Journal of Educational Psychology

A Person-Centered Approach to Action-Control Beliefs of Students With Special Educational Needs and Their Relation to Student Performance and Time on Task

Laura Nyman, Satu Koivuhovi, Samuel Greiff, Risto Hotulainen, Todd D. Little, and Mari-Pauliina Vainikainen

Online First Publication, December 1, 2025. https://dx.doi.org/10.1037/edu0001000

CITATION

Nyman, L., Koivuhovi, S., Greiff, S., Hotulainen, R., Little, T. D., & Vainikainen, M.-P. (2025). A person-centered approach to action-control beliefs of students with special educational needs and their relation to student performance and time on task. *Journal of Educational Psychology*. Advance online publication. https://dx.doi.org/10.1037/edu0001000

AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Educational Psychology

© 2025 The Author(s)
ISSN: 0022-0663

https://doi.org/10.1037/edu0001000

A Person-Centered Approach to Action-Control Beliefs of Students With Special Educational Needs and Their Relation to Student Performance and Time on Task

Laura Nyman[1, 2], Satu Koivuhovi[2, 3], Samuel Greiff[4], Risto Hotulainen[2], Todd D. Little[5, 6], and Mari-Pauliina Vainikainen[1, 2]

[1] Research Centre for Education, Assessment and Learning, Faculty of Education and Culture, Tampere University
[2] Centre for Educational Assessment, Faculty of Educational Sciences, University of Helsinki
[3] INVEST Research Flagship Centre, Faculty of Social Sciences, University of Turku
[4] TUM School of Social Sciences and Technology, Technical University of Munich
[5] College of Education, Texas Tech University
[6] Optentia Research Focus Area, North-West University

While effort and motivation are crucial for academic success, research on their relation to academic success of students with special educational needs (SEN) is inconclusive, largely due to the heterogeneity of students with SEN and their diverse motivational characteristics. The aim of this study is to address this gap by utilizing person-centered latent profile analysis to identify distinct profiles based on students' control-related motivational beliefs, and to examine how students' SEN status is associated with the likelihood of exhibiting certain profiles. In addition, we explore how these motivational profiles differ in terms of student performance, including academic achievement (student-reported grade point average) and cognitive tasks (learning to learn tasks), as well as task behavior, specifically time on task (log data) as an indicator of effort. Analyzing national-level data from Finnish ninth graders with and without SEN status ($N = 6{,}942$), four motivational profiles emerged: agentic, moderate, avoidant, and mixed. Although SEN students were depicted in all motivational profiles, they were more likely to belong to profiles demonstrating more maladaptive motivational patterns, less time on task, and lower cognitive task achievement. Through these findings, we highlight the importance of a person-centered approach to students' beliefs in identifying different reasons and consequences for performance. We also contribute to research on students' motivational patterns and behavior-related factors explaining differences in task performance that can be further explored using computer-based assessment and log analytics. Educators and policy makers can apply these valuable insights to support students with diverse motivational profiles and learning needs.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Matthew L. Bernacki served as action editor.

Laura Nyman https://orcid.org/0000-0001-9293-0237

Preliminary interpretation of the data and research has been presented at two conferences: annual conference of Finnish Educational Research Association (FERA; Joensuu, Finland) and annual meeting of American Educational Research Association (AERA; Chicago, Illinois, United States). AERA conference article can be found in AERA's Online Paper Repository (https://www.aera.net/Publications/Online-Paper-Repository/AERA-Online-Paper-Repository). This study was partially funded by the Emil Aaltonen Foundation. We thank Sirkku Kupiainen for her expertise in research on time on task in low- and high-stakes assessment and Paul Ilsley for his editorial comments. The authors declare that they have no conflicts of interest.

This work is licensed under a Creative Commons Attribution-Non Commercial-No Derivatives 4.0 International License (CC BY-NC-ND 4.0; https://creativecommons.org/licenses/by-nc-nd/4.0). This license permits copying and redistributing the work in any medium or format for noncommercial use provided the original authors and source are credited and a link to the license is included in attribution. No derivative works are permitted under this license.

Laura Nyman served as lead for conceptualization, formal analysis, visualization, writing–original draft, and writing–review and editing and contributed equally to methodology and funding acquisition. Satu Koivuhovi contributed equally to formal analysis, supervision, and writing–review and editing. Samuel Greiff contributed equally to writing–review and editing. Risto Hotulainen served in a supporting role for conceptualization and contributed equally to supervision and writing–review and editing. Todd D. Little served in a supporting role for formal analysis, methodology, and writing–review and editing. Mari-Pauliina Vainikainen contributed equally to conceptualization, methodology, funding acquisition, formal analysis, supervision, and writing–review and editing.

Correspondence concerning this article should be addressed to Laura Nyman, Research Centre for Education, Assessment and Learning, Faculty of Education and Culture, Tampere University, Åkerlundinkatu 5, P.O. Box 700, FI-33014 Tampere, Finland. Email: laura.k.nyman@tuni.fi

Educational Impact and Implications Statement
Our research revealed that students with special educational needs displayed more maladaptive patterns than their peers without special educational needs, which was worthy of investigation. Upon further investigation, more maladaptive patterns of motivational beliefs were associated with less time on task and poorer cognitive performance, as indicated by the log data. This crucial insight underlines the importance of recognizing and addressing the diverse motivational pathways that influence students' educational outcomes. By customizing interventions to the unique motivational and task-behavioral patterns, it is possible to create more effective educational strategies that better address students' specific needs and promote academic success.

Keywords: motivational beliefs, effort, time on task, students with special educational needs, student performance

Supplemental materials: https://doi.org/10.1037/edu0001000.supp

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Research on students' task behavior indicates the salience of motivation and effort in students' short- and long-term achievement and performance (Eccles & Wigfield, 2002; Kupiainen et al., 2014; Malmberg et al., 2013) even after accounting for relevant covariates such as cognitive ability (e.g., Sideridis, Morgan, et al., 2006; Sideridis, Mouzaki, et al., 2006). However, while students with special educational needs (SEN) exhibit academic achievement below their peers (e.g., Hienonen et al., 2018; T. D. Lackaye & Margalit, 2006), the nature of their motivational characteristics and the relationship to student performance have yielded conflicting and ambiguous results (e.g., N. Heath et al., 2011; Klassen, 2006; Stone & May, 2002). These results may reflect heterogeneity in the population of students with SEN and the existence of distinct SEN subgroups (e.g., Kavale & Forness, 1987; Mamlin et al., 2001; Polychroni & Antoniou, 2013). In such studies, motivation and effort have often been measured and evaluated by self-reports, but their validity is affected by subjectivity and student motives when explaining motivation and effort. This concern has been identified overall (Wise & Gao, 2017; Wise & Kong, 2005), and it specifically applies to students with SEN (e.g., Graham & Harris, 1989; Polychroni & Antoniou, 2013; Wong, 2003).

This research is designed to overcome the challenges described above. Firstly, the focus is on a person-centered approach to motivational factors, which can help to theoretically explain both differences in achievement and students' task behavior in an achievement situation. Even though the person-centered approach toward motivational factors is well-recognized, relevant findings through the lens of SEN are still relatively sparse (Martin et al., 2020; Sideridis, 2009). Secondly, by utilizing log data to track students' time on task (TOT), we can overcome the limitations associated with self-reports and more objectively and comprehensively analyze how motivation and effort are connected to performance (Wise & Gao, 2017; Wise & Kong, 2005). Still, research is limited on the potential of log data analysis in academic assessment, especially concerning students with SEN and the person-centered approach to effort and its underlying motivational factors. This need was addressed by analyzing log data collected from a nationally representative sample of ninth graders in Finland ($N = 6{,}942$, of which 83.5% received general support, 9.9% intensified support, and 6.6% special support).

Regarding its impact on the literature, this study serves to extend previous research by exploring computer-based assessment (CBA) and the possibilities of utilizing log data for identifying task behavior-related factors and explaining student performance among those who struggle academically. In this study, we use TOT as an indicator of effort exertion. The person-centered perspective gives a more nuanced picture of the patterns of effort and motivation, that may remain undetected if only self-reports are used. Furthermore, with the special education approach, we gain a firmer grip on the various motivational patterns of students with SEN.

Context of the Study: Special Education in Finland

The term students with SEN describes students with disabilities, difficulties, or disadvantages that make it harder for them to learn and perform at the same level as most other students of same age, and therefore, they require additional support over and above the resources generally available to students (ISCED, 2012; OECD, 2007).[1] The given special education in the context of this study refers to the Finnish three-tiered support model called support in learning and school attendance (FNBE, 2016) that can be functionally contrasted with the well-known response to intervention (RTI) model in the United States (Jahnukainen & Itkonen, 2016). The main factors differentiating the Finnish model from the American model are that (a) the Finnish three-tier model is mandatory nationally (Basic Education Act 1998) whereas in the American RTI model is legally recommended and the amount of provided Tiers can vary, (b) the intensity, duration, and content of support are not specifically defined, which makes the Finnish support model more of a pedagogically built concept (see Ahtiainen, 2017) than a highly defined, evidence-based interventions (see Fuchs et al., 2012), and (c) the support given on behalf of the schools in Finland does not require formal diagnosis for any Tier (Björn et al., 2016; Honkasilta et al., 2019; Jahnukainen & Itkonen, 2016).

[1] We acknowledge that in the United States the term special educational needs may be viewed as ableist, and its use is not recommended in the APA manual. However, the term is widely used internationally and used for example by the OECD (2023; Guez et al., 2024) as a general term describing students with disabilities, difficulties or disadvantages in learning. Therefore, we have chosen to use it to describe students who, for various reasons, require more individualized support than what mainstream instruction can offer. However, we want to emphasize that we do not use the term as an intention to suggest any inferiority or deficiency but only to ensure the clarity in communication to an international audience in the field of education.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

The three Finnish tiers are called general (Tier 1), intensified (Tier 2), and special support (Tier 3; universal, targeted, and intensified in the United States; Jahnukainen & Itkonen, 2016). General support is offered to every student as part of good-quality basic education (Thuneberg et al., 2013). This form of support can mean additional support, such as remedial instruction or part-time special education. Intensified support (Tier 2) is provided when students regularly need support or several types of support in their learning and schooling, and it is based on a pedagogical assessment and recorded learning plan (Thuneberg et al., 2013). The decision to give intensified support is made in a multiprofessional collaboration with student welfare professionals (e.g. special education teacher, school psychologist, and school social worker; FNBE, 2016). When the support measures in intensified support are not sufficient to meet the goals set for student's development and learning, the third Tier, special support, would be considered. Special support is provided based on an official decision (Thuneberg et al., 2013), and as such, it is equivalent to the classification of SEN used in many other countries (Jahnukainen & Itkonen, 2021). The education provider makes the official decision based on a pedagogical statement, which include written reports from the teachers and the multiprofessional team of student welfare professionals (FNBE, 2016). When a student needs services outside of the scope of the support given in school, such as therapy or medication, only then is a formal diagnosis required (Björn et al., 2016). On the basis of inclusive special education (Björn et al., 2016), support in every Tier is primarily given in mainstream classes and secondarily in part-time small-group settings (Björn et al., 2016; Thuneberg et al., 2013). In the case of special support, special classes or other appropriate settings may also be considered if the initial classes or settings do not meet a student's needs (Basic Education Act 1998; Honkasilta et al., 2019; Thuneberg et al., 2013).

In this study, students with SEN are defined as the students in intensified support (Tier 2) and special support (Tier 3) who are found to need support in their learning beyond general support (Tier 1), and are thereby provided with support based on documented decision.

Students' Motivational Beliefs About School Achievement: Action-Control Theory

How students engage in certain behaviors, such as persisting on a task despite recurring difficulties or giving up in the early stages, is shaped by their experiences with how their needs, values, and goals are met in their interaction with the environment. Through these experiences, students form their worldviews on and beliefs about their control over outcomes in different contexts. These beliefs that mediate motivated action (Little et al., 2002) are conceptualized in action-control theory (Skinner et al., 1988) that integrates significant theories concerning perceived control, such as locus of control (Levenson, 1973; Rotter, 1966), causal attributions (Weiner, 1985), learned helplessness (Abramson et al., 1978), and self-efficacy (Bandura, 1977). According to the theory, control-related beliefs in the school domain, with their reciprocal impact on performance (e.g., Little, 1998; Skinner et al., 1998), highlight individuals' general understanding about what it means to do well at school, how to attain outcomes that determine school performance and whether they have the control to influence those outcomes (M. Chapman et al., 1990; Little, 1998; Skinner et al., 1988, 1998). These beliefs form a belief system with a sequential distinction among agent, means and ends, that are connected to three sets of beliefs: agency beliefs, means-ends beliefs, and control beliefs (Skinner et al., 1988), also known as control expectancy (Little et al., 1995, 1998). Together, action-control beliefs constitute human agency as motivational, volitional, intentional, self-regulated, and goal-directed behavior (Geldhof & Little, 2011; Skinner, 1995; Skinner et al., 1988).

Self-related agency beliefs are directed to the relationship between the agent and means, reflecting students' perceptions about the extent they can utilize means (e.g., effort, ability) for achieving certain outcomes (Chang et al., 2017; Little et al., 1999, 2001; Skinner et al., 1988). For example, students can believe that they can use their abilities (i.e., they believe in their ability) to succeed or that they can put in effort when it comes to school. Agency beliefs are closely related to the concept of self-efficacy (Bandura, 1977) but differ in that agency beliefs are specific in terms of utilizing a range of different means (Chang et al., 2017; Little et al., 1995). In turn, self-efficacy covers individuals' judgments of the overall ability to utilize means that are effective to attain desired outcomes (Bandura, 1977; Chang et al., 2017; Little et al., 1995). Therefore, as Chang et al. (2017) describe, self-efficacy also overlaps with control expectancy, which refers to individuals' perceptions about the control over their actions toward desired outcomes without specifying the means one believes to be necessary for attaining these outcomes (Skinner et al., 1988).

Individuals possessing a strong sense of personal agency and control expectancy often have high aspirations, are persistent when facing obstacles, and while finding proper actions for reaching their goals, they create, try out, and regulate various strategies despite encountering failures (Chang et al., 2017; Little, 1998; Skinner et al., 1998). In addition, they are more likely to have high cognitive ability and self-evaluation accuracy and engage in activities that require effort, originality, and creativity (Chang et al., 2017; Demetriou & Kazi, 2001). These actions are associated with metacognitive calibration skills (Pieschl, 2009) and overall executive function (R. Elliott, 2003; Follmer & Sperling, 2020; Wehmeyer & Shogren, 2020). Conversely, individuals with low agency beliefs and control expectancy tend to struggle with basic problem-solving skills, have feelings of helplessness when facing challenges, and question their capabilities with decreasing effort in the future learning situations (Chang et al., 2017; Little, 1998; Malmberg & Little, 2007; Schmitz & Skinner, 1993; Skinner et al., 1998). According to Chang et al. (2017), the differences in students' sense of agency can be revealed especially when presenting novel tasks, as they require problem-solving skills as well as the ability to adapt and apply previously learned knowledge or skills.

Means-ends beliefs refer to socioculturally shaped general beliefs about which means, or actions, are most likely to produce desired academic outcomes (Little et al., 1995; Little & Lopez, 1997; Skinner et al., 1988). These can be considered to reflect students' worldviews on causality of events that affect students' sense of control (Malmberg & Little, 2007; Malmberg et al., 2008). According to the theory, students might consider desired academic results to be determined by effort or ability (internal means). Students can also believe that certain outcomes can be produced with external factors, such as the help of teachers, pure luck, or unknown causes (Little & Lopez, 1997; Little et al., 1995, 1999).

