

Digital Literacy, Motivation, Self-Regulation, Interest, and Task Difficulty as Predictors of Performance in Online Learning: A Path Analysis

Betty Essuman¹, Harry Barton Essel², Rudolf Steiner³, Aaron Daniel Akuteye⁴, Albert Benjamin Essuman⁵

Article Info

Article Type

Original Research

Article History

Received:

25 February 2025

Accepted:

29 April 2025



© 2025 by the

author(s).

(CC BY-NC 4.0)

Abstract


Studio-based art and design education, especially in hands-on fields like ceramics, faces significant challenges during crises requiring remote learning. The sudden shift to online environments disrupts the experiential learning essential to such courses. This study examined the effectiveness of the Studio-Based Clay Course Model, which integrates multimedia tools and instructional videos to support clay instruction in both physical and virtual formats. The study investigated how digital literacy, motivation, self-regulation, course interest, and task difficulty predict academic performance in an online learning context. Data were collected via a structured questionnaire from 148 students in Ghana. Path analysis, conducted using Jamovi software, revealed that motivation, course interest, and self-regulation significantly predicted academic performance ($\beta = .6121$, $p < .001$), and task difficulty had a notable impact ($\beta = .2339$, $p = .024$). Digital literacy did not directly predict performance ($\beta = .0892$, $p = .367$) but influenced it indirectly through motivation and self-regulation. The model explained 71.4% of the variance in academic performance. While limitations such as limited digital access and challenges in replicating hands-on activities online were noted, the findings suggest that the Studio-Based Clay Course Model fosters resilience and supports student success in remote studio-based learning environments.


Keywords:


Academic performance. Clay courses, Course interest, Digital literacy, Motivation, Online education, Self-regulated learning, Task difficulty.


Citation:


Essuman, B., Essel, H. B., Steiner, R., Akuteye, A. D., & Essuman, A. B. (2025). Digital literacy, motivation, self-regulation, interest, and task difficulty as predictors of performance in online learning: A path analysis. *International Journal of Current Education Studies (IJCES)*, 4(1), 23-46. <https://doi.org/10.46328/ijces.164>

¹ Corresponding Author, Dr., Kwame Nkrumah University of Science and Technology (ROR ID: 00cb23x68), Kumasi, Ghana. betessuman@gmail.com,  Orcid ID: 0009-0006-0754-2525

² Dr., Kwame Nkrumah University of Science and Technology (ROR ID: 00cb23x68), Kumasi, Ghana. hbessel.knust.eist@gmail.com,  Orcid ID: 0000-0001-7232-3640

³ Dr., Kwame Nkrumah University of Science and Technology (ROR ID: 00cb23x68), Kumasi, Ghana. rsteiner.art@knust.edu.gh,  Orcid ID: 0000-0002-1307-7205

⁴ Dr., Kwame Nkrumah University of Science and Technology (ROR ID: 00cb23x68), Kumasi, Ghana. aaronakuteye@gmail.com,  Orcid ID: 0009-0000-2951-509X

⁵ Dr., Kwame Nkrumah University of Science and Technology (ROR ID: 00cb23x68), Kumasi, Ghana. albertessuman@yahoo.com,  Orcid ID: 0009-0006-1245-0465



Introduction

The clay studio is a firmly established physical location with a distinctive teaching approach where lecturers with experience in clay-forming techniques teach students individually or in groups. This technique occasionally includes a "learning by doing" approach to instruction. The lecturer demonstrates the processes through actions, discussing, and showing clay-forming techniques. In studio-based learning, students solve problems and complete projects by thinking and acting. The clay studio is an active learning environment. During COVID-19, tertiary institutions used technology to teach and learn to prevent the spread of the virus. According to UNESCO (2020), over 1.6 billion students were affected by the pandemic at its height worldwide, which prompted a spike in the number of online learning resources and platforms to keep up with the demand. During the peak of COVID-19, online teaching and learning became the norm in educational institutions to reduce the spread of the virus, causing some students to be absent from school (Owusu-Fordjour et al., 2020). The Ministry of Education introduced an online teaching and learning platform to ensure the successful completion of the academic calendar. Studio-based clay courses in tertiary institutions relied heavily on face-to-face demonstrations to teach practice-based learning in studio environments. Most studio-based clay students in Ghanaian tertiary institutions did not attend lectures due to the lockdown implementation by the government of Ghana. They also ignored the problem of their coursework, causing poor academic performance of students. Lecturers and students hoped that technology could accompany and assist students in reviewing and preparing lessons. The lack of resilience regarding teaching studio-based practical or hands-on activities in clay courses was challenging because of the global COVID-19 pandemic. However, if there had been a resilient pedagogy, there would not have been issues teaching studio-based clay courses during the pandemic. Response to a study conducted by Adarkwah (2021) revealed that traditional teaching and learning were suitable compared to online learning, representing more than half of the study responders. Most students were unwilling to attend online lessons due to challenges such as a lack of social interactions and IT skills. They preferred traditional rather than online learning (Adarkwah, 2021). However, during the COVID-19 pandemic, the literature did not investigate how well students performed. Accordingly, the research aims to identify the factors influencing students' academic performance. Therefore, the purpose of this study is to examine the current method of teaching and learning studio-based clay courses and to present a resilient methodological pedagogic framework that could be used to incorporate the teaching and learning of studio-based practical clay courses that take into account students' motivation, course interest, digital literacy, self-regulatory learning, task difficulty and test its effectiveness with the integration of instructional technology on student's academic performance in order to ensure that tertiary students in Ghana learn effectively in times of crisis.

In architectural studios, the most widely used online teaching platforms are Zoom, Microsoft Teams, and Blackboard Collaborate Ultra (Rongrong et al., 2022). The ability for lecturers to sketch on top of students' work emulates the traditional face-to-face studio approach of sketching, making Blackboard Collaborate well-liked. No recent studies have examined the effects of traditional face-to-face versus online studio-based clay courses on students' academic performance, particularly within tertiary design education. Although flipped learning and micro-lectures are widely adopted in studio-based contexts abroad (Haritha et al., 2024; Bakir & Alsaadani, 2022), their implementation in clay instruction remains underexplored. Most tertiary students in Ghana possess smartphones, laptops, or tablets, allowing institutions and lecturers to integrate technology-enhanced learning into



clay studio practice. While digital tools have improved collaboration, feedback, and creativity in design studios (Hafizah & Zairul, 2023; Fleischmann, 2022), limited research addresses their specific impact on academic performance in ceramic education. There is a critical need to investigate the factors influencing academic outcomes in online studio-based learning and to understand students' perceptions of their learning achievements. This study analyzed the factors affecting clay students' academic performance using online studio-based teaching and learning methods. The information provided is relevant to lecturers and provides valuable insights into the effectiveness of a resilient pedagogical framework for online teaching studio-based clay courses during crises. While the Studio-Based Clay Course (SB-CC) model has shown promise in enhancing academic performance, motivation, and self-regulation, challenges remain regarding digital access and the difficulty of fully replicating the hands-on nature of practical courses in an online environment.

