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The Relationship Between Instructional Behaviors, Learning Motivation, and Learning Approach: Enhancing the Quality of Mathematics Education Teaching and Learning in High School

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ABSTRACT
This study explores the relationship between instructional behaviors specifically namely instructional clarity, instructional support and feedback, support for student autonomy, and support for cooperative learning and various dimensions of learning motivation intrinsic motivation, extrinsic motivation, and subjective task value. Additionally, it examines how these factors relate to students' learning approaches, specifically surface and deep learning approaches, using a correlational design. Data were collected from grade 12 students, revealing significant correlations among the variables in the context of teaching and learning mathematics. Utilizing a correlational design, data were collected from a sample of 625 students through structured questionnaires. The findings indicate significant positive correlations between instructional behaviors and intrinsic motivation, as well as subjective task value, both of which are associated with the adoption of deep learning approaches. In contrast, extrinsic motivation was linked to surface learning approaches. These results highlight the critical role of instructional clarity and supportive practices in enhancing student motivation and fostering deeper engagement in mathematics. The study underscores the necessity for educators to implement targeted instructional strategies that cultivate a motivating learning environment, ultimately leading to improved educational outcomes in mathematics education.

Keyword: instructional behaviors, learning motivation, learning approach

Introduction

Mathematics, a cornerstone of scientific and technological advancement, often presents a challenge for students (Steen, 2001). Understanding the factors that influence student learning mathematics is crucial for educators to foster deeper comprehension and engagement because effective mathematics instruction extends beyond merely delivering content. It encompasses a range of teachers' instructional behaviors that can significantly impact student learning. These behaviors include clear explanations, engaging activities, supportive feedback, and positive classroom environment (Marzano, 2007). It has been demonstrated that teachers who exhibit specific instructional behaviors can to cultivate a conducive learning atmosphere, thereby influencing student learning motivation and strategies (Carnine et al., 1994; Maccini & Gagnon, 2005). Student learning motivation and strategies encompassing both intrinsic and extrinsic drives, plays a pivotal role in academic success. Students who are intrinsically motivated find inherent enjoyment in the subject matter, while those who are extrinsically motivated are driven by external rewards or pressures from society and especially their teachers (Ryan & Deci, 2000). In mathematics, a student's level of motivation can profoundly affect their engagement, persistence, and ultimately, their achievement. Therefore, it is essential to investigate how teacher behaviors correlate with and potentially shape student motivation in mathematics (Abdulrahman et al., 2023; Bontempi, 2019; Rahayu et al., 2024). Furthermore, students adopt various learning approaches when tackling mathematical problems. Some may employ a deep approach, focusing on understanding concepts and making connections, while others may opt for a surface approach, relying on rote memorization and procedural learning (Biggs, 1987; Marton & Säljö, 1976). The choice of selecting these learning approaches can significantly influence the quality of learning outcomes.

In this study, we aim to examine how high school teacher instructional and student motivation relate to the adoption of different learning approaches in mathematics. To address these questions, a correlational design was employed. This design allows for the examination of the relationships between the aforementioned variables without manipulating them directly. By analyzing the strength and direction of these correlations, we can gain insights into the potential influences of teacher behaviors on student motivation and learning approaches within the specific context of mathematics. This research results will contribute to a deeper understanding of the complex interplay between these factors, ultimately informing instructional practices and fostering improved mathematics learning outcomes.

Literature review

Instructional behaviors

Instructional behaviors are teaching styles or physical education utilizing various teaching as the underpinnings of appropriate instructional behaviors and, ultimately student learning action (Borich, 1974) . Defined as an effective physical educator, the teacher is the one who meets the unique needs of all learners by selecting a variety of instructional approaches, provides maximal opportunity to practice tasks, teaches in small groups of students, limits competition, and utilizes appropriate amounts and types of equipment and space to promote self-directed learning (Morris, 2019). One theory that has been linked to students' motivation for learning is self-determination theory (SDT) (Ryan, 2024), which posits that people are motivated to take actions towards psychological growth when they perceive that their basic psychological needs for autonomy (i.e., a sense of ownership in their actions or behaviors), for competence (i.e. the feeling of mastery), and for relatedness (i.e. a sense of belonging and connectedness) are satisfied.

The construct of instructional behavior is divided into four subconstructs. The fist is "instructional clarity" which is one of the most important prerequisites for instructors to engage in teaching activities, and is a critical component of effective teaching (Blaich et al., 2016), Instructional clarity was defined as a teacher's ability to explain or otherwise assist students in thoroughly understanding the teaching and learning materials (Blaich et al., 2017; Maulana et al., 2020; Metcalf & Education, 1992). This subconstruct refers to the teaching that is easy to understand in terms of clear responses to students' queries, linking new lessons to past knowledge, and attempting to integrate what is taught with students' daily experiences, especially in mathematics class. In this sense, instructional clarity is also related to the contents of the current study because it contains teachers' activation of students' thinking. The second subconstruct the "instructional support and feedback" which an active process where a teacher provides guidance, assistance, and constructive criticism to students during their learning process (de Kleijn & Education, 2023), The third subconstruct is the "instructional support for student autonomy" refereing to teaching practices that actively encourage students to take ownership of their learning by providing choices, explaining rationales behind tasks, soliciting student input, and fostering a classroom environment where students feel empowered to make decisions and manage their learning process, and ultimately leading to greater intrinsic motivation and engagement (Reeve & Cheon, 2021; Skinner et al., 2008; Stefanou et al., 2004). Student motivation revolves around the concept of intentionality (Ryan & Deci, 2020). An intention of this subconstruct is the determination to engage students in a particular behavior, and it is equivalent to motivating students to act. An example of a student's intention to act might be "I intend to write my research paper." Such an intention sometimes originates from within and is fully endorsed by the student's sense of self. When this is so, intentions reflect high autonomy and are associated with autonomous types of motivation (e.g., an intrinsic motivation and identified regulation in self-determination theory (Ryan & Deci, 2020). The fourth subconstruct is the "instructional support for cooperative learning" refereing to (e.g., structuring groups actively, assigning clear roles, monitoring student interactions, providing feedback, teaching necessary social skills, and facilitating group processing to ensure the all students contribute and learn effectively from each other within collaborative environments (Biggs et al., 2017; Johnson & Johnson, 2017; Miquel & Duran, 2017). Overall, an instructional behavior is the way a teacher interacts with students in the classroom to help them learn. It includes how the teacher manages the classroom, how clear their instructions are, and how they distribute control over learning activities (de Kleijn & Education, 2023).

