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Effects of the Self-Regulated Learning and Motivation on Learning Achievements of the Programming Courses

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Abstract: This study investigated the impact of self-regulated learning (SRL) motivation and strategies on academic performance in a programming course using learning analytics techniques. Data were collected from 250 students, including their coding behaviors, SRL motivations, and strategies. K-means clustering was applied to categorize students into two distinct groups based on SRLmotivation, SRLstrategy, code_copy, code_execution, code_speed, code_paste, and code_length, with the silhouette coefficient confirming the optimal number of clusters. Subsequent analysis revealed significant differences in the academic performance of the two clusters. Structural Equation Modeling (SEM) was employed to examine the mediating role of SRL motivation between SRL strategies and academic performance. The model demonstrated a good fit (AGFI = 0.927, CFI = 0.964, RMSEA = 0.067), confirming the reliability of the proposed relationships. Bootstrap tests further validated the mediating effect of SRL motivation. Our findings indicate that SRL strategies positively influence academic performance both directly and through SRL motivation, establishing a partial mediation effect. This research contributes to the understanding of SRL in online learning environments, highlighting the importance of motivation and strategic learning behaviors for enhancing student outcomes. The implications for designing effective educational interventions and fostering self-regulated learning practices are discussed.

Keywords: Self-Regulated Learning, Learning Analytics, Programming Education, Structural Equation Modeling

1. Introduction

Learning analytics (LA) plays a pivotal role in the online learning environment. It involves the collection, measurement, analysis, and reporting of data about learners and their contexts. These data are used to understand and optimize learning and the environments in which it occurs. Learning analytics helps educators identify patterns and trends in learner behavior, predict performance, and provide timely interventions. By leveraging LA, educators can personalize learning experiences, improve engagement, and enhance the overall effectiveness of online education. Classic studies, such as Siemens and Long (2011), have laid the foundation for understanding the significance of LA in modern educational settings.

Self-regulated learning (SRL) is crucial for success in online learning environments. SRL refers to the process whereby learners actively manage their learning through setting goals, monitoring progress, and adjusting strategies as needed. This autonomy is essential in online education, where direct supervision by instructors is limited. SRL encompasses various dimensions, including motivation and strategy use. Motivation in SRL involves the intrinsic and extrinsic factors that drive learners to engage in and persist with their learning tasks. Intrinsic motivation refers to engaging in learning for its inherent satisfaction, while extrinsic motivation involves performing tasks for external rewards or to avoid negative outcomes. Motivation is a key component of SRL as it influences the effort, persistence, and strategies that learners employ. Pintrich and De Groot (1990) have extensively discussed these motivational components and their impact on academic performance. SRL strategies are the specific methods or techniques that learners use to facilitate their learning. These can include cognitive strategies like summarization and elaboration, metacognitive strategies such as planning and self-monitoring, and resource management strategies like time management and help seeking. Effective use of SRL strategies enables learners to better understand, retain, and apply knowledge. Zimmerman (2002) provided a comprehensive overview of these strategies and their importance in the learning process.

The relationship between SRL motivation and SRL strategy is dynamic. High levels of motivation often lead to the adoption of effective learning strategies. Conversely, the use of successful strategies can enhance motivation by creating a sense of competence and achievement. For instance, a learner who is highly motivated to excel in a course is more likely to engage in planning and self-monitoring activities, leading to better performance and further reinforcing their motivation. Understanding this relationship helps educators design interventions that simultaneously address both motivation and strategy use, fostering a more supportive online learning environment. Research by Schunk and Zimmerman (1998) underscores the interplay between these elements.

In exploring the relationship between students' SRL motivation, SRL strategies, and their academic performance, it is essential to consider how these cognitive and metacognitive components manifest in observable behaviors. One of the key insights of this research is the ability to infer students' SRL motivation and strategies through their coding behaviors in programming courses. These coding behaviors are not just mechanical outputs; they offer a window into the underlying SRL motivation and strategies that students employ (Chuang & Chang, 2024). By analyzing these behaviors, we can gain a deeper understanding of how students regulate their learning in a programming context and how these processes contribute to their academic success.

