Motivation and Engagement as Mediators between Self-Regulation and Academic Success in Online Learning among Chinese University Students

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ABSTRACT

This study examines the direct and mediating relationships among students' self-regulation, motivation, engagement, and academic success in online learning. Grounded in self-regulated learning theory and engagement frameworks, the proposed structural model posits that self-regulation predicts academic success both directly and indirectly through motivation and engagement. A quantitative cross-sectional design was employed, and data were collected from 1,521 undergraduate students enrolled in online courses at three public universities in Qinghai Province, China. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model demonstrated satisfactory reliability and validity (composite reliability = .915–.953; AVE = .604–.693). Structural results revealed that self-regulation had a significant direct effect on academic success (β = .355, $p < .001$), engagement significantly predicted academic success (β = .348, $p < .001$), and motivation also had a positive but smaller effect (β = .099, $p < .001$). Self-regulation strongly predicted engagement (β = .821, $p < .001$) and motivation (β = .699, $p < .001$). Mediation analysis indicated significant indirect effects through engagement (β = .285, $p < .001$) and motivation (β = .069, $p < .001$), confirming partial mediation. The model explained 71.6% of the variance in academic success ($R^2 = .716$), demonstrating substantial explanatory power. The findings underscore the central role of self-regulation in online academic achievement and highlight engagement as the strongest mediating mechanism linking self-regulation to success. The study contributes to the literature by integrating key learner variables within a unified predictive model and offers practical implications for enhancing online higher education practices.

Keywords: Self-Regulation; Student Engagement; Motivation; Academic Success; Online Learning; Structural Equation Modeling

INTRODUCTION

The shift toward online learning has significantly transformed the educational experiences of university students, particularly in China, where digital platforms have become a central component of higher education. As learning increasingly takes place in virtual environments, understanding how these settings influence key factors—such as self-regulation, motivation, and engagement—has become essential. These factors are widely recognized as critical determinants of academic success, especially in self-directed learning contexts. COVID-19, which the World Health Organization designated a pandemic in 2020, has completely disrupted educational activity, forcing most colleges to close completely, affecting hundreds of millions of students and educators around the world (Shahzad et al., 2021). For many years, education and training that displayed within a triangle of school-teacher- student has now utilized the "online learning" as new, multifaceted, multi-channel alternatives with the help of technologies in the education system. With its flexibility, accessibility, and convenience, online learning (synchronous or asynchronous) acts as an alternative to assist the continuation of education during a pandemic when traditional learning and teaching are no longer a possibility (Adedoyin, and Soykan, 2020; Selvanathan et

al., 2020). As a result, most higher education institutions switched from face-to-face learning to emergency remote teaching aiming at preventing the spread of the coronavirus and ensuring the continuation of education during the difficult periods of lockdown among students and educators (Bayham & Fenichel, 2020; Wang et al., 2020) and online learning has become a popular way for students to gain more access to higher education. University and faculty members have begun to learn and master offering online instruction to their students; they are keen to improve learning outcomes with online education (Shahzad et al., 2021).

Background of Study

Many factors influence the success of e-learning, including accessibility, the use of appropriate methodologies, course content, and evaluation criteria (Agarwal & Kaushik, 2020). Researchers from other countries than China studied the constructs of students' motivation, engagement, self- regulation, and student success in combinations of two or more constructs at a time (Basuony et al., 2020; Hassan et al., 2021; Jackson, 2015; Johnson, 2017; Kuh et al., 2007; Larose, 2010; Meyer, 2014; Moore, 1989; Pellas, 2014; Puzziferro, 2008; Shahzad et al., 2021; Sharp & Sharp, 2016; Wandler & Imbriale, 2017; Zhang et al., 2015; Zimmerman, 2011). The researcher couldn't find any studies in China on the relationship between these constructs and student success from the perspectives of university students. The unique and innovative combination of those constructs as one research project was a gap in the literature.