Learning motivation

Learning motivation can be behaviors into intrinsic, extrinsic and task value forms based on different reasons in learning an action objectives. In this persective and linked to the SDT, learning motivation is associated with being into two subconstructs: intrinsic and extrinsic motivations (Ryan & Deci, 2020). Intrinsic motivation refers to a motivation originating from the inside of an individual rather than from any outside rewards, while extrinsic motivation refers to a motivation induced by tangible rewards or punishments, dependent upon to success or failure in a mission task of learning (Liao et al., 2017; Ryan & Deci, 2020). Learning motivation in this study is considered as students' motivation to learn, conceptualized from the perspective of students' intrinsic motivation. Moreover, it refers to students' desire to apply by themselves to possess knowledge and skills on a continuing learning basis (Lee & Brophy, 1996). Intrinsic motivation, moreover has emerged as an important phenomenon for learning and achievement that can be systematically catalyzed or undermined by student practices (Stiller & Ryan, 1992), because intrinsic motivation results in high quality satisfactions in learning, creativity, interesting and enjoyable things, and ability improvement (Brown &

Innovation, 2021; Liao et al., 2017; Ryan & Deci, 2020). Extrinsic motivation, on the other hand, engages students to do things because of reasons such as instrumental values, obligations, rewards, performance, competition, and evaluation by others(Brown & Innovation, 2021; Liao et al., 2017; Ryan & Deci, 2020). In the education context, intrinsic learning motivation drives students' behaviors towards mastery learning, challenging learning tasks, and learning satisfaction while extrinsic learning motivation drives students' behaviors towards grades; performance; competition; evaluation by their teachers, classmates, and families (Pintrich, 1991). Indeed, students are motivated to learn in their course for both the satisfaction of learning as well as the highest grades (Torres & Turner, 2016). A research by Taylor et al., (2014) revealed that students who have high levels of intrinsic learning motivation are more likely to earn higher academic achievement.

Another type of learning motivation is the students' relative autonomous motivation, which balances intrinsic and extrinsic learning motivations and, has a significant effect on students' self- regulated learning, which in turn enhances their academic achievement (Kusurkar et al., 2013). Similarly, prior studies found positive associations between students' intrinsic learning motivation and their self-regulated learning and academic achievement (Chan et al., 2023; Lee & Turner, 2018; Oz et al., 2018). Task value of expectancy-value theory is considered another type of motivation (Eccles & Wigfield, 2020). When applied in education, task value is the importance of learning tasks that students appreciate (Eccles & Wigfield, 2020). Referring to expectancy-value theory, students are motivated to learn when they value what they learn (Loh, 2019; Oz et al., 2018; Wigfield & Eccles, 2000). A research work by Huang et al., (2014) has indicated that students tend to acquire more knowledge and skills and solve complex problems when they believe their courses are worth learning. Moreover, students who think what they learn is necessary for reaching their future goals appear to use knowledge building strategies (Lee & Turner, 2018). Students can perform extrinsically motivated actions with high responsibility of learning, resistance learning, and alternatively, with an attitude of willingness that reflects an inner acceptance of the task value (Eccles & Wigfield, 2020). In the former case the classic case of extrinsic motivation one feels externally propelled into the learning action (Wigfield & Eccles, 2000).

Learning approach

The term learning approach is referred to how students tackled their specific to learning tasks within all courses (Säljö, 1981). However, it has been examined and considered as a general course level. According to the teaching-learning model introduced by Biggs (1996) students' learning approach combines the motivation and the strategy that the students adopt during the learning processes. This teaching-learning model focuses on both the deep and surface learning approaches, which were first coined by Marton and Saljo (Marton & Säljö, 1976; Säljö, 1981).

The despite widespread adoption of the deep learning and surface learning framework in high school in Kampong Cham Province, Cambodia, some concerns have been voiced from the outset about these categories. Marton and Saljo distinguished between the deep and the surface strategies, on the basis of qualitative analysis performed in their research that defined the differences in the students' approach towards written texts.

The following by students' characteristics reflect the use of the deep approach: the ability to relate new information to previously acquired knowledge; to study different aspects of the material in order to obtain the entire picture; to search for a relevant meaning and a connecting point between the learning material and daily life and personal experiences. Other students' characteristics of this approach include the students' tendency to use cognitive skills, to develop learning materials that create a basis for new ideas, to offer other solutions from an inquisitive-critical perspective, and from there, to search and discover their 'inner own self' (Beishuizen et al., 1999; Biggs, 2014; Biggs & development, 1989; Entwistle & Waterston, 1988). Thus, these students are often academically high achievers by (Brown & Nelson, 1983; Bruch et al., 1986; Entwistle & Nisbet, 2013; Nelson & DeBacker, 2008) and maintain feelings of great satisfaction (Biggs et al., 2001; Biggs, 1987). The definition of the deep strategy is based on the students' personal commitment to the learning process. This approach results from an inner need to reach a complete understanding of the subject material. Behind their choice of the deep strategy, hides a search for self-fulfillment (Biggs, 1996) or, in other words, deep motivation or intrinsic motivation.

