recognizing the innovation-driven nature of STEM fields, the value placed on non-cognitive skills ensures that students cultivate critical thinking, creativity, and problem-solving abilities, preparing them for real-world applications. The interdisciplinary nature of STEM projects necessitates strong collaboration, making non-cognitive skills indispensable for students navigating diverse domains within the STEM landscape. Beyond technical expertise, these skills contribute to career readiness, bolstering students' global competitiveness in an interconnected world. Moreover, the emphasis on non-cognitive skills aligns with the goal of creating a culturally sensitive and inclusive learning environment. In essence, Kazakhstan's commitment to nurturing non-cognitive skills underscores their pivotal role in producing well-rounded, adaptable, and globally competitive graduates equipped to thrive in the dynamic realm of STEM education and professions.

In Kazakhstan, educators and policymakers have recently recognized the importance of non-cognitive skills. They aim to integrate these skills into educational frameworks to better prepare students for academic success and lifelong learning. Aligning with the global trend, this particular aspect is more extensively studied at the higher education level in Kazakhstan (e.g., Sultanova et al., 2017, 2018). While research has explored teaching and learning within secondary STEM education (e.g., Yessingeldinov et al., 2022, 2023), there remains a gap in understanding the development of non-cognitive skills among students. To address this gap, a group of educators from the national STEM schools has developed a theoretical framework that encompasses 26 non-cognitive skills organized across four domains. The selection of these skills was informed by a review of prior research and an analysis of best practices sourced from platforms such as BESSI (Soto and Tackett, 2015), CASEL (Shriver, 2022), and EASEL lab (Jones and Doolittle, 2017). Justification for the inclusion of these specific skills and their allocation among domains is not within the scope of this research, as the study adopts an established framework designed for the national STEM schools.

As part of this broader initiative, the present study seeks to examine both the direct and indirect impact of non-cognitive skills on the academic achievement of students in STEM subjects, specifically identifying non-cognitive skills that have immediate effects on academic performance and act as mediators between non-cognitive skills and academic performance (Farrington et al., 2012; Wanzer et al., 2019). The study focused on students from STEM secondary schools, as these schools are becoming increasingly popular, also in transition economies, and where students tend to rely heavily on their cognitive skills (Brophy et al., 2008). By examining the interplay between non-cognitive skills and achievement outcomes, this research seeks to contribute to the understanding of the multifaceted factors influencing student success in STEM education. To measure the impact of non-cognitive skills, an exploratory research design was adopted, allowing for a comprehensive investigation of the relationships between the assessed non-cognitive skills and students' academic achievement. This design facilitated an open-ended and flexible approach to data collection and analysis, enabling the identification of both expected and unexpected patterns or associations.

After formulating the theoretical framework for non-cognitive skills and designing surveys to assess their influence on academic achievement, researchers initiated a pilot study at a prominent STEM secondary school. This institution, part of the nationally supported elite STEM schools, accommodates middle school students from Grade 7 to Grade 10 and high school students from Grade 11 to Grade 12. With a rich history and the largest student and teacher population among STEM schools, it provided a robust testing ground. Both students and teachers were briefed on the study's objectives, aiming to uncover the impact of non-cognitive skills on STEM academic achievement. While these skills were integrated into both STEM (Mathematics, Physics, etc.) and non-STEM (Languages, History, etc.) subjects to some extent, teachers had not received specialized professional development on non-cognitive skills.

In this study, the key variables are teachers' assessment and students' self-assessment of non-cognitive skills as well academic achievement of students. The independent variables encompass the assessment results of 26 skills, categorized into four domains (Table 1): Domain 1 "Academic Behaviors" (11 skills), Domain 2 "Emotional Skills" (5 skills), Domain 3 "Social Skills" (6 skills), and Domain 4 "Identity" (4 skills). The dependent variable is academic achievement, which encompasses performance in four STEM subjects, i.e., Mathematics, Computer Science, Physics, and Chemistry. Academic achievement is measured using the students' grades in internal assessment conducted by the teacher and external assessments conducted by external examiners in each subject. Only non-cognitive skills having a positive effect on academic achievement were taken into consideration to provide tailored recommendations for teachers of each subject.

2.2 Participants and data collection

The study involved 395 students from a single STEM school in Kazakhstan spanning grades 8 through 12, with an age range of 13–18 years old. Participants were selected using a stratified random

TABLE 1 The framework of non-cognitive skills for STEM schools in Kazakhstan.

#	Description of Skills
Domain 1 "Academic Behaviors"	
1	Decision-making skill (decis): make well-reasoned decisions
2	Detail management (detai): do careful and thorough work
3	Organizational skill (organ): organize personal spaces and objects
4	Task management (task): work persistently to complete task and achieve goals
5	Time management (time): use time effective while accomplishing goals
6	Capacity for consistency (consis): reliably perform routine tasks
7	Goal regulation (goal): set clear and ambitious personal task
8	Information processing skill (infor): process and apply new information
9	Creative skill (create): generate new ideas
10	Abstract thinking skill (abstr): engage with abstract ideas
11	Capacity for independence (indep): think, work, and make decisions by oneself
Domain 2 "Emotional Skills"	
12	Expressive skill (expre): communicate one's thoughts and feelings to other people
13	Capacity for optimism (optim): maintain a positive attitude in difficult circumstances
14	Energy regulation (energy): channel energy in a productive way
15	Impulse regulation (impul): intentionally resist impulses
16	Self-awareness (self): ability to recognize and understand one's own thoughts, emotions, strengths, weaknesses, and values
Domain 3 "Social Skills"	
17	Leadership skill (leade): assert one's views and speak in a group
18	Social awareness (socia): understanding and empathizing with others' perspectives, emotions, and social dynamics for effective communication
19	Teamwork skill (team): work with others to achieve shared goals
20	Adaptability (adapt): try new things and adapt to change
21	Responsibility management (respo): fulfill promises and commitments
22	Rule-following skill (rule): follow instructions, rules, and norms
Domain 4 "Identity"	
23	Grit (grit): combination of perseverance, resilience, and passion for long-term goals
24	Growth mindset (growth): embracing a belief in personal development and the capacity to grow, leading to resilience, learning, and achievement
25	Learn how to learn (learn): ability to effectively acquire knowledge and develop learning strategies for continuous personal growth and success
26	Ethical competence (ethic): behave ethically, even in difficult circumstances

sampling technique to ensure representation across grade levels and STEM subject areas. The sample was composed of 124 students in grade 8 (31.4%), 63 students in grade 9 (15.9%), 131 students in grade 10 (33.2%), 33 students in grade 11 (8.4%), and 44 students in grade 12 (11.1%). Almost two thirds of students were male (245 students or 62%). The participants were enrolled in the same program and had completed identical assessment tasks that were relevant to their respective grade levels. This research adhered to ethical guidelines for research involving human participants. Informed consent was obtained from all participants, and data collection procedures ensured anonymity and confidentiality.

All measures except for grades were collected during November 2022. At the end of the first half of 2022–2023 academic year in December 2022, academic achievement of students was obtained from school records. Academic achievement was measured by the grades of internal and external assessments. The exams covered four STEM subjects, i.e., Mathematics, Computer Science, Physics, and Chemistry. The 26 non-cognitive skills of students were assessed by 109 teachers using a 9-point Likert scale (1 is "lowest, worst" and 9 is "highest, best") and students using a 5-point Likert scale (1 is "lowest, worst" and 5 is "highest, best"). While students answered 180 questions to assess their own skills, i.e., 6 to 18 questions per skill, teachers answered 26 questions to assess the skills of each student, i.e., one question per skill. The 6 items were measured on reversed 5-point Likert scales (1 is "highest, best" and 5 is "lowest, worst") and then recoded to have an expected positive relationship with grades.