In China, the pandemic was first detected in December 2019, reached its peak in mid-February 2020, the unprecedented swift and strict quarantine measures starting from late January in China have kept students away from their schools. During school closures, college students were quarantined during school closures and attended their classes via online learning (C. Wang et al., 2020). Colleges and universities are already extolling the benefits of Web-based education and are quickly establishing online classes to satisfy the demands of students all around the world. The increases in the number of online courses offered by colleges have been rather considerable over a previous couple of years (Paul & Jefferson, 2019). Many postsecondary courses include some form of technological augmentation, which has advantages for both postsecondary institutions and students (Sharp & Sharp, 2016). Statistics mentioned that billions of students joined online classes and online learning become more popular comparing with face-to-face learning (Gherheș et al., 2021). The popularity and high demand for online learning experiences has drastically altered the educational system that has shifted dramatically because of online learning experiences (Hoskins, 2011). With the rapid growth of online education, a growing number of research have looked into the characteristics of online learners (Seaman et al., 2018). Much of this research has focused on both these students' personal traits (such as motivation, self-discipline, or self-efficacy) and their amount of computer knowledge or access to technology and has discovered that motivation and self-discipline predict performance in online courses (Stark et al., 2013).

Student engagement in education refers to the level of attention, curiosity, interest, optimism, and passion that student's display when learning or being taught, as well as their motivation to learn and advance in their education. In general, "student engagement" assumes that learning increases when students are curious, interested, or inspired, and that learning suffers when students are bored, disinterested, disillusioned, or otherwise "disengaged." Educators frequently state that they want to increase student involvement or improve student engagement (Ashwin & McVitty, 2015). Engagement is crucial to student academic success in online courses. The definition of engagement has been extensively explored in distance and online learning literature for decades. Student engagement is defined as "the student's psychological investment in and effort directed toward learning, understanding, or mastering the knowledge, skills, or crafts that academic work is intended to promote"(Balan et al., 2020).

Studies on the constructs of students' motivation, engagement, and self- regulation practices have been conducted in combinations of two constructs at a time (Jackson, 2015; Johnson, 2017; Kuh et al., 2007; Larose, 2010; Mello, 2016; Pellas, 2014; Puzziferro, 2008; C.-H. Wang et al., 2013; Zhang et al., 2015). Previous research in online learning has concentrated on the relationships between (1) students perception about learning environment and student engagement (Jackson, 2015; Johnson, 2017; Kuh et al., 2007; Larose, 2010); (2) student self-regulation and engagement (Mello, 2016; Pellas, 2014; Zhang et al., 2015); and (3) self-regulation and students perception about learning environment (Puzziferro, 2008; C.-H. Wang et al., 2013). Although

studies on two constructs at a time have been undertaken, there is a gap in the literature when it comes to evaluating four constructs at a time in both the conventional teaching and the online environment. The researcher couldn't find any studies in the Chinese institutions that neither investigate the four constructs together nor studies on the relationship between these constructs and student success from the perspectives of university and college students. Therefore, the main goal of this study is to determine the relationship between the variables of students' motivation, engagement, self-regulation, and students' satisfaction, as well as how this relationship influences perceptions of student success in higher education institutions' online learning. As a result, this study will provide a deeper understanding of how the online learning environment influences university students' self-regulation, motivation, and engagement, and how these factors contribute to their academic success.

Conceptual framework

The theoretical framework for this study encompassed self-regulated learning theory (Zimmerman, 1989b, 1989a), Cybergogy Model (M. Wang & Kang, 2006) and the self-determination learning theory and the integrated theory of online learning. These theories support the constructs of student's motivation, engagement, self-regulation practices, and students' perception in terms of enhancing student learning success in the online environment (Kauffman, 2015), the research framework is shown in figure 1.1 below. Connectivism as a learning theory for the digital age (Siemens, 2005), it has been proposed as a successor to behaviourism, cognitivism and constructivism. Stated simply, connectivism is social learning that is networked, it is characterized as a reflection of the society, which is changing rapidly, more complex, connected socially, global, and mediated by increasing advancements in technology (Duke et al., 2013). Because connectivism is primarily reliant on digital learning possibilities, such as online courses, webinars, social media, and blogs (West, 2018), it will be more useful than traditional learning theories to explain learning that occurred through technologies in educational institutions (Banihashem & Aliabadi, 2017).