Alternatively, the following characteristics describe the surface approach: a student's tendency to choose the quickest way to accomplish the task; to acquire the learning material without asking in-depth questions, to study the material in a linear manner; to relate to minimal aspects of material or to a problem without showing interest; or the need to understand it in its entirety; to learn by rote by relying on memory and not on comprehension; and to be concerned with the time needed to fulfil the learning task (Biggs, 1996). This learning approach, which focuses on memorizing the main elements, has almost no use for or expression of cognitive skills. This minimization of learning characterized by the 'surface strategy' is motivated by the student's need to avoid failure at school and the desire to minimize effort while completing assigned tasks. In other words, the surface strategy is connected to surface motivation, or to extrinsic motivation (Biggs, 1987; Biggs, 1988; Biggs & development, 1989; Biggs & Development, 1982).

Present study and research questions

The present study aims to explore the intricate relationships between instructional behaviors, learning motivation, and learning approaches in the context of teaching and learning mathematics. As mathematics education continues to evolve, understanding how different instructional strategies impact students' motivation and their approach to learning is crucial for enhancing educational outcomes. This research seeks to identify effective instructional behaviors that foster a positive learning environment, promote intrinsic motivation and learning approaches. By examining these dynamics, the study aims to provide insights that can inform educators and policymakers in developing strategies that improve mathematics instruction.

What is the relationship between specific teacher instructional behaviors and student learning motivation and learning approach in mathematics?

Key Concepts and Theoretical Frameworks

It's important to understand the interconnectedness of teacher instructional behaviors, student learning motivation, learning approach, and the specific context of mathematics teaching and learning. By understanding and applying these key concepts and frameworks, teachers can create effective learning environments that promote student motivation and success in teaching and learning mathematics. Here's a breakdown of key concepts and theoretical frameworks:

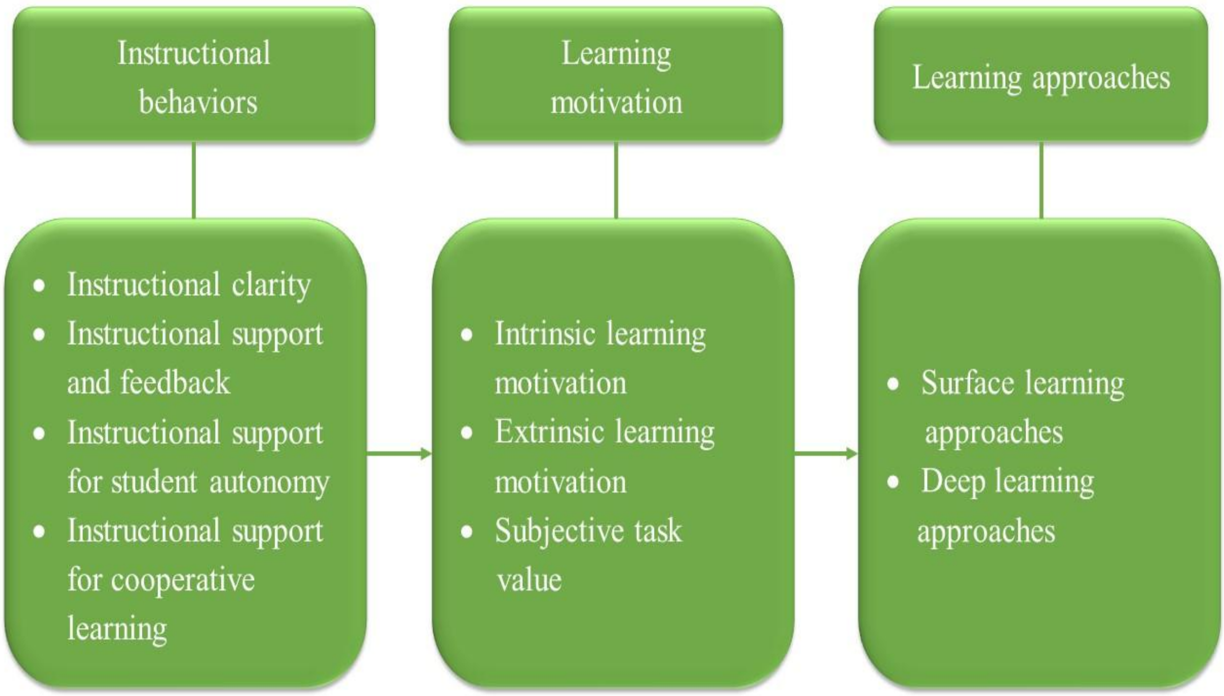


Figure 1. Conceptual model for the relationship between instructional behaviors, learning motivation, learning approach.

Methods

Participants

In this study were grade 12 high school students who studying in Kampong Cham Province, Cambodia. We used the simple random sampling technique to recruit these grade 12 students with 7 public high schools and 1 private high school (36 students) in Kampong Cham province. Among the public high schools, 4 are located in urban area (347 students) and 3 in non-urban area (242 students). The final sample for analysis was 625 students (42.9% males = 268 and 57.1% females = 357, mean age of 15-20 (15-year-old = 4 = 0.6%, 16-year-old = 78 = 12.5%, 17-year-old = 353 = 56.5%, 18-year-old = 164 = 26.2%, 19-year-old = 25 = 0.4%, 20-year-old = 1 = 0.2% with SD of 0.365).

Instrumentation

The purpose of this instrumentation is to evaluate the relationships among instructional behaviors, learning motivation, learning approaches, and the effectiveness of teaching and learning in mathematics. By employing a correlational design, this study aims to identify how these variables interact and influence one another, ultimately providing insights for improving mathematics education.