Agency belief for ability and effort and control expectancy have the most prominent effect on performance among students and

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

their effect increases with age (M. Chapman et al., 1990; Hotulainen et al., 2020; Little et al., 1999; Lopez et al., 1998; Malmberg et al., 2013). Concerning means-ends beliefs, the findings on the connections to performance seem to be more complex. According to these findings, students who believe in effort as a means for school success have also performed better, while means-ends beliefs about external factors, especially luck and unknown causes, have been seen as maladaptive (Little et al., 1995, 1999; Skinner et al., 1988). Regarding means-ends belief for ability, findings have been inconclusive as these beliefs have been detected to correlate both positively and negatively with academic and cognitive performance (e.g., Hautamäki et al., 2003, 2005; Little et al., 1995, 1999; Niemivirta, 2000). Inconsistent findings can partially be explained by differing underlying mindsets regarding ability (i.e., malleable vs. fixed, see Dweck, 1986). Means-ends belief for ability can be adaptive in cases where belief in one's own ability is strong (Malmberg & Little, 2007; Schmitz & Skinner, 1993; Skinner et al., 1988, 1990). However, a counteractive effect can be expected if students do not believe they are capable of utilizing the means that they perceive to be central to attaining certain outcomes (Bandura, 1977), which can in terms of ability mean that these students do not believe that they can succeed, as they are not capable in the first place. Therefore, the adaptive and maladaptive effect of these beliefs on performance seems to be dependent on what kinds of other beliefs students hold, such as the perceptions of their own effort exertion or ability, and thus yield the importance of approaching these beliefs in terms of how they are companied with each other. With such distinctions of different beliefs contributing to perceived control, the action-control theory offers a good basis for detecting differences in beliefs that determine effort in student performance.

Motivation Research on Students With SEN

In the context of SEN, action-control theory has been incorporated as part of broader theoretical framework for interventions targeting students or individuals with particular disabilities (Shogren et al., 2015). However, its use as a standalone focus and comparative studies involving students with and without SEN remains a relatively untouched and outdated area of research. In a few studies, Finnish students with SEN have been shown to exhibit stronger maladaptive beliefs including means-ends beliefs for ability and luck (Vainikainen, 2014) as well as lower self-reported agency for effort (Vainikainen & Hautamäki, 2018). These findings can be contrasted to the special educational perspective addressed in relation to associated and integrated control related theories, such as academic self-efficacy (e.g., Brunswick & Bargary, 2022; Klassen, 2007; T. D. Lackaye & Margalit, 2006; Martin et al., 2017; Sideridis, Morgan, et al., 2006; Tabassam & Grainger, 2002), locus of control (e.g., Grolnick & Ryan, 1990; Mamlin et al., 2001), perceived competence (Grolnick & Ryan, 1990), attributions (Núñez et al., 2005, 2011; Tabassam & Grainger, 2002), and learned helplessness (Sideridis, 2003) as well as other motivational constructs, such as self-concept (Núñez et al., 2005, 2011; Tabassam & Grainger, 2002), intrinsic and extrinsic motivation (Lee & Zentall, 2012, 2017; Zentall & Beike, 2012), and goal orientations (e.g., Schwab & Hessels, 2015; Sideridis, 2003; Sideridis et al., 2016; Sideridis, Morgan, et al., 2006). Within such studies, in contrast to their peers without SEN, students with SEN have been shown to exhibit lower confidence in their academic abilities (J. W. Chapman, 1988; T. D. Lackaye & Margalit, 2006; Núñez et al., 2005; Sideridis, 2003), less intrinsic motivation (Lee & Zentall, 2017; Zentall & Beike, 2012), greater learned helplessness (i.e., no control of an outcome regardless of actions taken; Abramson et al., 1978; Sideridis, 2003), lower expectations for future academic success (J. W. Chapman, 1988), more negative emotional states, such as anxiety and depression (T. Lackaye et al., 2006; T. D. Lackaye & Margalit, 2006; Palladino et al., 2000), and ultimately, greater task avoidance (Lee & Zentall, 2012, 2017; Schwab & Hessels, 2015; Sideridis, 2003; Zentall & Beike, 2012), and reduced effort (T. Lackaye et al., 2006; T. D. Lackaye & Margalit, 2006; Sideridis, 2003). Moreover, it has been found that students with SEN are more likely to attribute their successes to external factors, such as powerful others and luck, and failures to own ability (Grolnick & Ryan, 1990; Palladino et al., 2000).

The findings mentioned above reveal that differing motivational, emotional, and behavioral correlates among students with SEN are often intertwined with experiences of poor performance and academic failure. However, challenges are shaped not only by individual factors but also by environmental influences such as class environment (Sideridis et al., 2016), class placement (regular vs. special class; J. W. Chapman, 1988; Hienonen et al., 2021; Holm et al., 2020; Kocaj et al., 2018), instructional style (Deci & Chandler, 1986; Ryan & Grolnick, 1986), diagnostic practices (Brunswick & Bargary, 2022), and teacher–student interactions (Grolnick & Ryan, 1990; Kocaj et al., 2018; Schwab & Hessels, 2015). These environmental aspects as well as varying learning-related difficulties and their comorbidity may contribute to the mixed findings also reported in previous research, showing differences of varying magnitude compared to students without SEN or findings that hold true only in specific domains (e.g., Gans et al., 2003; Lee & Zentall, 2012, 2017; Stone & May, 2002; Tabassam & Grainger, 2002; Zentall & Beike, 2012). Findings of similar or even more positive self-evaluations of students with SEN on their academic abilities and control over outcomes compared to their peers have in some cases been interpreted as reflecting a pattern of overestimation (N. Heath et al., 2011; N. L. Heath, 1995; Klassen, 2006; Martin, 2012; Schwab & Hessels, 2015; Stone & May, 2002). Overestimation, as has been argued, serves as a self-protective function, especially against learning difficulties (Hoza et al., 2004; Klassen, 2006; Owens et al., 2007). Slight overestimations are thought to be common among all students and can help students when faced with new challenges (Bandura, 1989; Lopez et al., 1998). A gross overestimation, however, is most likely to adversely affect performance resulting from difficulties in metacognitive skills (Stone & May, 2002), such as when preparations for subsequent tasks are insufficient. When a lack of preparation is based on a failure to judge one's capabilities against the requirements of the task, the resulting effort is likely to be less than needed (Bandura, 1989; Klassen, 2006, 2007).

In summary, students with SEN form a diverse group characterized by a range of learning-related difficulties and environmental influences. These collectively shape students' confidence in their academic abilities, perceptions of control over outcomes, motivation, and ultimately, task behaviors, impacting academic performance in both linear and nonlinear ways. Thus, this underscores the necessity for adopting person-centered approaches to understand the nuanced motivational action-control-belief patterns of students

with SEN. Similarly, while research on the motivation of students with SEN exists, studies on motivational beliefs, and especially on effort, remain limited. Alongside person-centered approaches, research conducted by using objective measures of task behavior is important for identifying different patterns of motivation and effort and for clarifying mixed findings, including potential overestimation of abilities.

A Person-Centered Approach to Motivation

The use of person-centered approach in research methodology enables one to observe heterogeneity between and within individuals, both quantitatively and qualitatively (Hickendorff et al., 2018). This way it is possible to identify key patterns of values across variables (Bergman & Magnusson, 1997), through which a researcher can more accurately detect hindering nonlinear and interactive effects compared to the variable-centered approach (Bergman et al., 2003). For these advantages, the person-centered approach has been increasingly utilized in motivation research to detect different motivational patterns with distinct relations to academic performance, as well as performance-related factors like student well-being, stress, and school burnout (Malmberg & Little, 2007; Tuominen-Soini et al., 2008). There is quite well-established research, especially on students' goal orientation profiles (for a review, see Niemivirta et al., 2019) but, to the best of our knowledge, less research is available on action-control theory and its' theoretically related constructs, and even less on the motivational profiling of students with SEN.

Malmberg and Little (2007) identified five qualitatively distinct profiles of students based on their agency beliefs regarding ability and effort, as well as perceived task difficulty. They examined how these profiles relate to worldviews, such as means-ends beliefs and beliefs about the nature of ability (Dweck, 1986), as well as self-determined motivation (self-determination theory; Deci & Ryan, 2000) and school adjustment (e.g., school well-being and achievement). Some of the profiles were distinctly adaptive or maladaptive, while others were found to demonstrate both adaptive and maladaptive elements. The Adaptive (21.5%) profile was the most related to high academic performance, school well-being and intrinsic motivation. Students in this profile possessed strong agency beliefs for effort and ability with an emphasis on effort as a means for school success. Two profiles associated with clear maladaptive patterns in terms of motivation and school adjustment were challenged and disengaged profiles. The challenged profile (9.3%) was characterized by the most maladaptive patterns with emphasized beliefs on the role of ability on achievement, low confidence in own's abilities and effort, extrinsic motivation, and relatively high perceived task difficulty—reflecting signs of learned helplessness (Malmberg & Little, 2007; Seligman, 1975). These characteristics can be connected to patterns found in other studies in terms of high task avoidance, low self-esteem and well-being (Tuominen-Soini et al., 2008), off-task behavior (Parhiala et al., 2018; Roeser et al., 2002), and higher perceived learning difficulties and risk for school dropout (Korhonen et al., 2014). Alongside the challenged profile, the disengaged students (23.8%) struggled with school adjustment and expressed relatively low levels of agency beliefs in ability and effort but demonstrated a reasonably midrange perceived level of difficulty. In this profile, ability and effort as means for school success mattered the least, and these students displayed a pattern of amotivation. Yet, their achievement was at a normative level. This kind of profile could reflect a disengaged profile in the study of Tuominen-Soini et al. (2008), as they hypothesized it to reflect students described as "bright but bored" (Seifert, 2004; Tuominen-Soini et al., 2008). The one profile characterized as adaptive as well as maladaptive in Malmberg and Little's (2007) study was named Strivers (11.9%), in which students had a high level of agency and means-ends belief in effort but simultaneously perceived learning new material most difficult. Even though these students believed in their ability to be above average, their means-ends belief for ability was even higher. According to the results, students had an average level of school adjustment as well as achievement. The maladaptive side of this profile might occur in the sensitiveness to situations of potential failure and the consequential effect of school setbacks, which could likely be connected to high emotional distress (see Tuominen-Soini et al., 2008). The last of the five profiles of Malmberg and Little (2007) was identified as Normative (33.4%), which was associated with close to average levels of profile indicators and related outcomes.

In profile studies concerning students with SEN, Núñez et al. (2005) found that, in their two-cluster solution using the K-means method, 54.9% of the students with learning difficulties thought that successes are caused mainly by circumstances other than themselves while attributing failures to internal causes (helplessness profile; Núñez et al., 2005). These students were found to perceive themselves and their capabilities more negatively (self-concept; Marsh, 1988), lack persistence following failure, and be less motivated in terms of learning and achievement. Núñez and colleagues also found that these students ultimately showed poorer achievement in multiple areas, not just in their specific area(s) of disability. However, they did not differ in measured intellectual skills compared to the other profile that was considered adaptive (45.1%). On a similar note, Sideridis, Mouzaki, et al. (2006) concluded that students with learning difficulties (reading) predominantly fell into two profiles (43.8% in helpless and 45.2% in motivated low achievers), demonstrating low achievement but differing motivational characteristics. The third profile (11%) was characterized by high achievement and average motivation and, comprised mostly students without reading difficulties. the helpless profile was associated with low perceptions of self-efficacy and high levels of depression, anxiety, and negative affect. Motivated low achievers, on the other hand, exhibited high levels of motivation despite their low achievement. However, their high competitiveness suggests that the pursuit of outperforming their peers (ego-involved; see Nicholls, 1984) could establish circumstances that hinder learning, as posited by goal orientation theory (performance goals; see E. S. Elliott & Dweck, 1988; Midgley et al., 2001).

Consequently, heterogeneity in motivational patterns has also been identified regarding students with SEN. Still, the limited studies suggest that these students are predominantly belonging to profiles associated with lower achievement, though in seemingly different ways. However, in some cases, students with SEN have demonstrated similar heterogeneity in motivational characteristics without higher proportions of maladaptive pattern (Núñez et al., 2011). Nevertheless, these differing results could be due to recognized limitations such as small sample sizes and the broad age range of students.

Through this study, three key contributions are made to the literature on motivational profiles. First, we extend the research on motivational profiles grounded in action-control beliefs by applying

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

profiles to a previously unexamined population of students with SEN. Second, we address methodological limitations in earlier studies by using a large sample of adolescents, an age group associated with more accurate and conservative self-evaluations (e.g., Demetriou & Kazi, 2001). Thirdly, given the scarcity of research on the relationship between motivational profiles and actual task behavior, we address the gap by incorporating objective indicators of effort during tasks, such as TOT.

Effort and TOT

Motivation and effort have often been measured using self-report questionnaires, which are limited by their subjectivity and timing, usually being administered before or after task completion. In this study, we address these limitations by utilizing student log data related to TOT as a measure of effort, complemented by self-evaluated motivational scales. This approach aligns with solutions found in CBA research, in which log data are utilized to measure changes in students' task behavior objectively without interfering with the task activity (Goldhammer et al., 2014; Greiff et al., 2016; Wise & Gao, 2017).

Compared to self-reported questionnaires alone, researchers have determined that motivation and effort can be measured more comprehensively by also considering the amount of time students spend on tasks. This logged information has been found to be strongly connected to students' motivational beliefs (Wise & Gao, 2017; Wise & Kong, 2005), especially concerning maladaptive beliefs (Kupiainen et al., 2014; Vainikainen, 2014; Vainikainen & Hautamäki, 2018). Similarly, rapid guessing has been shown to be an indicator of a lack of effort and engagement (Schnipke & Scrams, 1997; Setzer et al., 2013; Wise & Gao, 2017; Wise & Kong, 2005), as the overly rapid response time does not allow for the time needed to fully consider the proper solution (Schnipke, 1995; Wise & Gao, 2017). The utilization of objective measures of effort has recently also been criticized, as simply spending more time does not necessarily lead to better outcomes for all students (e.g., Dunlosky et al., 2020); however, even the criticism is often accompanied by an acknowledgement of the role of time use in identifying the overly rapid responses, compared to the time needed to even read the instructions or attempt to solve the task.

The basis of treating time use as a measure of motivational investment in a task can be derived from Carroll's model of school learning from 1963 (Carroll, 1989). As Carroll (1989) reminds us, students with lower initial competence need more time and effort to learn a task than students with higher initial competence (see also Schmitz & Skinner, 1993). In addition to initial competence level, the amount of time a student requires to learn depends on the quality of the instruction and student's ability to understand and apply the instruction to construct knowledge. However, the time the student uses to learn depends on the time provided for learning and how much one is willing to spend time on learning. The actual time spent, on the basis of the individual time required, influences student learning and performance and explains differences among students.

The amount of time the student requires to spend on a task also depends on the processes needed. We see it, in this case, from the point of view of two different cognitive processes, automated and controlled (see Schneider & Chein, 2003). According to the dual processing theory (Schneider & Shiffrin, 1977), automatic processing is considered to occur without conscious control as a result of repetitive and consistent training and activation of a certain response to a particular input configuration. Automatic processing is fast, requires little effort and can operate in parallel with situations that are high in workload (Schneider & Chein, 2003). In contrast, controlled processes are present in novel situations where there is no internal automatic response (Schneider & Shiffrin, 1977). Controlled processes are flexible in the way that they can be learned in a single trial and altered and applied to varied conditions. However, they are tightly limited by capacity and require a lot of effort, resulting in them being slow and sequential in nature (Schneider & Chein, 2003).

Derived from the above, tasks that require controlled processes—such as problem solving—require more time to complete. According to research on the TOT effect and achievement in different types of tasks (Goldhammer et al., 2014; Naumann & Goldhammer, 2017), students are more likely to succeed on complex tasks requiring controlled processes when they readily devote their time to process relevant information from the task to solve it (i.e., allocate cognitive resources). Consequently, the impact of time on success is contingent upon the diverse characteristics of students. Students operating at a lower level of ability would necessitate relatively more cognitive resources, while less time is needed in easier tasks and when more automatic processes can be used (Goldhammer et al., 2014; Naumann & Goldhammer, 2017). The tasks used in the present study are novel to the participants, and they require more complex thinking and problem-solving skills instead of relying on automatic processes. As shown in earlier research by using the same measures (e.g., Kupiainen et al., 2014), even high-performing students benefit from an increased time use in these tasks.

Understanding the various types of tasks is crucial when examining the connection between time spent on a task and performance. The extent to which students are willing to invest in a particular task significantly influences this relationship. Even if students require more time due to their prior abilities or the nature of the task, their sense of personal agency derived from action-control beliefs is pivotal in determining their actual actions and results. With log data, we can get closer to understanding how the combinations of beliefs of the students come into play while performing tasks.