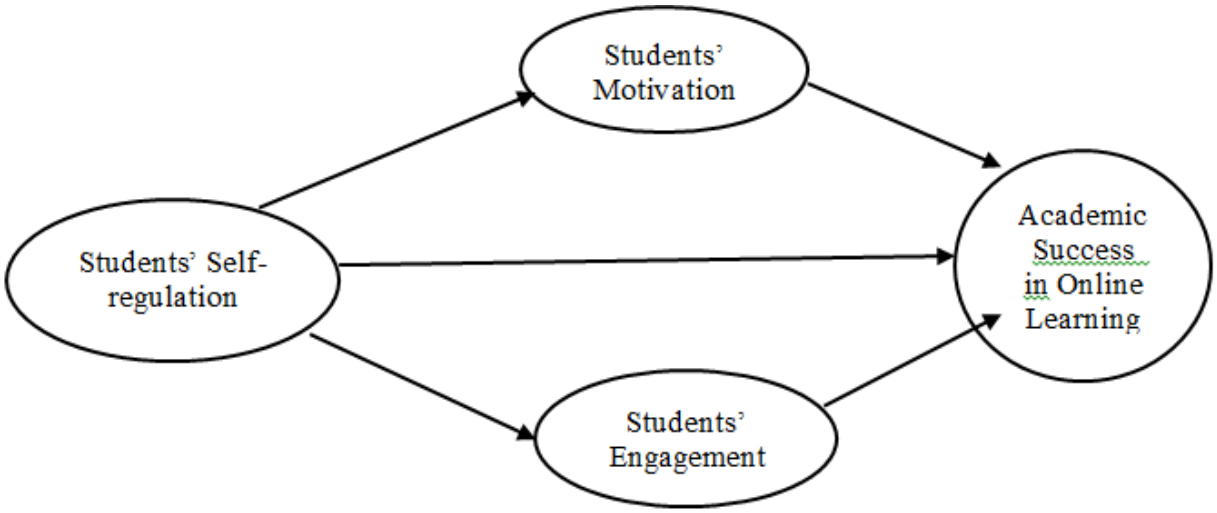

Figure 1. Proposed Research Framework

The framework of this study integrates Self-Regulated Learning Theory (Zimmerman, 1989), Self-Determination Theory (Deci & Ryan, 1985), the Cybergogy Model (Wang & Kang, 2006), Connectivism (Siemens, 2005), and Constructivism to explain the effects of self-regulation, motivation, engagement, on academic success. Existing literature highlights the complex interplay of these variables in digital education, underscoring the necessity of a structured theoretical foundation. Student engagement and motivation serve as a central mechanism in this framework, mediating the effect of the Self-regulation on academic performance and success. Hamdan et al. (2021) found that students with higher self-regulation skills were better able to adapt to online learning, maintain focus, and persist through challenges, leading to improved academic performance. This aligns with Zimmerman's (1989) Self-Regulated Learning Theory, which posits that learners who set goals, monitor their progress, and reflect on their performance achieve higher levels of success. Similarly, Elsayed et al. (2021) highlighted that students who actively regulate their learning in online experience greater engagement and deeper learning experiences compared to those with passive learning habits.

Engagement is another key construct influenced by both self-regulation and motivation. The Cybergogy Model (Wang & Kang, 2006) and Connectivism (Siemens, 2005) emphasize the importance of interactive and networked learning experiences in maintaining student engagement. Martin & Bolliger (2018) demonstrated that learner-instructor interaction, collaborative activities, and real-time feedback significantly enhance engagement, which in turn improves learning outcomes. Similarly, Rajabalee & Santally (2021) found a positive correlation between student satisfaction, engagement, and performance in online learning, highlighting the role of well-designed digital environments in fostering deep learning. On the other hand, motivation and self-regulated learning have emerged as particularly salient constructs in explaining engagement in autonomous learning contexts. Motivation influences learners' willingness to initiate engagement, whereas self-regulated learning governs how learners manage time, effort, and strategies over time.

