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Student motivation and need satisfaction in GenAI-supported classrooms: A self-determination theory perspective☆

Sabine Schweder *, Gerda Hagenauer, Diana Raufelder

Department of Educational Sciences and School of Education of University of Salzburg, 17489 Greifswald, Germany

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ABSTRACT

This study examines how generative AI (GenAI), specifically ChatGPT, relates to student motivation and basic psychological need satisfaction in lower-secondary education from a self-determination theory perspective. While generative AI is increasingly used in classrooms, it remains unclear how its use is associated with different motivational profiles across instructional contexts.

Using a cross-sectional sample of 2464 students (grades 7–8), we compared two instructional contexts: (a) rubric-based, self-regulated competency-based learning (CBL) implemented with or without ChatGPT integration, and (b) teacher-directed learning (TDL) organized in a traditional 45-minute lesson format with limited self-regulated phases. To capture both overall differences and profile-specific patterns, we combined person-centered latent profile analysis with variable-centered mean comparisons.

The results show that ChatGPT use in CBL is associated with higher autonomy support and competence satisfaction, but also with a greater proportion of low-quality motivational profiles compared to non-AI CBL. At the same time, these profiles in the ChatGPT-supported context exhibit higher intrinsic and identified motivation than comparable profiles in both non-AI CBL and TDL. In contrast, relatedness appears less pronounced in the ChatGPT-supported context, which may help explain why the overall motivational distribution does not exceed the already high baseline of non-AI CBL.

These findings point to systematic differences in motivational quality associated with ChatGPT use and highlight the importance of considering learner heterogeneity when integrating generative AI into autonomy-supportive instructional settings.

Educational Relevance Statement

This study provides one of the first large-scale investigations combining person- and variable-centered approaches to examine how generative AI (GenAI), specifically ChatGPT, relates to student motivation and basic psychological need satisfaction in authentic lower-secondary classrooms. Within rubric-based competency-based learning (CBL), the integration of ChatGPT was associated with higher autonomy support and perceived competence.

At the same time, the findings indicate that GenAI-supported instruction does not uniformly enhance motivation. While the overall distribution of highly adaptive motivational profiles did not exceed that of an already strong non-AI CBL condition, students in less adaptive profiles within the ChatGPT-supported context showed more internalized forms of motivation than comparable students in both non-AI CBL and teacher-directed learning. This points to a differentiated role of ChatGPT, particularly for learners who struggle with autonomous engagement.

In addition, relatedness played a less pronounced role in the ChatGPT-supported context, highlighting that generative AI cannot replace interpersonal interaction. From an educational perspective, this underscores the importance of embedding GenAI within structured, autonomy-supportive, and socially grounded instructional designs. Its value lies less in uniformly increasing motivation and more in supporting specific learner profiles within diverse classroom settings.

Student Motivation and Need Satisfaction in GenAI-Supported Classrooms: A Self-Determination Theory Perspective

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* Corresponding author at: Department of Educational Science, University of Greifswald, Ernst-Lohmeyer-Platz 3, Greifswald, 17489, Germany.
E-mail address: sabine.schweder@uni-greifswald.de (S. Schweder).

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Introduction

Improving student motivation remains a key challenge in secondary education, particularly in teacher-directed classrooms where students' basic psychological needs—autonomy, competence, and relatedness—are often insufficiently supported [1]. In response, many schools have adopted learner-centered models such as rubric-based, competency-based learning (CBL), which emphasize self-regulated progression, individualized goals, and need-supportive instruction [2, 3]. From a learning-theoretical perspective, such environments are designed to foster core self-regulated learning (SRL) processes, including goal setting, progress monitoring, strategy adjustment, and self-evaluation [4]. Empirical studies have linked these approaches to higher motivational quality through stronger support for students' basic psychological needs for autonomy, competence, and relatedness [5–7].

More recently, the emergence of generative artificial intelligence (GenAI) tools—particularly ChatGPT—has introduced new dynamics into this instructional landscape [8–13]. These tools provide on-demand feedback, language scaffolds, and content suggestions [14–17], thereby potentially enhancing students' perceived autonomy and competence [18,19] and, in turn, their motivation [8]. At the same time, concerns have been raised that such technologies may reduce cognitive engagement or encourage shortcut strategies [20].

This tension raises a central empirical question: Can GenAI tools meaningfully support motivation in learner-centered, self-regulated classrooms where autonomy is already foregrounded, or might they, despite this autonomy-supportive context, inadvertently promote more externally regulated forms of engagement? While Self-Determination Theory (SDT) [21,22] provides a strong conceptual framework to address this question, research on GenAI's motivational role in authentic lower-secondary settings remains scarce [8]. Emerging evidence from a situated expectancy–value perspective suggests that ChatGPT-supported learning may be associated with more balanced motivational–emotional profiles, reducing extreme patterns while increasing moderate ones [23]. From an SRL perspective, such affordances may externalize cognitively demanding regulatory processes—such as monitoring understanding, identifying errors, and selecting next steps—thereby potentially supporting autonomous engagement, particularly for students with weaker self-regulatory skills [12].

A self-determination theory perspective on motivation

Despite growing interest in GenAI in education, its motivational effects in real-world secondary classrooms remain underexplored [24,25]. Existing research has primarily focused on higher education or experimental contexts [26], offering limited insight into how students engage with GenAI tools in environments already designed to foster autonomy and self-regulation.

This study adopts SDT as its guiding framework. SDT distinguishes between autonomous and controlled forms of motivation and posits that internalization—and thus more autonomous forms of motivation—is fostered through the satisfaction of the basic psychological needs for autonomy, competence, and relatedness [27,28].

Intrinsic motivation refers to engagement driven by inherent enjoyment and satisfaction. All other forms are considered extrinsic and exist along a continuum from controlled to autonomous regulation. External regulation involves behavior driven by rewards, punishment, or external demands. Introjected regulation reflects internal pressures, such as guilt or self-worth contingencies. Identified regulation refers to engagement based on personal importance, where individuals recognize the value of an activity. Integrated regulation, in contrast, "occurs when personally endorsed behaviors become coherent with other dimensions of the self" ([29], p. 61). From an empirical perspective, identified regulation can be measured with relative clarity, whereas integrated regulation remains more difficult to capture reliably and is therefore typically not included in established measurement instruments.

With regard to basic needs, autonomy reflects "integrity" ([30], p. 85), that is, acting in accordance with one's own goals. Competence reflects the perception of mastery and self-efficacy, and relatedness refers to feeling safe and warmly connected to others [30]. In general, research indicates that intrinsic motivation and autonomous forms of extrinsic motivation (i.e., identified and integrated regulation) have positive effects on various educational outcomes, including persistence, the use of deep learning strategies, students' well-being, and academic achievement [31,32].

The importance of autonomous motivation for learning in general, and for SRL environments in particular, has been well documented [33–36]. SRL research further emphasizes that learners differ substantially in their capacity to initiate, sustain, and adapt self-regulatory processes, especially in open, learner-directed settings.

GenAI use, need satisfaction, and student motivation

Empirical evidence on the relationship between GenAI and student motivation remains scarce, particularly in K–12 education. Liu et al. [37] synthesized 49 empirical studies, 12 of which explicitly examined student motivation. They found that GenAI use was positively associated with both academic achievement (Hedges' $g = 0.857$) and motivation ($g = 0.803$), with stronger motivation effects in K–12 ($g = 1.651$) and stronger achievement effects in higher education ($g = 0.959$). Similarly, Deng et al. [8] reported a positive effect ($g = 0.881$) of GenAI on students' affective–motivational states, although most studies in their synthesis focused on college students. Both meta-analyses conceptualized motivation in broad terms and did not explicitly ground their definitions in SDT.

A growing, though still limited, body of research draws on SDT to examine how GenAI influences student motivation and the satisfaction of basic psychological needs [38]. One such study by Chiu et al. [19] employed a Delphi method with expert assessments from teachers in Hong Kong. The findings suggest that GenAI use in self-regulated K–12 learning settings primarily supports students' need for competence by providing immediate, individualized feedback that helps them monitor progress and fosters a sense of mastery. The need for autonomy is also promoted through the development of learner agency and responsibility, as well as through individualized learning environments that make students feel their ideas, interests, and needs are more fully considered. In contrast, evidence regarding the need for relatedness was less clear, with experts expressing hesitation about the extent to which GenAI can support students' sense of social connection. This reflects broader concerns raised by Molina et al. [39], who argue that digital learning environments often fail to meet the need for relatedness unless deliberately designed to foster interaction and collaboration.

Further, Chiu [18] found that teacher support remains critical in GenAI-enhanced environments—particularly for satisfying the need for relatedness and for supporting students with limited GenAI experience [40]. Similarly, Li et al. [41] emphasized that the fulfillment of psychological needs depends on classroom implementation; for example, peer collaboration can enhance relatedness.

If GenAI-supported environments satisfy basic psychological needs, higher autonomous motivation should follow. Li et al. [41] confirmed this in a college sample, reporting that AI use was associated with greater autonomous motivation and improved self-regulation. However, more research is needed to examine how GenAI affects SDT-based forms of motivation in K–12 classrooms.

Person-centered approaches to student motivation

Building on SDT, recent motivational research increasingly employs person-centered methods, such as latent profile analysis (LPA), to identify naturally occurring constellations of motivational regulations [42,43]. These approaches cluster individuals into distinct motivational profiles based on their relative levels of intrinsic, identified, introjected, and external regulation. Typical profiles include [44,45]:

- High-quality profiles (high intrinsic and identified regulation).
- High-quantity profiles (high autonomous and controlled regulation).
- Low-quality profiles (predominantly controlled), and
- Low-quantity profiles (low across all regulation types).

These profiles differ in both prevalence and educational outcomes. High-quality configurations are reliably associated with academic engagement, persistence, and well-being, whereas low-quality profiles tend to predict surface learning, disengagement, and academic stress [46]. More complex profiles have also been documented, including profiles marked by amotivation [47] and hybrid patterns combining different regulation types [48,49]. For a recent synthesis in school-based contexts ([48,49]; see also [35]).

Crucially, motivational profile membership is context-sensitive [50]. Longitudinal findings suggest that students shift between profiles over time depending on the perceived instructional environment. For example, Schweder et al. [35] found that transitions toward more self-determined profiles occurred more frequently in learner-directed, inquiry-based classrooms, where autonomy, competence, and relatedness were more strongly supported than in teacher-directed phases of instruction. However, motivational profiles grounded in SDT that emerge in GenAI-enhanced teaching and learning environments remain unexplored and are therefore the focus of this study.

Generative AI in self-regulated learning environments – the case of competence-based learning using rubrics

CBL provides a theoretically relevant context for examining motivational processes in AI-supported classrooms because it closely aligns with the core assumptions of SDT. According to SDT, high-quality, self-determined motivation emerges when learners experience support for autonomy, competence, and relatedness [21]. CBL environments are designed to support these needs by combining transparent performance standards with opportunities for learner choice and self-paced progression [7,36]. At the process level, rubric-based CBL operationalizes SRL by enabling learners to plan their learning trajectories, monitor progress via formative criteria, and adjust strategies accordingly.

In rubric-based CBL, learning goals are articulated as clearly defined competencies, and progress is structured around explicit success criteria. Students select goals aligned with their current level, work through learning activities at an individualized pace, and monitor progress using formative feedback. This combination of pedagogical structure and learner-directed regulation reflects what SDT describes as structured autonomy support: learners are guided by clear expectations while retaining meaningful control over how and when they engage with learning tasks. Prior research shows that such environments can foster more internalized forms of motivation and support SRL, particularly when instructional structure is paired with autonomy-supportive practices [51,52].

Within this instructional logic, GenAI systems introduce a qualitatively new element. Unlike traditional instructional resources, GenAI can function as an interactive, non-human support agent that responds dynamically to learner input. From an SDT perspective, this raises important theoretical questions. On the one hand, GenAI's affordances—such as immediacy, adaptivity, and on-demand explanations—may enhance perceived competence by reducing impasses during problem solving and providing individualized feedback aligned with learners' needs [53]. Similarly, the voluntary use of such tools within self-paced environments may strengthen perceived autonomy by allowing learners to decide when and how to seek support [39]. From an SRL perspective, GenAI may function as a process-level scaffold that supports regulatory activities—such as clarification, feedback interpretation, and strategy refinement—without replacing learner agency, particularly for students who struggle to initiate or sustain SRL independently.