Present Study

With a firm understanding of the importance of motivational beliefs in shaping task behavior and performance, the aim of this study is to investigate the various combinations of action-control beliefs observed among students, particularly those who, for one reason or another, require support in their learning. In addition, we seek to understand how such belief profiles are reflected in academic and cognitive performance, and especially the extent to which time spent on novel problem-solving tasks can act as an indicator of students' exertion of effort. Thus, research questions (RQs) were formed as follows:

RQ1: What types of patterns of action-control beliefs do students demonstrate?

RQ2: How are SEN connected to the combination of student action-control beliefs?

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

RQ3: How are the identified profiles reflected on students' prior academic performance, performance in cognitive tasks, and TOT?

Hypothesis 1: On the basis of the theory and research on action-control theory (e.g., Chang et al., 2017; Hotulainen et al., 2020; Little et al., 1999; Skinner et al., 1988) and especially on the study of Malmberg and Little (2007), we expect to find profiles that should be adaptive, maladaptive, or combinations of adaptive and maladaptive characteristics. Students with adaptive patterns perceive their effort exertion and ability to be higher and have stronger control expectancy. Conversely, combinations that would be maladaptive and detrimental for learning and performance would include more negative beliefs about one's own ability and effort, accompanied by worldviews highlighting external causes for academic performance, such as luck and low expectations of one's own control. As demonstrated by the theoretical background and studies concerning means-ends belief for ability (e.g., Hautamäki et al., 2005; Little et al., 1999; Malmberg & Little, 2007; Skinner et al., 1988), the adaptiveness of such a belief can vary. In some cases, means-ends belief for ability may have maladaptive or adaptive characteristics depending on their conjunction with other beliefs, such as how a student perceives their own ability or control over desired outcomes (control expectancy).

Hypothesis 2: Based on the prior research on the motivation research on students with SEN with variable-centered (e.g., Grolnick & Ryan, 1990; Hienonen et al., 2021; Klassen, 2007; Lee & Zentall, 2017; Ryan & Grolnick, 1986; Schwab & Hessels, 2015; Tabassam & Grainger, 2002) and person-centered perspective (Núñez et al., 2005, 2011; Sideridis, Mouzaki, et al., 2006), it would be expected that students with SEN demonstrate various kinds of motivational characteristics, as students vary in their academic difficulties and their environmental resources for adaptive motivational beliefs to develop. However, in previous studies, students with SEN have appeared to exhibit, to a greater or lesser extent, motivational patterns that are shown to have maladaptive aspects. This is since students with SEN evidently struggle with academic performance and the reoccurrence of these experiences of struggle would lead to students' deteriorating evaluations of their own possibilities to succeed and have control over academic outcomes. However, these students might also exhibit profiles that might seem adaptive, but in a new learning situation or more demanding tasks might show signs of maladaptation.

Hypothesis 3: Based on theory and previous studies, students with differing combinations of action-control beliefs have their own adaptive or maladaptive characteristics that demonstrate differing task behavior leading to differing academic performance and performance in new cognitive tasks. Accordingly, it is assumed that students with agentic motivational patterns would have high prior academic performance and use time to solve novel cognitive tasks that require more problem-solving skills as they are more ready to do so (Chang et al., 2017; Goldhammer et al., 2014; Naumann & Goldhammer, 2017; Schneider & Chein, 2003). However, lower achieving students, might need and use even more time and effort to complete cognitive tasks (Carroll, 1989; Goldhammer et al., 2014; Naumann & Goldhammer, 2017; Schmitz & Skinner, 1993). However, as maladaptive patterns have been stated to be related to poorer achievement and effort (e.g., Malmberg & Little, 2007; Schmitz & Skinner, 1993), students exhibiting maladaptive patterns, which would be more likely to include students with SEN, would use less time than would be needed to succeed in a task (Vainikainen, 2014; Vainikainen & Hautamäki, 2018).

Method

Participants and Procedure

Data used in this research originated from the computer-based Finnish National learning to learn assessment (LTL) of ninth-grade students conducted in the spring of 2017. The LTL belongs to Finnish national thematic assessments and as such schools are obligated to participate to the assessment (Vainikainen & Hautamäki, 2022). The assessment is used to evaluate both the overall level and national equity of learning to learn skills, which are key goals for lifelong learning. The cognitive tasks used in LTL assessments do not directly measure curricular contents of any school subjects, but they focus on cross-curricular, more general competences that develop as a result of studying different subjects and that are needed in all learning. These competences, for example, have been defined in a separate section of the National Core Curriculum (FNBE, 2016), and they are explicitly linked to the subject-specific learning goals. In national LTL assessments, the focus of measurement is in reading comprehension, and reasoning and problem-solving skills in verbal, quantitative, and visuospatial domains (Vainikainen & Hautamäki, 2022). The assessments are organized by national or local educational authorities, and students' participation within schools is expected but voluntary. The cognitive tests used are low stakes for the test takers.

In the beginning of the LTL assessment, in 1996, a nationally representative sample was acquired from Statistics Finland. In the following rounds, the same school sample has been used resembling characteristics of the original school sample. All 83 schools formed a nationally representative sample described in detail in Vainikainen and Hautamäki (2022). From these schools, 8,507 students participated in the assessment. From these students, only those were selected who informed their level of support ($N = 6{,}942$).[2]

The students ranged from 14 to 18 years of age ($N = 6{,}462$, $M_{age} = 15.28$ years, $SD = 0.48$). Participants over 18 years old ($n = 4$) were excluded as outliers to retain a sample representative of the secondary school population. The gender distribution of the sample in this study was 49.7% for girls and 50.3% for boys, which was similar in both the overall sample of the LTL assessment and the students who did not participate. At the time, other gender options were not available for the participants.

[2] The selection of students based on the availability of complete information on their level of support was undertaken to ensure the reliability of subsequent analyses. A robustness check was conducted to compare the characteristics of students included in the sample ($N = 6{,}942$) with those excluded ($N = 1{,}565$). This analysis confirmed that the students excluded from the sample did not significantly differ from those included except for GPA (see S1 in the online supplemental materials). However, this difference was extremely small (Cohen's $d = 0.072$), supporting the validity of our findings.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Data indicating students' level of support was gained from special education teachers at each school. Most of the students received general support (Tier 1, $n = 5{,}796$, 83.5%), followed by intensified support (Tier 2, $n = 688$, 9.9%), and special support (Tier 3, $n = 458$, 6.6%). In Tier 1, a little over half of the students were girls (52%). In Tiers 2 and 3, most students were boys (59.7% and 64.8%, respectively). The information about the level of support was gained after the assessment session, and no accommodations of assessment tasks were provided for these students during the session.

Measures

Cognitive Tasks

In this study, LTL performance was operationalized as the average percentage of correct responses across seven cognitive tasks. Five tasks measured reasoning skills, from which three tasks (deductive reasoning, missing premises, and analysis of relevant and irrelevant information) were adapted from the Ross Test of Higher Cognitive Processes (Ross & Ross, 1979). Two remaining reasoning tasks, control of variables and mechanical reasoning, were based on a modified version (Hautamäki, 1984) of one of the science reasoning tasks of Shayer (1979), and the geometric analogies test of Hosenfeld et al. (1997), respectively. Lastly, two of the cognitive tasks measured mathematical thinking skills: hidden arithmetical operators by Demetriou et al. (1991, 1996), and invented mathematical operators modified from Sternberg's (Sternberg et al., 2001) Triarchic Test (H version) Creative Number scale. Despite the tasks measuring different dimensions of reasoning and thinking skills, researchers have confirmed that there is a strong common core (general factor) that correlates with students' school achievement relatively strongly (depending on the study, $r \sim .60$, see Vainikainen et al., 2015). The possible scores for all tasks ranged from 0 to 10, except for deductive reasoning and missing premises, where the possible score ranges were 0–6 and 0–9, respectively.

Grade Point Average (GPA)

GPA was used to represent students' prior academic achievement. It was calculated based on students' self-reported grades in the following subjects: Finnish, mathematics, English, history, and chemistry. In Finnish primary and secondary education, school grades range from 4 (*failed*) to 10 (*excellent*).

Motivational Belief Scales

Motivational beliefs were measured with scales based on action-control theory (Skinner et al., 1988). The focus was on student agency beliefs for ability (e.g., "I have sufficient ability to succeed at school") and effort (e.g., "I work hard to do well at school"), control expectancy (e.g., "I can get good grades at school if I want to"), and means-ends beliefs for ability (e.g., "Poor grades are due to lack of ability") and luck (e.g., "Failure at school is mainly due to bad luck"). Each scale contained three items with a 7-point Likert-type scale (1 = *not true at all* to 7 = *very true*).

Table 1 presents the descriptive statistics for the study variables. The reliability coefficients (Cronbach's alpha and McDonald's omega) were acceptable for all variables. Detailed correlation matrix for the study variables is provided in Appendix A.

TOT

TOT was extracted from log files for each student as a summary of the time used in each task, starting from the opening of the task to the submission when finished. TOT was counted in seconds. The participants were aware of the 90-min time limit for the assessment session as a whole, but no time limits were given on the individual tasks. The participants were not explicitly instructed to focus on the time spent on the tasks, as this was not the goal of the original assessment study the data derives from. TOT was extracted for secondary analyses of the data. Earlier research has shown it is a valid measure of students' effort in tasks requiring higher order thinking skills and complex problem-solving processes, in which quick automatized processes do not help even higher-performing students (Goldhammer et al., 2014). Based on earlier TOT research in which the same tasks have been utilized (Kupiainen et al., 2014), it can be confirmed that the task types used in the present study belong to this category. Therefore, it was concluded that TOT could be used as an indicator of effort in this context.

Following Kupiainen et al. (2014), the time variable in each task was graphically examined for possible outliers that could indicate delayed task submission, for example, by opening a new task and later returning to submit an earlier one. In deductive reasoning, six students were excluded whose TOT was $> 1{,}671$ s; in relevance of information, 11 excluded students had TOT $> 1{,}267$ s; in invented mathematical concepts, one excluded student had TOT $> 2{,}495$ s; in hidden arithmetical operators, two students had TOT $> 2{,}555$ s; in control of variables, 11 excluded students had TOT $> 1{,}068$ s; in missing premises, one student had $> 2{,}237$ s; in mechanical reasoning, 11 students had TOT > 949 s. In addition, some students had zero seconds due to a technical challenge with logging the start time and therefore, these times were excluded. The sum variable was created out of the TOTs from each task for the students who had TOTs on all the tasks. These exclusions decreased the observations in TOT to 5,902 from 5,975.

Data Analysis

In this study, all analyses except for descriptive statistics were conducted with Mplus Version 8.3 (Muthén & Muthén, 1998–2017). Descriptive statistics were analyzed with IBM SPSS Statistics 29.0. According to the normality test (Kolmogorov–Smirnov), the variables used in the study were not normally distributed (Appendix B). However, the variables had skewness and kurtosis values between −1 and 1 (or very close to it), indicating that the distribution was close to normal (see Kline, 2016). Nevertheless, maximum likelihood with robust standard errors (MLR) was used as it is robust to nonnormality. The means and distributions of all variables are presented in Table 1. As the intraclass correlations of the motivational variables ranged from .014 to .016, student clustering within schools was not accounted for in subsequent analyses.

Confirmatory factor analysis was conducted for the motivational scales prior to the latent profile analysis (LPA). In addition, measurement invariance of the latent factors was examined between support groups. The fit of the model was evaluated using the root-mean-square error of approximation (RMSEA), comparative fit index (CFI), Tucker–Lewis index (TLI), and standardized root-mean-square residual (SRMR). While the correlations (see Appendix A) between the agency beliefs for ability and control

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Table 1
Descriptive Statistics for the Action-Control Beliefs and Distal Outcome Variables

Variable	*N*	*M*	*SD*	Range	Skewness/*SE*	Kurtosis/*SE*	Items	ω	α
AgeAb	6,482	5.38	1.22	1–7	−0.761/0.030	0.242/0.061	3	.88	.80
AgeEf	6,422	4.62	1.25	1–7	−0.377/0.031	−0.106/0.061	3	.82	.80
MEAb	6,422	3.53	1.14	1–7	0.094/0.031	−0.071/0.061	3	.68	.66
MELu	6,421	2.29	1.17	1–7	1.069/0.031	1.069/0.061	3	.75	.75
CoEx	6,480	5.28	1.27	1–7	−0.683/0.030	0.097/0.061	3	.91	.90
LTL	6,476	44.21	16.61	0–100	0.311/0.030	−0.543/0.061	7	.85	.84
GPA	6,464	7.87	1.13	4–10	−0.193/0.030	−0.534/0.061	5	.90	.90
TOT	5,902	2,088.91	932.28	48–5,749	0.073/0.032	−0.591/0.064	7		

Note. AgeAb = agency: ability; AgeEf = agency: effort; MEAb = means-ends: ability; MELu = means-ends: luck; CoEx = control expectancy; LTL = cognitive tasks (learning to learn); GPA = grade point average; TOT = time on task.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

expectancy indicated the possibility of a single underlying structure, the belief constructs were treated as separate in accordance with the action-control theory (e.g., Little et al., 1999; Skinner et al., 1988). The good model fit demonstrated in confirmatory factor analysis (RMSEA = .049, CFI = .964, TLI = .953; SRMR = .055; Little, 2013) further supported this decision. Measurement invariance testing showed that the measurement model was sufficiently invariant across groups based on the cutoff criteria for unequal sample sizes (Chen, 2007), that is, the change for metric invariance was less than .005 in CFI, .010 in RMSEA, and .025 in SRMR. Accordingly, the change for scalar invariance was less than .005 in CFI, .010 in RMSEA, and .005 in SRMR (see Appendix C).

LPA was used to detect motivational profiles with different configurations of motivational belief measures. In the model, variances were constrained to be equal across profiles, and the variables were assumed to be uncorrelated, following Mplus defaults. For deciding class enumeration, the following most recommended fit indices (e.g., Diallo et al., 2017; Hickendorff et al., 2018; Marsh et al., 2009; Nylund et al., 2007; Tein et al., 2013; Tofighi et al., 2007; Tolvanen, 2007; Yang, 2006) were chosen as prior fit indices: Bayesian information criterion (BIC; Schwarz, 1978), sample size adjusted BIC (SABIC; Sclove, 1987), the consistent Akaike information criterion (CAIC; Bozdogan, 1987), Vuong–Lo–Mendel–Rubin likelihood ratio test (VLMR; Vuong, 1989), adjusted VLMR (Lo et al., 2001), and bootstrap loglikelihood ratio test (BLRT; McLachlan & Peel, 2000). Additional fit indices, Akaike information criterion (AIC) and entropy were considered despite being less effective (e.g., Nylund et al., 2007; Tein et al., 2013; Yang, 2006). BIC, SABIC, CAIC, and AIC are information criterion indices that refer to comparisons across several plausible models, with the lowest value indicating the best fitting model. In turn, VLMR (unadjusted and adjusted) and BLRT are likelihood ratio statistical tests that indicate with a *p*-value if the k-class model is a significantly better fitting model against the *k*–1 class (Nylund et al., 2007; Tein et al., 2013). Entropy value varies from 0 to 1 depending on how accurately the model classifies cases to classes with higher value representing a better fit (>0.80 indicating high classification accuracy; Clark & Muthén, 2009). Although certain fit indices are effective, challenges arise with sample size dependence, especially for information criterion indices in large samples (Marsh et al., 2009). Therefore, the elbow plot method (see Morin et al., 2011) for information criterion indices was used as well to determine the optimal number of profiles. Given fit index challenges, qualitative investigation against substantive theory and prior studies were equally crucial for class enumeration (Collins & Lanza, 2010; Marsh et al., 2009).