2.3 Procedures and data analysis

In this study, the analysis of survey data was conducted in three steps reflecting the perspective of Van der Kleij (2019). First, correlational analyses were performed to investigate the association between achievement levels in each of the four STEM subjects and 26 skills.

Secondly, linear regression analyses, which is a common method used in educational research (He et al., 2021; Boman, 2023), were conducted for each of the four STEM subjects. Thirdly, path models were developed and analyzed to examine the joint association between non-cognitive skills of students and their academic performance. Path analysis is a specialized form of structural equation modeling that is increasingly being utilized in educational research (e.g., Tibken et al., 2022). This method is applied to determine the magnitude and strength of effects within a hypothesized causal system (Stage et al., 2004; Lleras, 2005). Maximum likelihood estimation was used to calculate the parameters in a path analysis model (Schumacker and Lomax, 2010).

For each subject, the initial path analysis was performed on the skill that was most strongly correlated with academic achievement. Additional skills were then included until the following goodness-of-fit statistics were supported (Hu and Bentler, 1999): chi-square, root mean square error of approximation (RMSEA), and comparative fit index (CFI). A non-significant Chi-square indicates that there is no difference between the hypothesized and observed patterns of relationships. RMSEA is a measure of absolute fit that adjusts for the complexity of the hypothesized model and indicates a better fit with values of 0.06 or less. CFI is an incremental fit index that compares the hypothesized model to a null model in which all variables are uncorrelated and shows a good fit with values of 0.95 or greater. Besides, the Tucker-Lewis index (TLI) was examined as recommended by Hair (2009). The TLI is similar to the CFI but gives more importance to parsimony. A TLI value of 0.90 or higher is usually required for good fit.

The skills were added to the path analysis model based on both the results of the regression analysis and the modification indices. Modification indices were used as a guide to identify areas of the model that could be improved, while also ensuring that any added relationships were theoretically justified (Hair et al., 2018). Modification indices with values of approximately 4.0 or higher were used as a criterion to guide the decision of whether to include or exclude specific paths, indicating that these paths have the potential to significantly improve the model fit if they are estimated. Consequently, the non-cognitive skills were divided into two groups with direct and indirect effects on academic achievement.

In path analysis, indirect effects refer to the effects of an independent variable on a dependent variable that are transmitted through one or more intervening variables, known as mediator variables (Lleras, 2005). To calculate indirect effects in path analysis, one typically uses a product of coefficients method (Loehlin and Beaujean, 2016). This involves multiplying the path coefficients (i.e., regression coefficients or structural coefficients) of the causal chain connecting the independent variable to the mediator variable and the mediator variable to the dependent variable (Lleras, 2005). The resulting product represents the magnitude and direction of the indirect effect of the independent variable on the dependent variable through the mediator variable (Loehlin and Beaujean, 2016).

The statistical analysis and modeling for regression and path analysis were performed using the R programming language. The "lm" function from the base R package was used for regression analysis and the "lavaan" package in R was employed for path analysis. These packages offered efficient functionalities for estimating regression coefficients, evaluating model fit, and exploring direct and indirect effects within the analytical framework, ensuring robust and accurate results (Rosseel, 2012).

3 Results

3.1 Descriptive statistics

The descriptive statistics of academic achievement in STEM subjects are presented in Table 2. On the tasks of internal assessment, the students performed relatively well with mean scores ranging from 71.7 (SD = 14.6) for Mathematics to 87.1 (SD = 8.1) for Computer Science. On the tasks of external assessment, however, they performed relatively worse with mean scores ranging from 39.3 (SD = 17.6) for Mathematics to 56.3 (SD = 17.9) for Computer Science.

The descriptive statistics for the results of teachers' assessments and students' self-assessment of non-cognitive skills are presented in Table 3. The students assessed their own non-cognitive skills relatively low, with mean scores ranging from 3.3 (SD = 0.7) for Domain 2 "Emotional Skills" to 3.7 (SD = 0.5) for Domain 4 "Identity." The teachers assessed the non-cognitive skills of students relatively high, with mean scores ranging from 7.5 for Domain 1 "Academic Behaviors" (SD = 1.2) and Domain 3 "Social Skills" (SD = 1.1) to 7.7 for Domain 2 "Emotional Skills" (SD = 1.0) and Domain 4 "Identity" (SD = 1.1). In contrast to teachers, students assessed low their "Emotional skills," including among other skills "capacity for optimism" and "impulse regulation." Both teachers and students assessed high the skills of Domain 4 "Identity", including among other skills "grit" and "growth mindset." To assess the reliability of the responses, Cronbach's alpha coefficients were calculated. The Cronbach's alpha coefficient for teachers and students was 0.932 and 0.982 respectively, indicating a high level of internal consistency in both groups.

The correlations between students' self-assessment of non-cognitive skills and internal assessment (Domain 1–0.08, Domain 2–0.04, Domain 3–0.14, Domain 4–0.10) as well as external assessment (Domain 1–0.05, Domain 2–0.03, Domain 3–0.10, Domain 4–0.05) are weak. The correlation of students' self-assessment

TABLE 2 Descriptive statistics – internal and external assessment of academic achievement.

	Mathematics		Computer Science		Physics		Chemistry	
	Internal	External	Internal	External	Internal	External	Internal	External
Mean	71.1	39.3	87.1	56.3	79.2	53.8	73.6	55.7
SD	14.6	17.6	8.1	17.9	11.4	15.9	13.1	15.3
Min	34.8	0.0	56.7	0.0	39.5	5.0	39.8	5.0
Max	100.0	94.3	100.0	90.0	99.1	95.0	98.8	90.0

TABLE 3 Descriptive statistics – teachers' and students' assessment of non-cognitive skills.

	Domain 1		Domain 2		Domain 3		Domain 4	
	Teachers	Students	Teachers	Students	Teachers	Students	Teachers	Students
Mean	7.5	3.6	7.7	3.3	7.5	3.6	7.7	3.7
SD	1.2	0.6	1.0	0.7	1.1	0.6	1.1	0.5
Min	3.0	1.9	3.5	1.0	3.3	1.6	2.5	2.3
Max	9.0	5.0	9.0	4.8	9.0	4.8	9.0	5.0

with internal assessment is slightly stronger (0.04–0.14) than external assessment (0.03–0.10). The correlation between internal assessment and teachers' assessment of students' non-cognitive skills is considerably higher (Domain 1–0.41, Domain 2–0.45, Domain 3–0.44, Domain 4–0.46) than by students' self-assessment of non-cognitive skills (0.04–0.14). The correlation between external assessment and teachers' assessment of students' non-cognitive skills is notably higher (Domain 1–0.20, Domain 2–0.21, Domain 3–0.24, Domain 4–0.23) than by students' self-assessment of non-cognitive skills (0.03–0.10). The correlation between internal assessment and teachers' assessment of students' non-cognitive skills is considerably higher (0.41–0.46) than the correlation with external assessment (0.20–0.24). Overall, the correlation between students' self-assessment and teachers' assessment of students' non-cognitive skills is weak (Domain 1–0.08, Domain 2–0.06, Domain 3–0.09, Domain 4–0.14).

To mitigate the subjectivity that is inevitably present in any assessment, composite scores were generated for both dependent and independent variables. The composite score, combining students' self-assessment and teachers' assessments, addresses subjectivity in evaluating non-cognitive skills. Recognizing divergent self-perceptions and external observations, the integration aims for a comprehensive and balanced representation. Merging introspective insights with expert perspectives mitigates biases and enhances reliability. This approach leverages unique viewpoints, creating a robust metric that accurately depicts students' overall non-cognitive abilities in STEM. The rationale lies in capturing a holistic understanding, acknowledging the value each perspective brings to a more nuanced assessment.