Ultimately, the integration of these constructs leads to academic success in online learning environments. Studies by Eom (2015) and Kauffman (2015) confirm that self-regulation, motivation, and engagement collectively influence students' ability to navigate digital learning spaces and achieve academic goals. Furthermore, Korobova & Starobin (2015) emphasized that students who experience higher levels of engagement and motivation in online courses demonstrate better academic performance and course completion rates. This framework posits that the online learning environment directly affects students' self-regulation, motivation, and engagement, which subsequently influence academic success. The model also considers the mediation effect of self-regulation on engagement and motivation, explaining how students develop learning strategies that enhance performance. The integration of Self-Regulated Learning Theory, Self-Determination Theory, the Cybergogy Model, Connectivism, and Constructivism provides a comprehensive explanation of how digital learning environments shape student behaviors and outcomes.

Research Hypotheses

The following hypotheses will be tested:

H01: Students' self-regulation, motivation, and engagement have a significant direct effect on their academic success in online learning.

H02: Students' motivation significantly mediates the effect of the of self-regulation on academic success.

H03: Students' engagement significantly mediates the effect of self-regulation on academic success.

METHOD

Research Design

This study employed a quantitative cross-sectional research design to examine the structural relationships among self-regulation, motivation, engagement, and academic success in online learning. A cross-sectional approach was appropriate because the objective was to test theoretically grounded relationships among latent constructs using self-reported data collected at a single point in time. The design allows simultaneous examination of multiple variables and the estimation of direct and indirect effects within a structural equation modeling framework.

Population and Sampling

The population consisted of undergraduate students enrolled at three public universities in Qinghai Province, Northwest China: Qinghai University, Qinghai Normal University, and Qinghai Nationalities University. These institutions implemented online learning as a primary instructional modality during recent academic periods, making them suitable contexts for examining online learning processes.

Given the large population size (approximately 40,000 undergraduate students across the three institutions), a multi-stage sampling approach was employed for practical and administrative feasibility. Faculties were first

identified as clusters, and students enrolled in online courses within selected faculties were invited to participate. The sampling unit was individual undergraduate students who had experienced online learning.

A total of 1,600 questionnaires were distributed electronically. Of these, 1,521 were returned (response rate = 95%). After data screening procedures (described below), 1,230 valid responses were retained for final analysis. This sample size substantially exceeds minimum recommendations for structural equation modeling and provides adequate statistical power for estimating complex mediation models.

Instrumentation

Data were collected using a structured, self-administered questionnaire designed to measure four core constructs in online learning: students' motivation, engagement, self-regulation, and perceived academic success. The instrument was developed through a literature-based process and aligned with established measurement traditions in online learning research. Items were adapted and refined based on well-established frameworks and scales commonly used in this field, including motivation perspectives grounded in self-determination theory (Deci & Ryan), engagement conceptualizations covering behavioral, emotional, and cognitive dimensions (e.g., Fredricks et al.; Community of Inquiry), and self-regulated learning indicators such as goal setting, time management, strategy use, self-monitoring, and help-seeking (e.g., Zimmerman; Pintrich et al.). In addition, the wording and structure of several items were guided by widely used online learning constructs such as usability/technology acceptance (e.g., Davis) and feedback principles relevant to learning outcomes (e.g., Hattie & Timperley; Nicol & Macfarlane-Dick).

All items were measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicated higher levels of the measured construct. The questionnaire began with a short introduction explaining the study purpose, confidentiality, and response instructions. Demographic items were included to describe the sample (e.g., gender, program/faculty, academic year, and prior online learning experience). Following expert review and refinement, the final instrument included four subscales totaling 82 items: Motivation (14 items), Engagement (24 items), Self-regulation (24 items), and Perceived academic success (20 items).

Because respondents were Chinese university students, the instrument was translated into Mandarin Chinese. A forward–backward translation procedure was used to maintain semantic equivalence between English and Mandarin versions, and language specialists reviewed the wording to ensure clarity and cultural appropriateness. Content validity was evaluated by five experts in pedagogy, educational psychology, and online learning. Experts reviewed each item for clarity, relevance, and construct representation, and minor wording revisions were made accordingly, while redundant or overlapping items were deleted or reclassified.