Literature Review

Online Studio-Based Clay Course

Online studio-based clay courses involve an infusion of Information Communication Technologies (ICTs) into learning and teaching in all education sectors. Technology in education involves delivering instructional content and allowing students to observe lectures, discussions, and demonstrations in the comfort of their homes or hostels. Thanks to these technologies, lecturers can give a course synchronously and asynchronously, which creates a mobile and flexible environment. Students could study whenever and wherever they wanted to because online learning is flexible. Online studios need to provide dynamic communication between students and lecturers for clay courses to succeed during emergencies.

Mobile learning in Studio-Based Clay Course

Mobile learning is important in an educational pattern, particularly with swift technological advancements and the increasing number of mobile devices. Mobile learning has advanced from instructional materials to a flexible and easy-to-use resource, paving the way for new directions in tertiary institutions due to technological revolutions (Gizeh, 2023). The perception of mobile technologies, when developed and applied in a way that makes them appropriate for learning, has the vast potential to change the education area completely.

Along with other educational technologies, it became a sought-after tool for remote schooling during the COVID-19 epidemic, especially tablets and smartphones. The meaning emphasizes the mobility of technology, learning, and students, which is important in understanding the transformative possibility of mobile learning in various institutions (Moustaka, 2018). Even though mobile learning has been there for a while, the epidemic has made it a part of higher education. Face-to-face teaching and learning activities have had to be moved online, and lecturers must adjust to the new conditions. Due to these, lecturers and students needed specialized and effective assistance curricula. The importance of mobile learning has increased due to the widely used internet infrastructure and mobile technologies (Tolstoukhova et al., 2019). This has permitted students to participate in educational content anytime and anywhere, enabling flexible and personalized learning practices (Gong et al., 2023). Since mobile learning enables a more dynamic and student-centered approach to education, research suggests it can improve



student motivation and engagement (Shahrol, 2020). Research has shown that students used their mobile devices for group projects, discussed material, and shared ideas with coursemates, improving learning outcomes and building collaborations (Gong et al., 2023). Arts-based learning approaches adapted for m-learning provide creative outlets for expression and foster essential social interactions, pivotal for successful learning outcomes (Perry & Edwards, 2019). It is important to note that mobile technology does not ensure successful learning outcomes; student preferences for learning applications often prioritize convenience over effectiveness, which may not always align with educational goals (Uther & Ylinen, 2018). By providing students with access to informative resources and chances for teamwork, mobile technologies can make online studio-based clay courses successful and promote equity of education in tertiary institutions.

Student Academic Performance

A significant component in meeting graduation requirements is the motivation and learning style of the students (Tokan, 2019). Motivation and learning behaviors such as course interest (Sun et al., 2017), digital literacy (Pala & Başıbüyük, 2023), and self-regulatory learning (Lilian et al., 2021; Zheng et al., 2024) are important factors in influencing students' academic performance. Student achievement is a measure of academic success (Gunawan, 2017). The relationship between what students expect and receive in a course can be used to determine course satisfaction. It has been demonstrated by earlier research that students engaged in their classes typically receive better marks on their final exams (Puzziferro, 2008). A substantial amount of signal indicates that course fulfillment significantly impacts academic performance. However, it can also be jeopardized due to the restricted interaction and numerous potential disturbances. The quality of the course evaluation, the relationship between students and their instructors, students' learning processes, self-efficacy, and the degree of student happiness and achievement can all be related to these elements (Owusu-Fordjour et al., 2020). Therefore, students happy with their learning experience also perform well academically, which is how studio-based clay learning can succeed.

Study Model and Hypothesis Development

The research questions were answered using students' digital literacy, motivation, course interest, self-regulatory learning, and task difficulty to test the educational goal of the student's academic performance. The variables significantly impact academic performance. This study combined motivation, course interest, digital literacy, self-regulatory learning, task difficulty, and academic performance as predictors from the literature review. Online studio-based clay teaching and learning activities are innovative and may relate to students' satisfaction and academic performance. Figure 1 shows a more complete proposed model.

Education has paid significant attention to the complex field of study on the relationship among, digital literacy, course interest, task difficulty, motivation, self-regulated learning, and academic performance. Students' involvement and interest in their courses are greatly influenced by their digital literacy, which is the capacity to use digital tools to navigate, assess, and produce knowledge successfully. Wahyuni et al. (2023) indicated a positive correlation between applying digital literacy-based learning and enhancing student motivation and social interaction skills within educational environments. The findings indicate that when students engage with digital

tools effectively, their overall interest in course content and participation increases due to the interactive nature of e-learning platforms. Moreover, incorporating interactive and multimedia components into course design has significantly increased students' course interest, encouraging deeper engagement with the course (Budiarto & Jazuli, 2021).

H1: Students studying clay who are more digitally literate will be more interested in online studio-based clay courses.

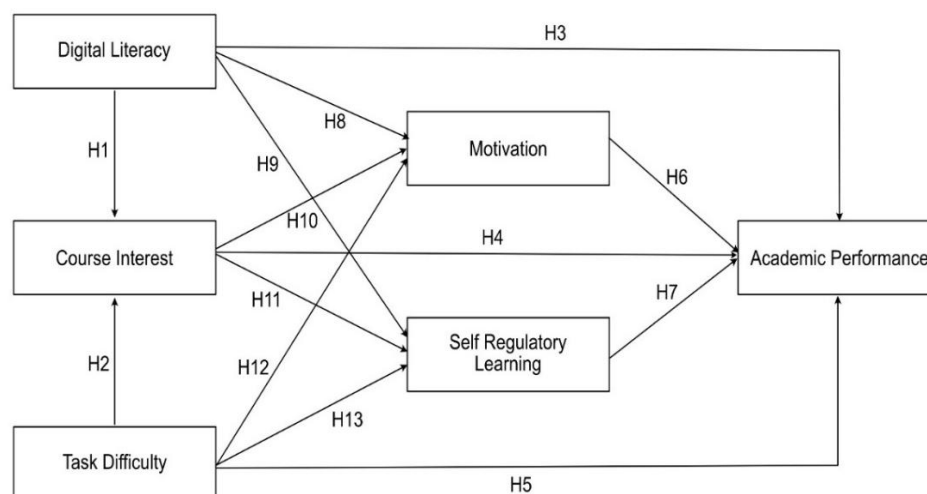


Figure 1. Research Model and Initial Hypothesis Source: Authors' Construct (2025)

Another significant component that affects course interest is task difficulty. Nuutila et al. (2021) argued that interest and self-efficacy are interlinked, suggesting that students who feel competent in engaging tasks are more likely to maintain interest even as challenge levels rise. This tendency is especially noticeable in studio settings where students are encouraged to work together and discuss the course materials, as these interactions can help challenging assignments appear more doable and pertinent (Jones, 2011). Task complexity also plays a role in shaping these perceptions. Liang (2022) indicates that task complexity can impact performance outcomes, affecting students' interest levels in learning environments. To keep students interested and engaged, lecturers must carefully balance task difficulty when assigning students to online studio-based clay courses.

H2: The perceived task difficulty in the clay studio practical has a positive impact on students' interest in the course.