Composite scores are employed to represent small sets of data points that are conceptually and statistically interrelated (Song et al., 2013). Especially in structural equation models, using composites resulted in improved overall model fit as compared to treating all items as individual indicators (Landis et al., 2000) and even as common factors (Hair and Sarstedt, 2019). To calculate a composite score, (a) the data were scaled to put all the values on a Standard Normal Distribution ranging from 1 to −1; (b) a composite score column was created by summing the values across the columns; and (c) the composite score column was scaled with the Min-Max Scale for eliminating negative values. The composite score for each non-cognitive skill was derived by merging the self-assessment of students with the assessment of teachers. Similarly, the composite score for academic achievement in each subject was computed by combining the grades for both internal and external assessments in Mathematics, Computer Science, Physics, and Chemistry. Tables 4–15 present the results of correlational, regression and path analysis conducted using the composite scores.

3.2 Outcomes of correlational analysis

Correlational analysis allowed for the identification of potential associations between specific non-cognitive skills and academic success. To examine the bivariate relationships between non-cognitive skills and academic achievement in each STEM subject, Pearson correlation coefficients were calculated. The correlational analysis revealed several statistically significant relationships between non-cognitive skills and academic achievement in four STEM subjects (Table 4).

Students with higher scores for "information-processing skill" ($r = 0.373$, $p < 0.001$), "rule-following skill" ($r = 0.365$, $p < 0.001$), "decision-making skill" ($r = 0.341$, $p < 0.001$) and "responsibility management" ($r = 0.341$, $p < 0.001$) tended to achieve higher grades in Mathematics. Students with higher scores for "responsibility management" ($r = 0.302$, $p < 0.001$), "information processing skill" ($r = 0.293$, $p < 0.001$) and "growth mindset" ($r = 0.281$, $p < 0.001$) achieved higher grades in Computer Science. Students with higher scores for "decision-making skill" ($r = 0.309$, $p < 0.001$), "information processing skill" ($r = 0.293$, $p < 0.001$) and "ethical competence" ($r = 0.292$, $p < 0.001$) achieved higher grades in Physics. Students with higher scores for "growth mindset" ($r = 0.285$, $p < 0.001$), "task management" ($r = 0.282$, $p < 0.001$) and "grit" ($r = 0.265$, $p < 0.001$) achieved higher grades in Chemistry.

The survey responses of students indicated some gender differences in 5 out of 26 skills, i.e., "energy regulation" [$t(393) = -2.825$, $p = 0.005$], "impulse regulation" [$t(393) = -2.165$, $p = 0.031$], "learn how to learn" [$t(393) = 2.950$, $p = 0.003$], "rule-following skill" [$t(393) = 2.293$, $p = 0.022$], and "social awareness" [$t(393) = 2.640$, $p = 0.009$]. Girls had higher scores in "energy regulation" and "impulse regulation" while boys had higher scores in "learn how to learn" "rule-following skill" and "social awareness." Since there were only small gender differences in most non-cognitive skills, the impact of gender was not explored further. This approach has been taken in previous studies when no considerable gender differences were found (e.g., Van der Kleij, 2019).

3.3 Outcomes of regression analysis

Multiple linear regression analysis was conducted for each of the four STEM subjects to identify which non-cognitive skills have a significant impact on academic performance. Only non-cognitive skills that positively affect academic achievement in these subjects were considered referring to the concept of this study. The outcomes of regression analysis are given in Table 5.

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TABLE 4 Correlations between non-cognitive skills and academic achievement.

Skills	Mathematics		Computer Science		Physics		Chemistry	
	Pearson's *r*	*p*	Pearson's *r*	*p*	Pearson's *r*	*p*	Pearson's *r*	*p*
indep	0.288	<0.001	0.262	<0.001	0.178	<0.001	0.194	<0.001
task	0.304	<0.001	0.237	<0.001	0.263	<0.001	0.282	<0.001
abstr	0.300	<0.001	0.258	<0.001	0.234	<0.001	0.170	<0.001
consis	0.291	<0.001	0.235	<0.001	0.260	<0.001	0.221	<0.001
creat	0.267	<0.001	0.268	<0.001	0.250	<0.001	0.189	<0.001
decis	0.341	<0.001	0.276	<0.001	0.309	<0.001	0.245	<0.001
detai	0.325	<0.001	0.255	<0.001	0.280	<0.001	0.234	<0.001
goal	0.302	<0.001	0.277	<0.001	0.265	<0.001	0.221	<0.001
infor	0.373	<0.001	0.293	<0.001	0.293	<0.001	0.237	<0.001
organ	0.241	<0.001	0.214	<0.001	0.231	<0.001	0.197	<0.001
time	0.256	<0.001	0.236	<0.001	0.258	<0.001	0.232	<0.001
expre	0.226	<0.001	0.229	<0.001	0.201	<0.001	0.184	<0.001
optim	0.307	<0.001	0.180	<0.001	0.238	<0.001	0.217	<0.001
energ	0.218	<0.001	0.204	<0.001	0.225	<0.001	0.206	<0.001
impul	0.242	<0.001	0.235	<0.001	0.220	<0.001	0.211	<0.001
self	0.333	<0.001	0.273	<0.001	0.290	<0.001	0.264	<0.001
leade	0.244	<0.001	0.217	<0.001	0.222	<0.001	0.175	<0.001
socia	0.232	<0.001	0.220	<0.001	0.235	<0.001	0.164	0.001
team	0.259	<0.001	0.264	<0.001	0.252	<0.001	0.180	<0.001
adapt	0.283	<0.001	0.249	<0.001	0.216	<0.001	0.223	<0.001
respo	0.341	<0.001	0.302	<0.001	0.271	<0.001	0.262	<0.001
rule	0.365	<0.001	0.266	<0.001	0.290	<0.001	0.260	<0.001
grit	0.303	<0.001	0.156	0.002	0.239	<0.001	0.265	<0.001
growth	0.340	<0.001	0.281	<0.001	0.281	<0.001	0.285	<0.001
learn	0.331	<0.001	0.266	<0.001	0.267	<0.001	0.253	<0.001
ethic	0.319	<0.001	0.206	<0.001	0.292	<0.001	0.246	<0.001

In Mathematics, four skills, i.e., "information processing skill" ($\beta = 0.54$, $p < 0.001$), "capacity for optimism" ($\beta = 0.27$, $p = 0.008$), "rule-following skill" ($\beta = 0.26$, $p = 0.005$), and "growth mindset" ($\beta = 0.20$, $p = 0.043$) showed a significant positive relationship with academic achievement. Another three skills, i.e., "creative skill" "energy regulation" and "adaptability" are significant, but negatively associated with the academic performance in this subject. In Computer Science, only "growth mindset" ($\beta = 0.23$, $p = 0.017$) was positively associated with academic achievement. In Physics, four skills, i.e., "information processing skill" ($\beta = 0.23$, $p = 0.024$), "self-awareness" ($\beta = 0.21$, $p = 0.011$), "decision-making skill" ($\beta = 0.19$, $p = 0.032$), and "growth mindset" ($\beta = 0.19$, $p = 0.018$) showed a significant positive relationship with academic achievement. Another two skills, i.e., "capacity for independence" and "adaptability," did not positively predict the academic performance in this subject. In Chemistry, the only skill positively associated with academic achievement is "growth mindset" ($\beta = 0.19$, $p = 0.042$). One more skill, i.e., "abstract thinking skill," did not positively predict academic performance in this subject.