The Mplus command MODEL CONSTRAINT was used for substantiating the differences between the emerged profiles according to the means of the indicators used. The automated three-step method for multinominal logistic regression (R3STEP; Asparouhov & Muthén, 2014) was conducted to examine the effect of the level of support on the motivational profile membership. The interpretations of the probability of membership in one support group over another in comparisons between motivational profiles were made using OR, in which a value over 1 compared to the reference group (i.e., profile group) reflects more than 1 time of the odds for an outcome to happen (i.e., to belong to a particular support group) in the target group. Lastly, the automated the Bolck–Croon–Hagenaars (BCH) method for continuous distal outcomes (Asparouhov & Muthén, 2021) using the Wald test for the equality of means was employed to examine mean-level differences in TOT, GPA, and the success rate in cognitive tasks. The BCH method is based on the work of Bolck et al. (2004) and Bakk and Vermunt (2016). The validity of the results concerning the distal outcomes was ensured by using the level of support as a covariate to see if the profiles still explained differences in the outcomes even when the level of support was controlled for. The results of the manual three-step BCH method (Asparouhov & Muthén, 2021) for conducting this investigation can be found in Tables S4–S6 online supplemental materials. The significance threshold for the group comparisons of distal outcomes was adjusted using the Bonferroni correction.

Missing data for the variables of interest were evaluated prior to analyses. The share of missing data in the variables ranged from 6.6 to 12.8% (see Table S2 in the online supplemental materials). According to Little's missing completely at random test, the data were not completely missing at random, $\chi^2(757) = 2{,}815.584$, $p < .001$. However, the missing data were considered to be missing at random as both the level of support and gender correlated with the missingness in the variables (see Table S3 in the online supplemental materials). For limiting any biasness, full-information maximum likelihood was used in LPA.

Transparency and Openness

The determination of sample size, all data exclusions, all manipulations, and all measures in the study are reported according to JARS (Appelbaum et al., 2018). Since this study is a secondary analysis of previously collected assessment data, the authors are not in a

position to make the original data available. Analysis syntax, however, can be acquired by emailing the corresponding author. This study was not preregistered.

During the preparation of this article, OpenAI's GPT-4 (OpenAI, 2024), Wordtune (2024), and Copilot (Microsoft, 2024) were occasionally utilized to improve clarity, grammar, and coherence by suggesting vocabulary or phrasing improvements in the initial writing phase. For accuracy and appropriateness, all AI suggestions were carefully reviewed and edited. Before submitting, the article has undergone several rounds of editing by the authors. Having used the tools for real-time text editing, the outputs are not applicable.

Results

Identified Motivational Profiles

The first RQ of this study was to find out if there were distinctive combinations of motivational beliefs among the students and, if so, whether they were theoretically consistent with the prior research. To answer this question, LPA was applied. Fit indices of this LPA are presented in Table 2. Looking solely at the values of AIC, CAIC, SABIC, BIC, VLMR, adjusted VLMR, and BLRT, an ever-higher number of profiles would have been a better fit as the values of AIC, SABIC, and BIC continue decreasing, as well as *p*-values for BLRT continue being significant. This trend was also the case for VLMR and AVLMR, although according to these, the eight-profile solution did not seem superior compared to the seven-profile solution. This result was somewhat expected in terms of the sample size. However, the difference in the information criterion indices between solutions started to narrow after the difference between the four-profile and five-profile solutions (Table 2). When inspecting from the elbow plot (Figure 1), the slopes of AIC, CAIC, SABIC, and BIC began to decrease linearly after the five-profile solution, which reflected the numerical inspection from Table 2 as described above. However, five or more profiles would only have provided a slightly different version of two other profiles (Profiles 3 and 4; see Figure 2) presented in the four-profile solution, so that the pattern was the same but had even milder differences in the mean levels between the belief measures. As such, the additional profiles only differed in magnitude in terms of the patterns and did not add meaningful insights. In addition, the entropy value was slightly higher for four-profile solution. In turn, the three-profile model would not have presented a profile that was theoretically unique with high means in every belief measure, despite having a slightly similar pattern to Profiles 3 and 4 (Profile 4). Moreover, entropy value was the highest in four-profile solution. Ultimately, based on theoretically driven qualitative observations, the four-profile solution was considered the best fit. The average latent class posterior probabilities for most likely latent class membership are presented in Appendix D.

The profiles and their sample means for the motivational belief scales are presented in Figure 2. Student mean scores are also presented as standardized scores relative to students' average level of beliefs in the whole data set in Figure 3. The mean differences in profile indicators revealed that all four profiles differed significantly from one another across all measures ($p < .01$), with one exception: Profiles 3 and 4 did not differ significantly in agency belief for effort ($p = .764$; see Figure 2).

All standardized profile indicators differed significantly from the overall average in each profile. Specifically, agency beliefs related to ability and control expectancy in Profile 2 were significant at $p < .05$, while all other values were significant at $p < .001$ (see Figure 3).

In Profiles 2 ($n = 2{,}262$, 34.3%), 3 ($n = 3{,}275$, 50.1%), and 4 ($n = 335$, 5.7%), student agency beliefs on effort and ability as well as control expectancy were elevated compared to means-ends beliefs on ability and luck. In Profile 3, student ability and control over school achievement rose the most positive way. Their means-ends beliefs for luck and ability were the lowest compared to the other beliefs and other profiles. Therefore, Profile 3 was named as agentic. Profile 2 was named moderate based on the comparisons to other groups in raw means, especially the agentic group. These students had the second lowest means in means-ends beliefs on ability and luck but did not have such high perceptions of their ability, effort exertion and control compared to the other two profiles (3 and 4) and their own means-ends beliefs. Thus, this profile group could be considered as a "milder" version of the agentic group. However, compared to the overall sample, students in this profile exhibited somewhat diminished agency beliefs regarding their ability and effort, lower control expectancy, and slightly elevated means-ends beliefs related to ability and luck, which shared similarities with Profile 1. These two profiles, agentic and moderate, accounted for 84% of all students. In Profile 4, students' perceptions of their ability as well as effort were also among the most positive compared to the remaining groups. However, at the same time, these students had the most positive beliefs about the role of luck and ability in school success over all the other groups. The level

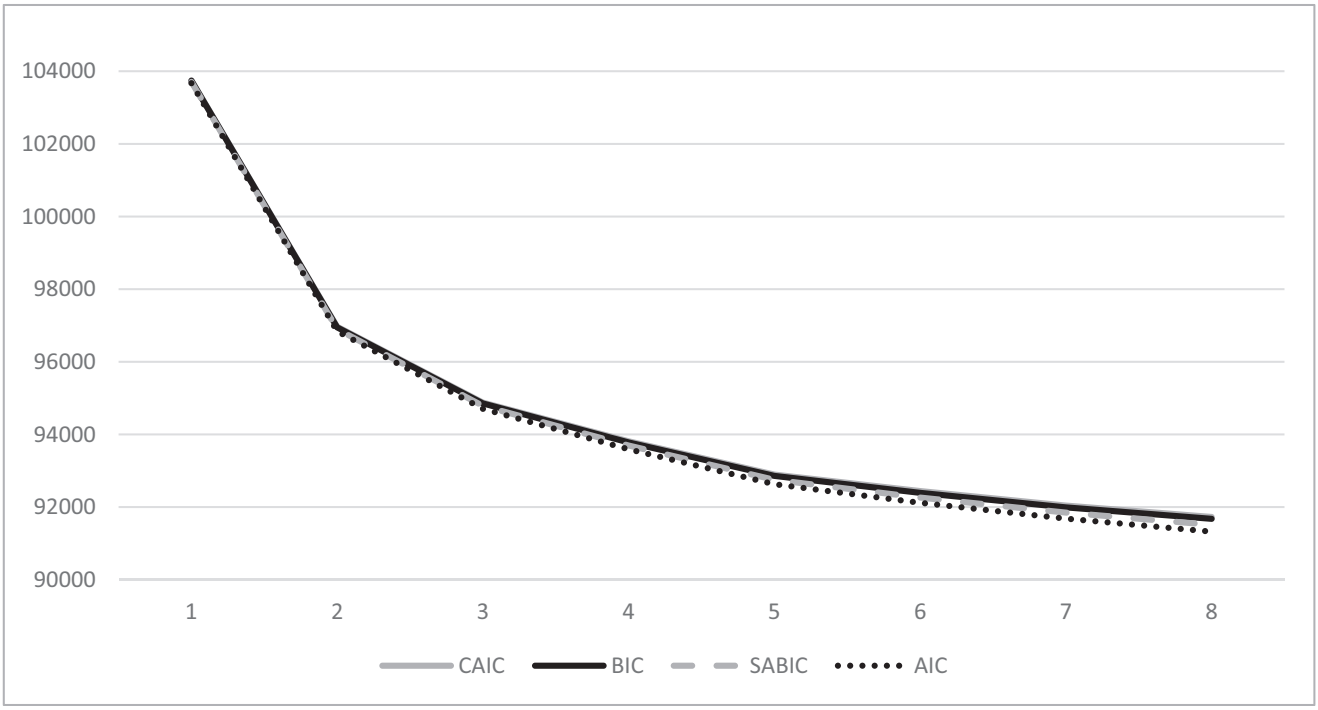
Table 2
Fit Indices for the Latent Profile Analysis

Class	AIC	CAIC	SABIC	BIC	Entropy	BLRT	AVLMR	VLMR	Group sizes	Smallest class (%)
1	103,669.976	103,747.747	103,705.969	103,737.747						
2	96,838.642	96,963.076	96,896.232	96,947.076	.824	.000	.000	.000	2,211 | 4,273	34
3	94,705.569	94,876.665	94,784.755	94,854.665	.824	.000	.000	.000	646 | 2,495 | 3,343	10
4	**93,590.891**	**93,808.649**	**93,691.673**	**93,780.649**	**.838**	**.000**	**.000**	**.000**	**612 | 2,262 | 3,275 | 335**	**5.7**
5	92,628.387	92,892.808	92,750.765	92,858.808	.808	.000	.000	.000	275 | 1,380 | 2,020 | 2,483 | 326	4.5
6	92,117.532	92,440.616	92,261.506	92,388.616	.794	.000	.000	.000	302 | 659 | 817 | 2,005 | 2,353 | 348	4.7
7	91,680.07	92,037.817	91,845.640	91,991.817	.788	.000	.000	.000	300 | 263 | 1,869 | 2,241 | 660 | 831 | 320	4.6
8	91,322.282	91,726.691	91,509.448	91,674.691	.796	.000	.058	.056	62 | 393 | 259 | 710 | 1,888 | 791 | 2,102 | 279	1

Note. Bolded values indicate the chosen profile solution. AIC = Akaike information criterion; CAIC = consistent Akaike information criterion; SABIC = sample size adjusted Bayesian information criterion; BIC = Bayesian information criterion; BLRT = bootstrap loglikelihood ratio test; AVLMR = adjusted Vuong–Lo–Mendell–Rubin likelihood ratio test; VLMR = Vuong–Lo–Mendell–Rubin likelihood ratio test.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Figure 1
Elbow Plot for Information Criterion Indices



Note. CAIC = consistent Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample size-adjusted Bayesian information criterion; AIC = Akaike information criterion.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

of means-ends beliefs for ability was higher than the agency belief for ability when compared to the mean level of the whole data (Figure 3). However, in profile-specific means, agency belief for ability was slightly higher than means-ends belief. Based on these characteristics, this profile was named, mixed. Profile 1 ($n = 612$, 10%) had the lowest beliefs about own ability, effort, and control. Contrary to other groups, means-ends belief for ability in this profile was the most positive compared to one's own ability, effort, and control expectancy. In other words, these students seem to have a relatively low perception of their ability, effort, and control over success while perceiving school outcomes as dependent on ability. Also, they believed in luck as a means of succeeding almost as much as their control over success based on the raw means. This profile was named, avoidant.

Profile Membership According to the Level of Support

To answer the second RQ, R3STEP was utilized to examine the effect of the level of support on motivational profile membership. Among the support groups, general support (Tier 1) was used as a reference category, as it is a starting point for providing special educational support and is offered for all students. Table 3 shows student proportions in each motivational profile based on each type of support.

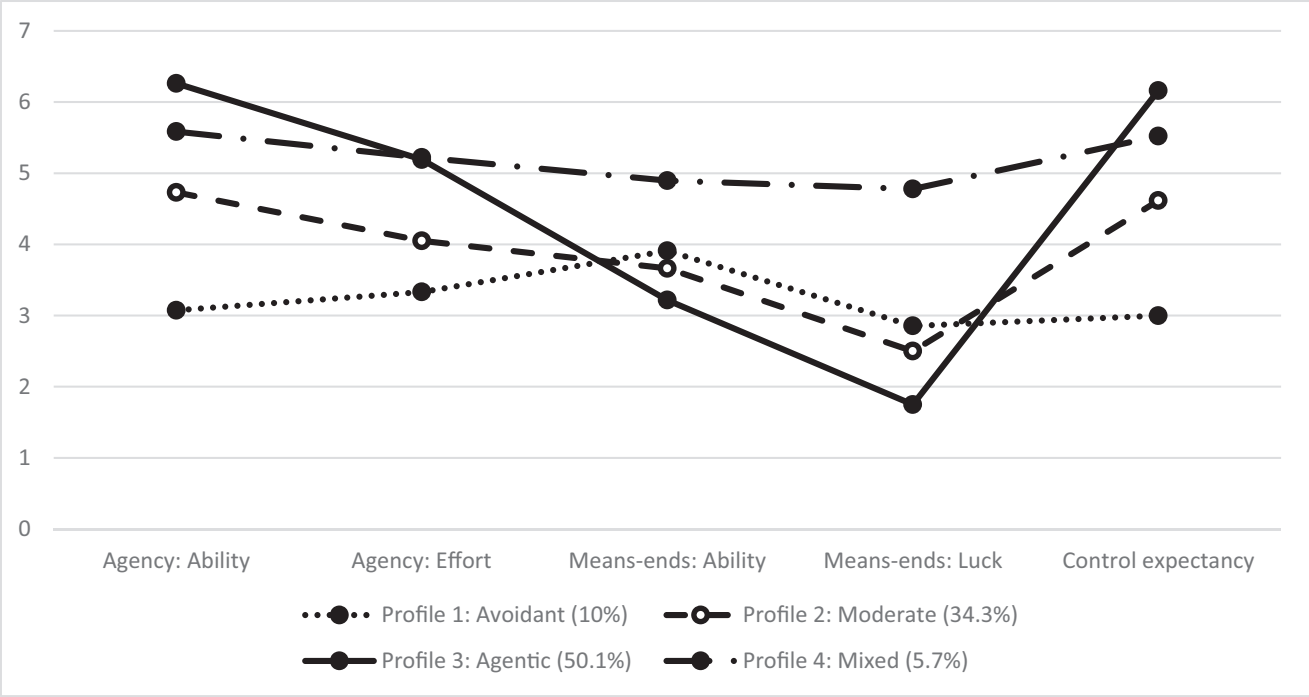
The effect of level of support on the motivational profiles is displayed in Table 4. When compared to the agentic profile, the probability of belonging to all the other motivational profiles was statistically significantly higher for students in Tier 2 or Tier 3 over Tier 1. This result was most evident when comparing the agentic and avoidant profiles. The odds of students in Tier 2 of belonging to the avoidant profile were over 10 times higher, and for students in Tier 3, over 16.5 times higher. Regarding the Mixed profile, the odds for students in Tier 3 of belonging to this profile were 12 times greater compared to the agentic group. For students in Tier 2, the odds were not as pronounced but were over 3 times higher for them as well. The odds were quite equally higher for students in Tier 2 and 3 to belong to the moderate than agentic profile (4.019 and 4.429, respectively). For students in Tier 2, however, it was still more likely to belong to the avoidant profile than any other profile. In turn, there were 2.7 times greater odds of belonging to the mixed profile than moderate for students receiving support according to Tier 3, but equal odds compared to the avoidant profile.

Between-Group Differences in GPA, LTL Tasks, and TOT

To examine how the identified motivational profiles differed from each other in terms of their TOT, task performance, and GPA, the BCH method with Wald tests was used. According to the overall Wald tests (see Table 5) there were differences in the motivational profiles in all of the outcome variables.

After applying the Bonferroni correction, the significance threshold for the pairwise comparisons was set at $p = .0083$. According to the pairwise Wald tests (see Table 6) with the Bonferroni correction, Agentic students performed the best in cognitive tasks and spent the most time completing them, followed by Moderate students.

Figure 2
Profiles and Their Sample Means for Action-Control Belief Scales



They also had the highest GPA. In turn, avoidant students had the lowest GPA, but they performed and used time at the same level with mixed students, who in turn had the second highest mean for GPA. Although they did not differ significantly from moderate students in GPA, they performed worse and spent less time on cognitive tasks.