Instructional behaviors

Our measures of instructional behaviors were adapted from multiple studies (Cabrera et al., 2001; Feldman, 1986; Heng & Practice, 2014; Lam et al., 2007; Marsh et al., 2006; Marsh et al., 2012; Norton et al., 2005; Tani et al., 2021) (see Appendix A). We assessed instructional behaviors through students' perceptions of mathematics students' instructional clarity (5 items, e.g. "My math teacher explained the purpose of the lesson clearly", Mean = 4.24, SD = 0.529, α = 0.777) (Norton et al., 2002); instructional support and feedback (5 items, e.g. "My math teacher advises me when I have a problem with lesson content or homework.", Mean = 3.99, SD = 0.627, α = 0.764) (Chan et al., 2023), instructional support for student autonomy (5 items, e.g. "mathematics teacher accept student suggestions when designing assignments", Mean = 3.61, SD = 0.739, α = 0.767) (Lam & Aman, 2007), and instructional support for cooperative learning (5 items, e.g. "My math teacher discusses ideas with me and the other students in the group.", Mean = 3.33, SD = 0.504, α = 0.823) (Tani et al., 2021). The construct reliabilities for instructional clarity, instructional support and feedback, instructional support for student autonomy, and instructional support for cooperative learning were Mean = 4.24, SD = 0.529, α = 0.777, Mean = 3.99, SD = 0.627, α = 0.764, Mean = 3.61, SD = 0.739, α = 0.767, Mean = 3.33, SD = 0.504, α = 0.823, respectively.

Learning motivation

Measures of learning motivation were adapted from prior studies (García & Pintrich, 1991; Hilpert et al., 2012; Hilpert et al., 2013), (see Appendix B). Mathematic students' learning motivation was measured through their perceived intrinsic learning motivation (5 items, e.g. "In this education course, I prefer course content from which I can learn new things", Mean = 4.06, SD = 0.612, α = 0.768) (Pintrich, 1991), perceived extrinsic learning motivation (5 items, e.g. "In this education course, if I can, I want to get better grades than most of my classmates", Mean = 3.89, SD = 0.731, α = 0.777) (Pintrich, 1991), and perceived subjective task value (5 items, e.g. "I will be able to use what I learn in this education course in my future teaching career", Mean = 4.29, SD = 0.521, α = 0.788) (Hilpert et al., 2012). The construct reliability values for intrinsic learning motivation, extrinsic learning motivation, and subjective task value were Mean = 4.06, SD = 0.612, α = 0.768, Mean = 3.89, SD = 0.731, α = 0.777, Mean = 4.29, SD = 0.521, α = 0.788, respectively.

Learning approach

Measures of learning approach were adapted from student learning can be either direct or indirect (Barak et al., 2011; Beichner et al., 2006; Dori & Belcher, 2005) (see Appendix C). Mathematic students' learning approach was measured through their perceived surface learning approach (5 items, e.g. "to understand math, students must try to do more research" Mean = 4.19, SD = 0.501, α = 0.765). and perceived deep learning approach (5 items, e.g. "new knowledge and factual information make students enjoy learning" Mean = 4.04, SD = 0.591, α = 0.755). The construct reliability values for surface learning, deep learning approach were " Mean = 4.19, SD = 0.501, α = 0.765, Mean = 4.04, SD = 0.591, α = 0.755, respectively.

Measurement Tools:

First, the original scales in English were adapted by the researchers and then translated into Khmer by two bilingual Cambodian researchers. Using the translated version, we translated the scales back into English. Before data collection, we compared the Khmer and the English versions of the scales to see if each item was able to match the initial meaning. Khmer version of the scales was applied to 36 grade 12 students answer with 63 items. Second, the Khmer version of the scales was applied to 625 grade 12 students answer with 63 items in different high schools in Kampong Cham province (Private, Public School, Urban and Non-urban). Private school (1=36), public school = (7) Urban (4=347), non-urban (3=242) and after data collection will be check with validity by construct validity (convergent validity, divergent/discriminant validity), factor analysis. Third, after consulting with validity, and then consulting with internal consistency reliability (Cronbach's Alphas, construct/composite reliability). In this study, we used a self-report method to assess subjective perceptions of the items in each adapted scale, which might lead to response bias. In all the scales, students had to rate each item on a 5-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree").

To make the subconstructs fit into the Cambodian teacher context and to check the construct validity of the model, confirmatory factor analysis (CFA) was conducted. Before the CFA, we checked for normal distribution and multicollinearity. The normal distribution of the data was measured by the skewness and kurtosis of each item (Cohen et al., 2018),. The most commonly used values for skewness and kurtosis are −1 to +1 and −1.96 to +1.96, respectively (Hair et al., 2024). In this study, the skewnesses and kurtoses of all the items used ranged between -0.01 and + 0.03 and between -0.03

and +0.03, respectively. The multicollinearity occurs when the intercorrelation between variables or items is higher than 0.83 (Kline et al., 2000).The Shapiro-Wilk test and Kolmogorov Smirnov test, but for sample smaller then 300; Sig.> .05= normal distribution and Z score are -3 and +3= no outliers (Kline et al., 2000). The multicollinearity occurs when the intercorrelation between variables or items is higher than 0.90 (Kline et al., 2000). The intercorrelations in the present study ranged between 0.08 and 0.71, which eliminates multicollinearity problems. According to (Hair et al., 1998), construct validity is ensured by assessing convergent and discriminant validities (Messick, 1995). In so doing, the average variance extracted (AVE), maximum shared variance (MSV), and average shared variance (ASV) were calculated and compared. The AVE should be 0.50 or higher to suggest adequate convergent validity, which means that a set of measured items share a high proportion of variance in the same construct, and the AVE should be greater than the MSV and the ASV to ensure acceptable discriminant validity, which means that the construct is distinct from other constructs (Hair et al., 1998). The model was tested using a sample of 652 participants, and the following fit indices were evaluated to assess the model's adequacy: Chi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). According to the guidelines established by Hu and Bentler (1999), a CFI and TLI value above 0.90 and an RMSEA value below 0.08 indicate a good fit for the model.