Pilot Testing and Construct Validation

A pilot study was conducted with 300 university students not included in the main data collection. Construct validity was examined using Exploratory Factor Analysis (EFA) performed separately for each construct. Results supported the suitability of the data for factor analysis, with excellent KMO values and statistically significant Bartlett's tests across constructs ($p < .001$). The EFA findings confirmed unidimensional structure within each construct, with strong factor loadings (all above the acceptable threshold of .70) and substantial explained variance, ranging approximately from 66% to 74%. These findings provided empirical support that the refined items coherently represented their intended constructs and that the instrument was appropriate for subsequent measurement model testing. In the main analysis, the measurement model was further evaluated in PLS-SEM using standard criteria for internal consistency reliability, convergent validity (AVE), and discriminant validity (Fornell–Larcker and HTMT), as reported in the Results section.

Data Screening and Preliminary Assessment

Prior to hypothesis testing, the dataset was screened to ensure accuracy and suitability for structural equation modeling. The screening process included examination of missing data, identification of outliers, and assessment of distributional properties. Incomplete responses and cases exhibiting extremely low response variance were

removed. Multivariate outliers were identified and excluded prior to final analysis. After cleaning procedures, 1,230 valid cases remained for analysis. Although PLS-SEM does not require strict multivariate normality, Mardia's multivariate skewness and kurtosis were examined to assess distributional characteristics. The results indicated non-normality ($p < .001$), which further justified the use of PLS-SEM, as this method is robust to deviations from multivariate normality.

Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). This method was selected because it is suitable for complex predictive models, supports mediation analysis, and is robust to non-normal data distributions. The analysis followed a two-step procedure: (1) assessment of the measurement model, including reliability and validity testing; and (2) evaluation of the structural model to test direct and indirect hypotheses using bootstrapping procedures.

The Findings

This section presents the evaluation of the measurement and structural models using Partial Least Squares Structural Equation Modeling (PLS-SEM). The assessment follows a two-step approach: first, the reliability and validity of the measurement model are examined; second, the structural relationships, mediation effects, explanatory power, model fit, and predictive relevance are analyzed.

Measurement Model Assessment

The measurement model was evaluated in terms of internal consistency reliability, convergent validity, discriminant validity, and collinearity. These procedures ensure that the constructs are measured accurately and are statistically distinct from one another.

Internal Consistency Reliability and Convergent Validity

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (ρc). Convergent validity was examined using the average variance extracted (AVE). According to commonly accepted thresholds, Cronbach's alpha and composite reliability values should exceed 0.70, and AVE should exceed 0.50 to demonstrate adequate reliability and convergence.

As presented in Table 1, all constructs met these criteria. Cronbach's alpha values ranged from .883 to .944, while composite reliability values ranged from .915 to .953. AVE values ranged from .604 to .693, exceeding the minimum requirement of .50. These results confirm that the constructs demonstrate strong internal consistency and satisfactory convergent validity.

Table 1 Internal Consistency Reliability and Convergent Validity

Construct	**Cronbach's α**	**Composite Reliability (ρc)**	**AVE**
Engagement	.883	.915	.684
Self-Learning	.944	.953	.693
Success	.921	.935	.644
Motivation	.927	.938	.604

Indicator loadings ranged from .721 to .867, all exceeding the recommended threshold of .70, further supporting indicator reliability.

Collinearity Assessment

Before assessing structural relationships, collinearity among indicators was examined using the variance inflation factor (VIF). VIF values below 5.0 (and preferably below 3.3) indicate that multicollinearity is not a concern. In this study, VIF values ranged from 1.497 to 3.296, remaining within acceptable limits. Therefore, collinearity does not threaten the stability of the estimated parameters.

Discriminant Validity

Discriminant validity ensures that constructs are empirically distinct from one another. It was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio.

Fornell–Larcker Criterion

According to this criterion, the square root of the AVE of each construct should be greater than its correlations with other constructs. As shown in Table 2, the diagonal values (square roots of AVE) exceed the corresponding inter-construct correlations, indicating adequate discriminant validity.

Table 2 Fornell–Larcker Criterion

Construct	Engagement	Self-Learning	Success	Motivation
Engagement	**.827**			
Self-Learning	.821	**.832**		
Success	.795	.814	**.803**	
Motivation	.715	.699	.669	**.777**

HTMT Ratio

The HTMT ratio provides a more stringent assessment of discriminant validity. Values below .90 indicate satisfactory discriminant validity.