Discussion

With a person-centered approach, this study was designed to examine combinations of students' action-control beliefs, how students' SEN status predicts these combinations and how the combinations are related to different performance outcomes. According to the LPA conducted here, four distinct profiles were identified, agentic, moderate, avoidant, and mixed, which had significant differences in TOT, GPA, and cognitive tasks performance. Students' motivational profiles explained the differences in these outcomes even after controlling for the level of support (see the online supplemental materials).[3]

Students in the agentic profile saw their ability and control over school achievement most positively compared to believing that luck and ability would determine school outcomes. Agentic students had the highest GPA and success rate in cognitive tasks and used more time on the tasks compared to other profiles. These characteristics reflected the most adaptive motivational profile in terms of personal agency (Chang et al., 2017; Little, 1998; Skinner et al., 1998), resembling the adaptive profile in Malmberg and Little's (2007) study. Moderate students exhibited a belief pattern that resembled that of Agentic students when compared within profiles, though the pattern was less pronounced. However, at the same time, they demonstrated similarities with the avoidant profile when compared to means of all students. Accordingly, as these students did have a modest tendency to diminish perceptions of their ability, effort, and control relative to the overall mean, they seemed to reflect the typical lower secondary school student in other studies in Finland (see Niemivirta, 2000; Tuominen-Soini et al., 2008). Nevertheless, in this study, the agentic seemed to be the prototypical profile. Moderate students performed in the cognitive tasks second best and used the second longest time in the tasks; however, when looking at the mean differences in the outcomes, they seemed somewhat closer to the other profiles than the agentic profile.

Avoidant students had the lowest adaptive beliefs and attributed school outcomes to ability over other beliefs. Based on these patterns, this profile was considered clearly maladaptive, as it is similar to the challenged profile in Malmberg and Little's (2007) study and therefore, could be associated with poor well-being and commitment (Malmberg & Little, 2007; Tuominen-Soini et al., 2008), and high task avoidance and off-task behavior (Parhiala et al., 2018; Roeser et al., 2002; Tuominen-Soini et al., 2008). The fact that avoidant students also had the lowest GPA and spent less time on the tasks than students in the agentic and moderate profile, supports these associations.

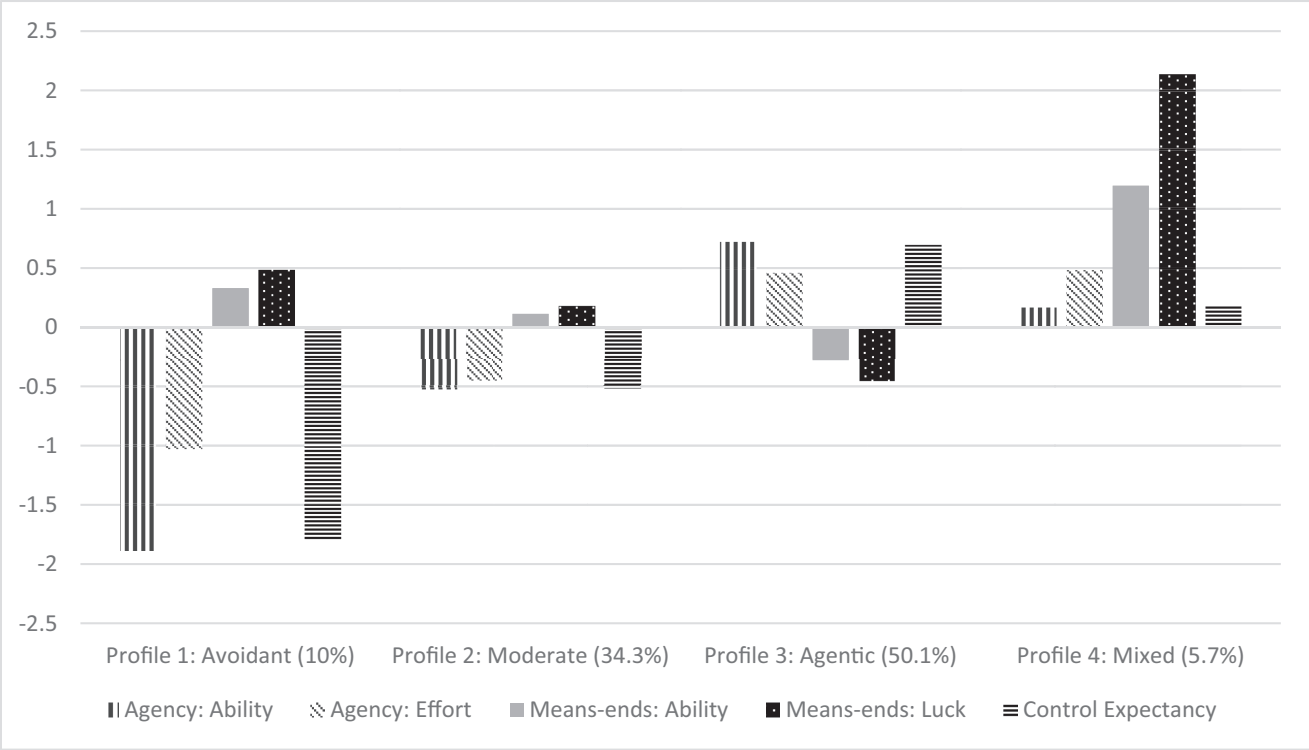
Students belonging to the avoidant profile did not differ in task performance and TOT from students in the mixed profile. However, students in mixed profile had higher GPA. In the mixed profile, students had one of the most positive beliefs about own effort and

[3] The study results were consistent with the supplementary analyses using the manual BCH method, except for the Wald tests applied for pairwise comparisons. These revealed differences in GPA that were all statistically significant in the supplementary analyses.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Figure 3

Profiles' Standardized Mean Scores for the Action-Control Belief Scales



ability with the agentic profile but similarly possessed the most positive means-ends beliefs on ability and luck. This emerging pattern in the motivational measures had similarities to the strivers profile found in the study of Malmberg and Little (2007). Based on their study, high means-ends belief with high agency belief for ability can be sensitive when confronted with novel and cognitively taxing tasks that could be considered difficult (high perceived difficulty, see Malmberg & Little, 2007). That is, the perceived higher risk of failure can explain the observed least amount of time spent in the cognitive tasks and therefore, the least amount of effort as a possible self-protective action (see also Tuominen-Soini et al., 2008). Similarly, the high mean in means-ends beliefs about luck could indicate a highlighted self-protective (or self-serving) attribute so, in case of failure, the

Table 3

Frequencies of Students at Different Levels of Support According to Motivational Profiles

Level of support	Motivational profiles				
	Avoidant	Moderate	Agentic	Mixed	Total
Tier 1					
n	359	1,792	3,050	247	5,448
%	6.6	32.9	56.0	4.5	100
Tier 2					
n	141	297	147	34	619
%	22.8	48.0	23.7	5.5	100
Tier 3					
n	112	173	78	54	417
%	26.9	41.5	18.7	12.9	100
Total					
n	612	2,262	3,275	335	6,484
%	9.4	34.9	50.5	5.2	100

Table 4

Level of Support as a Predictor of Motivational Profile Membership (R3STEP Method)

Level of support	*B*	*SE*	*p*	*OR*	95% CI
Avoidant versus agentic					
Tier 2	2.310	0.148	<.001	10.075	[12.117, 22.495]
Tier 3	2.804	0.188	<.001	16.510	[7.903, 12.844]
Moderate versus agentic					
Tier 2	1.389	0.133	<.001	4.012	[3.224, 4.992]
Tier 3	1.488	0.190	<.001	4.429	[3.240, 6.055]
Mixed versus agentic					
Tier 2	1.208	0.245	<.001	3.348	[2.238, 5.008]
Tier 3	2.488	0.231	<.001	12.040	[8.236, 17.601]
Avoidant versus moderate					
Tier 2	0.921	0.138	<.001	2.511	[2.001, 3.151]
Tier 3	1.316	0.162	<.001	3.728	[2.855, 4.868]
Avoidant versus mixed					
Tier 2	1.102	0.242	<.001	3.009	[2.022, 4.479]
Tier 3	0.316	0.200	.114	1.371	[0.987, 1.905]
Mixed versus moderate					
Tier 2	−0.181	0.235	.442	0.835	[0.567, 1.229]
Tier 3	1.000	0.199	<.001	2.718	[1.958, 3.774]

Note. Tier 1 (general support) as a reference group for the support group comparisons. R3STEP = automated three-step method for multinominal logistic regression; CI = confidence intervals for the odds ratios.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Table 5
Mean Differences Between Motivational Profiles in TOT, GPA, and Cognitive Tasks (Overall Wald Test)

Dependent	Independent	*M*	*SE*	$\chi^2(3)$	*p*
TOT	Motivational profile				
	Moderate	1,831.94	22.11	1,410.96	<.001
	Agentic	2,525.66	16.36		
	Avoidant	1,404.84	35.75		
	Mixed	1,229.67	61.20		
GPA	Motivational profile				
	Moderate	7.30	0.02	3,373.51	<.001
	Agentic	8.57	0.02		
	Avoidant	6.57	0.04		
	Mixed	7.48	0.07		
LTL	Motivational profile				
	Moderate	37.91	0.34	2,085.23	<.001
	Agentic	52.78	0.29		
	Avoidant	31.31	0.54		
	Mixed	29.07	0.85		

Note. TOT = time on task; GPA = grade point average; LTL = learning to learn assessment.

cause is considered to be external (Clem et al., 2018; Mezulis et al., 2004; Suter et al., 2022). However, in the present study, the means-ends beliefs were measured with a sum variable formed with positive and negative items. Additionally, the means-ends beliefs here do not pertain specifically to one's own successes and failures but rather to general beliefs about how school outcomes come to be. Thus, no interpretations can be made regarding attributions directly related to failure or those concerning the self. The person-centered approach requires more precise distinctions of success and failure to achieve a clear image of the meaning of the sample means in these means-ends beliefs.

Motivational Profiles of Students With SEN

The specific aim of this study was to provide insight into how SEN status predicts membership in different motivational profiles. Most of the students receiving general support belonged to the Agentic profile over the other profiles and students receiving intensified or special support were underrepresented in this profile. Students receiving intensified (Tier 2) or special support (Tier 3) we more likely to belong to the Moderate profile over agentic, but even more so in the avoidant profile. Especially the overrepresentation of students receiving intensified support (Tier 2) in the avoidant profile over the other profiles is

Table 6
Pairwise Wald Tests for Motivational Profiles in Distal Outcomes

Profile	$\chi^2(1)$	M_{diff}	95% CI
TOT			
Avoidant versus mixed	6.144	175.17	[36.25, 314.09]
Agentic versus mixed	409.777*	1,295.99	[1,171.83, 1,420.15]
Mixed versus moderate	80.647*	−602.27	[−729.81, −474.73]
Avoidant versus agentic	819.097*	−1,120.82	[−1,197.89, −1,043.76]
Avoidant versus moderate	92.284*	−427.10	[−509.49, −344.71]
Agentic versus moderate	572.924*	693.72	[639.81, 747.64]
GPA			
Avoidant versus mixed	132.992*	−0.91	[−1.07, −0.76]
Agentic versus mixed	242.009*	1.09	[0.96, 1.23]
Mixed versus moderate	6.114	0.18	[0.04, 0.32]
Avoidant versus agentic	1,983.213*	−2.01	[−2.09, −1.92]
Avoidant versus moderate	214.856*	−0.73	[−0.82, −0.64]
Agentic versus moderate	1,859.191	1.27	[1.22, 1.33]
LTL			
Avoidant versus mixed	4.999	2.24	[0.27, 4.21]
Agentic versus mixed	678.778*	23.72	[21.31, 26.12]
Mixed versus moderate	87.427*	−8.85	[−10.65, −7.05]
Avoidant versus agentic	1,250.619*	−21.48	[−22.67, −20.28]
Avoidant versus moderate	96.845*	−6.61	[−7.85, −5.36]
Agentic versus moderate	986.384*	14.87	[13.99, 15.75]

Note. CI = confidence intervals for mean differences; TOT = time on task; GPA = grade point average; LTL = learning to learn assessment.
* After Bonferroni correction, $p < .0083$.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

consistent with research on the motivational characteristics of students with SEN. According to earlier studies, students exhibiting learning-related difficulties often display motivational profiles with lower self-confidence, task avoidance, and reduced effort (Lee & Zentall, 2012; Núñez et al., 2005). The overrepresentation of students with SEN in the avoidant profile is of concern because such motivational factors can act as an additional burden on students with preexisting learning-related difficulties, further complicating their schooling. This phenomenon can be reflected in the Helplessness profile in the Núñez et al.'s (2005) study, depicting some students with learning difficulties as distinctly different from other students and performing poorly in areas other than those targeted by the learning difficulty. Especially for these students, it is vital to consider what supportive actions could be directed toward their perceptions of what it takes to do well in school and their own ability to do so, for example, by providing feedback in school, shaping the social environment in the classroom, and giving support at home.

Compared to students receiving general support, students receiving special support were more likely to belong to the mixed profile over moderate and agentic profiles. Considering research on overestimations of students with SEN (Pintrich et al., 1994; Schwab & Hessels, 2015), this result could mean that these students have elevated beliefs about their abilities and control over their school performance compared to their actual performance in cognitive tasks. The elevated beliefs could be partially associated with the possibility that these students are studying in a special class, in which students evaluate themselves against others at the same performance level (Bakker et al., 2007; Belfi et al., 2012; Hienonen et al., 2021; Törmänen & Roebers, 2018). Additionally, SEN students can be rewarded for their effort as a substitute for actual lower performance (Rojewski et al., 1991). This rewarding can lead to higher grades than what students with equivalent performance would achieve in regular classes (Hienonen et al., 2021), thereby possibly contributing to the relatively high GPA in this study. In addition, as Hienonen et al. (2021) argued, the rationale for higher grading in the special class environment can be connected to detected strivings for higher grades in a competitive, ego-oriented manner by seeking recognition and extrinsic rewarding. This kind of motivational pattern for students with learning difficulties has been detected in other studies as well (Sideridis, Mouzaki, et al., 2006) without considering class placement. Accordingly, students' beliefs could be reinforced as a motivating factor, which in a novel performance situation—especially in the mixed profile—might not drive them to make their best effort but rather lead to self-protective task withdrawal (Middleton et al., 2004). With students with SEN, this motivational pattern could then be a combination of elevated agentic beliefs that operate in a self-protecting manner when facing more demanding tasks. Factoring in more situational factors, such as students' evaluations on task performance and perceived task difficulty, could confirm matters. Of course, students with SEN who exhibit elevated beliefs might appear in other profiles as well. Future studies should investigate these possibilities by comparing students with SEN to others within the profiles and explore the relationships between GPA, TOT, and task performance.

Overall, with consideration of students with SEN, it was found that they lean more into more maladaptive profiles. However, it is crucial to note that these students were also present in all the other profiles, reflecting previous heterogeneous results with hindering varying internal and external protective and threatening factors. On the one hand, it may be that within different profile groups students with SEN differ from others, especially in terms of school achievement and cognitive performance, which may reflect the areas of disabilities. On the other hand, it is not known how much influence motivation has, per se. Therefore, it would be interesting to determine how students with SEN differ within and between profiles, and whether, for example, students with SEN in the avoidant profile appear even more disadvantaged because of their possible double burden. Supplemental analyses indicate that students with SEN do differ across profiles in the outcome variables, but this should be investigated in further studies. Nevertheless, the importance of a more individualized perspective when examining the different determinants of SEN, such as motivation and competence and the protective and threatening factors of the environment, is supported by the findings of this study.