On the other hand, SDT cautions that external supports can undermine motivational quality if they shift learners' focus from mastery and self-endorsement toward efficiency or external regulation [32]. In SRL contexts such as CBL, where learners are responsible for pacing, goal pursuit, and strategy selection, GenAI could function as a shortcut that reduces productive struggle or effort investment [20]. Thus, the motivational implications of GenAI cannot be inferred from its technological capabilities alone but depend on how learners perceive and integrate the tool within an instructional ecology that distributes agency between students, teachers, and learning materials.

This distinction is particularly salient in authentic classroom settings, where GenAI is embedded within established pedagogical frameworks rather than replacing instruction. In rubric-based CBL classrooms, teachers act as facilitators who support SRL through progress monitoring, formative feedback, and goal-setting guidance, while students assume primary responsibility for navigating learning pathways [3]. Within such contexts, GenAI may complement rather than substitute human support, potentially amplifying certain need-supportive affordances (e.g., competence support through immediate clarification) while leaving others (e.g., social relatedness) largely unchanged. Importantly, whether and how GenAI contributes to psychological need satisfaction remains an empirical question, particularly given concerns about novelty effects and the short-term nature of many classroom interventions [54].

Against this theoretical background, the present study examines students' motivation and basic psychological need satisfaction across three instructional contexts that differ in learner autonomy and the availability of GenAI support: rubric-based CBL with access to ChatGPT, rubric-based CBL without GenAI, and traditional TDL. By situating GenAI within a structured, autonomy-supportive learning environment, the study moves beyond technology-centered explanations and adopts a contextualized perspective on motivation. Combining variable-centered and person-centered approaches, the study captures both overall differences in motivational quality and qualitative differences in motivational profiles across instructional contexts in ecologically valid lower-secondary classrooms.

Guided by the conceptual framework illustrated in Fig. 1, the present study examines how the availability of generative AI across instructional contexts is associated with students' motivational regulation, basic psychological need satisfaction, and motivational profile membership.

Research questions and hypotheses

This study examines how the availability of GenAI across instructional contexts is associated with students' motivational regulation, basic psychological need satisfaction, and motivational profile membership. Drawing on SDT, it adopts both variable-centered and person-centered approaches to capture overall differences in motivational quality as well as qualitative heterogeneity in motivational configurations.

Specifically, motivation and perceived basic psychological need support are compared across three instructional contexts that differ in instructional structure and the availability of GenAI support. The TDL group serves as a reference condition for interpreting motivational patterns observed in the two rubric-based SRL contexts.

The study is guided by the following research questions and hypotheses.

Research questions

RQ1: Do students in ChatGPT-assisted and non-assisted instructional settings differ in their levels of motivation and perceived basic psychological need satisfaction?

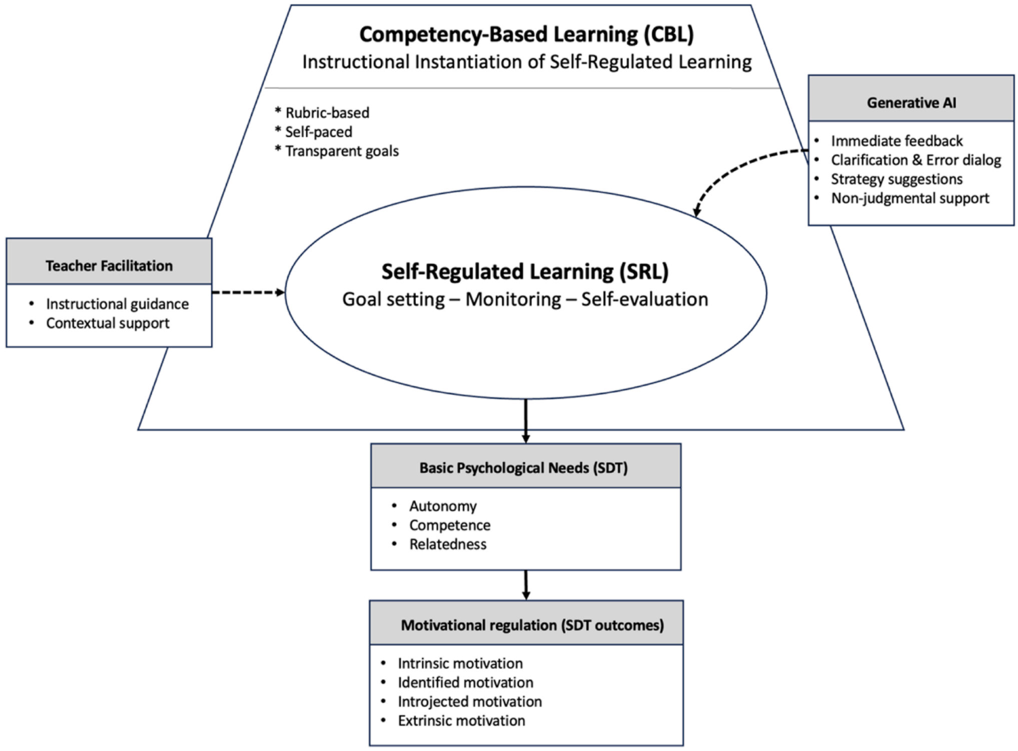


Fig. 1. Conceptual model linking competency-based learning, self-regulated learning, generative AI support, and motivational regulation
Note. CBL = competency-based learning; SRL = self-regulated learning; GenAI = generative artificial intelligence; SDT = Self-Determination Theory. The figure depicts the conceptual relations among instructional context, SRL processes, basic psychological needs, and motivational regulation. SRL processes were not directly measured in the present study.

RQ2: How are motivational profiles distributed across the three instructional groups (TDL, non-assisted CBL, and ChatGPT-assisted CBL)?

RQ3: To what extent is perceived basic psychological need satisfaction associated with students' motivational profile membership across instructional contexts?

Hypotheses

H1 (Variable-centered): Students in the ChatGPT-assisted CBL group report significantly higher levels of autonomous motivation (intrinsic and identified regulation) and basic psychological need satisfaction (autonomy and competence) than students in the non-assisted CBL and TDL groups. Differences in relatedness satisfaction are explored without a directional hypothesis.

H2 (Person-centered): The distribution of motivational profiles differs significantly across instructional conditions, with a greater proportion of students in the ChatGPT-assisted group expected to be classified in more adaptive profiles (e.g., high-quality) than in the non-assisted and teacher-directed groups.

H3 (Association-based): Perceived satisfaction of the basic psychological needs for autonomy, competence, and relatedness is associated with motivational profile membership across all groups, with higher need satisfaction linked to a greater likelihood of belonging to more self-determined profiles.

Methods

Participants and sample

The final sample comprised $N = 2464$ secondary school students ($M_{age} = 13.75$, $SD = 0.98$) from Grades 7 and 8, recruited from 14 urban schools across four German federal states (Berlin, Hamburg, Schleswig-Holstein, and Mecklenburg–Western Pomerania). Students were nested within three naturally occurring instructional contexts reflecting distinct pedagogical models (see Table 1a for sample characteristics and Table 1b for a parallel overview of instructional activities across conditions).

The ChatGPT-assisted CBL group ($n = 965$) consisted of students from mixed-track schools implementing a rubric-based CBL framework in which a centrally provided ChatGPT-3.5 account, managed by the teacher, was available for voluntary student use during regular instruction. The non–ChatGPT-assisted CBL group ($n = 709$) included students from comparably structured schools using the same rubric-based learning model but without access to generative AI or other digital learning tools. The TDL group ($n = 790$) comprised students attending high-track schools following a traditional 45-minute lesson format characterized by teacher-led instruction, limited opportunities for self-regulated learning, and no integration of generative AI (see Table 2).

Instructional conditions

ChatGPT-Assisted competency-based learning (CBL)

Instructional framework. In the ChatGPT-assisted CBL condition, students learned within a standardized, rubric-based competency framework and progressed through the same learning cycle across all participating CBL classrooms (see Figs. 2 and 3, Appendix Figure. A1–14). After a brief orientation phase, students selected competency goals and worked independently on corresponding learning tasks using printed materials and individual learning portfolios. Teachers acted primarily as facilitators by monitoring progress, answering procedural questions, and providing formative feedback aligned with the rubric criteria.

GenAI-supported learning (ChatGPT). ChatGPT was available exclusively in this condition as an optional learning support tool during the

Table 1a
Descriptive statistics and demographic information for the total sample and subsamples.

Group	n	Mage	SD age	Female (%)	Male (%)	School context	Concept of instruction	AI
1	965	13.35	1.17	42.5 % ($n = 413$)	55.5 % ($n = 538$)	Mixed-track urban schools	rubric-guided, competency-based learning	x
2	790	13.33	0.85	50.8 % ($n = 401$)	49.2 % ($n = 389$)	High-track urban schools	conventional teacher-led instruction	–
3	709	13.26	0.76	46.1 % ($n = 327$)	53.9 % ($n = 382$)	Mixed-track urban schools	rubric-guided, competency-based learning	–

Note. AI = ChatGPT. Gender in Group 1 comprised 42.8% female (n = 413), 55.8% male (n = 538), and 1.5% diverse (n = 14).

learning phase. Access was provided via a centrally managed teacher account. Students could use ChatGPT voluntarily for purposes such as conceptual clarification, feedback on solution strategies, and language formulation. No fixed prompts or scripted interactions were provided; instead, ChatGPT use was open-ended but restricted to task-related learning activities (see Appendix Material A15–16 for representative examples).

Usage constraints. The pedagogical role of ChatGPT was explicitly limited to scaffolding during learning activities; its use during assessment or performance demonstration phases was not permitted. Although the use of ChatGPT was optional at the individual student level, access to the tool was structurally restricted to this instructional condition and explicitly embedded as an available learning resource within the CBL framework.

Non–ChatGPT-assisted competency-based learning (CBL)

Instructional framework. The non–ChatGPT-assisted CBL condition followed the identical rubric-based learning cycle, competency goals, task formats, assessment procedures, and instructional time frame as the ChatGPT-assisted CBL condition (see Appendix Fig. A1–14). Students worked on the same learning tasks, documented their progress in learning portfolios, and received formative feedback from teachers aligned with the rubric criteria.

Absence of GenAI support. In contrast to the AI-assisted condition, no generative AI tools or other digital or technical resources were available. Learning activities relied exclusively on printed instructional materials, handwritten work, and teacher feedback. Students did not have access to search engines, digital devices, or AI-based support tools during the CBL period.

Teacher-directed learning (TDL)

Instructional structure. In the TDL condition, instruction followed a traditional 45-minute lesson structure characterized by teacher-led explanation, guided practice, and shorter phases of individual student work.

Learner control. Learning goals, task selection, and pacing were primarily determined by the teacher, and students had limited opportunities for self-regulated progression.

Ethical procedures

Following approval from the relevant educational authorities, parents were informed about the voluntary nature of their child's participation and assured of confidentiality. Students could decline to answer any item without penalty. Trained test administrators were present during data collection to provide clarification when needed. In accordance with German data protection regulations and institutional approval requirements, information on students' socio-economic background or ethnicity was not collected.

Statistical analysis

All latent variable analyses were conducted in Mplus 8.1 using robust maximum likelihood estimation (MLR). Diagnostic analyses of the nested data structure (intraclass correlation coefficients) were computed using random-intercept models in SPSS (Version 31.0).

Measurement instruments

Students' motivation and basic psychological needs were assessed using self-report questionnaires. Motivational regulation was measured with the Academic Self-Regulation Questionnaire [57], capturing four regulation types: intrinsic motivation, identified regulation, introjected regulation, and external regulation. Basic psychological need satisfaction—comprising autonomy, competence, and relatedness—was assessed using the Support of Basic Needs Scales for Adolescent Students [56]. All measures employed a 4-point Likert scale ranging from 1 (*does not apply at all*) to 4 (*fully applies*). Items were adapted to students' respective self-directed learning topics to ensure contextual relevance.