Scale Reliability Statistics: Mean=4.04, SD=0.365, Cronbach's α=0.799, McDonald's ω= 0.926. The CFA results revealed that the measurement model fitted the empirical data very well, Test for Exact Fit RMSEA 90% CI: χ^2=1627, df=998, p<.001. Fit Measures: CFI=0.947, TLI=0.943, SRMR=0.0382, RMSEA=0.0272, Lower=0.0249, Upper=0.0295, AIC=57167, BIC=57953. The SEM results revealed that the measurement model tests (User Model X^2=2612, df=998, p<.001. Baseline Model X^2=13057, df=1081, p<.001. Scaled Baseline X^2=12102, df=1081, p=<.001). Fit indices (Classical, SRMR=0.040, RMSEA=0.032, Lower=0.029, Upper=0.035, RMSEA p=1.000. Robust, SRMR=0.040, RMSEA=0.030, Lower=0.027, Upper=0.033, RMSEA p=1.000. Scale, SRMR=0.040, RMSEA=0.029, Lower=0.026, Upper=0.032, RMSEA p=1.000). Indicating that the ten subconstructs could match the Cambodian teacher and students' education context.

Data analysis

In this study, a structural equation modeling (SEM) was employed to investigate the relationships between various aspects of teacher instructional behavior, learning motivation, and learning approaches among students. The analysis aimed to determine how specific dimensions of teacher instructional behavior such as instructional clarity, instructional support and feedback, and instructional support for cooperative learning, engagement strategies correlate with students' learning motivation, which encompasses both intrinsic, extrinsic factors and subjective task value, as well as their preferred learning approaches, including deep and surface learning strategies (Schunk, 1991; Schunk, 2008).

In conclusion, the SEM analysis provides valuable insights into the interconnectedness of teacher behaviors, student motivation, and learning approaches, suggesting that targeted improvements in instructional strategies could enhance student learning outcomes.

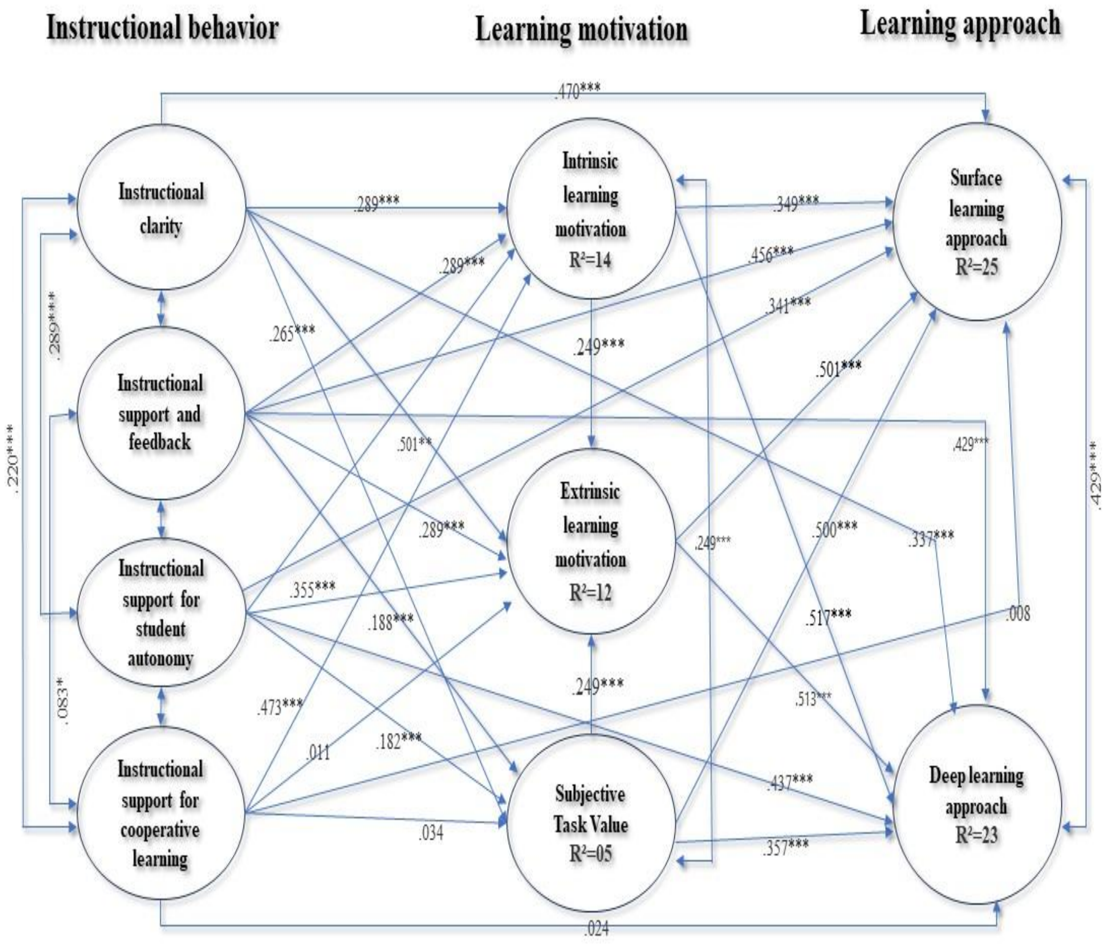
Table 1. Correlation coefficient of Pearson's correlations analysis between latent variables (N = 625)

	IC	ISF	ISSA	ISCL	ILM	ELM	STV	SLA	DLA
IC	—								
ISF	0.488***	—							
ISSA	0.400***	0.553***	—						
ISCL	-0.045	-0.083*	-0.068	—					
ILM	0.237***	0.336***	0.395***	-0.047	—				
ELM	0.220***	0.289***	0.355***	-0.011	0.473***	—			

Table 1. Correlation coefficient of Pearson's correlations analysis between latent variables (N = 625)

	IC	ISF	ISSA	ISCL	ILM	ELM	STV	SLA	DLA
STV	0.265***	0.188***	0.182***	-0.034	0.287***	0.249***	—		
SLA	0.470***	0.456***	0.341***	0.008	0.364***	0.349***	0.500***	—	
DLA	0.337***	0.429***	0.437***	-0.024	0.517***	0.513***	0.357***	0.501***	—

Note: IC = Instructional clarity, SF = Support and feedback, AS = Autonomy support, SCL = Support for cooperative learning, IM = Intrinsic motivation, EM = Extrinsic motivation, STV = Task value, SLA = Surface learning approach, DLA = Deep learning approach
Note. * p < .05, ** p < .01, *** p < .001



* p < .05, ** p < .01, *** p < .001

Figure 2. IC = Instructional clarity, ISF = Instructional support and feedback, ISSA = Instructional support for student autonomy, ISCL = Instructional support for cooperative learning, ILM = Intrinsic learning motivation, ELM = Extrinsic learning motivation, STV = Subjective task value, SLA= Surface learning approach, DLA = Deep learning approach.