Academic performance is directly impacted by digital literacy in addition to course interest. Studies have found that higher digital literacy correlates positively with improved academic outcomes, suggesting that strong digital skills are imperative for educational success in the modern age (Abbas et al., 2019). Additionally, educators' digital literacy is likewise connected to enhanced educator performance and pedagogical effectiveness, indicating that the capabilities of teachers to utilize digital resources are critical for enriching the learning environment (Wulandari et al., 2024). The theory on the significance of incorporating digital literacy instruction into academic courses to improve students' academic performance is highlighted by this relationship (Pogorskiy, 2018).



H3: Students' digital literacy in online studio-based clay courses strongly impacts their academic performance.

A significant predictor of academic performance is course interest. A student's likelihood of dedicating time and energy to their studies and attaining better results increases when they have a genuine interest in the subject matter (Luik et al., 2017). This connection is reinforced by findings showing that students who express more interest in their course naturally perform better academically because they are more driven to interact with the course materials and participate in class activities (Cortright et al., 2013).

H4: Students' interest in the online studio-based clay course positively affects their academic performance.

Moreover, a course interest can promote fundamental motivation, essential for students to remain engaged and succeed in academic settings (Milligan & Littlejohn, 2017). Students' motivation and interest to learn studio-based clay courses online using technology affect their academic performance positively. Aligning task difficulty with student capabilities enhances engagement and learning rates, reinforcing the connection between appropriate difficulty tasks and student achievement (Pavlov et al., 2021). On the other hand, if students perceive tasks as overwhelming, they may disengage, resulting in poor academic performance levels (Milligan & Littlejohn, 2016). Therefore, lecturers must consider the difficulty of tasks assigned to students to enhance their learning experiences and outcomes.

H5: Students' perceived task difficulty of the clay course work directly affects their academic performance.

Motivation can stem from various sources, including intrinsic interest in the subject matter, external rewards, and the perceived relevance of the material to students' personal and professional goals (Herpratiwi, 2022; Wang et al., 2021). Intrinsic motivation enhances students' decision-making and academic persistence (Effendi & Multahada, 2017; Hagger et al., 2005). In contrast, extrinsic motivation, such as rewards and recognition, can stimulate initial engagement but is less effective for long-term motivation (Cheng & Yeh, 2009; Wang et al., 2021). The perceived relevance of learning materials plays a critical role in motivating students, especially when they see connections to their personal goals and future careers (Vela et al., 2024; Wolgast et al., 2021). A balance of intrinsic and extrinsic motivation and relevant educational content is crucial for fostering continuous engagement and academic success (Cook & Artino, 2016; Safdari & Maftoon, 2017). Motivation is an important factor that influences entirely students' academic performance. Motivation is closely connected to self-regulated learning, as motivated students are likelier to set goals, monitor their progress, and regulate their approaches to improve their learning.

H6: Students' motivation positively impacts their academic performance in online studio-based clay courses.

Self-regulated learning, categorized by a student's capacity to succeed in his learning methods, is another significant predictor of academic performance (Miatun & Muntazhimah, 2018; Elesio, 2023). Research has established that students who employ self-regulation approaches, such as goal setting, self-monitoring, and self-



reflection, tend to perform better academically (Elesio, 2023; Cicchinelli et al., 2018). This connection mostly applies to online learning environments, where students must take greater accountability for their learning due to the lack of face-to-face instruction or direct lecturer support. Suan (2023) found that while self-regulation influences achievement, it accounts for only a portion of academic performance variability, indicating that factors such as socioeconomic status and teacher quality also play crucial roles.

H7: Students' self-regulatory learning ability positively influences their academic performance in online studio-based clay courses.

The capacity to use digital platforms efficiently can empower students to take control of their learning, leading to increased self-regulation and, ultimately, better academic performance (Bakar et al., 2023; Pogorskiy et al., 2018). Moreover, digital literacy is important in enhancing motivation and self-regulated learning. Students who were skillful in using digital tools were well-equipped to participate in course materials, search for extra information, and work with coursemates, all of which increased their motivation to learn. This highlights the importance of integrating digital literacy training into educational programs to support students' motivation and self-regulatory skills.

H8: Higher digital literacy amongst clay students increases their motivation for online studio-based clay course.

H9: Students' digital literacy positively impacts their ability to self-regulate learning.

Course interest positively influences motivation and self-regulated learning (Lai et al., 2023; Prasetya, 2023). When students find a course engaging, they are more likely to be motivated to participate actively and take ownership of their learning (Albelbisi & Yusop, 2019; Barba, 2016). This fundamental motivation can lead to implementing self-regulated learning approaches, as students become more invested in their academic success. Furthermore, Trautwein et al. (2015) shows that students interested in their courses are more likely to seek additional learning opportunities and resources, further enhancing their self-regulatory capabilities. Students interested in the studio-based clay course prefer studying and taking more programs outside lecture hours to enhance their academic performance.

H10: Students' motivation is positively impacted by their interest in an online studio-based clay course.

H11: Students' interest in the online studio-based clay course has a positive impact on their ability to master self-regulatory skills.

Task difficulty also affects motivation and self-regulated learning (Jurczyk et al., 2019; Bogнар et al., 2024). When students encounter challenging tasks, their motivation can either increase or decrease depending on their perceptions of the task's difficulty and their ability to succeed (Jurczyk et al., 2019). Tasks that are perceived as appropriately challenging can stimulate motivation and encourage students to employ self-regulated learning strategies to overcome obstacles (Wu et al., 2021). Students of studio-based clay courses have their practicals together, which enables them to tackle challenges together to overcome obstacles. On the contrary, if tasks are viewed as excessively difficult, students may become discouraged and disengaged, leading to lower motivation



and diminished self-regulatory efforts (Villarreal-Lozano et al., 2022; Bogнар et al., 2024). Consequently, lecturers must consider the difficulty of tasks assigned to students in online studio-based clay courses to not discourage learning but rather increase their learning experiences and academic performance.

H12: Students' perceived level of task difficulty with online clay-related courses has a positive impact on their motivation.

H13: Task difficulty in online clay courses has a positive effect on students' capacity for self-regulatory learning skills.

The interplay between digital literacy, task difficulty, course interest, motivation, self-regulated learning, and academic performance is complex and multifaceted. Digital literacy enhances course interest and academic performance by enabling students to engage more effectively with course materials in studio-based clay courses. Task difficulty influences course interest and academic performance by shaping students' perceptions of challenges and their motivation to succeed. Course interest, in turn, drives motivation and self-regulated learning, which are critical for academic success. Therefore, educators must consider these interrelationships when designing curricula and instructional strategies to optimize student engagement and academic performance in online studio-based clay courses. This study used intermediate variables of motivation, course interest, digital literacy, self-regulated learning, and task difficulty. Additionally, the dependent variable was Academic performance. The study proposed 13 hypotheses, presented in Figure 1.