In the ChatGPT-assisted CBL condition only, students additionally completed an exploratory three-item measure assessing perceived motivational support provided by ChatGPT during the learning phase (see Table A11 in the Appendix). These items were adapted from the Teacher-Related Motivational Support (T-REMO) framework [58] and conceptually informed by the artificial socializer perspective [20]. The items captured students' perceptions of motivational encouragement, clarification, and supportive feedback provided by ChatGPT (e.g., encouragement to persist, perceived belief in one's abilities, and motivation to improve following AI support).

Responses were recorded on the same 4-point Likert scale as the other measures. This scale showed acceptable internal consistency ($\alpha = 0.69$), given its exploratory nature and small number of items.

Importantly, this ChatGPT support measure was administered only in the ChatGPT-assisted condition and was not included in the latent measurement models, latent profile analyses, or invariance testing. Instead, it was used exclusively for descriptive and correlational analyses to contextualize students' subjective experiences with AI support. As such, it does not affect the comparability of motivational constructs across instructional conditions.

Although the instructional design was informed by principles of SRL, the present study did not include direct measures of SRL processes (e.g., planning, monitoring, or strategy use). References to SRL therefore serve as a theoretical lens for interpreting motivational patterns rather than as claims about measured regulatory behavior.

Statistical treatment of the nested data structure

Students were nested within classes ($N = 84$) and schools ($N = 14$), resulting in a hierarchical data structure. To account for the non-independence of observations, all latent variable models—including MG-CFAs, latent mean comparisons, and person-centered analyses—were estimated in Mplus using TYPE = COMPLEX, with clustering specified at the class level. This approach yields cluster-robust (sandwich) standard errors while retaining a single-level model specification.

In addition, clustering effects were examined diagnostically using random-intercept models. Intraclass correlation coefficients (ICCs) indicated small to moderate clustering at the class level and moderate clustering at the school level, with the majority of variance located at the

Table 1b
Overview of instructional activities across the three instructional conditions during the one-week unit.

Phase of learning cycle	CBL with ChatGPT (AI-assisted)	CBL without ChatGPT	Teacher-Directed Learning (TDL)
Orientation & goal setting	Students selected individual competency goals based on predefined rubrics. Teacher introduced the learning cycle and clarified expectations.	Same procedure as AI-assisted CBL: students selected goals using identical rubrics and received a brief orientation by the teacher.	Teacher introduced lesson objectives and content for the week. Goals and pacing were teacher-defined.
Independent learning phase	Students worked self-regulated on learning tasks aligned with their selected competencies using printed materials and learning portfolios.	Students worked self-regulated on identical task formats and materials as the AI-assisted group, without digital or AI support.	Students engaged in teacher-led instruction followed by short individual or guided practice tasks.
Scaffolding & support	Support was provided through teacher facilitation and voluntary use of ChatGPT (GPT-3.5) for explanations, feedback, and language formulation. No fixed prompts were provided.	Support was provided exclusively by the teacher through clarification, feedback, and brief individual guidance.	Support was provided by the teacher through explanation, questioning, and corrective feedback.
Feedback during learning	Continuous formative feedback from teachers and on-demand feedback from ChatGPT during the learning phase.	Continuous formative feedback from teachers only.	Feedback provided mainly by the teacher during or after instruction and practice phases.
Assessment phase	Competency checks were conducted using rubric-based criteria. Use of ChatGPT during assessment was prohibited.	Same rubric-based assessment procedures as AI-assisted CBL. No digital or AI tools were used.	Assessment followed traditional formats aligned with teacher-directed instruction.
Materials & resources	Printed learning materials, competency rubrics, learning portfolios, and a centrally managed ChatGPT-3.5 account.	Printed learning materials, competency rubrics, and learning portfolios. No technical or digital tools.	Textbooks, worksheets, and teacher-prepared instructional materials.
Role of teacher	Facilitator and monitor of self-regulated learning; ensured adherence to rubrics and appropriate AI use.	Facilitator and monitor of self-regulated learning; primary source of feedback and support.	Primary source of instruction, structure, pacing, and feedback.

Note. CBL = competency-based learning; TDL = teacher-directed learning. The learning cycle structure and assessment procedures are described in detail in Appendix Figure A1-A14. Representative student–AI interactions are provided in Appendix Material A15-A16.

individual student level. These results support the use of student-level analyses combined with cluster-robust inference.

Measurement invariance

To enable meaningful comparisons of latent constructs across instructional groups (RQ1/H1), a series of multi-group confirmatory factor analyses (MG-CFAs) were conducted in Mplus using robust maximum likelihood estimation (MLR). Measurement invariance was tested across the three instructional groups: (a) ChatGPT-assisted CBL, (b) non–ChatGPT-assisted CBL, and (c) TDL

Following the nested model approach described by Brown [59], invariance testing proceeded through four increasingly restrictive levels: configural, metric, scalar, and strict invariance. As required by Mplus, these models were tested pairwise for each group comparison (ChatGPT-assisted CBL vs. CBL, ChatGPT-assisted CBL vs. TDL, and CBL vs. TDL), with successive constraints imposed on factor loadings, intercepts, and residual variances.

Model fit was evaluated using conventional indices (CFI, TLI, RMSEA, SRMR). Changes in model fit were interpreted according to established guidelines (ΔCFI $\leq$ 0.01, ΔRMSEA $\leq$ 0.015) to assess support for measurement invariance [59,60]. Establishing measurement invariance was a necessary precondition for subsequent latent mean comparisons.

Table 2
Full scales with standardised CFA (λ) loadings.

		λ	λ*	α*
Intrinsic motivation				.90
1	I learn because I am interested in it.	.62	.85	
2	I learn because I enjoy dealing with this subject.	.66	.75	
3	I learn because I like to think about things in the field.	.64	.76	
		λ	λ*	α*
Identified motivation				.84
1	I learn because it gives me more options when choosing a career.	.65	.75	
2	I can use the things I learn here later on.	.74	.66	
3	I learn in order to be able to do further training later.	.69	.76	
		λ	λ*	α*
Introjected motivation				.81
1	I learn because I want my teacher to think I'm a good student.	.76	.66	
2	I learn because I want to be better than my classmates.	.70	.66	
3	I learn because I would like to receive praise.	.72	.62	
		λ	λ*	α*
Extrinsic motivation				.67
1	I learn because otherwise I get into trouble at home.	.65	.62	
2	I learn because I would otherwise get into trouble with my teachers.	.71	.66	
3	I learn because my parents demand it of me.	.65	.46	
		λ	λ*	α*
Autonomy support				.83
1	My teacher encourages me to ask my own questions.	.65	.82	
2	My teacher likes it when I find my own way of problem solving.	.71	.88	
3	My teacher tries to understand the way I see things.	.65	.85	
		λ	λ*	α*
Competence support				.85
1	My teacher helps me when I am stuck with a problem.	.67	.81	
2	I can ask my teacher about the material we are learning in the subject.	.69	.85	
3	My teacher shows me what I can do to improve.	.53	.80	
		λ	λ*	α*
Social relatedness				.88
1	it is important to my teacher that I feel comfortable.	.69	.82	
2	I have a good relationship with my classmates.	.80	.83	
3	I feel that my teacher understands me well.	.69	.88	

Note. λ = factor loadings, λ*= standardized factor loading, α* = Cronbach's alpha for motivation validated by Müller et al. [55], for basic needs validated by Müller and Thomas [56].

Latent profile analyses and multi-group modeling

To examine differences in motivational profile distributions across instructional conditions (RQ2/H2), separate LPAs were conducted for each instructional group (ChatGPT-assisted CBL, non–ChatGPT-assisted CBL, and TDL). Within each group, models specifying two to six profiles were estimated using robust maximum likelihood estimation (MLR).

Profile enumeration was guided by multiple criteria, including

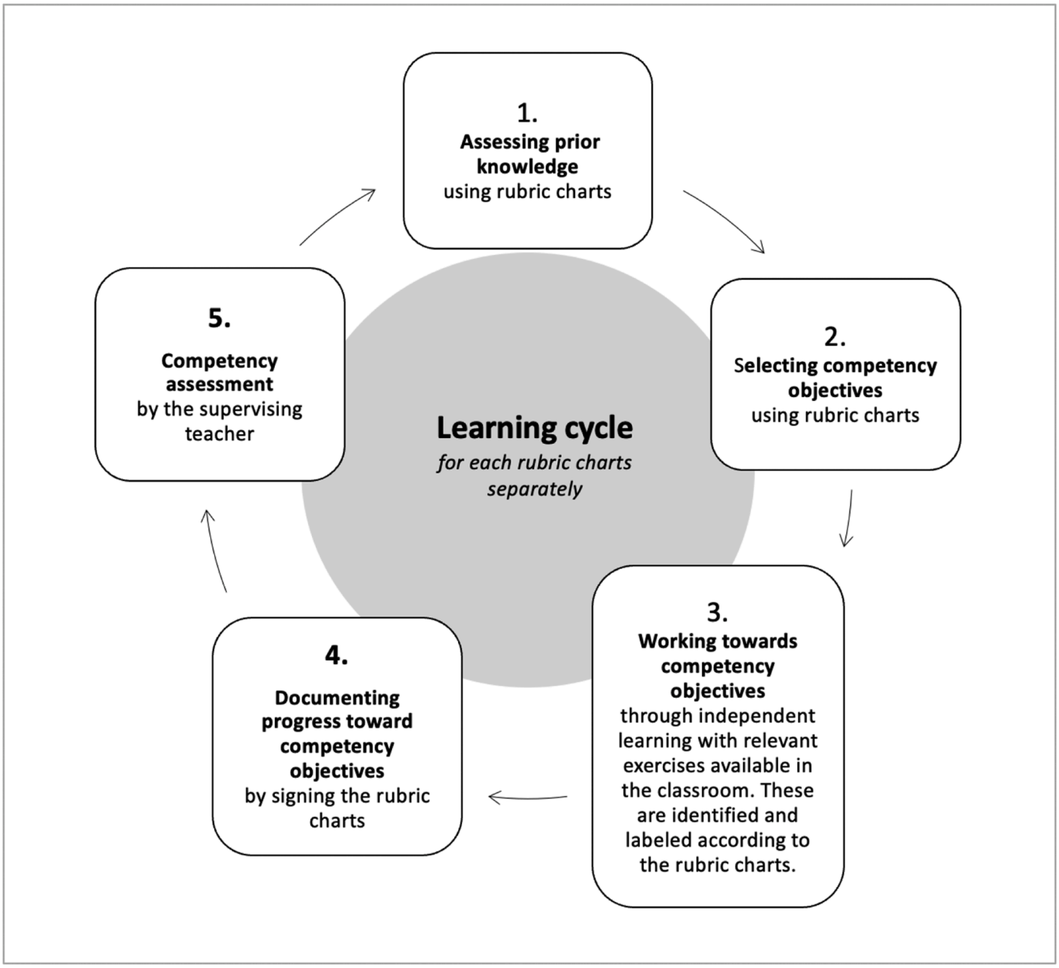


Fig. 2. Structured learning cycle using rubric charts to support competency-based learning.

Competency-based rubric for writing instruction in Grade 7

	Competency Objective	Performance Indicator 1	Performance Indicator 2	Performance Indicator 3	Assessment Format
1	**Planning and Structuring Writing**				
	I can plan and organize my writing effectively.	I can generate ideas and brainstorm relevant topics.	I can synthesize arguments from multiple sources.	I can plan and structure a text using an outline.	Outline for a text
2	**Writing Creative Texts**				
	I can write imaginative and coherent creative texts.	I can signal chronological order in narrative texts.	I can describe factual events or processes in a structured way.	I can change or continue a given text creatively.	Creative text
3	**Writing Argumentative Texts**				
	I can express my opinion and support it with arguments.	I can express opinions on literature or films.	I can critically assess arguments or possible solutions.	I can develop an argument logically in an essay.	Argumentative essay
4	**Writing Explanatory Texts**				
	I can explain topics clearly using factual information.	I can present a topic using visuals and short blocks of text.	I can describe a real event or process in detail.	I can summarize essential information from a text.	Summary

Fig. 3. Example of a rubric cart to support competency-based learning.

statistical fit indices (log-likelihood, AIC, BIC, adjusted BIC, SABIC, CAIC, AIC3), entropy (≥ 0.70), the Lo–Mendell–Rubin adjusted likelihood ratio test (LMR–LRT), the bootstrap likelihood ratio test (BLRT), minimum profile size (≥ 3 %), and conceptual interpretability. Final model selection was based on joint consideration of statistical and theoretical criteria [61,62]. Consistent with person-centered modeling conventions, emphasis was placed on substantive profile differentiation rather than formal effect size indices.