Results

Table 1 presents correlation coefficient of Pearson's correlations analysis between latent variables. All variables had to moderate correlations instructional behavior, learning motivation and learning approach (from 0.488 to 0.501), which allowed us to eliminate multicollinearity problems (Kline, 2005). Perceptions of instructional clarity, support and feedback, autonomy support, and support for cooperative learning were positively correlated with perceptions of intrinsic motivation, extrinsic motivation, and task value and with perceptions of affective, surface learning and deep learning. The perception of task value was positively correlated with perceived intrinsic and extrinsic motivation. Perceptions of intrinsic motivation, extrinsic motivation, and task value were correlated positively with perceptions of affective, surface learning and deep learning.

Figure 1 present the conceptual model for the relationship between instructional behaviors, learning motivation, learning approach. **Figure 2** presents the standardized path coefficients for the final model with significant paths of the relationship and effecting between instructional clarity, instructional support and feedback, instructional support for student autonomy, instructional support for cooperative learning, intrinsic learning motivation, extrinsic learning motivation, subjective task value, surface learning approach, deep learning approach. In this model, perceptions of learning motivation mediate the relationship between perceptions of instructional behaviors and perceptions of learning approaches. The overall fit of the final model was excellent, Exact Fit RMSEA 90% CI: χ^2=1627, df=998, p<.001. Fit Measures: CFI=0.947, TLI=0.943, SRMR=0.0382, RMSEA=0.0272, Lower=0.0249, Upper=0.0295, AIC=57167, BIC=57953. The model accounted for a large portion of the variance in the outcomes ($R2$ = 0.146 and 0.195 for intrinsic motivation, extrinsic motivation and task value, respectively; $R2$ = 0.250, 0.56, and 0.231 for affective, surface learning and deep learning, respectively). **Table 2**, the perception of support and feedback was positively associated with students' intrinsic motivation, extrinsic, task value (ß = 0.027). The perception that teachers' behaviors promote cooperative learning was associated positively with students' deep learning (ß= 0.73) and surface learning (ß= 0.16). Among the four measures of instructional behaviors, support and feedback was the strongest predictor of intrinsic motivation while support for cooperative learning was the most important determinant of deep learning. Among the measures of learning motivation, intrinsic motivation was the strongest predictor of surface learning and deep learning while task value was the most significant contributor to affective engagement.

Table 2. Direct, indirect, and total associations for Figure 2.

				Standardized coefficient (β)				
Type	Effect	Estimate	SE	Lower	Upper	β	z	p
Indirect	Instructional clarity ⇒ Intrinsic learning motivation ⇒ Deep learning approach	0.01119	0.01056	-0.00951	0.03189	0.01002	1.060	0.28931
	Instructional clarity ⇒ Extrinsic learning motivation ⇒ Deep learning approach	0.01555	0.01189	-0.00776	0.03886	0.01393	1.307	0.19108
	Instructional clarity ⇒ Task value ⇒ Deep learning approach	0.02171	0.00937	0.00334	0.04008	0.01944	2.317	0.02051
	Instructional clarity ⇒ Surface learning approach ⇒ Deep learning approach	0.06757	0.01613	0.03596	0.09918	0.06051	4.189	2.80e-5
	Instructional support feedback ⇒ Intrinsic learning motivation ⇒ Deep learning approach	0.03148	0.01091	0.01010	0.05285	0.03341	2.886	0.00390
	Instructional support feedback ⇒ Extrinsic learning motivation ⇒ Deep learning approach	0.02567	0.01145	0.00322	0.04812	0.02725	2.241	0.02503

Table 2. Direct, indirect, and total associations for Figure 2.

				Standardized coefficient (β)				
Type	Effect	Estimate	SE	Lower	Upper	β	z	p
	Instructional support feedback ⇒ Task value ⇒ Deep learning approach	0.00357	0.00440	-0.00506	0.01221	0.00379	0.812	0.41705
	Instructional support feedback ⇒ Surface learning approach ⇒ Deep learning approach	0.04884	0.01266	0.02402	0.07366	0.05185	3.857	1.15e-4
	Instructional support student autonomy ⇒ Intrinsic learning motivation ⇒ Deep learning approach	0.05149	0.01135	0.02924	0.07374	0.06443	4.536	5.73e-6
	Instructional support student autonomy ⇒ Extrinsic learning motivation ⇒ Deep learning approach	0.05251	0.01150	0.02996	0.07505	0.06570	4.565	4.99e-6
	Instructional support student autonomy ⇒ Task value ⇒ Deep learning approach	0.00512	0.00390	-0.00252	0.01276	0.00641	1.314	0.18890
	Instructional support student autonomy ⇒ Surface learning approach ⇒ Deep learning approach	0.01098	0.00673	-0.00222	0.02417	0.01374	1.631	0.10292
	Instructional support cooperative learning ⇒ Intrinsic learning motivation ⇒ Deep learning approach	-0.00318	0.00944	-0.02167	0.01532	-0.00271	-0.337	0.73648
	Instructional support cooperative learning ⇒ Extrinsic learning motivation ⇒ Deep learning approach	0.00548	0.01061	-0.01531	0.02627	0.00467	0.516	0.60571
	Instructional support cooperative learning ⇒ Task value ⇒ Deep learning approach	-0.00168	0.00413	-0.00978	0.00642	-0.00143	-0.407	0.68426
	Instructional support cooperative learning ⇒ Surface learning approach ⇒ Deep learning approach	0.01115	0.00799	-0.00452	0.02682	0.00951	1.395	0.16302
Direct	Instructional clarity ⇒ Deep learning approach	0.02115	0.03984	-0.05694	0.09925	0.01895	0.531	0.59546
	Instructional support feedback ⇒ Deep learning approach	0.10040	0.03652	0.02883	0.17197	0.10658	2.749	0.00597
	Instructional support student autonomy ⇒ Deep learning approach	0.09265	0.02970	0.03445	0.15086	0.11593	3.120	0.00181
	Instructional support cooperative learning ⇒ Deep learning approach	0.01022	0.03439	-0.05718	0.07763	0.00871	0.297	0.76630
Total	Instructional clarity ⇒ Deep learning approach	0.13718	0.04500	0.04897	0.22538	0.12285	3.048	0.00230

Table 2. Direct, indirect, and total associations for Figure 2.