In order to better understand the relationship between SRL motivation and strategy, this study constructed a model. To construct the model, the current study drew upon established research on SRL. Motivations in SRL, defined by intrinsic motivation, task value, control beliefs, and self-efficacy (Pintrich et al., 1993), are crucial as they drive students to engage proactively in learning activities. These motivational factors significantly impact academic performance, with high intrinsic motivation and task value being linked to greater persistence and achievement. Control beliefs and self-efficacy further influence academic success (Habók et al., 2020). For SRL strategies, we focused on critical thinking, effort regulation, and help-seeking. Critical thinking involves analyzing and evaluating information for reasoned judgments, while effort regulation pertains to maintaining focus despite challenges. Help-seeking is essential for managing difficult tasks (Pintrich et al., 1993). Research indicates that these strategies not only enhance learning outcomes but also positively influence motivation, thereby creating a feedback loop where improved strategies lead to higher motivation and vice versa (Chen et al., 2022). Thus, my model posits that SRL motivation mediates the relationship between SRL strategies and learning performance, aligning with established theoretical frameworks and empirical findings in SRL. Based on the description above, the following research questions are posed:

1. How do the identified clusters based on SRL motivation, SRL strategies, and online learning behaviors differ in their composition and characteristics?
2. What significant differences in academic performance exist between the clusters identified through SRL motivation, SRL strategies, and online learning behaviors?
3. Does SRL motivation mediate the relationship between SRL strategies and academic performance, and if so, to what extent does it influence this relationship?

2. Paper review

2.1 Definition of motivation in self-regulated learning (SRL) and its impact on academic performance

Motivation is a crucial component of SRL, which refers to the process by which learners actively manage their own learning through setting goals, monitoring progress, and regulating their cognitive, motivational, and behavioral processes. Understanding motivation within the context of SRL is essential as it significantly influences the extent to which students engage in and persist with their learning activities, thereby impacting their academic performance. Pintrich et al. (1993) defined motivation in SRL as comprising several interrelated components including intrinsic motivation, task value, control beliefs, and self-efficacy. These components collectively drive a student's engagement and persistence in learning tasks, influencing their overall academic success.

Intrinsic motivation refers to engaging in a task for the inherent satisfaction and interest it brings rather than for some separable consequence. When students are intrinsically motivated, they participate in learning activities because they find them enjoyable and fulfilling. *Task value* is another critical component of motivation in SRL. It encompasses the perceived importance and usefulness of a task, which in turn influences the effort and persistence students are willing to invest. *Control beliefs*, also known as expectancy beliefs, refer to students' perceptions of their ability to influence learning outcomes through their effort and actions. This concept is rooted in the expectancy-value theory, which posits that motivation is a function of the expectation of success and the value placed on that success. Students with strong control beliefs feel confident that their actions, such as studying and employing effective learning strategies, can lead to successful outcomes. *Self-efficacy* is the belief in one's capability to succeed in specific tasks. Self-efficacy influences students' choices of activities, the effort they exert, and their persistence in the face of difficulties.

2.2 Definition of strategies in self-regulated learning (SRL) and their impact on academic performance

Strategies in SRL are essential for helping students effectively manage their own learning processes. According to Pintrich et al. (1993), learning strategies are specific techniques or methods that students use to acquire, integrate, and apply new knowledge. These strategies play a critical role in enabling students to control their learning environments, behaviors, and motivations, thereby enhancing their academic performance.

In the context of SRL, critical thinking, effort regulation, and help seeking are three vital strategies that contribute to successful learning outcomes. *Critical thinking* involves the active and systematic process of evaluating information, arguments, and ideas to make reasoned judgments and decisions. *Effort regulation* refers to the ability to manage one's effort and stay focused on tasks despite potential distractions or difficulties. Students who effectively regulate their effort are more likely to persist in the face of challenges and maintain a consistent level of engagement with their studies. *Help seeking* is the essential strategy in SRL, involving the proactive pursuit of assistance when faced with learning difficulties. This strategy highlights the importance of recognizing when help is needed and knowing how to obtain it effectively. Effective help seeking reflects a student's ability to self-assess their understanding and take the necessary actions to improve it, thereby enhancing their overall academic performance.