After identifying optimal profile solutions within each instructional group, a multi-group latent profile analysis (MG-LPA) was conducted to examine configural similarity across groups. Although strict measurement invariance was established at the construct level, configural invariance was not supported at the profile level. Accordingly, and in line with current person-centered recommendations, motivational profiles were interpreted separately within each instructional context [63].

Correlate analyses: multinomial logistic regression

To examine contextual correlates of students' motivational profiles (RQ3/H3), separate multinomial logistic regression analyses were conducted for each instructional condition (TDL, non–ChatGPT-assisted CBL, and ChatGPT-assisted CBL). These analyses were performed after profile identification and were fully aligned with the study's cross-sectional, person-centered design.

Odds ratios (ORs) greater than 1 indicate a higher likelihood of profile membership as the predictor increases, whereas values below 1 indicate a reduced likelihood [64]. Ninety-five percent confidence intervals (CIs) were computed to assess the robustness of estimates, and predictors were considered statistically significant at $p < .05$.

All variables were measured concurrently; therefore, results are interpreted as correlational rather than causal. Drawing on Self-Determination Theory, students' perceived autonomy support, competence support, and social belonging were included as concurrent correlates of latent profile membership. These variables were entered as continuous predictors in separate multinomial logistic regression models for each instructional group. Odds ratios, standard errors, and confidence intervals are reported for all comparisons.

Results

The results are presented in the order of the research questions. First, group differences in motivational regulation are examined (RQ1). Second, the distribution and structure of motivational profiles across instructional contexts are analyzed (RQ2). Finally, associations between perceived basic psychological need satisfaction and motivational profile membership are reported (RQ3).

Descriptive statistics

Descriptive statistics for all study variables are presented in Table 3, separately for the ChatGPT-assisted CBL, non–ChatGPT-assisted CBL, and TDL groups. To explore group-specific relationships among variables, Pearson correlation coefficients were calculated separately for each instructional context (see Tables 4a–c).

Measurement invariance

Following established guidelines [60], a sequence of nested models was tested to examine configural, metric, scalar, and strict invariance. As shown in Table 5, changes in fit indices (ΔCFI, ΔRMSEA, and ΔSRMR) were mostly within acceptable thresholds, with partial strict invariance supported. This level of invariance permits meaningful comparisons of latent means and profile structures across groups [65].

RQ1: group differences in motivation and need satisfaction

To address RQ1, latent mean differences in motivational regulation were examined across instructional groups. Using the TDL group as the reference category, both non–ChatGPT-assisted and ChatGPT-assisted CBL groups exhibited significantly higher latent means for intrinsic motivation and identified regulation, indicating higher levels of autonomous motivation in both student-centered contexts.

Beyond these shared advantages, students in the ChatGPT-assisted CBL condition additionally reported significantly lower levels of introjected and external regulation, indicating reduced controlled motivation relative to the TDL group. Direct comparisons between the two CBL conditions revealed that students with ChatGPT access showed higher intrinsic motivation and lower external regulation than those in the non-assisted CBL condition. All effects reached conventional levels of statistical significance (see Table 6 and Fig. 4).

Table 3
Means (M), Standard Deviations (SD), range, skewness, Kurtosis, and Cronbach's alpha (α).

Variable	M	SD	Range	Skewness	Kurtosis	α
TDL non-ChatGPT-assisted group						
Intrinsic motivation	2.12	0.68	1–4	0.44	0.06	.77
Identified motivation	2.33	0.69	1–4	0.15	−0.39	.75
Introjected motivation	2.11	0.67	1–4	0.28	−0.50	.66
Extrinsic motivation	2.03	0.64	1–4	0.57	−0.03	.65
Social belonging	2.59	0.67	1–4	−0.01	−0.11	.74
Competence support	2.51	0.60	1–4	0.04	0.23	.68
Autonomy support	2.20	0.62	1–4	0.15	−0.04	.68
CBL non-ChatGPT-assisted group						
Intrinsic motivation	2.42	0.83	1–4	0.08	−0.80	.80
Identified motivation	2.91	0.70	1–4	−0.54	0.05	.73
Introjected motivation	1.97	0.73	1–4	0.64	−0.10	.66
Extrinsic motivation	2.06	0.73	1–4	0.49	−0.21	.74
Social belonging	2.83	0.74	1–4	−0.57	−0.02	.74
Competence support	2.41	0.69	1–4	0.18	−0.12	.66
Autonomy support	2.20	0.74	1–4	0.23	−0.43	.73
CBL ChatGPT-assisted group						
Intrinsic motivation	2.77	0.61	1–4	−0.14	−0.17	.71
Identified motivation	2.73	0.67	1–4	−0.17	−0.32	.73
Introjected motivation	1.90	0.72	1–4	0.66	−0.04	.77
Extrinsic motivation	1.77	0.67	1–4	0.77	0.08	.75
Social belonging	2.76	0.67	1–4	−0.07	−0.31	.77
Competence support	2.77	0.56	1–4	−0.03	−0.20	.66
Autonomy support	2.97	0.66	1–4	−0.26	−0.44	.73
ChatGPT assistance	2.66	0.70	1–4	−0.12	−0.51	.69

Note. TDL = teacher-directed learning; CBL = competence-based learning.

Latent mean differences in perceived basic psychological need satisfaction were examined within the person-centered analyses addressing RQ3, where need satisfaction was modeled as a correlate of motivational profile membership.

RQ2: Distribution and Structure of Motivational Profiles Across Instructional Contexts

Latent profile enumeration and model selection

Model selection followed a multi-criterion approach integrating statistical fit indices, classification quality, profile size, and theoretical interpretability. Across all instructional contexts, the five-profile solution provided the best balance between fit, parsimony, and interpretability (see Table 7 and Figs. 5–8).

In the TDL group, the five-profile solution showed lower AIC, BIC, SABIC, and AIC3 values than alternative models. Entropy was acceptable (0.72), and all profiles exceeded the minimum size threshold of 3 %. Although the six-profile model showed comparable fit, it included very small classes (<3 %), reducing interpretability.

A similar pattern emerged in the non–ChatGPT-assisted CBL group. The five-profile model outperformed alternatives on key information criteria (e.g., BIC = 5938.17; CAIC = 5961.17) and showed acceptable entropy (0.70). The six-profile solution introduced small classes (approximately 3–4 %), indicating over-extraction.

In the ChatGPT-assisted CBL group, the five-profile solution again represented the most balanced model (e.g., BIC = 6775.87; entropy = 0.74). Although the six-profile model yielded a marginally lower AIC, it did not improve entropy or likelihood-based fit (pVLMR = 0.10) and produced undersized profiles.

The five-profile solution was retained across all groups, providing a robust basis for subsequent analyses.

Table 4a
Bivariate correlations in the non–ChatGPT-assisted teacher-directed learning group.

		1	2	3	4	5	6	7	8
1	Intrinsic motivation	1	–	–	–	–	–	–	–
2	Identified motivation	.662**	1	–	–	–	–	–	–
3	Introjected motivation	.257**	.326**		–	–	–	–	–
4	Extrinsic motivation	.231**	.247**	.543**	1	–	–	–	–
5	Social belonging	.275**	.204**	.085*	.092**	1	–	–	–
6	Competence support	.518**	.515**	.185**	.138**	.331**	1	–	–
7	Autonomy support	.480**	.408**	.204**	.254**	.369**	.457**	1	–
8	Gender	.000	–.027	.083*	.080*	.048	.015	–.006	1
9	Age	–.156**	–.157**	–.014	.03	–.079*	–.067	–.036	.123**

Note. $p < .05$; $p < .001$.

Table 4b
Bivariate correlations in the non–ChatGPT-assisted competency-based learning group.

		1	2	3	4	5	6	7	8
1	Intrinsic motivation	1	–	–	–	–	–	–	–
2	Identified motivation	.537**	1	–	–	–	–	–	–
3	Introjected motivation	.200**	.170**	1	–	–	–	–	–
4	Extrinsic motivation	–.134**	–.053	.418**	1	–	–	–	–
5	Social belonging	.449**	.454**	.100**	–.113**		–	–	–
6	Competence support	.290**	.302**	.151**	.037	.338**	1	–	–
7	Autonomy support	.212**	.253**	.252**	.168**	.127**	.322**	1	–
8	Gender	.019	.064	.071	.010	.042	–.009	.009	1
9	Age	–.009	–.034	.053	.034	.017	–.034	–.027	.062

Note. $p < .05$; $p < .001$.

Table 4c
Bivariate correlations in the ChatGPT-assisted competency-based learning group.

		1	2	3	4	5	6	7	8
1	Intrinsic motivation	1	–	–	–	–	–	–	–
2	Identified motivation	.604**	1	–	–	–	–	–	–
3	Introjected motivation	.228**	.241**	1	–	–	–	–	–
4	Extrinsic motivation	.116**	.127**	.634**	1	–	–	–	–
5	Social belonging	.412**	.445**	.088**	.002	1	–	–	–
6	Competence support	.367**	.454**	.090**	.014	.361**	1	–	–
7	Autonomy support	.416**	.464**	.062	–.015	.438**	.465**	1	–
8	Gender	.036	.018	.162**	.209**	.019	.040	–.014	1
9	Age	–.098**	–.037	–.017	.087**	–.086**	.100**	–.018	.026

Note. $p < .05$; $p < .001$.

Table 5
Summary of results for tests of measurement invariance.

Model	df	χ^2 (p)	CFI	RMSEA	90 % CI	SRMR	ΔCFI	ΔRMSEA	ΔSRMR
Configural	504	1117.74 ($p < .001$)	0.942	0.039	0.035–0.042	0.043	–	–	–
Metric	532	1145.99 ($p < .001$)	0.942	0.037	0.035–0.040	0.046	0	–0.002	0.003
Scalar	557	1233.70 ($p < .001$)	0.936	0.038	0.036–0.041	0.049	–0.006	0.001	0.003
Strict	602	1529.19 ($p < .001$)	0.912	0.043	0.041–0.046	0.058	–0.024	0.005	0.009
Partial Strict	590	1358.61 ($p < .001$)	0.927	0.040	0.037–0.043	0.054	–0.009	0.002	0.005

Note. MI = measurement invariance; the final columns indicate model fit comparisons between the two subsequent models [60]: ΔCFI = decrease of ≤ 0.010; ΔSRMR = increase of ≤ 0.010; ΔRMSEA = increase of ≤.015.

Latent profile structures across learning contexts

To further address RQ2, motivational profiles were interpreted based on their latent means across intrinsic, identified, introjected, and external regulation, as well as their relative prevalence (see Tables 8a and 8b). Profile labeling followed the typology proposed by [35], which differentiates profiles by both qualitative and quantitative characteristics.

Across all instructional contexts, five profiles emerged consistently: high-quality, high-quantity, low-quality, low-quantity, and moderately motivated. High-quality profiles were characterized by high intrinsic and identified motivation and low controlled regulation. High-quantity profiles showed high levels across all regulation types. Low-quality profiles reflected relatively high controlled and low autonomous motivation, whereas low-quantity profiles were low across all dimensions. Moderately motivated profiles showed intermediate levels.

Although the same profile structure emerged across contexts, absolute latent means varied. For example, students in the ChatGPT-assisted CBL group showed the highest intrinsic motivation within both the high-quality (M = 3.56) and high-quantity (M = 3.33) profiles. These differences indicate functional non-invariance across contexts, underscoring the importance of group-specific interpretation.

Results for the TDL Group. Fig. 9 illustrates the five profiles identified in the TDL group. The high-quality profile (12.0 %) was

Table 6
Latent mean differences.