All HTMT values ranged between .721 and .898, remaining below the conservative threshold of .90. Therefore, discriminant validity is confirmed.

Structural Model Assessment

After confirming the adequacy of the measurement model, the structural model was evaluated. This included assessing path coefficients, mediation effects, coefficient of determination (R^2), model fit indices, and predictive relevance.

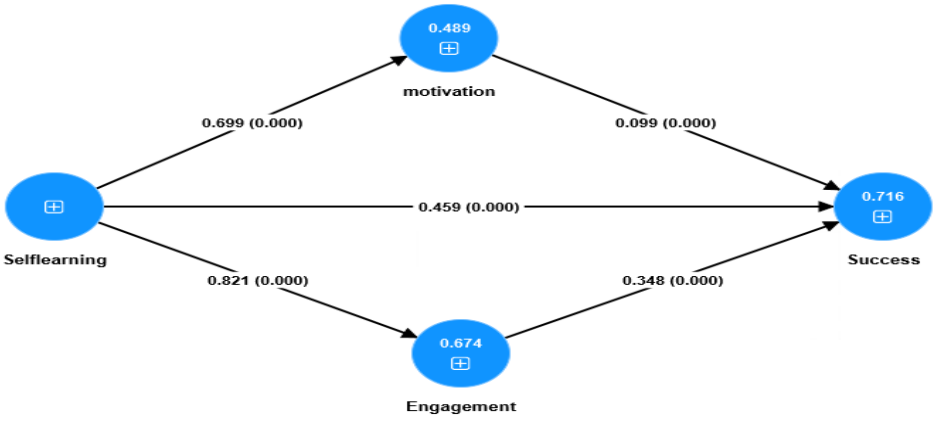

Figure **Error! No text of specified style in document.**2. Proposed Research Framework

Direct Effects

The structural relationships were examined using bootstrapping procedures. Table 3 presents the standardized path coefficients, standard errors, t-values, and p-values. Self-learning has a strong positive effect on engagement ($\beta = .821$, $p < .001$) and motivation ($\beta = .699$, $p < .001$). It also directly influences success ($\beta = .459$, $p < .001$). Engagement significantly predicts success ($\beta = .348$, $p < .001$), while motivation has a smaller but statistically significant effect on success ($\beta = .099$, $p < .001$). These findings indicate that self-learning plays a central role in shaping both mediators and directly enhancing success.

Table 3 Direct Effects

Path	**β**	**SD**	**t**	**p**
Self-Learning → Engagement	.821	.014	58.637	< .001
Self-Learning → Motivation	.699	.018	38.488	< .001
Self-Learning → Success	.459	.044	10.542	< .001
Engagement → Success	.348	.048	8.598	< .001
Motivation → Success	.099	.022	4.412	< .001

Mediation Analysis

Mediation effects were examined using bootstrapping to assess indirect effects. The results are presented in Table 4. Both indirect effects are statistically significant. Engagement partially mediates the relationship between self-learning and success ($\beta = .285$, $p < .001$), and motivation also serves as a mediator ($\beta = .069$, $p < .001$). Since the direct effect remains significant ($\beta = .355$, $p < .001$ for total direct effect after mediation), the mediation can be interpreted as partial mediation.

Table 4 Indirect Effects

Indirect Path	**β**	**SD**	**t**	**p**
Self-Learning → Engagement → Success	.285	.035	8.198	< .001
Self-Learning → Motivation → Success	.069	.016	4.371	< .001

Coefficient of Determination (R^2)

The explanatory power of the model was assessed using R^2 values. According to conventional guidelines, R^2 values of .25, .50, and .75 are considered weak, moderate, and substantial, respectively. The model explains 67.4% of the variance in engagement, 48.9% in motivation, and 71.6% in success. These values indicate moderate to substantial explanatory power.

Table 5 Coefficient of Determination

Endogenous Construct	**R^2**	**Adjusted R^2**
Engagement	.674	.673
Motivation	.489	.489
Success	.716	.716

Model Fit

Model fit was evaluated using the standardized root mean square residual (SRMR) and the normed fit index (NFI). The SRMR value for the estimated model was .064, which is below the recommended threshold of .08, indicating acceptable fit. The NFI value was .807, suggesting moderate overall fit.