2.3 Relationship between students' coding behavior and academic performance

The coding behaviors analyzed include code length, code copying, code execution, code pasting, and code speed. Code length, measured by lines of code (LOC) produced in a semester, reflects a student's effort and engagement. Greater coding practice enhances proficiency and understanding, leading to better academic outcomes (Falkner & Vivian, 2015).

Code copying, or how often a student copies code, can reflect learning behaviors. While it can streamline repetitive tasks, excessive copying without comprehension hinders true learning. Studies show students who rely on copying without understanding tend to perform poorly (Lopez et al., 2008). Code execution, the number of times code is run, indicates an iterative learning process. Frequent execution suggests regular testing and debugging, which improves code quality and fosters a deeper understanding of programming (Ahadi et al., 2016). Code pasting, like copying, has mixed implications (Lopez et al., 2008). It can improve efficiency, but over-reliance without understanding impedes learning. When used wisely, pasting enhances productivity. Code speed, measured as input digits per minute, reflects a student's coding fluency. Faster speeds often indicate familiarity with programming languages, enabling students to focus on problem-solving rather than syntax, which correlates with higher achievement (Robins et al., 2003).

3. Method

3.1 Participants and Data Collection

The study was conducted using data from a programming course, which provided a valuable opportunity to analyze student learning behaviors and strategies. The course originally included 467 students, with data collected through two well-designed learning systems. These systems measured two well-defined learning strategies: Self-Regulated Learning (SRL) and the Strategy Inventory for Language Learning (SILL). The comprehensive dataset, referred to as the Learning Behavior and Learning Strategies dataset (LBLS467), was made available for research purposes.

For the purposes of this study, the final scores of students, their VisCode activities, SRL Strategy, and SRL Motivation datasets were combined. After checking and integrating the userid labels across these datasets, a subset of 250 students who had complete data in all the relevant datasets was identified for analysis. This dataset allows for a thorough examination of the relationships between various coding behaviors, learning strategies, and academic performance.

3.2 Data Analysis

3.2.1 K-means

This study chose K-means clustering for its simplicity, efficiency, and ability to handle large datasets. It effectively partitions data into distinct, non-overlapping clusters by minimizing within-cluster variance and maximizing between-cluster variance. This makes it ideal for identifying clear groups of students based on SRL strategies, motivations, and coding behaviors.

K-means clustering is an unsupervised machine learning algorithm that partitions a dataset into k distinct clusters. The algorithm assigns each data point to the cluster with the nearest centroid, aiming to minimize the variance within each cluster. The steps involved in K-means clustering are:

Initialization: Randomly select k initial centroids.
Assignment: Assign each data point to the nearest centroid.
Update: Calculate new centroids by averaging the data points assigned to each cluster.
Repeat: Repeat the assignment and update steps until the centroids no longer change significantly.

To determine the optimal number of clusters, we used the silhouette coefficient, which measures the quality of clustering. The silhouette coefficient ranges from -1 to 1, with higher values indicating better-defined clusters.

3.2.2 SPSS Amos 26

To explore the mediating effects of SRLmotivation between SRLstrategy and academic performance, this study employed Structural Equation Modeling (SEM). SEM is a comprehensive statistical approach that allows for the examination of complex relationships among observed and latent variables. The SEM model was constructed based on theoretical frameworks and previous empirical studies. The key components of the model include:

SRLmotivation: Comprising intrinsic motivation, task value, control beliefs, and self-efficacy.
SRLstrategy: Comprising critical thinking, effort regulation, and help-seeking.
Academic Performance: Measured by the final scores of the students.

The path diagram of the SEM model includes direct paths from SRLstrategy to academic performance, from SRLmotivation to academic performance, and an indirect path from SRLstrategy to academic performance mediated by SRLmotivation.