	CBL non-ChatGPT-assisted estimate	CBL ChatGPT-assisted estimate
Reference group 1: TDL non-ChatGPT-assisted		
Intrinsic motivation	0.42**	1.33***
Identified motivation	0.95**	0.69***
Introjected motivation	–0.28*	–0.34**
Extrinsic motivation	0.03	–0.46***
Autonomy support	–0.01	1.35***
Competence support	–0.19	0.55***
Social relatedness	0.36***	0.26**
Reference group 2: CBL ChatGPT-assisted		
Intrinsic motivation	–	0.43***
Identified motivation	–	–0.29**
Introjected motivation	–	–0.09
Extrinsic motivation	–	–0.57***
Autonomy support	–	1.13***
Competence support	–	0.62***
Social relatedness	–	–0.12

Note. TDL = teacher-directed learning; CBL = competence-based learning; *$p < .05$; ** $p < .01$; ***$p > .001$.

characterized by elevated intrinsic ($M = 3.18$) and identified motivation ($M = 3.14$), accompanied by moderate levels of controlled regulation. The high-quantity profile (4.4 %) exhibited high levels across all motivational dimensions.

The low-quality profile (21.3 %) was characterized by low intrinsic ($M = 1.35$) and identified motivation ($M = 1.56$), alongside moderate levels of controlled regulation. The low-quantity profile (41.3 %) showed below-average levels across all motivational dimensions. The moderately motivated profile (21.3 %) displayed intermediate levels across all types of motivation.

Results for the CBL Non–ChatGPT-Assisted Group. Fig. 10 presents the five-profile solution for the non–ChatGPT-assisted CBL group. The high-quality profile (41.7 %) showed high intrinsic ($M = 2.92$) and identified motivation ($M = 3.22$) and low controlled regulation. The high-quantity profile (10.2 %) showed elevated levels across all dimensions.

The low-quality profile (5.3 %) showed low levels across all forms of motivation. The low-quantity profile (30.1 %) showed moderate levels, and the moderately motivated profile (12.4 %) showed intermediate levels across dimensions.

Results for the ChatGPT-Assisted Group. Fig. 11 presents the five profiles in the ChatGPT-assisted CBL group. The high-quality profile (10.7 %) showed high intrinsic ($M = 3.56$) and identified motivation ($M = 3.57$) with moderate controlled regulation. The high-quantity profile (7.6 %) showed high levels across all dimensions.

The low-quality profile (32.5 %) showed comparatively low autonomous motivation. The low-quantity profile (25.6 %) showed moderate levels, and the moderately motivated profile (23.5 %) showed balanced mid-range levels.

RQ3: associations between need satisfaction and profile membership

To address RQ3, associations between perceived autonomy, competence, and relatedness and motivational profile membership were examined using multinomial logistic regressions within each instructional group. Results are interpreted as correlational due to the cross-sectional design. Full results are reported in Tables A2–A10 in the Appendix.

CBL ChatGPT-assisted group

Perceived competence support was the strongest correlate of profile membership. Compared to the low-quality profile, higher competence support increased the likelihood of belonging to the high-quantity (OR = 4.35, $p < .001$) and high-quality profiles (OR = 2.97, $p = .017$). Autonomy support was associated with membership in the moderately motivated profile (OR = 2.70, $p = .038$).

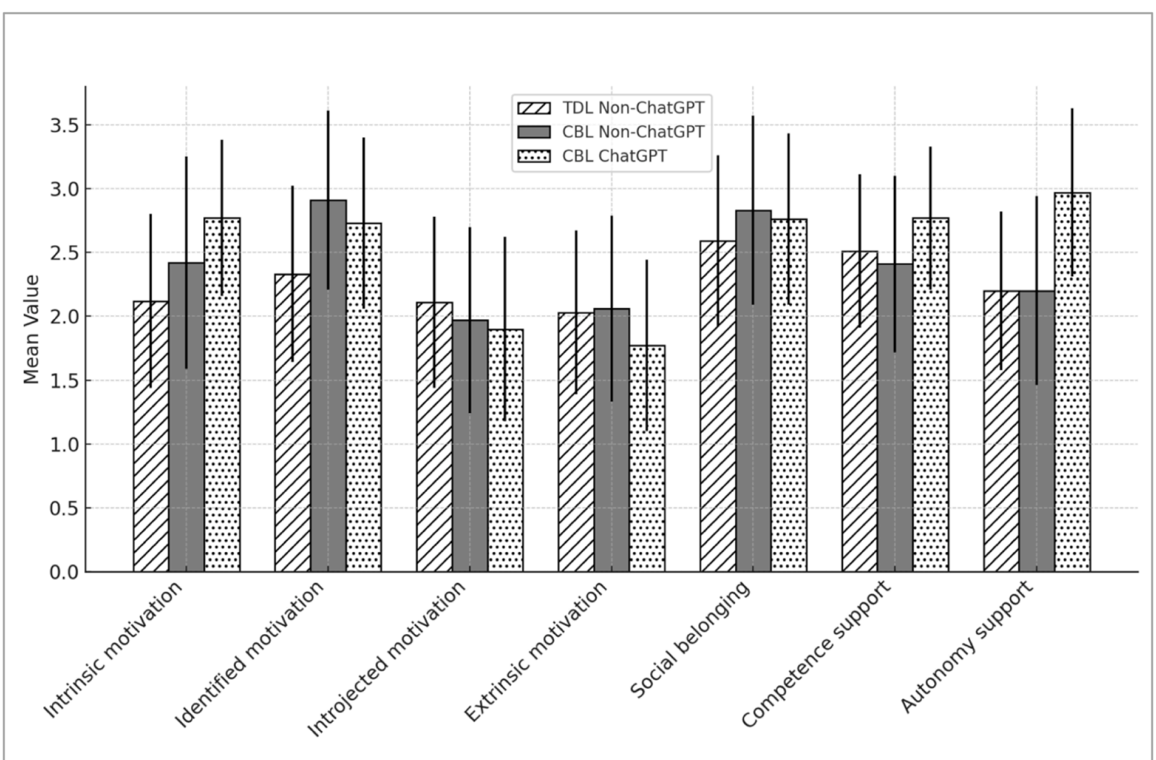


Fig. 4. Latent mean comparison with standard deviation.

Table 7
Information criteria for latent profile solutions based on the class-invariant diagonal model.

c	LL	npar	AIC	BIC	a.BIC	AIC3	SABIC	CAIC	entropy	pVLMR	BLRT	Profile sizes
TDL non-ChatGPT-assisted learning group												
2	–2966.00	13	5957.99	6018.73	5977.45	5983.99	5977.45	6031.73	0.68	0.00	0.00	477/313
3	–2899.42	18	5834.84	5918.94	5861.78	5870.84	5861.78	5936.94	0.71	0.07	0.07	231/126/433
4	–2840.88	23	5727.76	5835.21	5762.17	5773.76	5762.17	5858.21	0.66	0.65	0.66	219/122/332/117
5	–2791.31	28	5638.61	5769.43	5680.52	5694.61	5680.52	5797.43	0.72	0.14	0.15	326/95/168/35/166
6	–2783.13	33	5632.26	5786.44	5681.65	5698.26	5681.65	5819.44	0.76	0.39	0.40	159/96/3/32/164/336
CBL non-ChatGPT-assisted learning group												
2	–2989.33	13	6004.65	6063.98	6022.70	6043.65	6004.65	6076.98	0.64	0.00	0.00	274 / 435
3	–2954.2	18	5944.39	6026.54	5969.39	5998.39	5944.39	6045.54	0.67	0.34	0.35	54 / 324 / 331
4	–2898.44	23	5842.88	5947.85	5874.82	5911.88	5842.88	5969.85	0.67	0.01	0.01	51 / 317 / 257 / 84
5	–2877.19	28	5810.39	5938.17	5849.27	5894.39	5810.39	5961.17	0.70	0.07	0.07	38 / 296 / 88 / 73 / 214
6	–2858.91	33	5783.82	5934.43	5829.64	5882.82	5783.82	5960.43	0.70	0.10	0.11	25 / 98 / 76 / 86 / 146 / 278
CBL ChatGPT-assisted learning group												
2	–3634.12	13	7294.23	7357.63	7316.34	7307.23	7316.34	7370.63	0.64	0.00	0.00	474/491
3	–3445.87	18	6927.74	7015.51	6958.34	6963.74	6958.34	7033.51	0.71	0.00	0.00	426/316/223
4	–3359.28	23	6764.55	6876.70	6803.66	6810.55	6803.66	6899.70	0.73	0.02	0.02	365/234/294/72
5	–3315.37	28	6686.75	6823.28	6734.35	6742.75	6734.35	6851.28	0.72	0.00	0.00	248/104/224/74/315
6	–3274.48	33	6614.95	6775.87	6671.06	6680.95	6671.06	6808.87	0.74	0.10	0.11	100/104/171/68/263/259

Note. TDL = teacher-directed learning; CBL = competence-based learning; *c* = number of latent profiles in the model; LL = loglikelihood; npar = number of free parameters; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; a.BIC = sample-size adjusted BIC; AIC3 = corrected AIC; SABIC = sample-size adjusted Bayesian Information Criterion; CAIC = consistent AIC; entropy = classification accuracy; pVLMR = *p*-value of the Vuong–Lo–Mendell–Rubin likelihood ratio test; BLRT = *p*-value of the Bootstrap Likelihood Ratio Test.

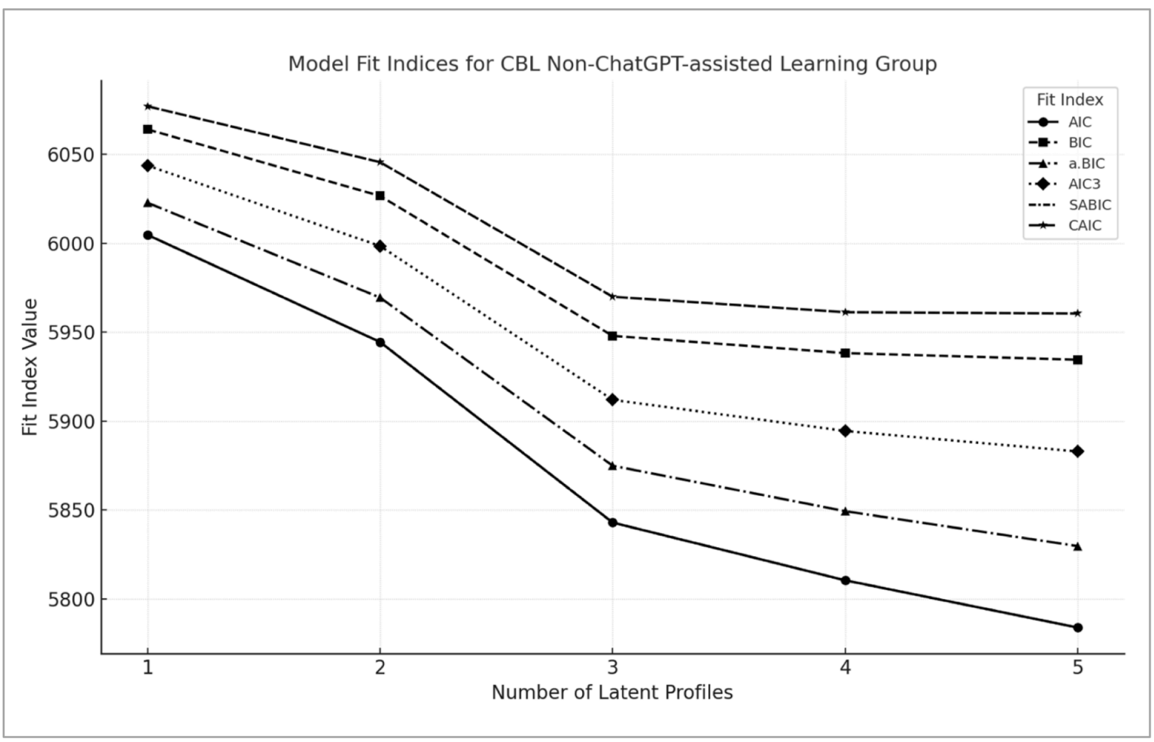


Fig. 5. Comparison of fit indices for latent profile solutions
Note. CBL = competence-based learning; Lower values indicate better model fit. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (adjusted BIC), AIC3, sample-size adjusted information criterion (SABIC), and consistent AIC (CAIC).