The regression analysis outcomes revealed that the majority of the 26 non-cognitive skills did not show a significant association with academic performance in the four STEM subjects: Mathematics (19 skills), Computer Science (25 skills), Physics (20 skills), and Chemistry (24 skills). The study employed linear regression analysis to identify non-cognitive skills that directly impact academic performance. To account for potential indirect impacts of other skills, path analytic models were also developed.

3.4 Outcomes of path analysis

In this study, structural equation modeling was used to conduct path analysis, investigating both direct and indirect effects of non-cognitive skills on academic achievement (Loehlin and Beaujean, 2016; Doménech-Betoret et al., 2017). This technique allowed for the examination of the mediating mechanisms through which non-cognitive skills influence academic outcomes (Alhadabi and Karpinski, 2020). The results showed that there were two groups of non-cognitive skills. The first group had a direct effect on academic achievement, indicating that these skills were straight related to academic success. The second group had an indirect effect on academic achievement, which means that the skills in this group influenced academic success mediated by the skills in the first group.

TABLE 5 Outcomes of regression analysis.

Domains/Skills		Mathematics		Computer Science		Physics		Chemistry	
		β	p	β	p	β	p	β	p
Domain 1 "Academic Behaviors"									
1	decis					0.19	0.032		
2	detai								
3	organ								
4	task								
5	time								
6	consis								
7	goal								
8	infor	0.54	<0.001			0.23	0.024		
9	creat	−0.31	0.016						
10	abstr							−0.22	0.046
11	indep					−0.29	<0.001		
Domain 2 "Emotional Skills"									
12	expre								
13	optim	0.27	0.008						
14	energ	−0.28	0.012						
15	impul								
16	self					0.21	0.011		
Domain 3 "Social Skills"									
17	leade								
18	socia								
19	team								
20	adapt	−0.23	0.043			−0.20	0.038		
21	respo								
22	rule	0.26	0.005						
Domain 4 "Identity"									
23	grit								
24	growth	0.20	0.043	0.23	0.017	0.19	0.018	0.19	0.042
25	learn								
26	ethic								

TABLE 6 The goodness-of-fit tests for initial and final path models.

	Initial model				Final model			
	Chi-square	RMSEA	CFI	TLI	Chi-square	RMSEA	CFI	TLI
Mathematics	$p<0.001$	0.070	0.949	0.896	$p<0.001$	0.054	0.991	0.950
Computer Science	$p=0.209$	0.023	0.993	0.985	$p=0.379$	0.013	0.999	0.996
Physics	$p=0.005$	0.047	0.968	0.934	$p=0.073$	0.034	0.995	0.975
Chemistry	$p=0.055$	0.035	0.970	0.939	$p=0.310$	0.017	0.998	0.992

Table 6 provides an overview of the goodness-of-fit statistics for both the initial and the final models calculated for each subject.

In Mathematics, the initial path analysis was conducted for "information processing skill" (Table 4), which was found to have the highest correlation with academic achievement (the goodness-of-fit tests: $p<0.001$, RMSEA = 0.070, CFI = 0.949, TLI = 0.896). After examining the outcomes of regression analysis and the modification indices, four additional skills were included: "rule-following skill," "growth mindset," "energy regulation," and "abstract thinking skill." Although the Chi-square test was significant ($p<0.001$), the other three goodness-of-fit tests showed that the model had a good fit (RMSEA = 0.054, CFI = 0.991, TLI = 0.950). In complex models, a significant chi-square value by itself may not indicate a poor fit if other fit measures indicate that the model has a good fit. Furthermore, the results showed that "energy regulation" and "abstract thinking skill" had a significant, but negative impact on academic achievement in Mathematics. As the study aimed to identify non-cognitive skills that positively impacted academic achievement, these skills were excluded from further analysis.

In Computer Science, the initial path analysis was conducted for "responsibility management" (Table 4), which was found to have the highest correlation with academic achievement (the goodness-of-fit tests: $p = 0.209$, RMSEA = 0.023, CFI = 0.993, TLI = 0.985). Based on the modification indices, another skill, namely "learn how to learn," was included in the analysis. The results of the goodness-of-fit tests showed that the Chi-square test of the user model was non-significant ($p = 0.379$), indicating that the hypothesized model fits the observed data well. Additionally, the RMSEA, CFI, and TLI values also suggested a good fit (RMSEA = 0.013, CFI = 0.999, TLI = 0.996).

In Physics, the initial path analysis was conducted for "decision-making skill" (Table 4), which was found to have the highest correlation with academic achievement (the goodness-of-fit tests: $p = 0.005$, RMSEA = 0.047, CFI = 0.968, TLI = 0.934). Referring to the outcomes of regression analysis and the modification indices, three additional skills, namely "self-awareness," "capacity for independence" and "growth mindset," were included in the model. The Chi-square test of the user model was not significant ($p = 0.073$), and the three other goodness-of-fit tests showed a good fit (RMSEA = 0.034, CFI = 0.995, TLI = 0.975). The results revealed that "capacity for independence" had a negative impact on academic achievement in Physics, and it was therefore excluded from further analysis.

In Chemistry, the initial path analysis was conducted for "growth mindset" (Table 4), which was found to have the highest correlation with academic achievement (the goodness-of-fit tests: $p = 0.055$, RMSEA = 0.035, CFI = 0.970, TLI = 0.939). Referring to the outcomes of regression analysis and the modification indices, one more skill, namely "task management", was included in the model. The user model's Chi-square test was non-significant ($p = 0.310$), and the three other goodness-of-fit tests also demonstrated a good fit (RMSEA = 0.017, CFI = 0.998, TLI = 0.992).

TABLE 7 Direct effects – Mathematics.

Dep	Pred	Estimate	SE	95% CI		β	z	p
				Lower	Upper			
math	infor	0.38	0.10	0.18	0.57	0.40	3.73	<0.001
	rule	0.24	0.07	0.11	0.38	0.24	3.59	<0.001
	growth	0.31	0.08	0.16	0.46	0.23	3.99	<0.001
	energ	−0.17	0.07	−0.30	−0.05	−0.18	−2.66	0.008
	abstr	−0.24	0.10	−0.43	−0.04	−0.24	−2.38	0.017
infor	indep	0.10	0.04	0.02	0.18	0.09	2.46	0.014
	decis	0.12	0.05	0.03	0.21	0.10	2.52	0.012
	detai	0.14	0.05	0.05	0.24	0.12	3.02	0.003
	adapt	0.24	0.05	0.15	0.34	0.20	4.90	<0.001
	create	0.43	0.05	0.33	0.52	0.36	8.78	<0.001
rule	indep	−0.10	0.05	−0.20	−0.01	−0.10	−2.10	0.036
	consis	0.16	0.06	0.03	0.28	0.15	2.46	0.014
	decis	0.18	0.06	0.07	0.29	0.18	3.20	0.001
	detai	0.17	0.06	0.06	0.28	0.16	2.95	0.003
	goal	−0.13	0.06	−0.25	−0.01	−0.13	−2.06	0.039
	organ	0.11	0.05	0.02	0.20	0.12	2.43	0.015
	time	0.16	0.06	0.05	0.28	0.15	2.71	0.007
	leade	−0.20	0.06	−0.32	−0.08	−0.18	−3.25	0.001
	respo	0.16	0.06	0.04	0.27	0.16	2.57	0.010
	ethic	0.28	0.05	0.17	0.38	0.26	5.16	<0.001
growth	indep	0.12	0.05	0.03	0.22	0.16	2.59	0.010
	self	0.16	0.05	0.06	0.26	0.20	3.10	0.002
	learn	0.21	0.05	0.11	0.31	0.26	3.96	<0.001
	grit	0.37	0.04	0.29	0.45	0.44	8.81	<0.001
	ethic	−0.15	0.05	−0.26	−0.05	−0.19	−2.97	0.003

3.5 Direct effects of non-cognitive skills

The direct effects of non-cognitive skills on academic performance are given in Tables 7–10. On academic achievement in Mathematics, "information processing skill" ($\beta = 0.40$, $p < 0.001$), "rule-following skill" ($\beta = 0.24$, $p < 0.001$) and "growth mindset" ($\beta = 0.23$, $p < 0.001$) have a direct positive impact (Table 7). Both "responsibility management" ($\beta = 0.22$, $p < 0.001$) and "learn how to learn" ($\beta = 0.13$, $p = 0.026$) have a direct positive impact on academic achievement in Computer Science (Table 8). Three skills, i.e., "decision-making skill" ($\beta = 0.26$, $p < 0.001$), "self-awareness" ($\beta = 0.24$, $p = 0.001$), and "growth mindset" ($\beta = 0.18$, $p = 0.005$), have a direct positive effect on academic performance in Physics (Table 9). On academic achievement in Chemistry, "growth mindset" ($\beta = 0.19$, $p < 0.001$) and "task management" ($\beta = 0.18$, $p = 0.001$) have a direct positive effect (Table 10).