The model was estimated using the maximum likelihood estimation (MLE) method. The values of these fit indices suggest that the model fits the data well. According to Hu and Bentler (1999), a CFI value greater than 0.95 means that the model fits reasonably well. Additionally, an AGFI value above 0.90 indicates an acceptable fit (Schumacker & Lomax, 2004). If the RMSEA is between 0.05 and 0.08, the model is said to have a fair fit (McDonald & Ho, 2002).

This study used the bootstrap as a test method for the mediating effect (Cheung & Lau, 2007). The estimation methods included bias-corrected. The procedure is to set the bootstrap at 1,000 times. All estimated values are at the 95% confidence level, and the upper and lower bounds of the indirect effect trust interval are obtained. If it does not contain 0, it can be proved to have a mediating effect (Cheung & Lau, 2007).

4. Result

4.1 Results of K-means.

The clustering analysis was performed to classify students based on SRLmotivation, SRLstrategy, code_copy, code_execution, code_speed, code_paste, and code_length. The number of clusters was determined using the silhouette coefficient, evaluating cluster numbers ranging from 2 to 6. The silhouette coefficient values indicated that the best clustering was achieved with 2 clusters, as shown in Table 1 and Figure 1.

Table 1. *K-means clustering schemes.*

Cluster number	Silhouette
2	0.391176556167403
3	0.19917934837556653
4	0.20640454650986767
5	0.2221107845125278
6	0.18621067892519472

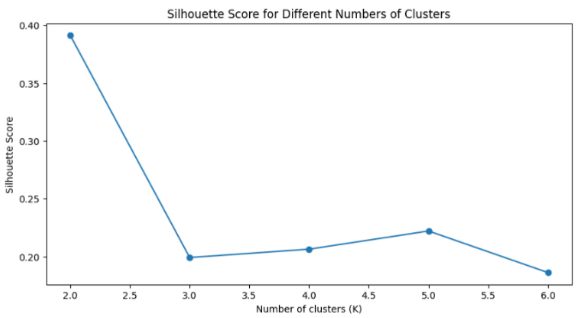

Figure 1. Clustering by silhouette coefficient.

Following the determination of the optimal cluster number, we generated box plots for each variable (SRLmotivation, SRLstrategy, code_copy, code_execution, code_speed, code_paste, and code_length) to visualize the distribution of these variables within the two clusters, shown as Figure 2, Figure 3, and Figure 4.

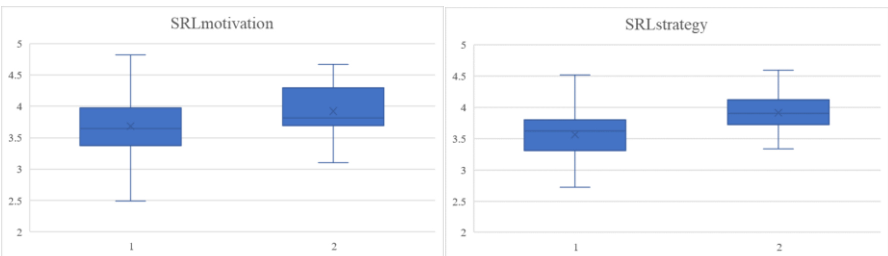

Figure 2. Box plot of SRLmotivation (left) and SRLstrategy (right) for the two groups.

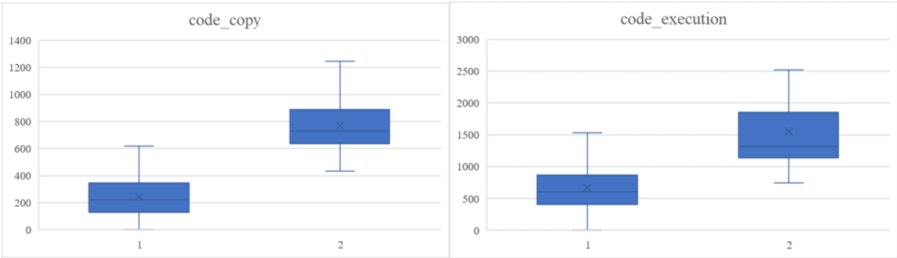

Figure 3. Box plot of code_copy and code_execution for the two groups.