CBL non-ChatGPT-assisted group

All three need dimensions were associated with profile membership. Autonomy support increased the likelihood of belonging to all profiles, with strongest effects for high-quantity (OR = 13.60) and low-quantity profiles (OR = 8.60). Relatedness showed the strongest overall effects, particularly for high-quantity (OR = 66.26) and high-quality profiles (OR = 22.64). Competence support also showed strong associations across profiles.

TDL group

In the TDL group, higher autonomy and competence support were associated with increased likelihood of belonging to high-quality and high-quantity profiles. Relatedness was particularly associated with high-quality and high-quantity profiles. Students in the moderately motivated profile also reported higher autonomy and competence than those in the low-quantity profile. To facilitate the interpretation of the findings in relation to the study hypotheses, a summary of key results is provided in Table 9.

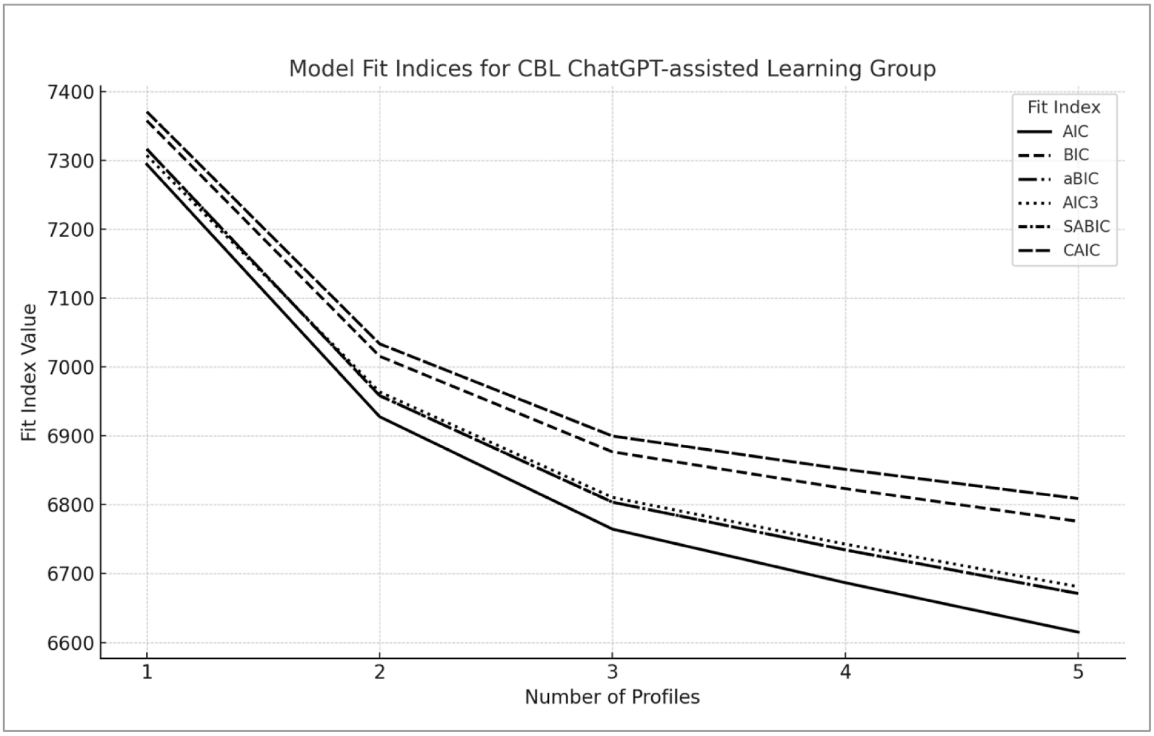


Fig. 6. Comparison of fit indices for latent profile solutions
Note. CBL = competence-based learning; Lower values indicate better model fit. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (adjusted BIC), AIC3, sample-size adjusted information criterion (SABIC), and consistent AIC (CAIC).

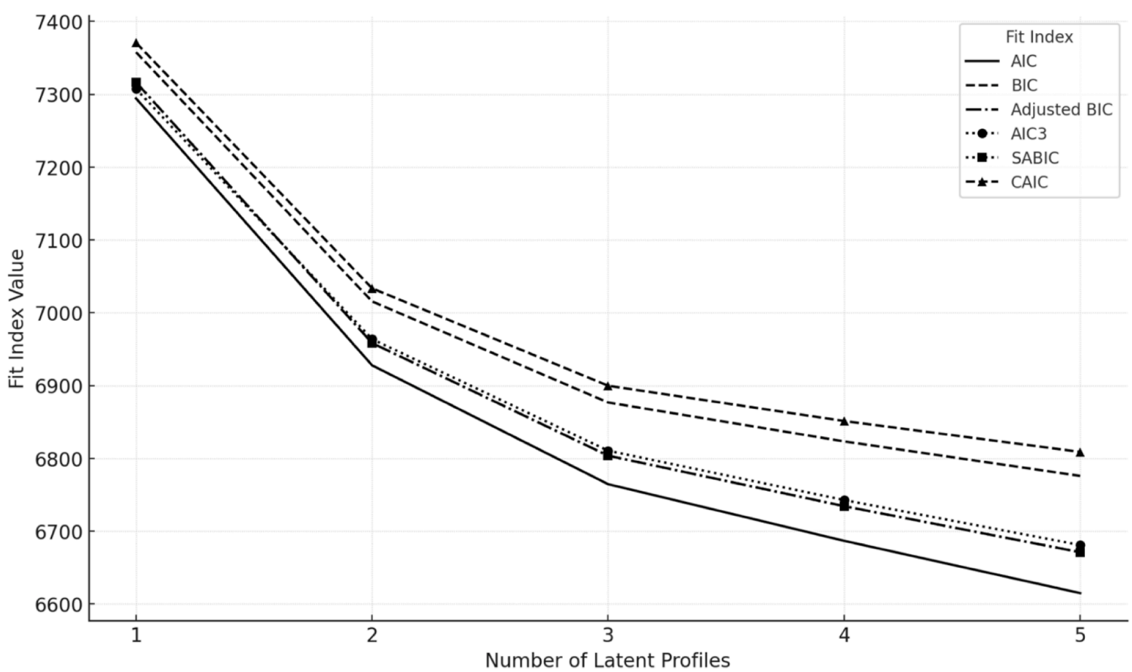


Fig. 7. Comparison of fit indices for latent profile solutions
Note. TDL = teacher-directed learning; CBL = competence-based learning; Lower values indicate better model fit. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (adjusted BIC), AIC3, sample-size adjusted information criterion (SABIC), and consistent AIC (CAIC).

Discussion

This study employed a cross-sectional design combining variable-centered and person-centered approaches to examine how secondary school students' motivation and motivational profiles—based on intrinsic, identified, introjected, and external regulation, as well as perceived support for autonomy, competence, and relatedness—vary across instructional contexts with and without access to generative artificial intelligence (GenAI). Guided by Self-Determination Theory [28], the primary aim was to provide initial empirical insights into how

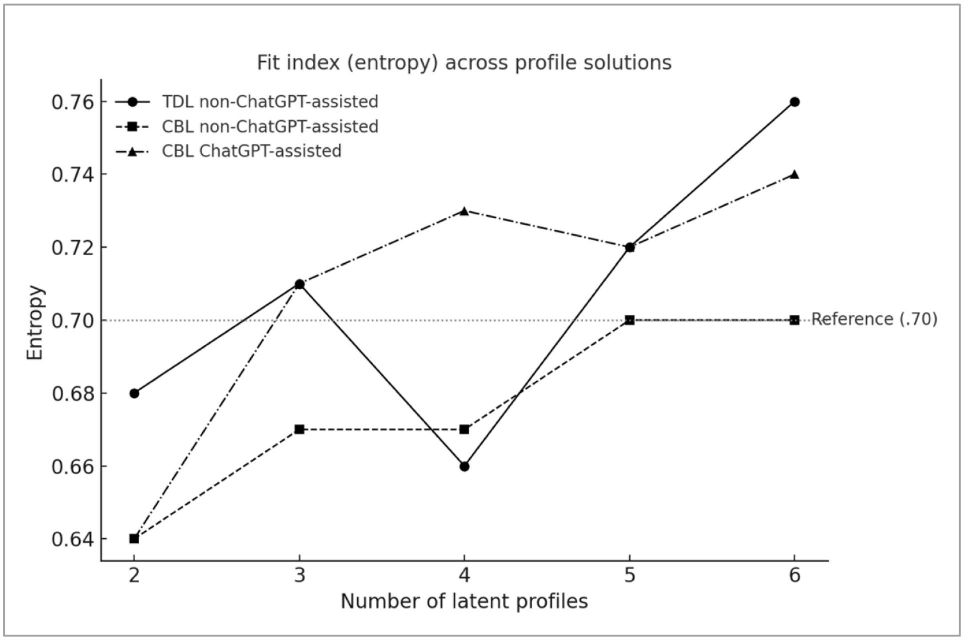


Fig. 8. Comparison of entropy for latent profile solutions.

Table 8a
Latent profile means for motivation constructs across all subsamples.

	Profile	Intrinsic motivation	Identified motivation	Introjected motivation	Extrinsic motivation
	TDL non-ChatGPT				
1	High-quality	3.18	3.14	2.01	1.86
2	High-quantity	3.13	3.45	3.01	3.14
3	Low-quality	1.35	1.56	1.75	1.99
4	Low-quantity	2.03	2.27	1.91	1.83
5	Moderately-motivated	2.27	2.54	2.67	2.66
	CBL non-ChatGPT				
1	High-quality	2.92	3.22	1.71	1.97
2	High-quantity	3.29	3.54	3.03	2.71
3	Low-quality	1.32	1.56	1.36	1.89
4	Low-quantity	2.11	2.69	2.80	2.54
5	Moderately-motivated	1.78	2.63	2.67	2.42
	CBL ChatGPT				
1	High-quality	3.56	3.57	1.64	1.56
2	High-quantity	3.33	3.29	3.32	3.07
3	Low-quality	2.15	1.98	1.59	1.67
4	Low-quantity	2.83	2.85	2.33	2.21
5	Moderately-motivated	2.79	2.75	1.33	1.46

Note. TDL = teacher-directed learning; CBL = competency-based learning.

Table 8b
Profile size.

Subsample	High-quality	High-quantity	Low-quality	Low-quantity	Moderately-motivated
Non-ChatGPT assisted TDL	12 %	4.4 %	21 %	41.3 %	21.3 %
Non-ChatGPT assisted CBL	41.7 %	10.2 %	5.3 %	30.1 %	12.4 %
ChatGPT assisted CBL	10.7 %	7.6 %	32.5 %	25.6 %	23.5 %

Note. TDL = teacher-directed learning; CBL = competence-based learning.

ChatGPT-integrated classroom environments compare with both non–AI-supported CBL and traditional TDL in supporting self-determined forms of motivation.

By integrating multi-group latent mean comparisons with context-specific latent profile analyses, and by examining associations between perceived need satisfaction and motivational profile membership using multinomial logistic regression, the study contributes to the emerging literature on GenAI-enhanced education. Specifically, it provides one of the first large-sample, ecologically valid investigations of motivational quality and heterogeneity associated with ChatGPT use in lower-secondary classrooms.

Hypothesis 1. ChatGPT-Assisted Instruction and Self-Determined Motivation

Consistent with Hypothesis 1, students in the ChatGPT-assisted CBL condition reported significantly higher levels of intrinsic motivation, identified regulation, and perceived autonomy and competence support than both comparison groups. These latent mean differences suggest that ChatGPT, when embedded within an autonomy-supportive instructional context, is associated with higher levels of self-determined motivation.