				Standardized coefficient (β)				
Type	Effect	Estimate	SE	Lower	Upper	β	z	p
	Instructional support feedback ⇒ Deep learning approach	0.20996	0.04182	0.12799	0.29192	0.22288	5.020	5.16e-7
	Instructional support student autonomy ⇒ Deep learning approach	0.21276	0.03376	0.14659	0.27892	0.26620	6.303	2.93e-10
	Instructional support cooperative learning ⇒ Deep learning approach	0.02199	0.04074	-0.05785	0.10183	0.01875	0.540	0.58932

*p < .05; **p < .01.

Discussion

The quality of mathematics education is profoundly influenced by the interplay between instructional behaviors, learning motivation, and students' learning approaches (Biggs, 1987; Hattie, 2009; Pintrich, 2003; Ryan & Deci, 2000). Effective instructional behaviors, such as interactive teaching, formative assessment, and differentiated instruction, are essential for fostering an engaging learning environment. Research indicates that when teachers employ varied instructional strategies, they can significantly enhance student understanding and retention of mathematical concepts (Witter & Hattie, 2024). Learning motivation is a critical factor that drives student engagement and achievement in mathematics. According to Deci and Ryan's Self-Determination Theory, intrinsic motivation stemming from personal interest and enjoyment leads to deeper engagement and better learning outcomes (Ryan & Deci, 2000). Educators can enhance motivation by creating a supportive classroom atmosphere that encourages autonomy and fosters a sense of competence (Reeve, 2016). The learning approach adopted by students whether deep or surface also plays a crucial role in their academic success. A deep learning approach, characterized by a thorough understanding and application of concepts, is often promoted through instructional behaviors that encourage critical thinking and problem-solving (Chan et al., 2023). Conversely, a surface approach, focused on rote memorization, can hinder meaningful learning. The interrelationship among these elements is vital; effective instructional strategies can boost motivation, leading students to adopt deeper learning approaches. For instance, collaborative learning techniques not only engage students but also promote a sense of community, enhancing motivation and understanding (Johnson & Johnson, 2009). In conclusion, to enhance the quality of mathematics teaching and learning, educators must focus on developing instructional behaviors that foster intrinsic motivation and encourage deep learning approaches. By doing so, they can create a more effective and enriching educational experience for students.

Limitations

When discussing the limitations of instructional behaviors, learning motivation, and learning approaches, it is essential to recognize that each of these factors can significantly impact student learning outcomes (Hattie et al., 2009). However, they also come with inherent limitations that can affect their effectiveness. Instructional behaviors effective instructional behaviors, such as clear communication, feedback, and engagement strategies, are crucial for facilitating learning, they can also have limitations. For instance, overly prescriptive teaching methods may stifle student creativity and critical thinking (Hattie & Timperley, 2007). Additionally, the effectiveness of instructional behaviors can vary significantly among diverse student populations, as cultural and individual differences may influence how students respond to different teaching styles (G. Gay, 2013; G. J. C. i. Gay, 2013) . This variability can lead to inequities in learning outcomes, as not all students may benefit equally from the same instructional approach. Learning motivation is a key driver of student engagement and achievement; however, it is not a one-size-fits-all construct. Intrinsic motivation, which is often linked to deeper learning, can be difficult to cultivate in all students, particularly in environments that emphasize extrinsic rewards (Ryan & Deci, 2000). Furthermore, factors such as socioeconomic status, prior experiences, and personal circumstances can significantly impact a student's motivation to learn (Koca & Leadership, 2016; Meece & Agger, 2018; Sakiz, 2008). As a result, motivational strategies that work for some students may not be effective for others, leading to disparities in academic performance. Learning approaches is distinction between deep and surface learning approaches is well-documented, yet the application of these concepts can be limited. For example, students may not consistently adopt a deep learning approach due to external pressures, such as high-stakes testing or a heavy workload, which can encourage surface learning behaviors (Entwistle & McCune, 2004). Additionally, students may lack the metacognitive skills necessary to recognize when to employ different learning strategies effectively (Chen & journal, 2002; Zimmerman, 2002). This limitation can hinder their ability to adapt their learning approaches to different contexts, ultimately affecting their academic success.

Conclusion and suggestions

This study employed a correlational design to explore the relationships between instructional behaviors, learning motivation, and learning approaches among math students. The findings indicate that effective instructional behaviors specifically instructional clarity, support and feedback, autonomy support, and cooperative learning are significantly correlated with enhanced learning motivation and the adoption of deep learning approaches. Instructional clarity emerged as a foundational element, facilitating students' understanding of learning objectives and expectations, which in turn positively influenced their motivation levels. Moreover, the study found that when educators provide robust instructional support and feedback, students are more likely to feel motivated, both intrinsically and extrinsically. This support not only fosters a sense of autonomy but also encourages cooperative learning, which enhances peer interactions and collaborative skills. The results suggest that students who experience high levels of instructional support are more inclined to engage in deep learning, characterized by critical thinking and meaningful engagement with the material, as opposed to surface learning, which is often marked by rote memorization and minimal cognitive effort.