Method

Design

Cross-sectional Correlation design was the research methodology adopted and used to construct hypotheses and analyze several attributes and outcomes simultaneously without losing track (Hackshaw, 2014; Solem, 2015). The primary focus of this approach is to examine the correlations between several constructs—digital literacy, perceived task difficulty, interest, motivation, and academic performance—serving as the analytical framework for comparing conventional and online studio-based clay education. Cross-sectional designs are frequently used in educational and psychosocial research to assess relationships among multiple factors, providing a snapshot supporting hypothesis testing and subsequent model development (Bui et al., 2021; Nurhidayah & Puspitosari, 2023). Questionnaires were distributed to students in tertiary institutions in Ghana who had taken studio-based clay courses before, during, and after the COVID-19 pandemic. This population was deliberately selected because they had experienced in-person and online delivery of clay courses, ensuring their responses' relevance and contextual validity. This methodological pattern aligns with recommendations from Spector (2019), who advocates for using cross-sectional designs with well-structured instruments to analyze correlational patterns in educational settings.

Instruments

A structured questionnaire comprising six key constructs—Academic Performance, Motivation, Self-Regulated



Learning, Task Difficulty, Course Interest, and Digital Literacy—was used to collect data, as detailed in Appendix A. All items were adapted from validated instruments in the literature and aligned with the study's conceptual framework. Academic Performance was measured using self-reported academic results. Prior studies used proxies such as task scores or game performance to assess academic outcomes (e.g., Scasserra, 2008; Lynch et al., 2013). Motivation was assessed using the Intrinsic Motivation Inventory (IMI) developed by McAuley et al. (1989) and a questionnaire adapted from Clément et al. (1994). The IMI subscales for effort/importance and perceived competence were rated on a 7-point Likert scale and are well-established regarding reliability and validity. Items reflected participants' engagement and confidence during tasks. Self-regulated learning was not directly measured in the reviewed literature but was captured through the IMI's perceived competence subscale, representing learners' confidence and self-management in learning contexts.

Task difficulty was evaluated using items from prior studies' self-reports and task manipulation techniques. For example, Scasserra (2008) used a single-item 7-point Likert scale, while Lynch et al. (2013) manipulated game speed and assessed perceived difficulty using a 5-point scale. These approaches provided both subjective and experimental perspectives on difficulty. Course interest was adapted from the Course Experience Questionnaire (CEQ), originally by Ramsden and Entwistle (1981) in the UK. Ramsden (1991) redesigned to evaluate students' perceptions at the course level, focusing on quality and accountability in higher education. The revised CEQ included 30 items across five scales: Good Teaching, Clear Goals and Standards, Appropriate Workload, Appropriate Assessment, and Emphasis on Independence. A 23-item version was later introduced, replacing "Emphasis on Independence" with "Generic Skills". Reliability was measured using Cronbach's alpha, showing moderate to high internal consistency (e.g., Good Teaching $\alpha = 0.87$). In a Malaysian study, the overall reliability was 0.80, indicating strong consistency. Responses were collected using a 5-point Likert scale, ranging from "Strongly Disagree" (1) to "Strongly Agree" (5), allowing for quantitative evaluation of students' course experiences. Digital Literacy was measured using a research questionnaire by Rafi et al. (2019), covering skills in using digital tools and online resources. The 5-point Likert scale items were expert-reviewed for clarity, though no reliability coefficients were reported.

Data Collection and Analysis

Online questionnaires were used to gather data to guarantee participant anonymity and voluntariness. Students were made aware that they were not obligated to complete the questionnaire. In the first stage, the data were entered into an Excel sheet and imported to JAMOV version 2.3.28 for the initial analysis—a free statistical tool. A total of 148 tertiary students of studio-based clay courses completed the survey. The respondents consisted of 102 Males and 46 females, with the majority of respondents between the 21-25 age group followed closely by those between the 18 and 20 age group. A few of the students were 25 years old or older.

Regarding tertiary institutions, 98 students were the majority of respondents from Kwame Nkrumah University of Science and Technology, followed by the University of Education Winneba, which had 41 respondents. Dr. Hilla Limann Technical University had five respondents, while Takoradi Technical University had at least four. The data were analyzed using partial least squares structural equation modeling (PLS-SEM) with the assistance



of Jamovi software. This method is widely used to analyze simultaneous relationships between variables and is particularly well-suited for exploratory research, where predictive accuracy and complex relationships need to be modeled effectively (Hair et al., 2019; Sarstedt et al., 2022). PLS-SEM has been shown to be effective in handling small to medium sample sizes, with studies suggesting that a sample size of 100 to 200 respondents is sufficient for reliable results in SEM studies (Hair Jr et al., 2017; Memon et al., 2021). This study's sample size of 148 is appropriate, as it falls within the range considered acceptable for conducting PLS-SEM analysis, ensuring robust estimation of the relationships between the constructs.

Results

Descriptive Statistics

When Table 1 is examined, students reported a moderate level of motivation ($M = 19.0$, $SD = 3.90$), with scores ranging from 11 to 25. The distribution was slightly negatively skewed (skewness = -0.49 , $SE = 0.26$) and platykurtic (kurtosis = -0.49 , $SE = 0.51$), indicating a slight left tail and a flatter-than-normal distribution. Digital literacy also had a moderate mean score ($M = 18.9$, $SD = 3.16$), ranging from 13 to 25, and showed near-normal distribution with minimal skewness (skewness = 0.05 , $SE = 0.26$) and slight platy kurtosis (kurtosis = -0.18 , $SE = 0.51$). Participants rated task difficulty similarly ($M = 19.0$, $SD = 3.79$), with scores ranging from 6 to 25. The distribution was moderately negatively skewed (skewness = -0.75 , $SE = 0.26$) and slightly leptokurtic (kurtosis = 0.89 , $SE = 0.51$), indicating a leftward tail and a more peaked distribution.

Table 1. Descriptive Statistics

	Mean	SD	Min	Max	Skewness		Kurtosis	
					Skewness	SE	Kurtosis	SE
Motivation	19.0	3.90	11	25	-.4894	.257	-.493	.508
Digital Literacy	18.9	3.16	13	25	.0541	.257	-.179	.508
Task Difficulty	19.0	3.79	6	25	-.7469	.257	.893	.508
Course Interest	16.5	4.92	5	25	-.3944	.257	-.133	.508
Self-Regulatory Learning	23.6	4.62	9	30	-.8812	.257	1.036	.508
Academic Performance	16.0	3.35	5	20	-1.0439	.257	1.556	.508

Course interest had a slightly lower mean ($M = 16.5$, $SD = 4.92$), with a range of 5 to 25. The distribution showed mild negative skew (skewness = $-.39$, $SE = 0.26$) and near-zero kurtosis (kurtosis = $-.13$, $SE = .51$), suggesting a relatively symmetrical and normal distribution. The mean for self-regulatory learning was higher ($M = 23.6$, $SD = 4.62$), with scores between 9 and 3. The distribution was negatively skewed (skewness = $-.88$, $SE = .26$) and moderately leptokurtic (kurtosis = 1.04 , $SE = .51$), suggesting a left skew and a more peaked distribution. Finally, academic performance had a mean score of 16.0 ($SD = 3.35$), ranging from 5 to 2. The distribution was notably negatively skewed (skewness = -1.04 , $SE = .26$) and leptokurtic (kurtosis = 1.56 , $SE = .51$), indicating a concentration of higher scores and a sharper peak than the normal curve. Skewness and kurtosis values for all



variables fell within an acceptable range (± 2), suggesting no severe violations of normality for the purposes of parametric analysis (Kim, 2013).