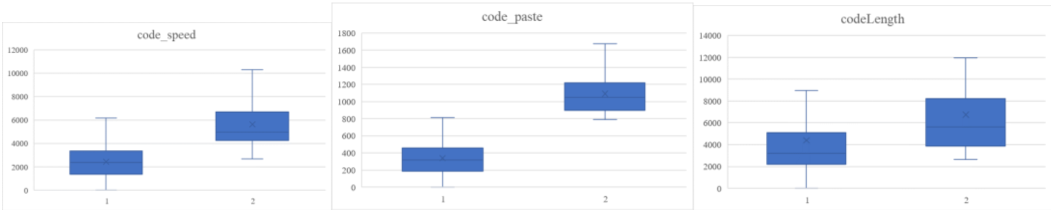

Figure 4. Box plot of code_speed and code_paste and codeLength for the two groups.

To statistically compare the variables between the two clusters, the Mann-Whitney U test was used. The results showed that every variable in the second cluster was significantly higher than those in the first cluster, as displayed in Table 2.

Table 2. *Results of Mann-Whitney U test.*

Dimensions	Group	N	Mean	SD	Mean Rank	Sum of Rank	U	W	Z
Learning Achievements	1	222	81.720	14.155	121.000	26862.5	2109.5	26862.5	2.771^{**}
	2	28	88.540	5.594	161.160	4512.5			
SRLmotivation	1	222	3.684	0.469	121.257	26919.0	2166.0	26919.0	2.613^{**}
	2	28	3.922	0.418	159.143	4456.0			
SRLstrategy	1	222	3.562	0.439	118.349	26273.5	1520.5	26273.5	4.403^{***}
	2	28	3.913	0.300	182.196	5101.5			
code_copy	1	222	243.523	159.342	111.923	24847.0	94.0	24847.0	8.359^{***}
	2	28	770.357	208.194	233.143	6528.0			
code_execution	1	222	666.500	408.352	114.200	25308.5	555.5	25308.5	7.079^{***}
	2	28	1552.786	643.985	216.661	6066.5			
code_paste	1	222	338.986	206.127	111.619	24779.5	26.5	24779.5	8.546^{***}
	2	28	1090.964	243.812	235.554	6595.5			
code_speed	1	222	2430.914	1408.827	113.392	25173.0	420.0	25173.0	7.455^{***}
	2	28	5633.143	1953.830	221.500	6202.0			
codeLength	1	222	4393.288	4334.012	118.372	26278.5	1525.5	26278.0	4.389^{***}
	2	28	6735.071	3934.355	182.018	5096.5			

$^{**}p<.01$; $^{***}p<.001$

4.2 Results of SEM.

To evaluate the structural equation model (SEM), we first examined the model fit indices to ensure that the proposed model accurately represents the data. The results for the model fit indices are as follows: AGFI = 0.927, CFI = 0.964, RMSEA = 0.067. Therefore, the model meets these criteria and confirms its reliability.

Figure 5 presents the structural equation model, illustrating the relationships between the latent variables: SRLmotivation, SRLstrategy, and academic performance. The model demonstrates how SRLmotivation acts as a mediator between SRLstrategy and academic performance. SRLstrategy is composed of three primary components: critical thinking, effort regulation, and help-seeking. These strategies enhance students' learning experiences, contributing to their overall motivation.

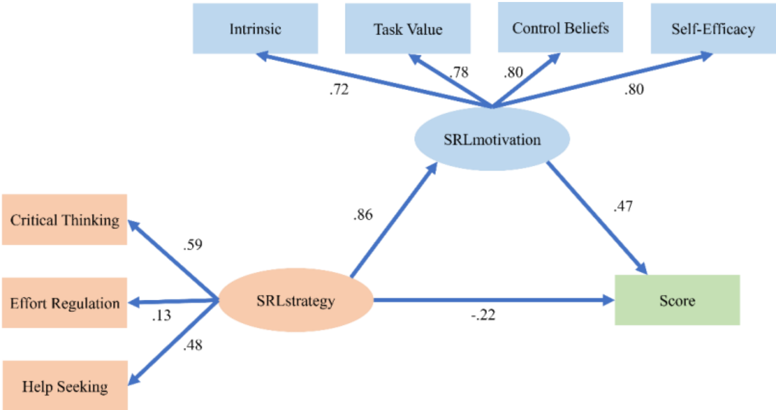

Figure 5. Model with SRL motivation as the mediating variable.