Suggestions for practical implications

The findings from this correlational study emphasize the interconnectedness of instructional behaviors, learning motivation, and learning approaches in the context of teaching and learning mathematics. To enhance student outcomes in mathematics, the following practical implications are proposed: *Enhance Instructional Clarity*: Mathematics educators should clearly articulate learning objectives and key concepts at the beginning of each lesson. Utilizing visual aids, step-by-step problem-solving processes (Leong et al., 2012), and real-world examples can help demystify complex mathematical ideas and make them more accessible to students (Boaler, 2016). *Implement Effective Instructional Support and Feedback*: Providing timely and constructive feedback on mathematical assignments and assessments is crucial (Hattie & Timperley, 2007). Educators should focus on specific areas of improvement and celebrate successes to motivate students. Additionally, incorporating formative assessments, such as quizzes and interactive activities, can help gauge student understanding and inform instructional adjustments. *Support Student Autonomy*: To foster intrinsic motivation in mathematics, educators should offer students choices in their learning activities, such as selecting problem sets or project topics (Reeve & Jang, 2006). Encouraging self-directed learning through goal-setting and reflection on their mathematical thinking can empower students to take ownership of their learning process (Wilcox, 1996). *Encourage Cooperative Learning*: Collaborative learning activities, such as group problem-solving tasks and peer tutoring, should be integrated into mathematics instruction (Chan et al., 2024). By assigning specific roles within groups, educators can ensure equitable participation and enhance students' understanding through discussion and shared reasoning. *Cultivate Intrinsic Motivation*: Connecting mathematical concepts to real-life applications and students' interests can enhance task value and stimulate intrinsic motivation (Chan et al., 2023). Educators should create an engaging classroom environment that encourages curiosity, exploration, and the relevance of mathematics in everyday life. *Balance Extrinsic Motivators*: While extrinsic rewards, such as grades or recognition, can be effective in motivating students (See, Chan et al., 2023), they should be used to complement intrinsic motivation. Celebrating achievements in a way that fosters a sense of accomplishment can help maintain student engagement without overshadowing their intrinsic interest in mathematics. *Promote Deep Learning Approaches*: Instructional strategies should focus on active learning techniques that encourage critical thinking and problem-solving in mathematics. Incorporating reflective practices, such as journaling about problem-solving processes or discussing different approaches to a problem, can help students deepen their understanding and connect new knowledge to prior experiences (Dolmans et al., 2016). *Professional Development for Educators*: Ongoing professional development opportunities should be provided to mathematics educators to equip them with the latest research-based instructional strategies and motivational techniques. Encouraging collaboration among educators can foster a community of continuous improvement in teaching practices, particularly in mathematics. In summary, the implications derived from this study highlight the essential role of effective instructional behaviors in fostering student motivation and promoting deeper learning approaches in mathematics education (Mundry, 2005). By implementing these suggestions, educators can create a more engaging and supportive learning environment that enhances student achievement in mathematics and cultivates a lifelong appreciation for the subject (Schlöglmann, 2006).

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Appendix A. Teaching self-efficacy

Efficacy for instructional strategies

In my future classes....................

- My math teacher uses a satisfying teaching method
- My math teacher has prepared enough teaching materials
- My math teacher inspires me to work together

- My math teacher explains again and again when I and other students do not understand the lesson
- My math teacher asked me questions to motivate me to learn.
- My math teacher can answer my difficult questions with other students

Efficacy for classroom management
In my future classes, . . .
- My math teacher can control my annoying behavior with other students
- My math teacher led me and other students to obey the classroom rules.
- My math teacher can control emotions when there is a disturbance or a loud noise in the classroom
- My math teacher can control me and other students who disrupt learning
- My math teacher creates a friendly atmosphere in the classroom for me and all students

Efficacy for student engagement
In my future classes, . . .
- My math teacher encourages me and other students who are less interested in learning to re-learn.
- My math teacher helps me and other students understand the value of learning
- My math teacher, can control his emotions when I feel tired of the lessons
- My math teacher gave me the confidence to do my homework well
- My math teacher motivates me to improve my learning weaknesses

Appendix B. Instructional Behaviors
Instructional clarity
In this education course, . . .
- My math teacher explained the purpose of the lesson clearly
- My math teacher explained the content of lesson clearly
- My math teacher explains exactly how to do homework
- My math teacher uses good examples to explain the content lesion and homework assignments
- My math teacher explained the main concepts or theories clearly

Instructional support and feedback
In this education course, . . .
- My math teacher advises me when I have a problem with lesson content or homework
- My math teacher monitoring me and other students to see that we really learned the lesson contents
- My math teacher gives me feedback to motivate me to study hard
- My math teacher gives me constructive feedback on homework
- My math teacher provided feedback that could improve my learning process

Instructional support for student autonomy
In this education course, . . .
- My math teacher decides with me that I should learn
- My math teacher gives me priority in deciding on teamwork
- My math teacher allows me to choose tasks that suit my personal interests
- My math teacher gives me more than one task so I can choose to do what they want to do
- My math teacher accepts my suggestions when I do my homework

Instructional support for cooperative learning
In this education course, . . .
- My math teacher discusses ideas with me and the other students in the group
- My math teacher tried to understand my ideas and the other students in the group
- My math teacher coaches me and the students in the group when we have problems with content, lessons and homework
- My math teacher inspires me to connect with other team members
- My math teacher cooperates with me to elect a team representative for the presentation

Appendix C. Learning Approach
Surface learning approach
In this education course, . . .
- To understand math I have to try to do more research
- To learn math, I need to be able to compare what I am learning and past experiences
- Summarizing math lessons helps me remember lessons longer
- Being creative in learning made me understand the main theories of the lesson
- Identifying similarities and differences makes me analyze
- Creating new ideas, learning methods, making math lessons easier to understand

Deep learning approach
In this education course, . . .
- Memorizing math lesson content is my focus
- New knowledge and facts make me love learning math
- Repeating the lesson over and over again made me remember the math lesson well
- Understanding the content of math lessons made me learn more deeply
- Mathematics is a major requirement, so I have to work hard to learn it
- Focusing on the content of the math lesson made me learn better