Correlation Analysis

A Pearson correlation analysis was conducted to examine the relationships among students' motivation, digital literacy, task difficulty, course interest, self-regulatory learning, and academic performance in an online studio-based clay course. The coefficients obtained are given in Table 2.

Table 2. Correlation Matrix

Variable	1	2	3	4	5	6
1. Motivation	—					
2. Digital Literacy	.68***	—				
3. Task Difficulty	.58***	.64***	—			
4. Course Interest	.54***	.50***	.50***	—		
5. Self-Regulatory Learning	.49***	.42***	.65***	.48***	—	
6. Academic Performance	.52***	.51***	.70***	.46***	.81***	—

*** $p < .001$

The results indicated statistically significant positive correlations among all variables (Table 2). Academic performance showed a strong positive correlation with self-regulatory learning ($r = .81, p < .001$), indicating that students who demonstrated higher self-management and learning strategies tended to achieve better academic outcomes. Task difficulty was also strongly correlated with academic performance ($r = .70, p < .001$), suggesting that students who perceived the course as more challenging tended to perform better, possibly due to increased engagement or effort. Moderate positive correlations were found between academic performance and both digital literacy ($r = .51, p < .001$) and motivation ($r = .52, p < .001$). These results suggest that students with higher digital skills and greater motivation were more likely to succeed in the online clay course. Course interest was positively correlated with motivation ($r = .54, p < .001$), self-regulatory learning ($r = .48, p < .001$), and academic performance ($r = .46, p < .001$), indicating that students who found the course engaging were also more motivated and self-directed, and tended to perform better. Task difficulty was also moderately correlated with motivation ($r = .58, p < .001$), digital literacy ($r = .64, p < .001$), and self-regulatory learning ($r = .65, p < .001$), showing that the perception of difficulty was linked to both internal drive and learning strategies.

Construct Validity of Measurements

The researcher employed a bootstrap of 1,000 samples to assess the stability of the estimates. This means that they used resampling methods to generate multiple datasets and then estimated the parameters for each dataset. This allows them to evaluate the reliability of the estimates and determine whether they are stable across different samples. The fit indices for the general path analysis indicate that the model fits the data well, with a non-



significant chi-squared test statistic ($\chi^2 = 1.92$, $p = .166$), a relatively small root mean square error of approximation (RMSEA = .102), and high values for the comparative fit index (CFI = .996), Tucker-Lewis index (TLI = .949), and root mean square residual (SRMR = .017). The overall model fit was assessed with various fit indices, including the Comparative Fit Index (CFI = .996), Tucker-Lewis Index (TLI = .949), and Root Mean Square Error of Approximation (RMSEA = .102, 95% CI [.000, .323], \backslash ($p = .212$ \backslash)), indicating an acceptable fit. The total variance explained in Academic Performance was 71%, \backslash ($R^2 = .714$ \backslash), showing that Digital Literacy, Task Difficulty, Course Interest, Self-Regulatory Learning, and Motivation collectively account for a substantial proportion of the variance in Academic Performance.

Path Analysis and Hypothesis Testing

The path analysis model illustrates the relationships among digital literacy, course interest, task difficulty, motivation, self-regulatory learning, and academic performance, as shown in Figure 2. The model demonstrates strong predictive validity with R^2 values of .309 for course interest, .525 for motivation, .448 for self-regulatory learning, and .714 for academic performance (Table 3).

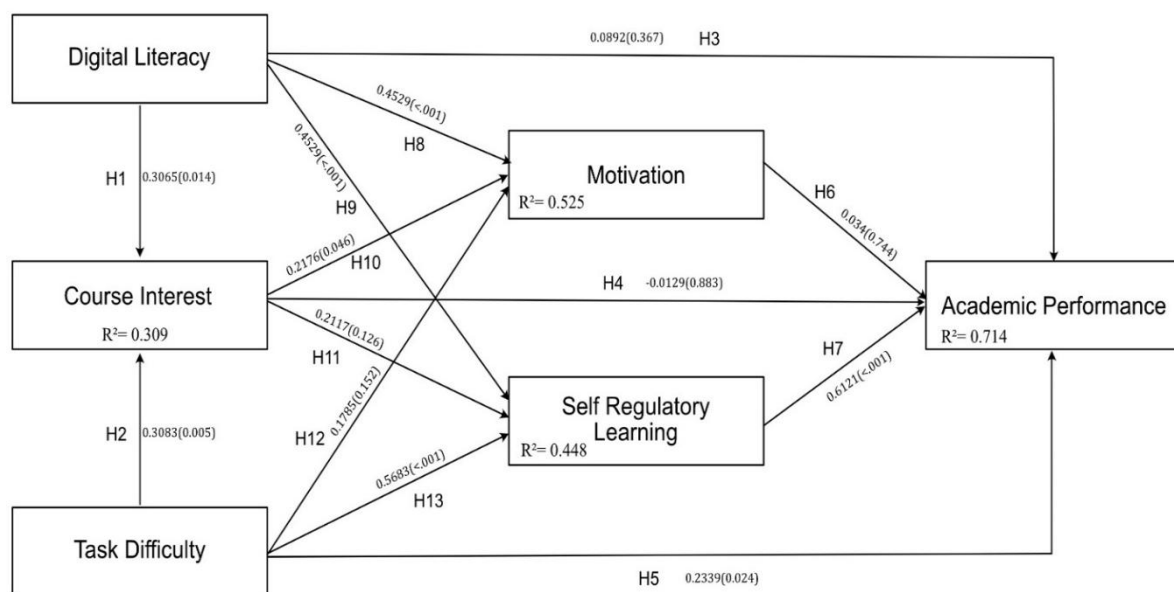


Figure 2. Path Analysis Source: Authors' Construct (2025)

Table 4 presents the parameter estimates for the tested model. Digital literacy positively impacts course interest ($\beta = .3065$, $p = .014$), as does task difficulty ($\beta = .3083$, $p = .005$), supporting the first two hypotheses. However, digital literacy does not have a significant direct effect on motivation ($\beta = .0892$, $p = .367$), nor does motivation directly impact academic performance ($\beta = .034$, $p = .744$). Self-regulatory learning, on the other hand, has a strong and significant positive effect on academic performance ($\beta = .6121$, $p < .001$), suggesting it is a critical predictor of academic outcomes.

Further relationships indicate that digital literacy significantly influences motivation ($\beta = .4529$, $p < .001$), while



task difficulty also contributes to motivation ($\beta = .2176$, $p = .046$). Non-significant paths include task difficulty to motivation (H10), course interest to self-regulatory learning (H11), and task difficulty to self-regulatory learning (H12), highlighting that not all hypothesised paths were supported. These findings suggest that while digital literacy and task difficulty enhance course interest and motivation, their impact on academic performance is likely mediated by self-regulatory learning. Hypotheses H1, H2, H7, H8, and H9 are confirmed, whereas H3, H6, H10, H11, and H12 are not. The analysis underscores the crucial role of self-regulatory learning in driving academic performance among students.