To further validate the mediating effect of SRLmotivation, we employed the bootstrap test method as suggested by Cheung and Lau (2007). This method involves generating 1,000 bootstrap samples to estimate the confidence intervals of the indirect effects. Table 3 shows the results of the bootstrap test, indicating the presence of a significant mediating effect. The bias-corrected confidence intervals at the 95% confidence level do not include zero, confirming the mediating role of SRLmotivation between SRLstrategy and academic performance.

Table 3. *Results of Bias-Corrected Confidence Intervals.*

Variable	Effect	Estimate	Bias-Corrected	
			Lower	Upper
SRLstrategy→Score	Direct effect	6.491	0.245	17.429
SRLstrategy→SRLmotivation→Score	Indirect effect	14.304	0.186	152.925
SRLstrategy→Score	Total effect	6.461	0.784	15.597

Since both the direct effect of SRLstrategy on academic performance and the indirect effect via SRLmotivation are significant, the mediated effect is considered to be partially mediated. This means that while SRLmotivation significantly contributes to the relationship between SRLstrategy and academic performance, there is also a direct impact of SRLstrategy on academic performance, independent of SRLmotivation. This partial mediation underscores the complexity of the interplay between strategies, motivation, and performance, indicating that effective SRL strategies directly enhance academic performance while also boosting motivational factors that further drive success.

5. Discussion

5.1 Clustering Based on SRL Motivation, SRL Strategy, and Code-Related Behaviors

Our first research question (RQ1) investigated whether clustering based on SRL motivation, SRL strategy, and various code-related behaviors (code_copy, code_execution, code_speed, code_paste, and codeLength) results in two significantly distinct groups of students. The results from the k-means clustering analysis, guided by silhouette coefficients, indicate that our dataset does indeed partition into two distinct clusters. This partition suggests meaningful differences in how students engage with SRL processes and coding activities. The distinct clustering underscores the variability in students' motivational levels, strategic approaches to learning, and engagement with coding tasks. These findings align with previous research which suggests that SRL components can effectively differentiate student groups based on their learning behaviors and outcomes (Pintrich, 1993; Zimmerman, 2008).

A deeper look at the code-related behaviors reveals significant insights into the distinct clusters. The variables include code_length, code_copy, code_execution, code_paste, and code_speed. Code_length refers to the number of lines of code (LOC) a student coded over the semester. This metric reflects the students' overall coding output and engagement with coding tasks. Higher values indicate more extensive coding practice, which is often associated with better coding proficiency and problem-solving skills.

Code_copy and code_paste capture the frequency with which students copy and paste code, respectively. These behaviors can be indicative of different learning and working styles. While frequent copying and pasting might suggest a reliance on external resources or repetitive tasks, it could also indicate efficiency in handling repetitive coding patterns. However, excessive dependence on copying and pasting without comprehension might hinder genuine learning and problem-solving skills.

Code_execution refers to the number of times a student executes their code. This behavior reflects the iterative nature of coding, where students frequently test and debug their code. Higher execution counts suggest a proactive approach to testing and refining code, which is crucial for developing robust and error-free programs.

Code_speed, measured as the average input digits per minute, provides insight into the students' typing proficiency and coding fluency. Higher code_speed values generally indicate greater comfort and familiarity with coding, enabling students to implement solutions more quickly.

Analyzing these code-related behaviors in conjunction with SRL motivation and strategies helps us understand the comprehensive profiles of the distinct student clusters. The cluster with higher academic performance demonstrated not only higher SRL motivation and effective strategies but also more optimal code-related behaviors. These students tended to produce more lines of code, execute their code more frequently, and maintain a balanced approach to copying and pasting. They also showed higher coding speed, suggesting greater proficiency and fluency in coding tasks.