Predictive Relevance (Q^2)

Predictive relevance was assessed using Q^2predict. Positive Q^2 values indicate that the model has predictive capability. All Q^2 values are positive, confirming that the model demonstrates satisfactory predictive relevance for all endogenous constructs.

Table 6 Predictive Relevance

Construct	Q^2predict	RMSE	MAE
Engagement	.673	.573	.398
Motivation	.488	.717	.514
Success	.661	.583	.421

Overall, the results demonstrate that self-learning significantly enhances engagement, motivation, and success. Engagement emerges as the stronger mediator in explaining academic success, while motivation plays a complementary role. The model exhibits substantial explanatory power and adequate predictive capability, supporting the robustness of the proposed theoretical framework.

DISCUSSION

This study examined the direct and mediating relationships among self-regulation, motivation, engagement, and academic success in online learning. The findings provide strong empirical support for the proposed model and align with established theoretical and empirical literature in online higher education. Direct Effects of Self-Regulation, Motivation, and Engagement on Academic Success (H01).

The results confirmed that self-regulation, engagement, and motivation each exert significant direct effects on academic success. Among these predictors, self-regulation demonstrated the strongest direct influence. This finding is consistent with social cognitive theory, which conceptualizes learners as active agents who plan, monitor, and adapt their learning processes to achieve desired outcomes (Zimmerman, 1989). In online learning environments—where autonomy is heightened and external regulation is reduced—self-regulatory competencies such as time management, metacognitive monitoring, and effort regulation become particularly critical.

Empirical evidence supports this interpretation. Broadbent and Poon (2015), in their systematic review of online higher education studies, identified self-regulated learning strategies as consistent predictors of academic achievement. Similarly, Credé and Kuncel (2008) demonstrated that study habits and self-regulatory behaviors significantly contribute to collegiate performance, independent of cognitive ability. The present findings extend this body of evidence by demonstrating that self-regulation retains a strong and independent effect even when motivation and engagement are simultaneously modeled.

Engagement also emerged as a substantial direct predictor of academic success. This aligns with the multidimensional conceptualization of engagement as behavioral, cognitive, and emotional involvement in learning activities (Fredricks et al., 2004). In online contexts, engagement reflects students' active participation, persistence, and investment in course activities, which are directly tied to performance outcomes. Dixson (2015) demonstrated that online student engagement significantly predicts course performance and behavioral learning indicators. Likewise, Rajabalee and Santally (2021) found positive associations between engagement,

satisfaction, and final academic performance in online modules. The present results reinforce the position that engagement functions as a proximal determinant of academic achievement.

Motivation also had a statistically significant effect on academic success, although its magnitude was smaller relative to self-regulation and engagement. This pattern is consistent with prior research indicating that while motivation is important, its effects on academic outcomes may be partly indirect or contingent on how motivational energy is translated into strategy use and engagement (Eom, 2015; Stark, 2019). Eom (2015) found that intrinsic motivation significantly predicted perceived e-learning outcomes, but its effects were intertwined with self-regulated learning practices. Thus, motivation contributes to success, but it appears most powerful when integrated with effective regulatory and engagement processes.

Mediating Role of Motivation (H02)

The findings supported the hypothesis that motivation mediates the relationship between self-regulation and academic success. Self-regulation significantly predicted motivation, which in turn predicted academic success. This suggests that students who effectively regulate their learning tend to experience higher levels of motivational activation, which contributes to improved performance. This pattern aligns with research showing that self-regulation and motivation are closely interconnected processes in online learning environments. Artino and Stephens (2009) demonstrated that motivational beliefs and self-regulation jointly predict online learning outcomes, with motivational factors reinforcing strategic learning behaviors. Additionally, Rahman et al. (2021) found that online learning motivation mediated the relationship between instructional and interaction variables and learning satisfaction, highlighting the mediating function of motivation in digital contexts. However, the magnitude of the motivational mediation effect in the present study was modest relative to engagement. This suggests that while self-regulation enhances motivation, the translation of motivational states into achievement likely depends on subsequent behavioral enactment. This interpretation is consistent with findings indicating that motivational beliefs alone may not guarantee performance unless accompanied by sustained learning engagement and strategy use (Stark, 2019; Eom & Ashill, 2016).