A central interpretive question concerns whether these effects can be attributed to the technological tool itself or to the instructional context in which it was embedded [66,67]. The present findings are most consistent with a mediated-effects perspective: ChatGPT did not function as an independent instructional treatment, but as a supportive resource within a rubric-based, autonomy-supportive CBL framework. Accordingly, the observed differences are unlikely to reflect the technology per se, but rather changes in students' learning processes, including increased opportunities for self-regulated problem solving, immediate feedback, and individualized support. In this sense, ChatGPT appears to have amplified existing instructional affordances rather than acting as a standalone driver of motivational change.

From an SDT perspective, integrating ChatGPT into a structured CBL environment may have supported autonomy and competence by combining transparent competency goals with meaningful choice over task selection and pacing. Features such as personalized explanations, real-time feedback, and support for idea generation plausibly contributed to these effects. Importantly, the measure of ChatGPT support captured perceived motivational assistance conditional on use rather

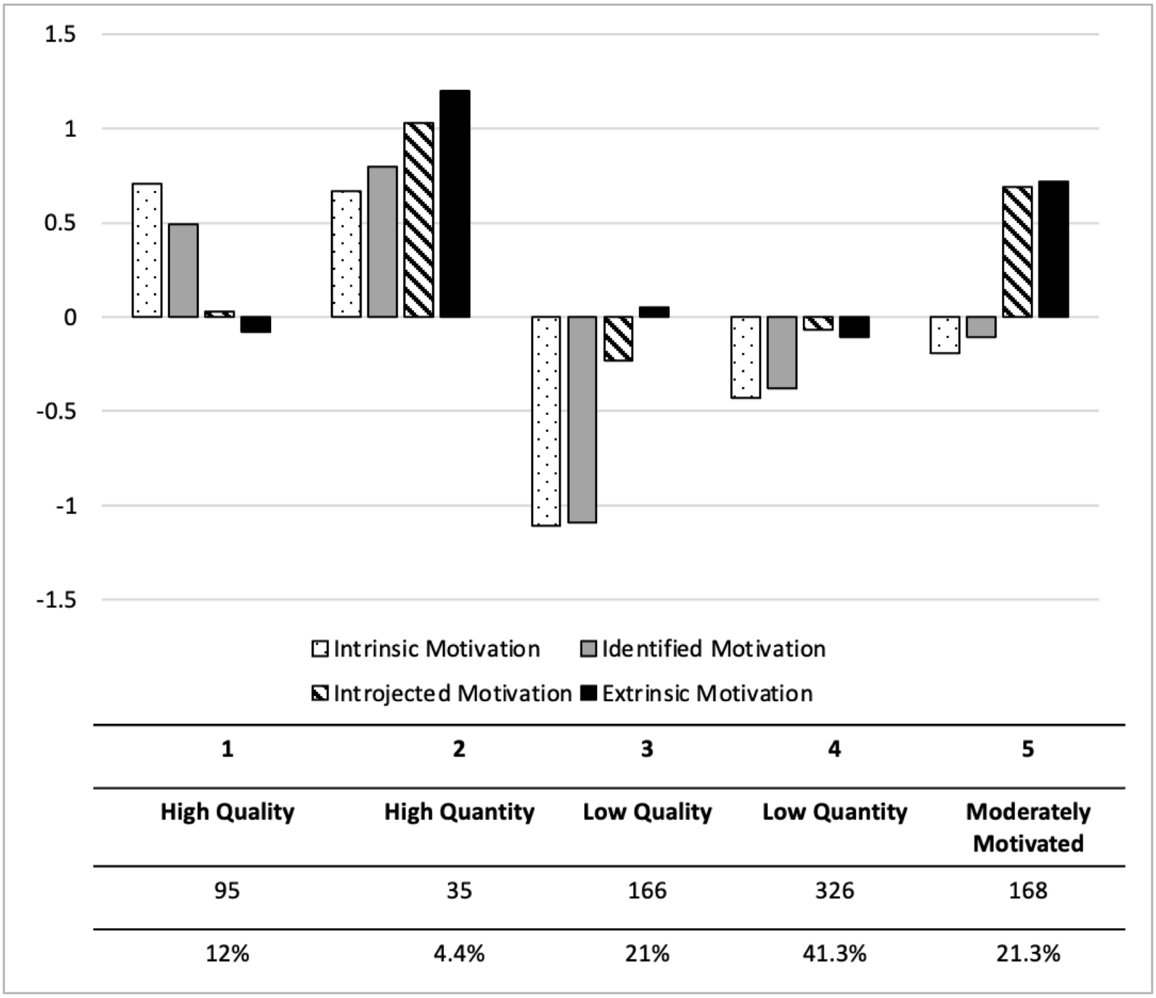


Fig. 9. Relative deviations from the sub sample mean across latent profiles in the TDL non-ChatGPT-assisted group.

than frequency or intensity of engagement. Thus, the findings reflect how supportive students experienced ChatGPT when used, rather than how often it was used, aligning with an SDT focus on motivational quality rather than behavioral exposure.

In contrast, perceived relatedness did not differ across instructional conditions, suggesting a structural boundary of AI-supported learning. While ChatGPT can facilitate individualized engagement, it cannot substitute for interpersonal interaction, which remains central to relatedness satisfaction.

Notably, compared to the non-assisted CBL group, only the ChatGPT-assisted condition showed consistent advantages across multiple indicators of self-determined motivation (excluding relatedness). This finding underscores that GenAI-based scaffolding may enhance motivational quality primarily when embedded within autonomy-supportive instructional designs. Consistent with prior work [23], the results reinforce the conclusion that instructional design—rather than technology alone—shapes the motivational impact of GenAI integration.

Finally, these findings should be interpreted as reflecting situational perceptions of need-supportive affordances rather than stable or enduring need satisfaction in the strong SDT sense. Given the cross-sectional design, they speak to momentary motivational experiences rather than long-term internalization processes.

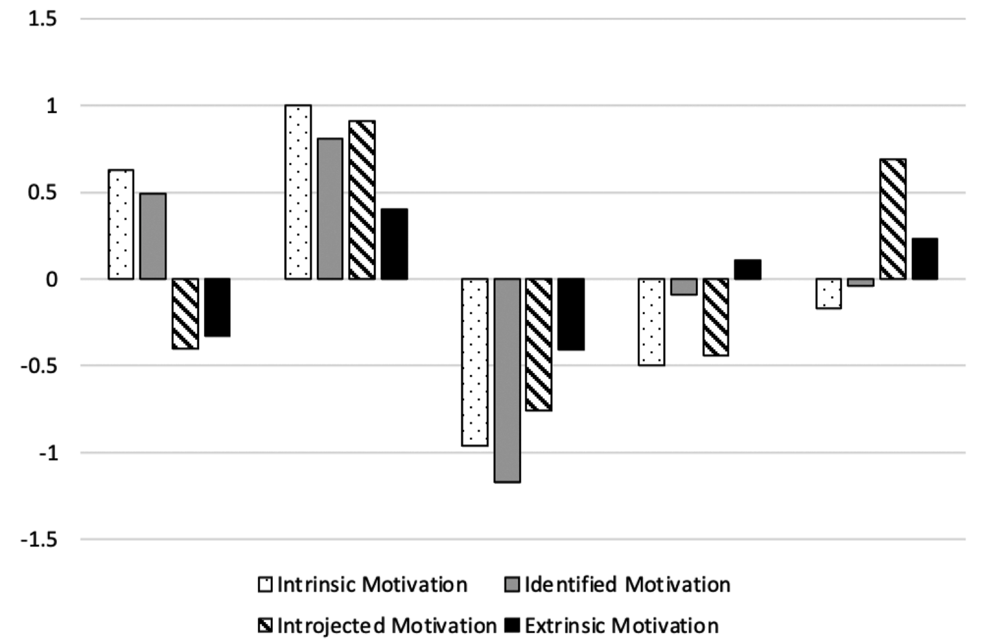
Hypothesis 2. Profile Differentiation Across Instructional Contexts

Hypothesis 2 proposed that motivational profile distributions would differ across instructional contexts, with a higher prevalence of adaptive profiles in the ChatGPT-assisted CBL group. This expectation was grounded in person-centered research on contextual sensitivity in motivation [63,68] and prior evidence suggesting that GenAI may support student motivation [8,37]. Consistent with previous research, five motivational profiles emerged across all contexts: high-quality, high-quantity, low-quality, low-quantity, and moderately motivated.

Multi-group analyses indicated that these profiles were not structurally equivalent across instructional contexts. Constrained model specifications resulted in substantial misfit, suggesting that motivational profiles represent context-specific configurations rather than directly comparable latent classes. At the same time, strict measurement invariance was established for the underlying constructs, allowing for meaningful comparisons of motivational quality across groups despite structural non-equivalence.

Descriptive results partially contradicted H2. The non–ChatGPT-assisted CBL group showed the highest proportion of students in the high-quality profile (41.7 %), compared to 10.7 % in the ChatGPT-assisted group and 12.0 % in the TDL group. However, the ChatGPT-assisted group exhibited a lower proportion of students in the low-quantity profile (25.6 %) than both comparison groups and a higher proportion of moderately motivated students. This pattern suggests that ChatGPT integration may not increase the prevalence of highly adaptive profiles, but may reduce the prevalence of the most maladaptive configurations.

Inspection of within-profile means further qualified this pattern. Within the ChatGPT-assisted group, students in the high-quality profile showed the highest levels of intrinsic (M = 3.56) and identified



1	2	3	4	5
High Quality	**High Quantity**	**Low Quality**	**Low Quantity**	**Moderately Motivated**
296	73	38	214	88
41.7%	10.2%	5.3%	30.1%	12.4%

Fig. 10. Relative deviations from the sub sample mean across latent profiles in the CBL non-ChatGPT-assisted group.

motivation ($M = 3.57$) across all contexts. Importantly, even within less adaptive profiles, students in the ChatGPT-assisted condition displayed more internalized forms of motivation than their counterparts in the non-assisted and TDL groups.

This is particularly evident in the low-quality profile, which—despite its classification—was characterized by substantially higher intrinsic ($M = 2.15$) and identified motivation ($M = 1.98$) than corresponding profiles in the other contexts, indicating a qualitatively distinct configuration marked by greater internalization.

One plausible interpretation is that ChatGPT functioned as a motivational scaffold for students who initially struggled with autonomous engagement. By providing immediate, non-judgmental, and on-demand support while preserving learner control, it may have lowered entry barriers and supported competence and autonomy satisfaction, consistent with SDT. In line with the media-versus-method perspective [66,67], these effects likely reflect how AI-mediated scaffolding interacts with instructional design rather than the technology itself.

However, the present data do not allow for direct tests of these mechanisms. The proposed scaffolding interpretation should therefore be understood as a theoretically grounded account rather than a tested mediation pathway.

These findings refine rather than refute H2. Although ChatGPT integration did not increase the prevalence of high-quality profiles, it was associated with higher motivational quality within profiles, particularly among less adaptive groups. This highlights the value of combining person-centered and variable-centered approaches to capture both structural and qualitative differences in student motivation.

Hypothesis 3. Associations Between Perceived Need Support and Motivational Profiles

Across all instructional contexts, the findings supported Hypothesis 3, showing that students' perceived autonomy, competence, and relatedness support were significantly associated with motivational profile membership. These associations, derived from multinomial logistic regression analyses, are consistent with a core proposition of Self-Determination Theory: students are more likely to exhibit adaptive motivational orientations when their basic psychological needs are supported [51,69].

In the ChatGPT-assisted CBL group, perceived competence support emerged as the most salient correlate of membership in high-quality and high-quantity profiles. This pattern suggests that ChatGPT may be particularly effective in strengthening students' sense of effectiveness when working toward transparent competency goals in self-paced learning environments [19,70]. Autonomy support was also associated with profile membership, although its effects were more pronounced for moderately motivated students, potentially reflecting the structured, rubric-guided nature of CBL, in which autonomy is scaffolded rather than fully open-ended [71].

Although relatedness did not differ across instructional contexts at the group level, it played a substantial role within contexts. In the ChatGPT-assisted group, students reporting higher social belonging were more likely to belong to adaptive profiles, indicating that relatedness remains a critical motivational resource even in AI-supported learning environments. In the non–ChatGPT-assisted CBL group, all three needs were robustly associated with profile membership, with particularly strong effects for relatedness. This underscores the continued importance of interpersonal support in peer-rich, teacher-facilitated self-regulated learning environments [36].