In contrast, the lower-performing cluster exhibited less favorable code-related behaviors, such as fewer lines of code, less frequent code execution, and potentially inefficient or excessive copying and pasting. Their coding speed was also lower, indicating less familiarity and comfort with coding tasks. These differences highlight the critical role of coding behaviors in conjunction with SRL components in influencing academic performance. By understanding these nuanced differences, educators can better tailor interventions to support students in developing both effective SRL skills and coding practices, thereby enhancing their overall learning outcomes.

5.2 Differences in Academic Performance Between Clusters

The second research question (RQ2) examined whether the two groups of students identified through clustering show significant differences in their final academic performance. Our analysis reveals that the two clusters are not only distinct in their SRL and coding behaviors but also in their academic outcomes. Specifically, one cluster consistently outperformed the other in terms of final academic performance. This significant difference underscores the critical role of SRL motivation and strategies in influencing academic success. Students in the higher-performing cluster demonstrated stronger intrinsic motivation, more effective use of SRL strategies, and more efficient coding behaviors. These findings echo the assertions of Chen et al. (2022), who highlighted that a high level of SRL motivation and the employment of effective learning strategies are closely linked to superior academic performance. Therefore, our results reinforce the importance of fostering robust SRL skills and effective coding practices to enhance students' academic outcomes.

5.3 Mediating Role of SRL Motivation

The third research question (RQ3) explored whether SRL motivation partially mediates the relationship between SRL strategy and academic performance. Our mediation analysis indicates that SRL motivation does indeed serve as a partial mediator in this relationship. This means that while SRL strategies directly impact academic performance, their effectiveness is significantly enhanced when mediated by high levels of SRL motivation. This finding is consistent with the theoretical frameworks proposed by Pintrich (1993) and supported by recent empirical studies (Broadbent & Poon, 2015; Chen & Law, 2016).

SRL strategies such as critical thinking, effort regulation, and help-seeking positively influence students' intrinsic motivation and self-efficacy, which in turn boosts academic performance. For instance, students who effectively regulate their efforts and seek help when needed develop stronger control beliefs and task value, driving them to achieve higher academic success. The partial mediation role of SRL motivation highlights the interconnected nature of motivation and strategic learning behaviors in achieving academic excellence.

Additionally, the findings from Dignath and Büttner (2008) reinforce this interconnectedness by demonstrating that SRL strategies significantly impact motivational aspects and, consequently, academic performance. Their meta-analysis of SRL interventions at primary and secondary school levels found that fostering SRL strategies effectively enhances both motivational components and learning outcomes. This supports our observation that SRL motivation acts as a crucial mediator, amplifying the positive effects of SRL strategies on academic performance.

5.4 Implications for Practice

The implications of our findings are substantial for educational practice. Educators and instructional designers should emphasize the development of both SRL strategies and motivational components. Interventions aimed at enhancing intrinsic motivation, task value, control beliefs, and self-efficacy can significantly amplify the positive effects of SRL strategies on academic performance. Practical applications could include goal-setting workshops, self-efficacy training, and the integration of motivational elements into curriculum design. Additionally, fostering efficient coding practices and strategic behaviors can further support academic success.

6. Conclusion and Future Work

In conclusion, our study demonstrates the significant impact of SRL motivation and strategies on academic performance and the distinct clustering of students based on these factors and coding behaviors. The partial mediation role of SRL motivation underscores the importance of fostering both motivational and strategic components in educational interventions. By leveraging these insights, educators can better support students in developing effective SRL skills and achieving academic success.

While our study provides valuable insights, it is not without its limitations. The sample size and specific demographic characteristics may limit the generalizability of our findings. Future research should involve larger and more diverse populations to validate and extend our results. Longitudinal studies could also provide deeper insights into the long-term effects of SRL strategies and motivations on academic performance. Additionally, exploring the interaction effects of different SRL components across various educational contexts would enhance our understanding of their dynamics.

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