Further Research

As already indicated, certain questions remain unresolved considering this study, and some areas warrant further investigation. Building on this, when considering students in the Mixed profile, their relatively high GPA combined with low time spent on cognitive tasks may indicate alternative explanations. One possibility is that these students perform well in school but are less inclined to invest effort in situations where the personal consequences are low. Essentially, they do the minimum required to perform well in school. This kind of motivational profile could partially explain higher means in almost every belief measure and the lowest performance in cognitive tasks, as the least time used in the tasks (which can, in problem-solving tasks, mean rapid guessing) would lead to the lowest probability of answering correctly (Barry et al., 2010; Goldhammer et al., 2014). Further investigation into the differences in the Mixed profile would be helpful to assess the importance students place on doing their best academically and/or in tests, as well as their perceptions of task difficulty and interest. Such an approach would bring us closer to understanding the actual task situation and the nature of the Mixed profile. Overall, the different motivational profiles aligned with students' effort, as measured by TOT, indicating that adaptive beliefs serve as an explanatory factor in students' effort. However, additional variables are needed to refine profiles that may appear similar in some motivational aspects but differ significantly in others, ultimately shaping distinct narratives. This aspect underlines the importance of general motivational beliefs as well as individual evaluations of test-specific or task-specific characteristics in terms of interest and task difficulty.

Some of the profiles suggested by research were not detected in this study. The Disengaged profile identified by Malmberg and Little (2007) was not distinct in this study. As culled from the theory, the beliefs of disengaged and challenged may not be distinct when using the measures in this study, and student GPAs and cognitive tasks performance can be at the higher end of the distribution. Disengaged students could also be present in the Mixed profile due to a lack of effort when completing the motivational measures as well as the cognitive tasks. Therefore, when reflecting the emerged profiles, it would be beneficial to consider other dimensions of motivation, such as goal orientations, in the profile analysis.

Limitations

In the previous sections, we have discussed certain limitations of this study. Building upon those, there are several other important points to consider. The first concerns the aggregate measurement

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

of students' motivational beliefs and TOT as proxies for effort. One risk of this approach is overlooking the potential variability in effort across different tasks and the potentially differing patterns in the level of effort across items (see Barry et al., 2010; Wise & Gao, 2017; Wise & Kong, 2005). A more nuanced examination of TOT could provide deeper insight into the consistency or variability of students' engagement with tasks and how different profiles of TOT associated with students' motivational profiles. Secondly, as already indicated in the introduction, we acknowledge that the time students use for tasks might not mean that the time is necessarily effective. For example, time can be spent on carefully consideration of the items and making meaningful decisions or playing with the learning environment. These strategies can vary in effectiveness depending on the required strategies to solve a certain type of task but also students' ability to use them. This can be true for the task types used in the present study as well, but this does not change the interpretation of the detrimental effects of insufficient time use (cf, Wise & Gao, 2017; Wise & Kong, 2005), which seems to be more typical for students with SEN. Even though TOT on learning has been researched for decades, its mechanisms regarding different task types and student subgroups are still partially unclear (Godwin et al., 2021). In this respect, through this present study we make an important contribution in shedding light on how students with SEN interact with tasks requiring higher order thinking skills measured with task types that in earlier research had been shown to be strongly influenced by TOT (Kupiainen et al., 2014; see also Goldhammer et al., 2014). Thirdly, the absence of information concerning the grounds for received support undermines the coherence of the person-centered approach when treating these students as a homogeneous group without the consideration of individual differences that learning-related difficulties have been stated to have in terms of the roles of motivational factors and cognitive abilities (e.g., Stone & May, 2002; Tabassam & Grainger, 2002; Zentall & Beike, 2012). Consequently, the time spent on a task—both in terms of its duration and the previously mentioned patterns—can mean different kinds of processing in terms of differing challenges in cognition. For instance, challenges in executive functions on their own may not be primarily caused by motivational factors and can lead to decreased efficiency or increased variability in response time across subsequent tasks (see, e.g., Dekkers et al., 2017). In addition, these differences apply to the heterogeneity in how much students with SEN would need time to complete tasks, as in the case for every student (see Goldhammer et al., 2014). However, collecting data for reasons of receiving support is against the Finnish policy of categorizing students with SEN based on diagnosis (see Hienonen et al., 2021). Nevertheless, when interpreting the results of future research, it would be crucial to consider or at least acknowledge the various areas of difficulties that these students experience. On this note, it is also important to note that the term students with SEN can have other meanings in different contexts which should be taken into account when considering the generalizability of the results to other contexts. Fourthly, regarding the GPA, as the grades behind the calculated GPA were reported by students and not retrieved from an official register, the higher grade of students in the Mixed profile could also be due to the individualized syllabus applicable to some students in special support (FNBE, 2016). In these syllabi, the individualized criteria for different grades are not equivalent to the learning objectives and grading in the standard curriculum. This issue is important to consider when interpreting the results with regard to GPA. Finally, while in our analytical approach we focused on investigating students' motivational profiles and examining differences in performance across them, we acknowledge that prior skills could also influence these relationships. Therefore, in future studies, this could be further elaborated by including prior skills or aptitudes into the profile analysis to see whether it changes the nature of the established profiles.

Despite these limitations and important considerations, through the results of this study, we have contributed to the prior research and similarly further deepened the understanding of the motivational patterns of students with SEN and how these overall motivational patterns are related to task behavior and performance. It is hoped that the current research will stimulate future investigation of this important area.

Conclusions

Through this study, we have provided insights into how distinct patterns of action-control beliefs reflect students' approaches to novel problem-solving situations outside their school context, highlighting the differing factors that contribute to grades. In other words, it may be that motivational beliefs may have varying effects on school grades due to how teachers perceive and assess students. However, as Chang et al. (2017) argue, the actual power of the beliefs on individual's agency emerges in new learning situations, and it is manifested in students' task behavior (i.e., time used in tasks and outcomes). In addition, beliefs that, on average, may seem adaptive in terms of schoolwork appear very differently related to performance in new situations and, in different combinations, lead to very different types of outcomes. Therefore, as revealed in this study, when looking at students' performance, it is important to take into account these motivational dimensions, but equally the amount of time students have spent on tasks in relation to their expected ability, to see which factors weigh most heavily on the overall picture of student performance. Applying this approach is particularly crucial for students who struggle academically, ensuring that the appropriate factors are addressed in their education and their approach to new learning challenges.

Several practical implications can be drawn from the findings of this study. One such implication is the potential for time-use monitoring to identify students who may not be exerting optimal effort, such as those belonging to the mixed profile of this study. Our research suggests the feasibility of implementing virtual tutoring system to assist and guide students during task completion, particularly if they answer questions prematurely without adequate consideration or even before fully reading the question. Additionally, spending less than the minimum required time to solve items could serve as a benchmark for identifying unmotivated students. This threshold could provide valuable feedback to test observers and teachers, enabling them to address motivational issues more effectively and in a timely manner.

References

Abramson, L. Y., Seligman, M. E., & Teasdale, J. D. (1978). Learned helplessness in humans: Critique and reformulation. *Journal of Abnormal Psychology*, *87*(1), 49–74. https://doi.org/10.1037/0021-843X.87.1.49

Ahtiainen, R. (2017). *Shades of change in Fullan's and Hargreaves's models* [Doctoral dissertation, University of Helsinki]. Helda. https://hdl.handle.net/10138/208038

Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

research in psychology: The APA Publications and Communications Board task force report. *The American Psychologist*, *73*(1), 3–25. https://doi.org/10.1037/amp0000191

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling*, *21*(3), 329–341. https://doi.org/10.1080/10705511.2014.915181

Asparouhov, T., & Muthén, B. (2021). Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model. *Mplus Web Notes*, *21*(2), 1–22. https://www.statmodel.com/examples/webnotes/webnote21.pdf

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling*, *23*(1), 20–31. https://doi.org/10.1080/10705511.2014.955104

Bakker, J. T. A., Denessen, E., Bosman, A. M. T., Krijger, E.-M., & Bouts, L. (2007). Sociometric status and self-image of children with specific and general learning disabilities in Dutch general and special education classes. *Learning Disability Quarterly*, *30*(1), 47–62. https://doi.org/10.2307/30035515

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215. https://doi.org/10.1037/0033-295x.84.2.191

Bandura, A. (1989). Human agency in social cognitive theory. *The American Psychologist*, *44*(9), 1175–1184. https://doi.org/10.1037/0003-066x.44.9.1175

Barry, C. L., Horst, S. J., Finney, S. J., Brown, A. R., & Kopp, J. P. (2010). Do examinees have similar test-taking effort? A high-stakes question for low-stakes testing. *International Journal of Testing*, *10*(4), 342–363. https://doi.org/10.1080/15305058.2010.508569

Basic Education Act, 628, Amendments up to 1136/2010. (1998). https://www.finlex.fi/en/laki/kaannokset/1998/en19980628.pdf/

Belfi, B., Goos, M., De Fraine, B., & Van Damme, J. (2012). The effect of class composition by gender and ability on secondary school students' school well-being and academic self-concept: A literature review. *Educational Research Review*, *7*(1), 62–74. https://doi.org/10.1016/j.edurev.2011.09.002

Bergman, L. R., & Magnusson, D. (1997). A person-oriented approach in research on developmental psychopathology. *Development and Psychopathology*, *9*(2), 291–319. https://doi.org/10.1017/S095457949700206X

Bergman, L. R., Magnusson, D., & El Khouri, B. M. (2003). *Studying individual development in an interindividual context: A person-oriented approach*. Lawrence Erlbaum Associates Publishers.

Björn, P. M., Aro, M. T., Koponen, T. K., Fuchs, L. S., & Fuchs, D. H. (2016). The many faces of special education within RTI frameworks in the United States and Finland. *Learning Disability Quarterly*, *39*(1), 58–66. https://doi.org/10.1177/0731948715594787

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, *12*(1), 3–27. https://doi.org/10.1093/pan/mph001

Bozdogan, H. (1987). Model selection and Akaike's Information Criterion (AIC): The general theory and its analytical extensions. *Psychometrika*, *52*(3), 345–370. https://doi.org/10.1007/BF02294361

Brunswick, N., & Bargary, S. (2022). Self-concept, creativity and developmental dyslexia in university students: Effects of age of assessment. *Dyslexia*, *28*(3), 293–308. https://doi.org/10.1002/dys.1722

Carroll, J. B. (1989). The Carroll model: A 25-year retrospective and prospective view. *Educational Researcher*, *18*(1), 26–31. https://doi.org/10.3102/0013189X018001026

Chang, R., Adams, N., & Little, T. D. (2017). Action-control beliefs and agentic actions. In M. L. Wehmeyer, K. A. Shogren, T. D. Little, & S. J. Lopez (Eds.), *Development of self-determination through the life-course* (pp. 285–295). Springer Science + Business Media. https://doi.org/10.1007/978-94-024-1042-6_22

Chapman, J. W. (1988). Learning disabled children's self-concepts. *Review of Educational Research*, *58*(3), 347–371. https://doi.org/10.2307/1170259

Chapman, M., Skinner, E. A., & Baltes, P. B. (1990). Interpreting correlations between children's perceived control and cognitive performance: Control, agency, or means-ends beliefs? *Developmental Psychology*, *26*(2), 246–253. https://doi.org/10.1037/0012-1649.26.2.246

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling*, *14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Clark, S. L., & Muthén, B. (2009). *Relating latent class analysis results to variables not included in the analysis* [Unpublished manuscript]. https://www.statmodel.com/download/relatinglca.pdf

Clem, A.-L., Aunola, K., Hirvonen, R., Määttä, S., Nurmi, J.-E., & Kiuru, N. (2018). Adolescents' domain-specific self-concepts of ability predict their domain-specific causal attributions: A longitudinal study. *Merrill-Palmer Quarterly*, *64*(4), 539–569. https://doi.org/10.13110/merrpalmquar1982.64.4.0539

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis with applications in the social, behavioural, and health sciences*. John Wiley & Sons. https://doi.org/10.1002/9780470567333

Deci, E. L., & Chandler, C. L. (1986). The importance of motivation for the future of the LD field. *Journal of Learning Disabilities*, *19*(10), 587–594. https://doi.org/10.1177/002221948601901003

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Dekkers, T. J., Agelink van Rentergem, J. A., Koole, A., van den Wildenberg, W. P. M., Popma, A., Bexkens, A., Stoffelsen, R., Diekmann, A., & Huizenga, H. M. (2017). Time-on-task effects in children with and without ADHD: Depletion of executive resources or depletion of motivation? *European Child & Adolescent Psychiatry*, *26*(12), 1471–1481. https://doi.org/10.1007/s00787-017-1006-y

Demetriou, A., & Kazi, S. (2001). *Unity and modularity in the mind and the self: Studies on the relationships between self-awareness, personality, and intellectual development from childhood to adolescence*. Routledge. https://doi.org/10.4324/9780203770092

Demetriou, A., Pachaury, A., Metallidou, Y., & Kazi, S. (1996). Universals and specificities in the structure and development of quantitative-relational thought: A cross-cultural study in Greece and India. *International Journal of Behavioral Development*, *19*(2), 255–290. https://doi.org/10.1177/016502549601900203

Demetriou, A., Platsidou, M., Efklides, A., Metallidou, Y., & Shayer, M. (1991). The development of quantitative-relational abilities from childhood to adolescence: Structure, scaling, and individual differences. *Learning and Instruction*, *1*(1), 19–43. https://doi.org/10.1016/0959-4752(91)90017-3

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2017). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in growth mixture models. *Psychological Methods*, *22*(1), 166–190. https://doi.org/10.1037/met0000084

Dunlosky, J., Badali, S., Rivers, M. L., & Rawson, K. A. (2020). The role of effort in understanding educational achievement: Objective effort as an explanatory construct versus effort as a student perception. *Educational Psychology Review*, *32*(4), 1163–1175. https://doi.org/10.1007/s10648-020-09577-3

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist*, *41*(10), 1040–1048. https://doi.org/10.1037/0003-066X.41.10.1040

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*(1), 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Elliott, E. S., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of Personality and Social Psychology*, *54*(1), 5–12. https://doi.org/10.1037/0022-3514.54.1.5

Elliott, R. (2003). Executive functions and their disorders. *British Medical Bulletin*, *65*(1), 49–59. https://doi.org/10.1093/bmb/65.1.49

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

FNBE. (2016). *National core curriculum for basic education 2014*. https://www.ellibs.com/book/9789521362590/national-core-curriculum-for-basic-education-2014

Follmer, D. J., & Sperling, R. A. (2020). The roles of executive functions in learning and achievement. In A. J. Martin, R. A. Sperling, & K. J. Newton (Eds.), *Handbook of educational psychology and students with special needs* (pp. 95–115). Routledge/Taylor & Francis Group. https://doi.org/10.4324/9781315100654-6

Fuchs, D., Fuchs, L. S., & Compton, D. L. (2012). Smart RTI: A next-generation approach to multilevel prevention. *Exceptional Children*, *78*(3), 263–279. https://doi.org/10.1177/001440291207800301

Gans, A. M., Kenny, M. C., & Ghany, D. L. (2003). Comparing the self-concept of students with and without learning disabilities. *Journal of Learning Disabilities*, *36*(3), 287–295. https://doi.org/10.1177/00222194030360030 7

Geldhof, G. J., & Little, T. D. (2011). Influences of children's and adolescents' action-control processes on school achievement, peer relationships, and coping with challenging life events. *New Directions for Child and Adolescent Development*, *2011*(133), 45–59. https://doi.org/10.1002/cd.303

Godwin, K. E., Seltman, H., Almeda, M., Davis Skerbetz, M., Kai, S., Baker, R. S., & Fisher, A. V. (2021). The elusive relationship between time on-task and learning: Not simply an issue of measurement. *Educational Psychology*, *41*(4), 502–519. https://doi.org/10.1080/01443410.2021.1894324

Goldhammer, F., Naumann, J., Stelter, A., Tóth, K., Rölke, H., & Klieme, E. (2014). The time on task effect in reading and problem solving is moderated by task difficulty and skill: Insights from a computer-based large-scale assessment. *Journal of Educational Psychology*, *106*(3), 608–626. https://doi.org/10.1037/a0034716

Graham, S., & Harris, K. R. (1989). Components analysis of cognitive strategy instruction: Effects on learning disabled students' compositions and self-efficacy. *Journal of Educational Psychology*, *81*(3), 353–361. https://doi.org/10.1037/0022-0663.81.3.353

Greiff, S., Niepel, C., Scherer, R., & Martin, R. (2016). Understanding students' performance in a computer-based assessment of complex problem solving: An analysis of behavioral data from computer-generated log files. *Computers in Human Behavior*, *61*, 36–46. https://doi.org/10.1016/j.chb.2016.02.095

Grolnick, W. S., & Ryan, R. M. (1990). Self-perceptions, motivation, and adjustment in children with learning disabilities: A multiple group comparison study. *Journal of Learning Disabilities*, *23*(3), 177–184. https://doi.org/10.1177/002221949002300308

Guez, A., Ketan, & Piacentini, M. (2024). *Mapping study for the integration of accommodations for students with Special Education Needs (SEN) in PISA* (OECD Education Working Paper No. 308). OECD. https://doi.org/10.1787/ed03c717-en

Hautamäki, J. (1984). *Peruskoululaisten loogisen ajattelun mittaamisesta ja esiintymisestä* [The measurement and distribution of Piagetian stages of thinking in Finnish comprehensive school]. University of Joensuu, Department of Social Sciences.