In three subjects, i.e., Mathematics, Physics, and Chemistry, "growth mindset" had a strong direct positive impact on academic achievement, which is consistent with findings from recent studies (Paunesku et al., 2015). Besides, "information processing skill" directly and positively affected academic performance in Mathematics, which is also supported by previous research (Peng et al., 2016). Recent studies have identified "decision-making skill," "task management," and "rule-following skill" as crucial for the academic performance of high school students (Duckworth and Seligman, 2005). The majority of non-cognitive skills with direct effects are found within Domain 1 "Academic Behaviors" with the other three domains of the Framework (Table 1) each featuring one or two skills. Some previous studies have found that "task management," "information processing skill," and "decision-making skill," which are the most "cognitive" among the non-cognitive skills (Farrington et al., 2012), positively affect grades in STEM subjects (Rimm-Kaufman and Hulleman, 2015). That "self-awareness" has a direct impact on academic achievement in Physics is in line with previous studies confirmed the effects of self-beliefs constructs on individual-level academic success in Mathematics (Lee and Stankov, 2018).

There were no significant covariances between non-cognitive skills with direct effects on Mathematics and Chemistry. In Computer Science, the covariance between "responsibility management" and "learn how to learn" was significant but negligible. In Physics, the covariance between "decision-making skill," "self-awareness," and "growth mindset" was significant but negligible as well. It means that these non-cognitive skills did not have a significant impact on each other and did not act as mediators for each other's effects on academic achievement. Instead, they had a direct effect on academic achievement without being influenced by other skills in the model.

3.6 Indirect effects of non-cognitive skills

The indirect effects of non-cognitive skills on academic performance in Mathematics are given in Table 11. In this subject, "decision-making skill," "detail management," "organizational skill," "time management," "capacity for consistency," "creative skill" and "capacity for independence" (Domain 1) as well as "self-awareness" (Domain 2), "adaptability," "responsibility management" (Domain 3), "grit," "learn how to learn," and "ethical competence" (Domain 4) have an indirect positive impact on academic achievement. Especially "creative skill" mediated by "information processing skill" ($\beta = 0.15$, $p < 0.001$) and "grit" mediated by

TABLE 8 Parameter estimates – Computer Science.

Dep	Pred	Estimate	SE	95% CI Lower	95% CI Upper	β	z	p
cs	respo	0.21	0.06	0.10	0.32	0.22	3.76	<0.001
	learn	0.13	0.06	0.02	0.25	0.13	2.23	0.026
respo	task	0.11	0.06	0.00	0.22	0.11	1.97	0.049
	decis	0.11	0.05	0.02	0.21	0.11	2.44	0.015
	goal	0.21	0.05	0.11	0.31	0.22	4.24	<0.001
	time	0.11	0.05	0.00	0.21	0.10	2.14	0.032
	energ	−0.12	0.05	−0.21	−0.02	−0.12	−2.41	0.016
	team	0.10	0.04	0.01	0.18	0.11	2.27	0.023
	adapt	0.34	0.05	0.25	0.44	0.32	7.24	<0.001
	rule	0.09	0.04	0.01	0.18	0.09	2.28	0.023
	ethic	0.14	0.05	0.05	0.22	0.13	3.02	0.003
learn	indep	0.26	0.04	0.17	0.34	0.26	5.80	<0.001
	task	0.13	0.06	0.00	0.25	0.13	2.04	0.041
	adapt	−0.15	0.05	−0.25	−0.05	−0.15	−2.85	0.004
	grit	−0.11	0.04	−0.19	−0.03	−0.11	−2.59	0.010
	ethic	0.12	0.05	0.03	0.22	0.12	2.46	0.014
	growth	0.19	0.05	0.10	0.28	0.16	4.22	<0.001
	self	0.40	0.04	0.32	0.49	0.41	9.22	<0.001

"growth mindset" ($\beta = 0.10$, $p < 0.001$) had the strongest indirect positive impact on academic achievement in Mathematics.

The indirect effects of non-cognitive skills on academic performance in Computer Science are given in Table 12. In this subject, "decision-making skill," "goal regulation" and "capacity for independence" (Domain 1) as well as "self-awareness" (Domain 2), "adaptability" (Domain 3), "growth mindset" and "ethical competence" (Domain 4) have an indirect positive impact on academic achievement. Notably, "adaptability" mediated by "responsibility management" ($\beta = 0.07$, $p < 0.001$) had the strongest indirect positive impact on academic achievement in Computer Science.

The indirect effects of non-cognitive skills on academic performance in Physics are given in Table 13. In this subject, "organizational skill," "information processing skill" and "abstract thinking skill" (Domain 1) as well as "leadership skill" (Domain 3) have an indirect positive impact on academic achievement. Especially "information processing skill" mediated by "self-awareness" ($\beta = 0.14$, $p = 0.002$) had the strongest indirect positive impact on academic achievement in Physics.

The indirect effects of non-cognitive skills on academic performance in Chemistry are given in Table 14. In this subject, "time management," "capacity for consistency," "goal regulation," "information processing skill" and "capacity for independence" (Domain 1) as well as "self-awareness" (Domain 2) and "leadership skill" (Domain 3) have an indirect positive impact on academic achievement. Notably, "capacity for independence" mediated by "task management" ($\beta = 0.08$, $p = 0.002$) had the strongest indirect positive impact on academic achievement in Chemistry.

The direct and indirect effects of non-cognitive skills on academic achievement in the four STEM subjects are summarized in Table 15. In Mathematics, "learn how to learn" has an indirect positive impact on academic performance, which is in line with the findings of recent research (León et al., 2015). That "self-awareness" has both direct (Physics) and indirect (other three subjects) impact on academic performance, also in line with recent research (Rimfeld et al., 2016). The two most important skills with the strongest effects are "creative skill" and "grit" which have an indirect positive impact on Mathematics. This finding is consistent with recent research (Duckworth et al., 2011; Muenks et al., 2015). The most important non-cognitive skills of Domain 1 with positive effects on academic achievement in the four STEM subjects are "organizational skill," "time management," "capacity for consistency," "goal regulation" and "capacity for independence," while "adaptability" and "ethical competence" are

TABLE 9 Direct effects – Physics.