Table 3. Explained Variance and Confidence Intervals

Variable	R ²	95% Confidence Intervals	
		Lower	Upper
Course Interest	.309	.154	.470
Self-Regulatory Learning	.448	.286	.594
Academic Performance	.714	.597	.803
Motivation	.525	.369	.658

Hypothesis 1, which posited a relationship between Digital Literacy and Course Interest, was supported with a significant estimate ($\beta = .4767$, $p = .014$). Similarly, Hypothesis 2, which explored the effect of Task Difficulty on Course Interest, was supported ($\beta = .4003$, $p = .005$). In contrast, Hypothesis 3, which examined the effect of Digital Literacy on Academic Performance, was not supported, as the p-value was .367, indicating no significant relationship. Similarly, Hypothesis 4, suggesting a relationship between Course Interest and Academic Performance, was not supported ($p = .883$).

Hypothesis 5, proposing a link between Task Difficulty and Academic Performance, was supported ($\beta = .207$, $p = .024$). The relationship between Motivation and Academic Performance in Hypothesis 6 was not supported ($p = .744$). On the other hand, Hypothesis 7, which examined the relationship between Self-Regulatory Learning and Academic Performance, was supported with a strong effect ($\beta = .4436$, $p < .001$). Hypothesis 8, proposing a positive relationship between Digital Literacy and Motivation, was also supported ($\beta = .5584$, $p < .001$).

Hypothesis 9, suggesting a relationship between Self-Regulatory Learning and Digital Literacy, was not supported ($p = .774$), while Hypothesis 10, indicating a positive effect of Course Interest on Motivation, was supported ($\beta = .1725$, $p = .046$). Hypothesis 11, which explored the relationship between Course Interest and Self-Regulatory Learning, was not supported ($p = .126$), as was Hypothesis 12, which examined the relationship between Task Difficulty and Motivation ($p = .152$). Finally, Hypothesis 13, which proposed a link between Task Difficulty and Self-Regulatory Learning, was supported ($\beta = .6938$, $p < .001$).



Table 4. Parameter Estimates

Hypothesis	Dep	Pred	Estimate	SE	95% Confidence Intervals		β	Z	P	Support
					Lower	Upper				
H1	Course Interest	Digital Literacy	.47668	.1948	.1193	.889	.3065	2.447	.014	Supported
H2	Course Interest	Task Difficulty	.40033	.141	.1329	.666	.3083	2.839	.005	Supported
H3	Academic Performance	Digital Literacy	.0945	.1048	-.1193	.303	.0892	.902	.367	Not Supported
H4	Academic Performance	Course Interest	-.0088	.0596	-.1318	.111	-.0129	-.148	.883	Not Supported
H5	Academic Performance	Task Difficulty	.20697	.0915	.0145	.378	.2339	2.263	.024	Supported
H6	Academic Performance	Motivation	.02923	.0895	-.1405	.224	.034	.327	.744	Not Supported
H7	Academic Performance	Self-Regulatory Learning	.44358	.0696	.2942	.568	.6121	6.375	<.001	Supported
H8	Motivation	Digital Literacy	.55837	.1287	.2782	.794	.4529	4.338	<.001	Supported
H9	Self-Regulatory Learning	Digital Literacy	-.06698	.2332	-.4876	.398	-.0458	-.287	.774	Not Supported
H10	Motivation	Course Interest	.17249	.0864	.000829	.342	.2176	1.996	.046	Supported
H11	Self-Regulatory Learning	Course Interest	.19908	.1301	-.0485	.459	.2117	1.53	.126	Not Supported
H12	Motivation	Task Difficulty	.18369	.1283	-.0397	.479	.1785	1.432	.152	Not Supported
H13	Self-Regulatory Learning	Task Difficulty	.69377	.1884	.2589	.987	.5683	3.683	<.001	Supported



Discussion

The study aimed to determine the predictors related to the academic performance of studio-based clay students in tertiary institutions in Ghana. It also proposed how these factors had a relationship with academic performance. In the hypothetical model, path analysis combined Digital Literacy, Task Difficulty, Course Interest, Self-Regulatory Learning, and Motivation to account for Academic Performance. This section discusses the findings related to the study model. The effectiveness of the SB-CC model, showing the results from our path analysis, highlighted several key factors influencing student performance.

The model showed that a large portion of the variation in students' academic performance could be explained by the factors examined, with self-regulated learning emerging as the most decisive influence. This suggests that students who could manage their learning schedules, set goals, and stay focused, experienced significant academic benefits from the online learning framework. This finding supports Pintrich's (2000) self-regulation theory, as well as the work of Miatun and Muntazhimah (2018), which emphasizes that the ability to control one's cognitive and behavioral processes is crucial for academic success—especially in less structured learning environments like online courses.

Other significant predictors of academic performance included task difficulty, showing that students who perceived the tasks as appropriately challenging tended to perform better academically. This aligns with the cognitive load theory, which suggests that moderately complex tasks can enhance learning by keeping students engaged without overwhelming them (Nawaz et al., 2022). The study's analysis further revealed that motivation, digital literacy, and course interest played important roles, although not all pathways were statistically significant. For example, digital literacy did not directly affect academic performance, but it had indirect effects through other mediators such as motivation and self-regulation. These findings indicate that while digital literacy is important, other factors like motivation and self-regulation may be more critical to success in online learning environments.

The SB-CC model also positively impacted students' course interest and motivation, as evidenced by participant feedback, and aligns with the Lai et al. (2023) study. The flexibility of the online platform allowed students to revisit video content and engage with the material at their own pace, thus boosting their course interest. This is consistent with existing literature, where increased flexibility in online learning has been shown to improve student engagement and motivation. Moreover, course interest was positively associated with self-regulated learning, albeit not significantly. This suggests that while interest in the course is a factor, its direct impact on self-regulated learning may be limited (Albelbisi & Yusop, 2019; Lai et al., 2023).

Our findings on the effects of motivation also align with previous research on the impact of intrinsic and extrinsic motivation in online learning environments (Wang et al., 2021; Wolgast et al., 2021). Students in our study who were motivated to engage with the online clay course framework showed improved academic performance. This is supported by the self-regulatory theory, which maintains that intrinsic motivation, which is driven by interest or enjoyment in the task itself, plays a crucial role in academic success, especially when students have control over their learning processes.



Furthermore, our study also uncovered some challenges associated with transitioning to online learning. Technological barriers, such as access to stable internet and digital devices, were a significant issue for some students, affecting their ability to engage with the SB-CC model fully. This is a limitation also observed in similar studies by Hodges et al. (2020) and Wahyuni et al. (2023), which highlighted the inequities caused by the digital divide, where students in less privileged circumstances face difficulties accessing online learning platforms (Alakrash & Razak, 2021). Addressing these issues is critical for ensuring that online learning is inclusive and equitable for all students.