Hautamäki, J., Arinen, P., Hautamäki, A., Kupiainen, S., Lindblom, B., Mehtäläinen, J., Niemivirta, M., Rantanen, P., Ruuth, M., & Scheinin, P. (2003). *Oppimaan oppiminen yläasteella. 2: Tilanne vuonna 2001 ja muutokset vuodesta 1997* [Learning to learn in upper secondary education. 2: Situation in 2001 and changes since 1997] (Oppimistulosten arviointi; no. 6/2003). Opetushallitus.

Hautamäki, J., Kupiainen, S., Arinen, P., Hautamäki, A., Niemivirta, M., Rantanen, P., Ruut, M., & Scheinin, P. (2005). *Oppimaan oppiminen ala-asteella 2: Tilanne vuonna 2003 ja muutokset vuodesta 1996* [Learning to learn in primary school 2: Situation in 2003 and changes since 1996]. (Oppimistulosten arviointi; no. 1/2005). Opetushallitus.

Heath, N., Roberts, E., & Toste, J. R. (2011). Perceptions of academic performance: Positive illusions in adolescents with and without learning disabilities. *Journal of Learning Disabilities*, *46*(5), 402–412. https://doi.org/10.1177/0022219411428807

Heath, N. L. (1995). Distortion and deficit: Self-perceived versus actual academic competence in depressed and nondepressed children with and without learning disabilities. *Learning Disabilities Research & Practice*, *10*(1), 2–10.

Hickendorff, M., Edelsbrunner, P. A., McMullen, J., Schneider, M., & Trezise, K. (2018). Informative tools for characterizing individual differences in learning: Latent class, latent profile, and latent transition analysis. *Learning and Individual Differences*, *66*, 4–15. https://doi.org/10.1016/j.lindif.2017.11.001

Hienonen, N., Hotulainen, R., & Jahnukainen, M. (2021). Outcomes of regular and special class placement for students with special educational needs—A quasi-experimental study. *Scandinavian Journal of Educational Research*, *65*(4), 646–660. https://doi.org/10.1080/00313831.2020.1739134

Hienonen, N., Lintuvuori, M., Jahnukainen, M., Hotulainen, R., & Vainikainen, M.-P. (2018). The effect of class composition on cross-curricular competences—Students with special educational needs in regular classes in lower secondary education. *Learning and Instruction*, *58*, 80–87. https://doi.org/10.1016/j.learninstruc.2018.05.005

Holm, M. E., Björn, P. M., Laine, A., Korhonen, J., & Hannula, M. S. (2020). Achievement emotions among adolescents receiving special education support in mathematics. *Learning and Individual Differences*, *79*, Article 101851. https://doi.org/10.1016/j.lindif.2020.101851

Honkasilta, J., Ahtiainen, R., Hienonen, N., & Jahnukainen, M. (2019). Inclusive and special education and the question of equity in education: The case of Finland. In M. J. Schuelka, C. J. Johnstone, G. Thomas, & A. J. Artiles (Eds.), *The Sage handbook of inclusion and diversity in education* (pp. 481–495). SAGE Publications. https://doi.org/10.4135/9781526470430.n39

Hosenfeld, B., van den Boom, D. C., & Resing, W. C. M. (1997). Constructing geometric analogies for the longitudinal testing of elementary school children. *Journal of Educational Measurement*, *34*(4), 367–372. https://doi.org/10.1111/j.1745-3984.1997.tb00524.x

Hotulainen, R., Vinni-Laakso, J., & Kupiainen, S. (2020). Development of learning to learn competence across secondary education and its association with attainment in Finnish/Swedish high-stake exit exam. *Thinking Skills and Creativity*, *38*, Article 100738. https://doi.org/10.1016/j.tsc.2020.100738

Hoza, B., Gerdes, A. C., Hinshaw, S. P., Arnold, L. E., Pelham, W. E., Molina, B. S. G., Abikoff, H. B., Epstein, J. N., Greenhill, L. L., Hechtman, L., Odbert, C., Swanson, J. M., & Wigal, T. (2004). Self-perceptions of competence in children with ADHD and comparison children. *Journal of Consulting and Clinical Psychology*, *72*(3), 382–391. https://doi.org/10.1037/0022-006X.72.3.382

ISCED. (2012). *International standard classification of education: ISCED 2011*. UNESCO Institute for Statistics. https://uis.unesco.org/sites/default/files/documents/international-standard-classification-of-education-isced-2011-en.pdf

Jahnukainen, M., & Itkonen, T. (2016). Tiered intervention: History and trends in Finland and the United States. *European Journal of Special Needs Education*, *31*(1), 140–150. https://doi.org/10.1080/08856257.2015.1108042

Jahnukainen, M., & Itkonen, T. (2021). Steps to inclusion?: The role of tiered intervention in Finland and in the United States. In A. Köpfer, J. J. W. Powell, & R. Zahnd (Eds.), *Handbuch Inklusion international: Globale, nationale und lokale Perspektiven auf Inklusive Bildung* [International handbook of inclusive education: Global, national and local perspectives] (1st ed., pp. 345–356). Verlag Barbara Budrich. https://doi.org/10.2307/j.ctv1f70kvj.22

Kavale, K. A., & Forness, S. R. (1987). Substance over style: Assessing the efficacy of modality testing and teaching. *Exceptional Children*, *54*(3), 228–239. https://doi.org/10.1177/001440298705400305

Klassen, R. M. (2006). Too much confidence? The self-efficacy of adolescents with learning disabilities. In T. Urdan & F. Pajares (Eds.), *Adolescence and education: Volume. Self-efficacy beliefs of adolescents* (pp. 181–200). Information Age Publishing.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Klassen, R. M. (2007). Using predictions to learn about the self-efficacy of early adolescents with and without learning disabilities. *Contemporary Educational Psychology*, *32*(2), 173–187. https://doi.org/10.1016/j.cedpsych.2006.10.001

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Kocaj, A., Kuhl, P., Jansen, M., Pant, H. A., & Stanat, P. (2018). Educational placement and achievement motivation of students with special educational needs. *Contemporary Educational Psychology*, *55*, 63–83. https://doi.org/10.1016/j.cedpsych.2018.09.004

Korhonen, J., Linnanmäki, K., & Aunio, P. (2014). Learning difficulties, academic well-being and educational dropout: A person-centred approach. *Learning and Individual Differences*, *31*, 1–10. https://doi.org/10.1016/j.lindif.2013.12.011

Kupiainen, S., Vainikainen, M.-P., Marjanen, J., & Hautamäki, J. (2014). The role of time on task in computer-based low-stakes assessment of cross-curricular skills. *Journal of Educational Psychology*, *106*(3), 627–638. https://doi.org/10.1037/a0035507

Lackaye, T., Margalit, M., Ziv, O., & Ziman, T. (2006). Comparisons of self-efficacy, mood, effort, and hope between students with learning disabilities and their non-LD-matched peers. *Learning Disabilities Research and Practice*, *21*(2), 111–121. https://doi.org/10.1111/j.1540-5826.2006.00211.x

Lackaye, T. D., & Margalit, M. (2006). Comparisons of achievement, effort, and self-perceptions among students with learning disabilities and their peers from different achievement groups. *Journal of Learning Disabilities*, *39*(5), 432–446. https://doi.org/10.1177/00222194060390050501

Lee, J., & Zentall, S. S. (2012). Reading motivational differences among groups: Reading disability (RD), attention deficit hyperactivity disorder (ADHD), RD + ADHD, and typical comparison. *Learning and Individual Differences*, *22*(6), 778–785. https://doi.org/10.1016/j.lindif.2012.05.010

Lee, J., & Zentall, S. S. (2017). Reading motivation and later reading achievement for students with reading disabilities and comparison groups (ADHD and typical): A 3-year longitudinal study. *Contemporary Educational Psychology*, *50*, 60–71. https://doi.org/10.1016/j.cedpsych.2015.11.001

Levenson, H. (1973). Perceived parental antecedents of internal powerful others, and chance locus of control orientations. *Developmental Psychology*, *9*(2), 260–265. https://doi.org/10.1037/h0035127

Little, T. D. (1998). Sociocultural influences on the development of children's action-control beliefs. In J. Heckhausen & C. S. Dweck (Eds.), *Motivation and self-regulation across the life span* (pp. 281–315). Cambridge University Press. https://doi.org/10.1017/CBO9780511527869.013

Little, T. D. (2013). *Longitudinal structural equation modeling*. Guilford Press.

Little, T. D., Hawley, P. H., Heinrich, C. C., & Marsland, K. W. (2002). Three views of the agentic self: A developmental synthesis. In E. L. Deci & R. M. Ryan (Eds.), *Handbook of self-determination research* (pp. 389–404). University of Rochester Press.

Little, T. D., & Lopez, D. F. (1997). Regularities in the development of children's causality beliefs about school performance across six sociocultural contexts. *Developmental Psychology*, *33*(1), 165–175. https://doi.org/10.1037/0012-1649.33.1.165

Little, T. D., Lopez, D. F., Oettingen, G., & Baltes, P. B. (2001). A comparative-longitudinal study of action-control beliefs and school performance: On the role of context. *International Journal of Behavioral Development*, *25*(3), 237–245. https://doi.org/10.1080/01650250042000258

Little, T. D., Oettingen, G., Stetsenko, A., & Baltes, P. B. (1995). Children's action-control beliefs about school performance: How do American children compare with German and Russian children? *Journal of Personality and Social Psychology*, *69*(4), 686–700. https://doi.org/10.1037/0022-3514.69.4.686

Little, T. D., Stetsenko, A., & Maier, H. (1999). Action-control beliefs and school performance: A longitudinal study of Moscow children and adolescents. *International Journal of Behavioral Development*, *23*(3), 799–823. https://doi.org/10.1080/016502599383801

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767–778. https://doi.org/10.1093/biomet/88.3.767

Lopez, D. F., Little, T. D., Oettingen, G., & Baltes, P. B. (1998). Self-regulation and school performance: Is there optimal level of action-control? *Journal of Experimental Child Psychology*, *70*(1), 54–74. https://doi.org/10.1006/jecp.1998.2446

Malmberg, L.-E., & Little, T. D. (2007). Profiles of ability, effort, and difficulty: Relationships with worldviews, motivation and adjustment. *Learning and Instruction*, *17*(6), 739–754. https://doi.org/10.1016/j.learninstruc.2007.09.014

Malmberg, L.-E., Walls, T. A., Martin, A. J., Little, T. D., & Lim, W. H. T. (2013). Primary school students' learning experiences of, and self-beliefs about competence, effort, and difficulty: Random effects models. *Learning and Individual Differences*, *28*, 54–65. https://doi.org/10.1016/j.lindif.2013.09.007

Malmberg, L.-E., Wanner, B., & Little, T. D. (2008). Age and school-type differences in children's beliefs about school performance. *International Journal of Behavioral Development*, *32*(6), 531–541. https://doi.org/10.1177/0165025408095558

Mamlin, N., Harris, K. R., & Case, L. P. (2001). A methodological analysis of research on locus of control and learning disabilities: Rethinking a common assumption. *The Journal of Special Education*, *34*(4), 214–225. https://doi.org/10.1177/002246690103400404

Marsh, H. W. (1988). *Self-Description Questionnaire I: Manual and research monograph*. Psychological Corporation.

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling*, *16*(2), 191–225. https://doi.org/10.1080/10705510902751010

Martin, A. J. (2012). Attention-deficit/hyperactivity disorder (ADHD), perceived competence, and self-worth: Evidence and implications for students and practitioners. In D. Hollar (Ed.), *Handbook of children with special health care needs* (pp. 47–72). Springer Science + Business Media. https://doi.org/10.1007/978-1-4614-2335-5_3

Martin, A. J., Burns, E. C., & Collie, R. J. (2017). ADHD, personal and interpersonal agency, and achievement: Exploring links from a social cognitive theory perspective. *Contemporary Educational Psychology*, *50*, 13–22. https://doi.org/10.1016/j.cedpsych.2016.12.001

Martin, A. J., Sperling, R. A., & Newton, K. J. (Ed.). (2020). *Handbook of educational psychology and students with special needs*. Routledge.

McLachlan, G., & Peel, D. (2000). *Finite mixture models*. John Wiley & Sons. https://doi.org/10.1002/0471721182

Mezulis, A. H., Abramson, L. Y., Hyde, J. S., & Hankin, B. L. (2004). Is there a universal positivity bias in attributions? A meta-analytic review of individual, developmental, and cultural differences in the self-serving attributional bias. *Psychological Bulletin*, *130*(5), 711–747. https://doi.org/10.1037/0033-2909.130.5.711

Microsoft. (2024). *Microsoft Copilot* [Large language model]. https://copilot.microsoft.com

Middleton, M. J., Kaplan, A., & Midgley, C. (2004). The change in middle school students' achievement goals in mathematics over time. *Social Psychology of Education*, *7*(3), 289–311. https://doi.org/10.1023/B:SPOE.0000037484.86850.fa

Midgley, C., Kaplan, A., & Middleton, M. J. (2001). Performance-approach goals: Good for what, for whom, under what circumstances, and at what cost? *Journal of Educational Psychology*, *93*(1), 77–86. https://doi.org/10.1037/0022-0663.93.1.77

Morin, A. J. S., Maïano, C., Nagengast, B., Marsh, H. W., Morizot, J., & Janosz, M. (2011). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling*, *18*(4), 613–648. https://doi.org/10.1080/10705511.2011.607714