Dep	Pred	Estimate	SE	95% CI		β	z	p
				Lower	Upper			
phys	decis	0.22	0.05	0.12	0.32	0.26	4.37	<0.001
	self	0.21	0.06	0.08	0.33	0.24	3.23	0.001
	indep	−0.24	0.07	−0.38	−0.11	−0.29	−3.62	<0.001
	growth	0.19	0.07	0.06	0.32	0.18	2.84	0.005
decis	abstr	0.11	0.05	0.01	0.22	0.12	2.18	0.029
	detai	0.21	0.05	0.11	0.31	0.21	4.26	<0.001
	goal	0.23	0.05	0.13	0.34	0.24	4.44	<0.001
	expre	−0.12	0.04	−0.20	−0.04	−0.11	−2.94	0.003
	optim	0.11	0.05	0.02	0.20	0.11	2.38	0.018
	impul	0.20	0.05	0.11	0.30	0.16	4.17	<0.001
	respo	0.13	0.05	0.02	0.23	0.13	2.43	0.015
	energ	−0.12	0.05	−0.22	−0.22	−0.13	−2.31	0.021
	rule	0.12	0.04	0.03	0.20	0.12	2.66	0.008
self	detai	−0.14	0.06	−0.24	−0.03	−0.14	−2.45	0.014
	socia	0.27	0.05	0.18	0.36	0.27	5.83	<0.001
	grit	0.10	0.04	0.02	0.18	0.09	2.32	0.020
	learn	0.58	0.04	0.50	0.66	0.57	14.09	<0.001
indep	abstr	0.18	0.06	0.06	0.30	0.19	2.95	0.003
	impul	0.23	0.06	0.11	0.34	0.18	3.96	<0.001
	learn	0.47	0.04	0.39	0.55	0.45	10.94	<0.001
	ethic	0.13	0.06	0.02	0.24	0.13	2.36	0.018
growth	infor	0.15	0.06	0.02	0.27	0.21	2.29	0.02
	ethic	−0.13	0.05	−0.24	−0.03	−0.17	−2.50	0.012
	grit	0.39	0.04	0.31	0.47	0.46	9.16	<0.001
	learn	0.36	0.04	0.28	0.45	0.44	8.72	<0.001

TABLE 10 Direct effects – Chemistry.

Dep	Pred	Estimate	SE	95% CI		β	z	p
				Lower	Upper			
chem	growth	0.22	0.07	0.09	0.36	0.19	3.34	<0.001
	task	0.17	0.05	0.07	0.28	0.18	3.23	0.001
growth	indep	0.11	0.05	0.01	0.20	0.14	2.21	0.027
	ethic	−0.14	0.05	−0.24	−0.03	−0.17	−2.57	0.010
	self	0.15	0.05	0.05	0.25	0.19	3.01	0.003
	grit	0.37	0.04	0.28	0.45	0.43	8.80	<0.001
	learn	0.22	0.05	0.12	0.32	0.27	4.16	<0.001
task	consis	0.16	0.05	0.07	0.25	0.16	3.49	<0.001
	detai	0.14	0.04	0.05	0.22	0.13	3.19	0.001
	goal	0.18	0.04	0.09	0.26	0.19	3.97	<0.001
	organ	0.07	0.03	0.00	0.14	0.08	2.05	0.040
	time	0.17	0.04	0.09	0.26	0.16	3.91	<0.001
	leade	−0.13	0.05	−0.22	−0.03	−0.12	−2.64	0.008
	socia	−0.13	0.04	−0.20	−0.06	−0.13	−3.63	<0.001
	energ	0.21	0.04	0.13	0.29	0.23	4.87	<0.001
	grit	0.08	0.03	0.02	0.14	0.07	2.52	0.012

TABLE 11 Indirect effects – Mathematics.

Description	Estimate	SE	95% CI		β	z	p
			Lower	Upper			
indep ⇒ infor ⇒ math	0.04	0.02	0.00	0.07	0.04	2.05	0.040
indep ⇒ growth ⇒ math	0.04	0.02	0.00	0.07	0.04	2.17	0.030
consis ⇒ rule ⇒ math	0.04	0.02	0.00	0.08	0.04	2.03	0.043
creat ⇒ infor ⇒ math	0.16	0.05	0.07	0.25	0.15	3.43	<0.001
decis ⇒ infor ⇒ math	0.04	0.02	0.00	0.09	0.04	2.09	0.037
decis ⇒ rule ⇒ math	0.04	0.02	0.00	0.08	0.04	2.39	0.017
detai ⇒ infor ⇒ math	0.05	0.02	0.00	0.01	0.05	2.35	0.019
detai ⇒ rule ⇒ math	0.04	0.02	0.00	0.08	0.04	2.28	0.023
organ ⇒ rule ⇒ math	0.03	0.01	0.00	0.06	0.03	2.01	0.044
time ⇒ rule ⇒ math	0.04	0.02	0.00	0.08	0.04	2.17	0.031
self ⇒ growth ⇒ math	0.05	0.02	0.10	0.09	0.05	2.45	0.014
leade ⇒ rule ⇒ math	−0.05	0.02	−0.09	−0.01	−0.04	−2.41	0.016
respo ⇒ rule ⇒ math	0.04	0.02	0.00	0.07	0.04	2.09	0.037
adapt ⇒ infor ⇒ math	0.09	0.03	0.03	0.15	0.08	2.97	0.003
learn ⇒ growth ⇒ math	0.06	0.02	0.02	0.11	0.06	2.81	0.005
grit ⇒ growth ⇒ math	0.11	0.03	0.05	0.18	0.10	3.63	<0.001
ethic ⇒ rule ⇒ math	0.07	0.02	0.02	0.11	0.06	2.95	0.003
ethic ⇒ growth ⇒ math	−0.05	0.02	−0.87	−0.01	−0.04	−2.38	0.017

those skills of Domains 3 and 4. These findings are in line with recent research (León et al., 2015; Peng et al., 2016).

To wrap it up, the path analysis outcomes revealed that 20 out of 26 skills have a direct and indirect impact on academic achievement in four STEM subjects. The rest of non-cognitive skills, including "expressive skill," "capacity for optimism," "energy regulation," "impulse regulation," "social awareness" and "teamwork skill," had no positive effect on the academic performance of students in Mathematics, Computer Science, Physics and Chemistry. All these non-cognitive skills are social and emotional skills from Domain 2 and Domain 3.

TABLE 12 Indirect effects – Computer Science.

Description	Estimate	SE	95% CI		β	z	p
			Lower	Upper			
indep ⇒ learn ⇒ cs	0.03	0.02	0.00	0.07	0.04	2.08	0.038
decis ⇒ respo ⇒ cs	0.02	0.01	0.00	0.05	0.03	2.05	0.041
goal ⇒ respo ⇒ cs	0.04	0.02	0.01	0.08	0.05	2.81	0.005
energ ⇒ respo ⇒ cs	−0.03	0.01	−0.05	−0.00	−0.03	−2.03	0.042
adapt ⇒ respo ⇒ cs	0.07	0.02	0.03	0.12	0.07	3.34	<0.001
ethic ⇒ respo ⇒ cs	0.03	0.01	0.00	0.05	0.03	2.35	0.019
growth ⇒ learn ⇒ cs	0.03	0.01	0.00	0.05	0.02	1.97	0.049
self ⇒ learn ⇒ cs	0.05	0.03	0.00	0.10	0.05	2.16	0.030

TABLE 13 Indirect effects – Physics.