The path analysis also identified task difficulty as a significant contributor to academic performance and motivation, aligning with the study by Pavlov et al. (2021). This reinforces the notion that when appropriately scaled, challenges can foster engagement and learning. However, when task difficulty exceeds a student's capacity, it can result in frustration and disengagement. Therefore, balancing task difficulty is essential for fostering motivation and academic success in online learning environments.

Limitation

This study has certain limitations related to staffing, scheduling, and the teaching context. The participants were drawn exclusively from tertiary institutions in Ghana offering studio-based clay courses. As such, the findings may not be generalizable to students from other universities or those studying other specializations. Future research could extend to other tertiary institutions across Ghana to validate the findings and generate more comprehensive quantitative data. The cross-sectional nature of the data limits the ability to draw causal conclusions. Future studies employing longitudinal designs are recommended to understand changes over time better. In addition, the small sample size limits the extent to which the findings can be generalized. Larger-scale studies involving broader and more varied samples would enhance the robustness and applicability of the results. Other specializations such as Painting, Sculpture, Textiles, Leatherworks, Picture Making, Bead Making, and others—could also adopt this model in different institutional settings to examine whether similar outcomes are achieved.

Conclusion

In conclusion, this study provides valuable insights into the effectiveness of a resilient pedagogical framework for online teaching of studio-based clay courses during crises. While the SB-CC model has shown promise in enhancing academic performance, motivation, and self-regulation, challenges remain regarding digital access and the difficulty of fully replicating the hands-on nature of practical courses in an online environment. Future research could explore strategies to further improve the integration of practical components into online learning, such as virtual reality tools or hybrid models that combine face-to-face and online instruction. Additionally, larger-scale studies could provide more generalizable insights and help refine the pedagogical framework to address better the diverse needs of students across different institutions and disciplines. Future research in various settings, particularly in developing nations, may benefit from the validity and dependability of the suggested model.



Author(s)' Statements on Ethics and Conflict of Interest

Ethics Statement: We hereby declare that research and publication ethics, as well as proper citation principles, were considered at all stages of the study. Ethical approval to collect data from students was obtained from the Ethics Committee of Humanities and Social Sciences and the Department of Educational Innovations in Science and Technology at KNUST (HuSEREC/AP/33/VOL 1: 30/06/2023).

Statement of Interest: We have no conflict of interest to declare.

Data Availability Statement: The underlying data for this study, including participant responses and raw classroom observation data, are available on Mendeley Data (<https://doi.org/10.17632/fjzy97nfwv.1>).

Funding: None

Acknowledgements: None

References

- Abbas, Q., Hussain, S., & Rasool, S. (2019). Digital literacy effect on the academic performance of students at higher education level in Pakistan. *Global Social Sciences Review*, 4(1), 108–116. [https://doi.org/10.31703/gssr.2019\(iv-i\).14](https://doi.org/10.31703/gssr.2019(iv-i).14)
- Adarkwah, M. A. (2021). "I'm not against online teaching, but what about us?" ICT in Ghana post Covid-19. *Education and Information Technologies*, 26(2), 1663–1681. <https://doi.org/10.1007/s10639-020-10331-z>
- Alakrash, H. M., & Abdul Razak, N. (2021). Technology-based language learning: Investigation of digital technology and digital literacy. *Sustainability*, 13(21), 12304. <https://doi.org/10.3390/su132112304>
- Albelbisi, N., & Yusop, F. (2019). Factors influencing learners' self-regulated learning skills in a massive open online course (MOOC) environment. *Turkish Online Journal of Distance Education*, 20(3), 1–16. <https://doi.org/10.17718/tojde.598191>
- Bakar, Y., Aziz, M., Rasit, Z., Hashim, M., & Muhammad, K. (2023). Online learning during COVID-19 pandemic: The mediating role of self-efficacy in the relationship between digital literacy and academic performance. *International Journal of Learning and Development*, 13(2), 89. <https://doi.org/10.5296/ijld.v13i2.20933>
- Bakir, R., & Alsaadani, S. (2022). A mixed methods study of architectural education during the initial COVID-19 lockdown: Student experiences in design studio and technology courses. *Open House International*, 47(2), 338–360. <https://doi.org/10.1108/ohi-09-2021-0206>
- Barba, K. G. A. M. (2016). The role of students' motivation and participation in predicting performance in a MOOC. *Journal of Computer Assisted Learning*, 32(3), 218–231. <https://doi.org/10.1111/jcal.12130>
- Bognar, M., Gyurkovics, M., Aczel, B., & van Steenberg, H. (2024). The curve of control: Nonmonotonic effects of task difficulty on cognitive control. *Journal of Experimental Psychology: General*, 153(12), 3130–3142. <https://doi.org/10.1037/xge0001637>
- Budiarto, F., & Jazuli, A. (2021). Interactive learning multimedia improving learning motivation elementary school students. In *Proceedings of the 1st International Conference on Social Sciences, ICONESS*, 19 July 2021, Purwokerto, Central Java, Indonesia. EAI. <https://doi.org/10.4108/eai.19-7-2021.2312497>



- Bui, T., Zackula, R., Dugan, K., & Ablah, E. (2021). Workplace stress and productivity: A cross-sectional study. *Kansas Journal of Medicine*, 14. <https://doi.org/10.17161/kjm.vol1413424>
- Cheng, Y., & Yeh, H. (2009). From concepts of motivation to its application in instructional design: Reconsidering motivation from an instructional design perspective. *British Journal of Educational Technology*, 40(4), 597–605. <https://doi.org/10.1111/j.1467-8535.2008.00857.x>
- Cicchinelli, V., Ponce, H., Ayala, C., Parada, H. A., Schenke, K., Valdiviezo-Díaz, P., & Burgos, D. (2018). Finding traces of self-regulated learning in activity streams. *International Journal of Educational Technology in Higher Education*, 15, 21. <https://doi.org/10.1186/s41239-018-0101-x>
- Clément, R., Dörnyei, Z., & Noels, K. A. (1994). Motivation, self-confidence, and group cohesion in the foreign language classroom. *Language Learning*, 44(3), 417–448. <https://doi.org/10.1111/j.1467-1770.1994.tb01113.x>
- Cook, D., & Artino, A. (2016). Motivation to learn: An overview of contemporary theories. *Medical Education*, 50(10), 997–1014. <https://doi.org/10.1111/medu.13074>
- Cortright, R. N., Lujan, H. L., Blumberg, A. J., Cox, J. H., & DiCarlo, S. E. (2013). Higher levels of intrinsic motivation are related to higher levels of class performance for male but not female students. *Advances in Physiology Education*, 37(3), 227–232. <https://doi.org/10.1152/advan.00018.2013>
- Effendi, D., & Multahada, E. (2017). Influence of intrinsic and extrinsic learning motivation in college students on choice of majors at state universities. *Jurnal Pendidikan Humaniora*, 5(1), 15–20. <https://doi.org/10.17977/um030v5i12017p015>
- Elesio, J. (2023). The influence of self-regulated learning strategies towards academic performance of college students. *East Asian Journal of Multidisciplinary Research*, 2(2), 823–838. <https://doi.org/10.55927/eajmr.v2i2.3029>
- Fleischmann, K. (2022). A paradigm shift in studio pedagogy during pandemic times: An international perspective on challenges and opportunities teaching design online. *Journal of Design, Business & Society*, 8(2), 247–272. https://doi.org/10.1386/dbs_00042_1
- Gizeh, J. M. D. (2023). Moving learning: A systematic review of mobile learning applications for online higher education. *Journal of New Approaches in Educational Research*, 12(2), 198–224. <https://doi.org/10.7821/naer.2023.7.1147>
- Gong, X., Kannan, S., & Ramakrishnan, K. (2023). Impact of mobile technology on collaborative learning in engineering studies. *European Journal of Educational Research*, 12(1), 397–406. <https://doi.org/10.12973/eu-jer.12.1.397>
- Gunawan, I. (2017). The application of instructional management-based lesson study and its impact on student learning achievement. *Malaysian Journal of Learning and Instruction*, 14(2), 45–60. <https://doi.org/10.2991/coema-17.2017.2>
- Hackshaw, A. (2014). Cross-sectional studies. In *A concise guide to observational studies in healthcare* (pp. 82–107). Wiley. <https://doi.org/10.1002/9781118527122.ch5>
- Hafizah, N., & Zairul, M. (2023). Examining technology adoption trends in studio-based learning. *International Journal of Academic Research in Business and Social Sciences*, 13(8), 573–595. <https://doi.org/10.6007/ijarbss/v13-i8/18084>