In the TDL group, need support also differentiated motivational

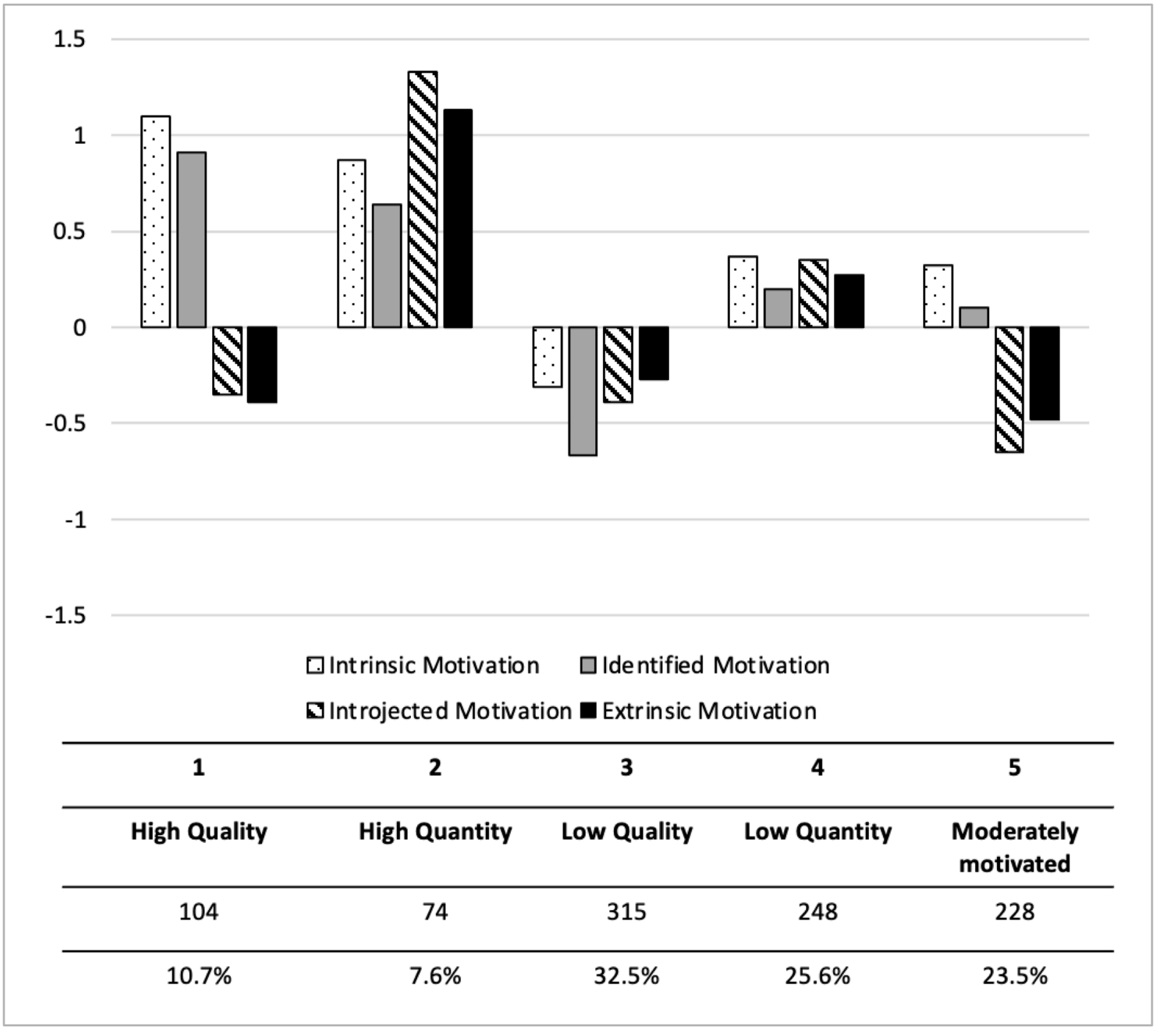


Fig. 11. Relative deviations from the sub sample mean across latent profiles in the CBL ChatGPT-assisted group.

Table 9
Summary of Hypotheses, Key Findings, and Interpretations.

Hypothesis	Expected Pattern	Key Empirical Findings	Support	Interpretative Summary
H1 (Variable-centered)	Higher autonomous motivation and need satisfaction in ChatGPT-assisted CBL	Higher intrinsic and identified motivation; lower introjected and external regulation; higher autonomy and competence; no group differences in relatedness	Supported (except relatedness)	GenAI, when embedded within autonomy-supportive CBL, is associated with more internalized motivation primarily via autonomy and competence support
H2 (Person-centered)	Higher prevalence of adaptive profiles in ChatGPT-assisted CBL	Five profiles across groups; non-ChatGPT CBL showed highest share of high-quality profiles; ChatGPT-assisted CBL showed fewer low-quantity profiles and higher autonomous motivation *within* profiles	Partially supported	ChatGPT did not shift overall profile distributions but was associated with higher motivational quality within profiles, particularly among less adaptive learners
H3 (Associative)	Higher need support associated with more adaptive profiles	Autonomy, competence, and relatedness predicted profile membership across groups; competence most salient in ChatGPT-assisted CBL	Supported	Basic psychological needs remain central correlates of motivational profiles; GenAI-supported contexts alter the relative salience of specific needs

Note. CBL = competency-based learning; TDL = teacher-directed learning; GenAI = generative artificial intelligence.

profiles, although patterns were less consistently aligned with adaptive configurations. Autonomy and competence support were associated with both adaptive and less adaptive profiles, suggesting that highly structured instructional formats may constrain internalization processes for some students, even when basic needs are supported [68].

Taken together, these findings highlight both shared and context-specific motivational dynamics. While basic psychological need satisfaction consistently relates to motivational profile membership, the relative importance of specific needs varies by instructional context. In ChatGPT-assisted CBL settings, competence support appears particularly salient, whereas relatedness plays a more central role in non-AI contexts. This differentiation helps explain why the overall distribution of motivational profiles in the ChatGPT-assisted group did not exceed that of the non–ChatGPT-assisted CBL group, despite clear within-profile gains in self-determined motivation.

Limitations

This study provides novel insights into the motivational implications of GenAI integration in secondary education; however, several limitations should be considered.

First, the cross-sectional design precludes causal inference. Although associations between perceived need support and motivational profiles are theoretically grounded in SDT, their directionality remains unclear. Longitudinal or experimental designs are required to determine whether GenAI use can sustainably foster autonomous motivation. Moreover, prior research suggests that positive motivational effects may diminish as the novelty of GenAI decreases [72], an issue not addressed in the present short-term design.

Second, the study relied on self-report measures of perceived ChatGPT support. Although internal consistency was acceptable, the instrument was novel and context-specific. It remains unclear how perceived support relates to actual usage behavior. Future research should incorporate system logs, usage analytics, or behavioral indicators to triangulate self-reports. In addition, although the findings are consistent with a scaffolding interpretation, SRL processes were not directly measured. Future studies should therefore assess SRL processes (e.g., monitoring, strategy use) to test this mechanism more directly.

Third, the intervention was brief (one week), and ChatGPT use was optional. Individual differences in frequency, purpose, and depth of engagement were not systematically captured. Consequently, motivational outcomes cannot be attributed to specific usage patterns and should be interpreted as short-term effects that may partly reflect technological novelty [54].

Fourth, the study was conducted under naturalistic classroom conditions across existing CBL and TDL settings in Grades 7–8. While this enhances ecological validity, it reduces experimental control. Variability in teacher facilitation, classroom norms, and prior exposure to GenAI may have influenced the observed effects.

Fifth, no condition combined TDL with ChatGPT use, as schools declined its implementation due to perceived incompatibility with teacher-directed formats. Accordingly, conclusions about GenAI effects cannot be generalized to teacher-centered instructional contexts.

Sixth, socioeconomic data were not collected due to anonymous data collection procedures. While this ensured compliance with data protection standards, it precludes subgroup analyses and limits conclusions regarding equity-related implications of GenAI-supported learning.

Strengths of the study

Despite its limitations, this study offers several strengths that position it as a substantive contribution to research on generative AI–enhanced instruction in secondary education.

First, the study is grounded in Self-Determination Theory and combines person-centered (latent profile analysis) and variable-centered approaches to capture both qualitative heterogeneity and mean-level differences in student motivation. This integrated analytic strategy reveals motivational patterns that would remain obscured in single-approach designs, showing that ChatGPT may enhance motivational quality within profiles without uniformly increasing adaptive engagement across entire classrooms.

Second, the study was conducted in ecologically valid classroom settings in Grades 7–8, comparing three authentic instructional models—rubric-based competency-based learning (CBL) with and without ChatGPT, and traditional teacher-directed learning (TDL)—in a large sample of over 2400 students. This real-world implementation strengthens both the external validity and practical relevance of the findings.

Third, strict measurement invariance of motivational regulation and perceived need support was established across instructional groups using multi-group confirmatory factor analysis. This provides a robust psychometric foundation for latent mean comparisons and person-centered profile interpretations.

Fourth, the study is among the first to examine perceived motivational support from generative AI alongside teacher-based support within the same instructional framework. By situating ChatGPT within a clearly defined, learner-centered CBL environment—rather than treating it as a standalone intervention—the study offers novel insights into how GenAI can function as a pedagogical support within structured instructional systems and provides a transferable model for theory-informed AI integration.

Practical implications for GenAI-enhanced instructional design

The present findings yield several implications for the integration of generative AI tools—specifically ChatGPT—into secondary education, particularly within learner-centered, rubric-based competency-based learning (CBL) environments.

First, GenAI tools appear most effective when embedded within clearly structured, autonomy-supportive instructional designs [73]. In this study, ChatGPT was integrated into a learning environment characterized by transparent goals, self-paced progression, and voluntary access to support. Within this framework, students reported higher motivational quality—especially intrinsic and identified regulation—suggesting that GenAI enhances engagement when aligned with learners' self-regulatory processes rather than used as a standalone intervention.

Second, the findings point to a differentiated motivational function of ChatGPT. Although the ChatGPT-assisted group did not show the highest prevalence of high-quality profiles, it exhibited higher levels of motivational internalization within less adaptive profiles. This suggests that ChatGPT may be particularly beneficial for students in transitional motivational states—those not yet fully self-determined but responsive to individualized, on-demand scaffolding. Rather than uniformly elevating motivation, ChatGPT appears to shift motivational quality within profiles.

Third, the results highlight the value of combining person-centered and variable-centered perspectives. Mean-level differences alone may obscure profile-specific dynamics, particularly among students with lower initial motivation. For instructional design, this implies that AI-based supports should be aligned with diverse motivational profiles—-providing additional structure for some learners while extending autonomy and strategic flexibility for others.

Fourth, social relatedness played a comparatively smaller role in the ChatGPT-assisted context than competence and autonomy. While ChatGPT supported individualized engagement, it did not substitute for relational processes typically provided by teachers and peers. This underscores a key boundary of AI-supported learning: generative tools can enhance personalized learning but cannot replace the social and affective dimensions of human interaction. Instructional designs should therefore deliberately preserve opportunities for interpersonal connection alongside AI-supported learning.

In sum, the findings suggest that GenAI tools such as ChatGPT can support student motivation when embedded within pedagogically grounded, need-responsive instructional systems. Their primary contribution lies not in technological novelty, but in their capacity to flexibly scaffold motivational internalization—particularly for students who are not yet fully self-determined.

Data availability statement

The datasets generated and analyzed during the current study are not publicly available due to institutional and data protection constraints involving secondary school students. An anonymized version of the data may be made available by the corresponding author upon reasonable request and pending ethical approval.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, we used ChatGPT (OpenAI) to support the formulation of ideas, language refinement, and clarity of expression. After using this tool, we carefully reviewed, revised, and edited the content and take full responsibility for the final version of the manuscript.

CRediT authorship contribution statement

Sabine Schweder: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Gerda Hagenauer:** Writing – original draft. **Diana Raufelder:** Supervision, Funding acquisition.

Declaration of competing interest

The author(s) declare that there is no conflict of interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2026.100348.

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