Muthén, L. K., & Muthén, B. O. (1998). *Mplus user's guide* (8th ed.).
Naumann, J., & Goldhammer, F. (2017). Time-on-task effects in digital reading are non-linear and moderated by persons' skills and tasks' demands. *Learning and Individual Differences*, *53*, 1–16. https://doi.org/10.1016/j.lindif.2016.10.002
Nicholls, J. G. (1984). Achievement motivation: Conceptions of ability, subjective experience, task choice, and performance. *Psychological Review*, *91*(3), 328–346. https://doi.org/10.1037/0033-295X.91.3.328
Niemivirta, M. (2000). "Ehkä osaisinkin, mutta kun ei huvita …": Motivaatio ja koulumenestys peruskoulun päättyessä [Motivation and school achievement at the end of the compulsory school]. In J. Hautamäki, P. Arinen, A. Hautamäki, M. Ikonen-Varila, S. Kupiainen, B. Lindblom, M. Niemivirta, P. Rantanen, M. Ruuth, & P. Scheinin (Eds.), *Oppimaan oppiminen yläasteella* [Learning to learn in lower secondary school] (pp. 121–150). Opetushallitus.
Niemivirta, M., Pulkka, A.-T., Tapola, A., & Tuominen, H. (2019). Achievement goal orientations: A person-oriented approach. In K. A. Renninger & S. E. Hidi (Eds.), *The Cambridge handbook of motivation and learning. Cambridge handbooks in psychology* (pp. 566–616). Cambridge University Press. https://doi.org/10.1017/9781316823279.025
Núñez, J. C., González-Pienda, J. A., González-Pumariega, S., Roces, C., Alvarez, L., González, P., Cabanach, R. G., Valle, A., & Rodríguez, S. (2005). Subgroups of attributional profiles in students with learning difficulties and their relation to self-concept and academic goals. *Learning Disabilities Research & Practice*, *20*(2), 86–97. https://doi.org/10.1111/j.1540-5826.2005.00124.x
Núñez, J. C., González-Pienda, J. A., Rodríguez, C., Valle, A., Gonzalez-Cabanach, R., & Rosário, P. (2011). Multiple goals perspective in adolescent students with learning difficulties. *Learning Disability Quarterly*, *34*(4), 273–286. https://doi.org/10.1177/0731948711421763
Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396
OECD. (2007). *Students with disabilities, learning difficulties and disadvantages: Policies, statistics and indicators*. https://doi.org/10.1787/9789264027619-en
OECD. (2023). *PISA 2022 Results (volume I): The state of learning and equity in education*. https://doi.org/10.1787/53f23881-en
OpenAI. (2024). *ChatGPT* (Version 4.0) [Computer software]. https://chat.openai.com/chat
Owens, J. S., Goldfine, M. E., Evangelista, N. M., Hoza, B., & Kaiser, N. M. (2007). A critical review of self-perceptions and the positive illusory bias in children with ADHD. *Clinical Child and Family Psychology Review*, *10*(4), 335–351. https://doi.org/10.1007/s10567-007-0027-3
Palladino, P., Poli, P., Masi, G., & Marcheschi, M. (2000). The relation between metacognition and depressive symptoms in preadolescents with learning disabilities: Data in support of Borkowski's model. *Learning Disabilities Research & Practice*, *15*(3), 142–148. https://doi.org/10.1207/SLDRP1503_4
Parhiala, P., Torppa, M., Vasalampi, K., Eklund, K., Poikkeus, A.-M., & Aro, T. (2018). Profiles of school motivation and emotional well-being among adolescents: Associations with math and reading performance. *Learning and Individual Differences*, *61*, 196–204. https://doi.org/10.1016/j.lindif.2017.12.003
Pieschl, S. (2009). Metacognitive calibration—An extended conceptualization and potential applications. *Metacognition and Learning*, *4*(1), 3–31. https://doi.org/10.1007/s11409-008-9030-4
Pintrich, P. R., Anderman, E. M., & Klobucar, C. (1994). Intraindividual differences in motivation and cognition in students with and without learning disabilities. *Journal of Learning Disabilities*, *27*(6), 360–370. https://doi.org/10.1177/002221949402700603
Polychroni, F., & Antoniou, A.-S. (2013). Social and emotional aspects of learning disabilities: Challenges and responses. In A.-S. Antoniou & B. D. Kirkcaldy (Eds.), *Education, family and child & adolescent health* (pp. 93–119). Diadrasi.
Roeser, R. W., Strobel, K. R., & Quihuis, G. (2002). Studying early adolescents' academic motivation, social-emotional functioning, and engagement in learning: Variable- and person-centered approaches. *Anxiety, Stress & Coping*, *15*(4), 345–368. https://doi.org/10.1080/10615800210000056519
Rojewski, J. W., Pollard, R. R., & Meers, G. D. (1991). Grading mainstreamed special needs students: Determining practices and attitudes of secondary vocational educators using a qualitative approach. *Remedial and Special Education*, *12*(1), 7–15. https://doi.org/10.1177/074193259101200105
Ross, C. H., & Ross, J. D. (1979). *Ross test of higher cognitive processes*. Academic Therapy Publications.
Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, *80*(1), 1–28. https://doi.org/10.1037/h0092976
Ryan, R. M., & Grolnick, W. S. (1986). Origins and pawns in the classroom: Self-report and projective assessments of individual differences in children's perceptions. *Journal of Personality and Social Psychology*, *50*(3), 550–558. https://doi.org/10.1037/0022-3514.50.3.550
Schmitz, B., & Skinner, E. (1993). Perceived control, effort, and academic performance: Interindividual, intraindividual, and multivariate time-series analyses. *Journal of Personality and Social Psychology*, *64*(6), 1010–1028. https://doi.org/10.1037/0022-3514.64.6.1010
Schneider, W., & Chein, J. M. (2003). Controlled & automatic processing: Behavior, theory, and biological mechanisms. *Cognitive Science*, *27*(3), 525–559. https://doi.org/10.1207/s15516709cog2703_8
Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, *84*(1), 1–66. https://doi.org/10.1037/0033-295X.84.1.1
Schnipke, D. L. (1995, April 19–21). *Assessing speededness in computer-based tests using item response times* [Paper presentation]. Annual Meeting of the National Council on Measurement in Education, San Francisco, CA, United States.
Schnipke, D. L., & Scrams, D. J. (1997). Modeling item response times with a two-state mixture model: A new method of measuring speededness. *Journal of Educational Measurement*, *34*(3), 213–232. https://doi.org/10.1111/j.1745-3984.1997.tb00516.x
Schwab, S., & Hessels, M. G. P. (2015). Achievement goals, school achievement, self-estimations of school achievement, and calibration in students with and without special education needs in inclusive education. *Scandinavian Journal of Educational Research*, *59*(4), 461–477. https://doi.org/10.1080/00313831.2014.932304
Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461–464. https://doi.org/10.1214/aos/1176344136
Sclove, S. L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*, *52*(3), 333–343. https://doi.org/10.1007/BF02294360
Seifert, T. (2004). Understanding student motivation. *Educational Research*, *46*(2), 137–149. https://doi.org/10.1080/0013188042000222421
Seligman, M. E. P. (1975). *Helplessness: On depression, development, and death*. W H Freeman/Times Books/Henry Holt & Co.
Setzer, J. C., Wise, S. L., van den Heuvel, J. R., & Ling, G. (2013). An investigation of examinee test-taking effort on a large-scale assessment. *Applied Measurement in Education*, *26*(1), 34–49. https://doi.org/10.1080/08957347.2013.739453
Shayer, M. (1979). Has Piaget's construct of formal operational thinking any utility? *British Journal of Educational Psychology*, *49*(3), 265–276. https://doi.org/10.1111/j.2044-8279.1979.tb02425.x
Shogren, K. A., Wehmeyer, M. L., Palmer, S. B., Forber-Pratt, A. J., Little, T. J., & Lopez, S. (2015). Causal agency theory: Reconceptualizing a functional model of self-determination. *Education and Training in Autism*

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

and Developmental Disabilities, *50*(3), 251–263. https://doi.org/10.1177/2154164715050003 02

Sideridis, G. D. (2003). On the origins of helpless behavior of students with learning disabilities: Avoidance motivation? *International Journal of Educational Research*, *39*(4–5), 497–517. https://doi.org/10.1016/j.ijer.2004.06.011

Sideridis, G. D. (2009). Motivation and learning disabilities: Past, present, and future. In K. R. Wentzel & A. Wigfield (Eds.), *Handbook of motivation at school* (pp. 605–625). Routledge/Taylor & Francis Group.

Sideridis, G. D., Morgan, P. L., Botsas, G., Padeliadu, S., & Fuchs, D. (2006). Predicting LD on the basis of motivation, metacognition, and psychopathology: An ROC analysis. *Journal of Learning Disabilities*, *39*(3), 215–229. https://doi.org/10.1177/00222194060390030301

Sideridis, G. D., Mouzaki, A., Simos, P., & Protopapas, A. (2006). Classification of students with reading comprehension difficulties: The roles of motivation, affect, and psychopathology. *Learning Disability Quarterly*, *29*(3), 159–180. https://doi.org/10.2307/30035505

Sideridis, G. D., Stamovlasis, D., & Antoniou, F. (2016). Reading achievement, mastery, and performance goal structures among students with learning disabilities: A nonlinear perspective. *Journal of Learning Disabilities*, *49*(6), 631–643. https://doi.org/10.1177/0022219415576524

Skinner, E. A. (1995). *Perceived control, motivation, & coping*. Sage Publications. https://doi.org/10.4135/9781483327198

Skinner, E. A., Chapman, M., & Baltes, P. B. (1988). Control, means-ends, and agency beliefs: A new conceptualization and its measurement during childhood. *Journal of Personality and Social Psychology*, *54*(1), 117–133. https://doi.org/10.1037/0022-3514.54.1.117

Skinner, E. A., Wellborn, J. G., & Connell, J. P. (1990). What it takes to do well in school and whether I've got it: A process model of perceived control and children's engagement and achievement in school. *Journal of Educational Psychology*, *82*(1), 22–32. https://doi.org/10.1037/0022-0663.82.1.22

Skinner, E. A., Zimmer-Gembeck, M. J., & Connell, J. P. (1998). Individual differences and the development of perceived control. *Monographs of the Society for Research in Child Development*, *63*(2–3), Article v-220. https://doi.org/10.2307/1166220

Sternberg, R. J., Castejón, J. L., Prieto, M. D., Hautamäki, J., & Grigorenko, E. L. (2001). Confirmatory factor analysis of the Sternberg Triarchic Abilities Test in three international samples: An empirical test of the triarchic theory of intelligence. *European Journal of Psychological Assessment*, *17*(1), 1–16. https://doi.org/10.1027/1015-5759.17.1.1

Stone, C. A., & May, A. L. (2002). The accuracy of academic self-evaluations in adolescents with learning disabilities. *Journal of Learning Disabilities*, *35*(4), 370–383. https://doi.org/10.1177/00222194020350040801

Suter, F., Karlen, Y., Merki, K. M., & Hirt, C. N. (2022). The relationship between success and failure causal attributions and achievement goal orientations. *Learning and Individual Differences*, *100*, Article 102225. https://doi.org/10.1016/j.lindif.2022.102225

Tabassam, W., & Grainger, J. (2002). Self-concept, attributional style and self-efficacy beliefs of students with learning disabilities with and without attention deficit hyperactivity disorder. *Learning Disability Quarterly*, *25*(2), 141–151. https://doi.org/10.2307/1511280

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling*, *20*(4), 640–657. https://doi.org/10.1080/10705511.2013.824781

Thuneberg, H., Vainikainen, M.-P., Ahtiainen, R., Lintuvuori, M., Salo, K., & Hautamäki, J. (2013). Education is special for all—The Finnish support model. *Gemeinsam Leben*, *21*(2), 67–78.

Tofighi, D., Enders, C. K., & Hancock, G. R. (2007). Identifying the correct number of classes in a growth mixture model. In G. R. Hancock (Ed.), *Mixture models in latent variable research* (pp. 317–341). Information Age.

Tolvanen, A. (2007). *Latent growth mixture modeling: A simulation study* [Doctoral dissertation, University of Jyväskylä]. JYX Digital Repository. https://jyx.jyu.fi/handle/123456789/22537

Törmänen, M. R. K., & Roebers, C. M. (2018). Developmental outcomes of children in classes for special educational needs: Results from a longitudinal study. *Journal of Research in Special Educational Needs*, *18*(2), 83–93. https://doi.org/10.1111/1471-3802.12395

Tuominen-Soini, H., Salmela-Aro, K., & Niemivirta, M. (2008). Achievement goal orientations and subjective well-being: A person-centred analysis. *Learning and Instruction*, *18*(3), 251–266. https://doi.org/10.1016/j.learninstruc.2007.05.003

Vainikainen, M.-P. (2014). *Finnish primary school pupils' performance in learning to learn assessment: A longitudinal perspective on educational equity* [Doctoral dissertation, University of Helsinki]. Unigrafia. https://helda.helsinki.fi/handle/10138/136364

Vainikainen, M.-P., & Hautamäki, J. (2018). Selittääkö yrittäminen oppilaiden osaamisessa havaittuja ryhmäeroja? Itsearvioitu yrittäminen, investoitu työaika ja osaamiserot lokitietoanalyysin valossa [Does effort explain the observed group differences in students' competence? Self-assessed effort, invested working time, and competence differences in the light of log data analysis]. *Psykologia*, *53*(2–3), 152–165. https://doi.org/10.62443/psykologia.v53i2-3.69816

Vainikainen, M.-P., & Hautamäki, J. (2022). Three studies on learning to learn in Finland: Anti-flynn effects 2001–2017. *Scandinavian Journal of Educational Research*, *66*(1), 43–58. https://doi.org/10.1080/00313831.2020.1833240

Vainikainen, M.-P., Hautamäki, J., Hotulainen, R., & Kupiainen, S. (2015). General and specific thinking skills and schooling: Preparing the mind to new learning. *Thinking Skills and Creativity*, *18*, 53–64. https://doi.org/10.1016/j.tsc.2015.04.006

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, *57*(2), 307–333. https://doi.org/10.2307/1912557

Wehmeyer, K. A., & Shogren, M. L. (2020). Self-determination and autonomous motivation: Implications for students with intellectual, developmental, and specific learning disabilities. In A. J. Martin, R. A. Sperling, & K. J. Newton (Eds.), *Handbook of educational psychology and students with special needs* (pp. 262–291). Routledge/Taylor & Francis Group. https://doi.org/10.4324/9781315100654-14

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review*, *92*(4), 548–573. https://doi.org/10.1037/0033-295X.92.4.548

Wise, S. L., & Gao, L. (2017). A general approach to measuring test-taking effort on computer-based tests. *Applied Measurement in Education*, *30*(4), 343–354. https://doi.org/10.1080/08957347.2017.1353992

Wise, S. L., & Kong, X. (2005). Response time effort: A new measure of examinee motivation in computer-based tests. *Applied Measurement in Education*, *18*(2), 163–183. https://doi.org/10.1207/s15324818ame1802_2

Wong, B. Y. L. (2003). General and specific issues for researchers' consideration in applying the risk and resilience framework to the social domain of learning disabilities. *Learning Disabilities Research & Practice*, *18*(2), 68–76. https://doi.org/10.1111/1540-5826.00060

Wordtune. (2024). *Wordtune* [Text editing tool]. https://www.wordtune.com

Yang, C.-C. (2006). Evaluating latent class analysis models in qualitative phenotype identification. *Computational Statistics & Data Analysis*, *50*(4), 1090–1104. https://doi.org/10.1016/j.csda.2004.11.004

Zentall, S. S., & Beike, S. M. (2012). Achievement and social goals of younger and older elementary students: Response to academic and social failure. *Learning Disability Quarterly*, *35*(1), 39–53. https://doi.org/10.1177/0731948711429009

(*Appendices follow*)

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Appendix A

Pearson Correlations Between the Action-Control Beliefs and Distal Outcome Variables

Variable	1	2	3	4	5	6	7	8
1. Agency: ability	—							
2. Agency: effort	.55**	—						
3. Mean-ends: ability	−.18**	.07**	—					
4. Means-ends: effort	−.30**	−.07**	.44**	—				
5. Control expectancy	.78**	.45**	−.21**	−.27**	—			
6. LTL	.48**	.21**	−.21**	−.40**	.42**	—		
7. GPA	.62**	.44**	−.16**	−.31**	.56**	.63**	—	
8. TOT	.40**	.28**	−.18**	−.39**	.36**	.70**	.49**	—

Note. LTL = cognitive tasks (learning to learn); GPA = grade point average; TOT = time on task.
** $p < .01$.

All rights, including for text and data mining, AI training, and similar technologies, are reserved.

Appendix B

Kolmogorov–Smirnov Test of Normality for the Action-Control Beliefs and Distal Outcomes

Variable	Statistic	*df*	*p*
Agency: ability	.117	6,482	<.001
Agency: effort	.083	6,422	<.001
Means-ends: ability	.063	6,422	<.001
Means-ends: luck	.144	6,421	<.001
Control expectancy	.115	6,480	<.001
GPA	.063	6,464	<.001
LTL	.050	6,476	<.001
TOT	.024	5,902	<.001

Note. GPA = grade point average; LTL = learning to learn assessment; TOT = time on task.

Appendix C

Measurement Invariance According to Level of Support

	RMSEA					
Model	Value	95% CI	*p*	CFI	TLI	SRMR
Configural	.050	[.047, .052]	.629	.963	.951	.055
Metric	.048	[.046, .050]	.926	.962	.954	.056
Scalar	.048	[.046, .050]	.904	.959	.953	.056

Note. RMSEA = root-mean-square error of approximation; CI = confidence interval; CFI = comparative fit index; TLI = Tucker–Lewis index; SRMR = standardized root-mean-square residual.

(*Appendices continue*)

Appendix D

Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column) in the Four-Profile Solution

Class	1	2	3	4
1	**.909**	.000	.001	.090
2	.000	**.941**	.010	.049
3	.002	.053	**.851**	.094
4	.039	.065	.021	**.874**

Note. Bolded values represent the average latent class posterior probabilities of students belonging to their assigned latent class.

Received August 6, 2024
Revision received July 4, 2025
Accepted August 25, 2025 ■

All rights, including for text and data mining, AI training, and similar technologies, are reserved.