Description	Estimate	SE	95% CI		*β*	*z*	*p*
			Lower	Upper			
detai ⇒ indep ⇒ phys	0.05	0.02	0.02	0.08	0.06	3.05	0.002
organ ⇒ decis ⇒ phys	0.05	0.02	0.02	0.08	0.06	3.11	0.002
impul ⇒ decis ⇒ phys	−0.03	0.01	−0.05	−0.01	−0.03	−2.44	0.015
leade ⇒ self ⇒ phys	0.02	0.01	0.00	0.05	0.03	2.09	0.037
socia ⇒ indep ⇒ phys	0.05	0.02	0.02	0.07	0.04	3.02	0.003
team ⇒ self ⇒ phys	−0.06	0.02	−0.10	−0.02	−0.05	−2.67	0.008
respo ⇒ indep ⇒ phys	0.06	0.02	0.02	0.09	0.07	2.83	0.005
abstr ⇒ self ⇒ phys	0.03	0.01	0.00	0.06	0.04	2.12	0.034
rule ⇒ indep ⇒ phys	0.07	0.03	0.02	0.13	0.08	2.71	0.007
infor ⇒ self ⇒ phys	0.12	0.04	0.05	0.20	0.14	3.15	0.002
infor ⇒ indep ⇒ both	−0.12	0.03	−0.18	−0.05	−0.13	−3.43	<0.001
rule ⇒ indep ⇒ phys	0.07	0.03	0.02	0.12	0.08	2.70	0.007
infor ⇒ indep ⇒ phys	−0.03	0.02	−0.06	0.00	−0.04	−1.98	0.048
infor ⇒ indep ⇒ phys	−0.04	0.02	−0.08	−0.01	−0.06	−2.28	0.022
infor ⇒ decis ⇒ phys	−0.03	0.01	−0.05	0.00	−0.03	−2.04	0.041
infor ⇒ decis ⇒ phys	0.03	0.01	0.00	0.05	0.03	2.27	0.023

4 Discussion

4.1 Significance of the study

This exploratory study sheds light on the potential direct and indirect impact of non-cognitive skills on academic achievement in four STEM subjects. The findings reveal initial patterns and associations between specific non-cognitive skills and student performance at one STEM school in Kazakhstan, a region where limited research has been conducted on this topic. However, it is important to note that these results are preliminary in nature, and further research is necessary to confirm and generalize these findings. The exploratory nature of this study highlights the complexity of the relationship between non-cognitive skills and academic achievement and calls for more comprehensive investigations in the future.

The findings indicate that out of 26 skills examined, eight had a direct impact on the academic achievement of students in the four STEM subjects, while another 12 had an indirect impact. The rest of six skills had no impact on academic achievement among middle and high school students in Mathematics, Computer Science, Physics, and Chemistry at one STEM school in Kazakhstan. The findings suggest that, although non-cognitive skills are important for academic success, different skills may have different impacts on academic achievement in STEM subjects. This study is the first to explicitly examine the impact of one group of non-cognitive skills on academic achievement in STEM subjects mediated by another group of these skills, illustrated through the case of Kazakhstan.

4.2 Implications for practice

The implications of this study for STEM education practices are profound. They suggest that educators and policymakers should recognize and actively cultivate non-cognitive skills alongside

TABLE 14 Indirect effects – Chemistry.

Description	Estimate	SE	95% CI		β	z	p
			Lower	Upper			
consis ⇒ task ⇒ chem	0.03	0.01	0.01	0.05	0.03	2.37	0.018
goal ⇒ task ⇒ chem	0.02	0.01	0.00	0.04	0.02	2.27	0.023
time ⇒ task ⇒ chem	0.03	0.01	0.01	0.05	0.03	2.51	0.012
leade ⇒ task ⇒ chem	0.03	0.01	0.01	0.05	0.03	2.49	0.013
abstr ⇒ task ⇒ chem	−0.02	0.01	−0.04	0.00	−0.02	−2.04	0.041
rule ⇒ task ⇒ chem	−0.02	0.01	−0.04	0.00	−0.02	−2.42	0.016
infor ⇒ task ⇒ chem	0.01	0.01	0.00	0.03	0.01	1.99	0.047
indep ⇒ task ⇒ chem	0.08	0.03	0.03	0.13	0.08	3.12	0.002
self ⇒ task ⇒ chem	0.05	0.02	0.01	0.09	0.05	2.60	0.009
decis ⇒ task ⇒ chem	−0.03	0.02	−0.06	0.00	−0.03	−2.04	0.042
infor ⇒ task ⇒ chem	0.04	0.01	0.01	0.06	0.04	2.70	0.007
self ⇒ growth ⇒ chem	0.03	0.02	0.00	0.07	0.04	2.23	0.026

cognitive abilities. Incorporating skill development programs that target growth mindset, self-awareness, responsibility management and other identified non-cognitive skills can enhance students' preparedness and aptitude in STEM subjects (Durlak et al., 2011; Pellegrino and Hilton, 2012; Yeager and Dweck, 2012). Furthermore, the subject-specific variations in the identified non-cognitive skills underscore the need for tailored educational approaches. Different STEM subjects demand distinct sets of non-cognitive attributes (Fonteyne et al., 2017). Teachers can adapt teaching methodologies and support mechanisms to align with these subject-specific needs. The practical implications of the finding that non-cognitive skills have both direct and indirect effects on academic achievement are significant for educators, policymakers, and researchers.

Firstly, teachers can use this information to enrich their teaching practices by prioritizing the development of non-cognitive skills in their students. Teachers can identify which specific skills are most relevant to their students and focus on developing these skills in the classroom. According to Rosenzweig and Wigfield (2016), students may respond more effectively to interventions that target specific skills in certain STEM subjects. The authors suggest considering the subject-specific skill levels of students when designing interventions to ensure that they are targeted to areas where students have the most room for improvement.

Secondly, policymakers can use this information to design interventions and programs that promote the development of non-cognitive skills in students. This could include incorporating the development of non-cognitive skills into curriculum and assessment frameworks, providing teacher training on how to develop these skills, and supporting research on effective practices for promoting non-cognitive skills development. It is worth noticing that a targeted improvement of specific non-cognitive skills in each subject can lead to the holistic development of all necessary skills for long-term success (Durlak et al., 2011; Farrington et al., 2012). The ultimate goal should be to contribute to the formation of a well-rounded individual with a harmonious set of skills.

Finally, researchers can utilize this information to conduct further investigations on the complex relationships between non-cognitive skills and academic achievement (Doménech-Betoret et al., 2017). This could entail exploring which non-cognitive skills are highly correlated with academic performance, how non-cognitive skills interact with one another, and how non-cognitive skills development can be effectively facilitated in different settings (Sanchez-Ruiz et al., 2016). Studying the patterns of skill interactions can lead to the creation of universal and user-friendly approaches that can benefit those researchers who may not have the resources to conduct extensive empirical research.

To recap, the practical implications of the finding that non-cognitive skills have both direct and indirect effects on academic achievement are wide-ranging and can inform various educational practices and policies aimed at promoting academic success.

4.3 Implications for research

The present study expands upon existing research by examining the direct and indirect effects of non- cognitive skills on academic achievement in STEM subjects. The findings contribute to the understanding of the complex relationship between non-cognitive skills and academic performance in a specific educational context. Based on the results, several implications for research and its further advancement can be identified.

This paper highlights that previous research has primarily focused on the direct effects of non-cognitive skills on academic achievement across various subjects. By additionally examining the indirect impact of non-cognitive skills specifically in STEM subjects, this study expands the research scope and provides insights into the unique dynamics within the STEM education context. Future research can build upon this approach to further explore the interplay between different non-cognitive skills and their combined effects on student performance in STEM subjects.

The paper investigates the relationship of a comprehensive set of 26 non-cognitive skills with academic performance in Mathematics, Computer Science, Physics, and Chemistry classes. This approach allows for a more nuanced understanding of the specific skills that contribute to student achievement in these STEM subjects. Future research should investigate these specific skills in more detail,

TABLE 15 Direct and indirect effects of non-cognitive skills on academic achievement.