Mediating Role of Engagement (H03)

Engagement emerged as a stronger mediator between self-regulation and academic success compared to motivation. The significant indirect pathway indicates that self-regulated learners are more engaged, and this engagement substantially contributes to academic success.

This finding is theoretically coherent with models that position engagement as the behavioral manifestation of internal learning processes. Pellas (2014) demonstrated that metacognitive self-regulation significantly predicts multidimensional engagement in online learning environments. Similarly, Xu and Qiu (2021) showed that self-regulation influences behavioral intention and learning outcomes through engagement mechanisms. These findings suggest that self-regulation enhances the likelihood that students will participate actively, persist through challenges, and cognitively invest in course tasks—behaviors that directly support achievement.

The stronger mediation through engagement also resonates with evidence from structural equation modeling studies. Kucuk and Richardson (2019) found that engagement plays a central role in linking instructional presence to learning satisfaction and outcomes. Furthermore, Lim et al. (2020) demonstrated that self-regulated learning mediated relationships between peer learning and satisfaction, underscoring the centrality of strategic and engaged participation in online success. Taken together, the present findings suggest that engagement functions as the primary mechanism through which self-regulation translates into academic achievement. Motivation contributes to this process, but engagement represents the more immediate and behaviorally consequential pathway.

Integrated Interpretation

The model explained a substantial proportion of variance in academic success ($R^2 = .716$), indicating strong explanatory capacity. When considered collectively, the findings suggest a hierarchical mechanism in which self-regulation serves as a foundational competence that shapes both motivation and engagement. Engagement,

in turn, acts as the most powerful conduit linking internal learning processes to measurable academic outcomes. This integrated pattern aligns with broader online learning research emphasizing the interdependence of self-regulation, motivation, and engagement in predicting success (Broadbent & Poon, 2015; Kucuk & Richardson, 2019). Importantly, the results demonstrate that these constructs are empirically distinct yet functionally interconnected, contributing uniquely and jointly to academic achievement.

Implications for Educational Practice and Policy

The findings highlight that self-regulation plays a central role in students' academic success in online learning, while engagement serves as the most important mechanism through which self-regulation translates into learning outcomes. These results suggest that improving online learning outcomes requires instructional strategies that strengthen students' ability to regulate their learning and actively participate in academic activities.

For educators, the results indicate the importance of integrating self-regulated learning support into online course design. Instructors should provide clear learning goals, structured timelines, and opportunities for students to monitor their progress through reflective activities, formative assessments, and regular feedback. At the same time, courses should include interactive learning activities, such as collaborative discussions, problem-based tasks, and multimedia learning resources, which can enhance behavioral and cognitive engagement. These strategies help translate students' motivation and self-regulation into active learning behaviors that support academic achievement.

At the policy level, universities should prioritize the development of students' digital learning competencies, particularly skills related to time management, goal setting, and independent learning in online environments. Institutions can implement orientation programs and training modules that prepare students for the demands of online learning. In addition, universities should invest in professional development for instructors to strengthen online pedagogical practices, including strategies for fostering engagement and providing effective feedback. By combining institutional support, effective course design, and learner-centered teaching practices, higher education institutions can create online learning environments that better support students' academic success.

CONCLUSION

The present study provides empirical evidence that academic success in online learning is strongly influenced by students' self-regulation, engagement, and motivation. Self-regulation emerged as the most influential direct predictor and also exerted significant indirect effects through both motivation and engagement. Engagement functioned as the stronger mediator, indicating that the behavioral and cognitive enactment of learning activities is central to translating internal regulatory capacity into achievement. These findings reinforce theoretical models of self-regulated learning (Zimmerman, 1989) and extend empirical work demonstrating the importance of engagement and motivation in online higher education (Broadbent & Poon, 2015; Rajabalee & Santally, 2021). From a practical perspective, the results suggest that enhancing academic success in online learning requires systematic efforts to develop students' self-regulatory skills while simultaneously designing learning experiences that foster sustained engagement. Future research may further examine how different dimensions of engagement (behavioral, emotional, cognitive) differentially mediate self-regulation and success, and whether these mechanisms vary across disciplines or levels of online learning experience.

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