Domains/Skills		Mathematics		Computer Science		Physics		Chemistry	
		Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
Domain 1 "Academic Behaviors"									
1	decis		0.04		0.03	0.26			
2	detai		0.05						
3	organ		0.03				0.06		
4	task							0.18	
5	time		0.04						0.03
6	consis		0.04						0.03
7	goal				0.05				0.02
8	infor	0.40					0.14		0.04
9	creat		0.15						
10	abstr						0.04		
11	indep		0.04		0.04				0.08
Domain 2 "Emotional Skills"									
12	expre								
13	optim								
14	energ								
15	impul								
16	self		0.05		0.05	0.24			0.05
Domain 3 "Social Skills"									
17	leade						0.03		0.03
18	socia								
19	team								
20	adapt		0.08		0.07				
21	respo		0.04	0.22					
22	rule	0.24							
Domain 4 "Identity"									
23	grit		0.10						
24	growth	0.23			0.02	0.18		0.19	
25	learn		0.06	0.13					
26	ethic		0.06		0.03				

examining their individual contributions to academic success and exploring how they can be cultivated and enhanced in educational settings.

Especially, the concept of Pedagogical Content Knowledge developed by Shulman (1986, 1987) aligns with the conclusion that effective teaching requires an understanding of how non-cognitive skills interact with the unique demands of each subject. The diversity in teaching approaches and the emphasis on student-centered instruction in Shulman's work parallel the present study's observation that non-cognitive skills manifest differently in Mathematics, Physics, Computer Science, and Chemistry. The call for specialized knowledge in effective teaching, as advocated by Shulman, supports the conclusion that the impact of non-cognitive skills is subject-specific. Together, these insights underscore the importance of tailored pedagogical approaches and targeted teacher training to optimize the influence of non-cognitive skills on academic achievement across diverse STEM subjects.

By explicitly examining the impact of one group of non-cognitive skills on academic achievement mediated by another group of these skills, this study introduces a novel perspective. It adds to the existing literature by shedding light on the complex interplay and indirect effects that non-cognitive skills may have on students' academic performance in STEM subjects. Future research can expand upon this mediation framework and investigate additional mediating factors or processes that may help explain the relationships observed in the study. This could involve exploring, for instance, the role of motivational factors that may mediate the effects of non-cognitive skills on academic performance in STEM subjects (Watt and Richardson, 2007; Stankov and Lee, 2014). Understanding these mediation effects can inform the development of interventions and

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strategies to promote non-cognitive skill development and enhance students' academic outcomes.

The study collected survey data from teachers and students at one STEM secondary school in Kazakhstan. The implications of this research can extend to similar educational settings in Kazakhstan as well as in Central Asia and potentially inform educational policies and interventions tailored to improving non-cognitive skills and academic achievement in STEM subjects. Future research should replicate the study in different settings to assess the robustness of the results and to explore potential cultural, social, or contextual factors that may influence the relationship between non-cognitive skills and academic achievement in STEM subjects.

The paper employed correlational, regression, and path analyses to explore the relationships between non-cognitive skills and academic performance. This methodological approach provides quantitative evidence and allows for the identification of direct and indirect impacts of non-cognitive skills on academic achievement in STEM subjects. The use of other statistical methods, such as hierarchical modeling, can provide valuable insights into the complex relationships between different non-cognitive skills and academic performance.

The implications of this research highlight the importance of considering both the direct and indirect effects of non-cognitive skills on academic achievement in STEM subjects. It contributes to the existing body of knowledge and provides insights that can inform future research, educational practices, and interventions aimed at enhancing students' non-cognitive skills and academic performance in the STEM domain. By addressing these research implications, future studies can deepen the understanding of the role and significance of non-cognitive skills in promoting academic achievement in STEM subjects and contribute to the development of effective educational strategies and interventions.

In brief, teachers can benefit from the growing understanding of the dynamic relationships, direct and indirect, between non-cognitive factors and academic performance by developing interventions and designing curricula that empower students as learners and enhance their intrinsic motivation, academic and emotional self-efficacy in a myriad of domains, ensuring their optimal academic success (Sanchez-Ruiz et al., 2016).

4.4 Limitations of the study

While every effort was made to ensure the rigor of the study, several limitations should be acknowledged. These limitations should be addressed to provide a comprehensive understanding of the research findings.

Firstly, the study focused on a specific educational context, namely a STEM secondary school in Kazakhstan. The findings may not be directly generalizable to other educational settings or cultural contexts. Factors such as curriculum differences, teaching methodologies, and student demographics in other contexts may influence the relationship between non-cognitive skills and academic achievement in STEM subjects differently. Furthermore, the study specifically focused on the relationship between non-cognitive skills and academic achievement in Mathematics, Computer Science, Physics, and Chemistry classes. While these subjects are important within the STEM domain, the findings may not apply equally to other academic subjects or disciplines.

Secondly, the study collected data from a relatively small sample of 109 teachers and 395 students. While efforts were made to ensure the sample was representative of the target population, the limited sample size may affect the generalizability of the findings. Results obtained from a larger and more diverse sample could provide a more robust and reliable understanding of the relationship between non-cognitive skills and academic achievement in STEM subjects. In addition, the study relied on survey data, which is subject to potential biases and limitations associated with self-report measures. Participants' responses may be influenced by social desirability biases, recall inaccuracies, or subjective interpretations. The use of additional objective measures or multiple sources of data could provide a more comprehensive and reliable assessment of non-cognitive skills and academic achievement.

Thirdly, the study employed a cross-sectional design, collecting data at a single point in time. This design limits the ability to establish causal relationships between non-cognitive skills and academic achievement. Longitudinal studies that track participants over time would be valuable to examine the developmental trajectories of non-cognitive skills and their impact on academic outcomes (Moffitt et al., 2011). Furthermore, the study explored the mediating role of certain non-cognitive skills on the relationship between other non-cognitive skills and academic achievement. However, the mediation analysis is complex, and the observed mediating effects may be influenced by unmeasured variables or other confounding factors not accounted for in the study. Future research could employ other statistical techniques and explore alternative models to better understand the mechanisms and causal pathways involved.

It is important to consider these limitations when interpreting the findings of the study. While they may restrict the generalizability and robustness of the results, they also provide opportunities for future research to address these limitations and further advance the understanding of the complex relationship between non-cognitive skills and academic achievement in STEM subjects.

5 Conclusion

This paper has examined the impact of non-cognitive skills on academic achievement in STEM subjects, through both direct effects and indirect effects mediated by other non-cognitive skills. This study is the first to explicitly examine the impact of one group of non-cognitive skills on academic achievement in STEM subjects mediated by another group of these skills illustrated on the case of Kazakhstan. The identification of specific non-cognitive skills that are closely related to academic achievement in STEM subjects has significant implications for educators and policymakers. By focusing on developing these specific skills, teachers can more effectively support student success in STEM subjects. Additionally, the finding that some non-cognitive skills have indirect effects on academic achievement, mediated by other non-cognitive skills, emphasizes the need for a holistic approach to skill development. Future research could further investigate the interplay between different non-cognitive skills, explore additional mediating factors, consider cultural contexts, and conduct longitudinal and intervention studies to enhance the understanding of this important area of research. Overall, the results of this study highlight the potential benefits of targeted non-cognitive skills interventions and have significant implications for educators and policymakers aiming to promote academic achievement in STEM subjects.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by the Ethics Committee at the Center for Pedagogical Measurements. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin. Written informed consent was obtained from the minor(s)' legal guardian/next of kin for the publication of any potentially identifiable images or data included in this article.

Author contributions

GS: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Investigation, Conceptualization. AS: Writing – review & editing, Project administration, Investigation, Conceptualization. ZR: Writing – original draft, Validation, Formal analysis, Data curation, Conceptualization. AR: Writing – original draft, Investigation, Data curation, Conceptualization. NS: Writing – review & editing, Validation, Software, Data curation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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