- Hagger, M., Chatzisarantis, N., Barkoukis, V., Wang, J., & Baranowski, J. (2005). Perceived autonomy support in physical education and leisure-time physical activity: A cross-cultural evaluation of the trans-contextual model. *Journal of Educational Psychology*, 97(3), 376–390. <https://doi.org/10.1037/0022-0663.97.3.376>
- Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107–123. <https://doi.org/10.1504/IJMDA.2017.087624>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Haritha, D., Manne, S., & Kavitha, D. (2024). Outcome based curriculum development for studio courses: Data mining an example course. *Journal of Engineering Education Transformations*, 37(IS2), 634–641. <https://doi.org/10.16920/jeet/2024/v37is2/24098>
- Herpratiwi, T. A. (2022). Learning interest and discipline on learning motivation. *International Journal of Education in Mathematics, Science and Technology*, 10(2), 424–435. <https://doi.org/10.46328/ijemst.2277>
- Hodges, N., Watchravesringkan, K., Min, S., Lee, Y., & Seo, S. (2020). Teaching virtual apparel technology through industry collaboration: An assessment of pedagogical process and outcomes. *International Journal of Fashion Design, Technology and Education*, 13(2), 120–130. <https://doi.org/10.1080/17543266.2020.1742388>
- Jones, B. D., Ruff, C., & Snyder, J. D. (2011). Motivation climate predicts situational interest and academic achievement in the active-learning classroom. *Learning and Instruction*, 21(1), 58–67. <https://doi.org/10.1016/j.learninstruc.2009.10.001>
- Jurczyk, V., Fröber, K., & Dreisbach, G. (2019). Increasing reward prospect motivates switching to the more difficult task. *Motivation Science*, 5(4), 295–313. <https://doi.org/10.1037/mot0000119>
- Kim, H. Y. (2013). Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry & Endodontics*, 38(1), 52–54. <http://dx.doi.org/10.5395/rde.2013.38.1.52>
- Lai, C., Chen, Q., Wang, Y., & Qi, X. (2023). Individual interest, self-regulation, and self-directed language learning with technology beyond the classroom. *British Journal of Educational Technology*, 55(1), 379–397. <https://doi.org/10.1111/bjet.13366>
- Liang, Y. (2022). The relationship between task complexity, task difficulty, and speaking performance: The case of Chinese EFL learners. *Journal of Education and Practice*, 13(20), 72–78. <https://doi.org/10.7176/jep/13-20-08>
- Lilian, A., Ah-Choo, K., & Soon-Hin, H. (2021). Investigating self-regulated learning strategies for digital learning relevancy. *Malaysian Journal of Learning and Instruction*, 18(1), 29–64. <https://doi.org/10.32890/mjli2021.18.1.2>
- Luik, P., Tönisson, E., & Sillaots, M. (2017). What motivates enrolment in programming MOOCs? *British Journal of Educational Technology*, 50(1), 153–165. <https://doi.org/10.1111/bjet.12617>
- Lynch, A.D., Lerner, R.M. & Leventhal, T. (2013). Adolescent Academic Achievement and School Engagement: An Examination of the Role of School-Wide Peer Culture. *J Youth Adolescence*, 42, 6–19. <https://doi.org/10.1007/s10964-012-9833-0>



- McAuley, E., Duncan, T., & Tammen, V. V. (1989). Psychometric Properties of the Intrinsic Motivation Inventory in a Competitive Sport Setting: A Confirmatory Factor Analysis. *Research Quarterly for Exercise and Sport*, 60(1), 48–58. <https://doi.org/10.1080/02701367.1989.10607413>
- Memon, M. A., Ramayah, T., Cheah, J. H., Ting, H., Chuah, F., & Cham, T. H. (2021). PLS-SEM statistical programs: A review. *Journal of Applied Structural Equation Modeling*, 5(1), 1-14. [https://doi.org/10.47263/JASEM.5\(1\)06](https://doi.org/10.47263/JASEM.5(1)06)
- Miatun, A., & Muntazhimah, M. (2018). The effect of discovery learning and problem-based learning on middle school students' self-regulated learning. *Journal of Physics: Conference Series*, 948(1), 012021. <https://doi.org/10.1088/1742-6596/948/1/012021>
- Milligan, C., & Littlejohn, A. (2016). How health professionals regulate their learning in massive open online courses. *The Internet and Higher Education*, 31, 113–121. <https://doi.org/10.1016/j.iheduc.2016.07.005>
- Milligan, C., & Littlejohn, A. (2017). Why study on a MOOC? The motives of students and professionals. *The International Review of Research in Open and Distributed Learning*, 18(2), 92–102. <https://doi.org/10.19173/irrodl.v18i2.3033>
- Moustaka, P., & Tsiatsos, T. (2018). Visual programming tools implementation for educational cultural heritage promotion. *European Journal of Engineering and Technology Research*, 3(10), 646–650. <https://doi.org/10.24018/ejers.2018.3.10.987>
- Nawaz, S., Srivastava, N., Yu, J. H., Khan, A. A., Kennedy, G., Bailey, J., & Baker, R. S. (2022). How difficult is the task for you? Modelling and analysis of students' task difficulty sequences in a simulation-based POE environment. *International Journal of Artificial Intelligence in Education*, 32, 233-262. <https://doi.org/10.1007/s40593-021-00242-6>
- Nurhidayah, N., & Puspitosari, A. (2023). The relationship between spiritual level and elderly leisure participation. *Asian Journal of Healthy and Science*, 2(10), 410–414. <https://doi.org/10.58631/ajhs.v2i10.77>
- Nuutila, K., Tapola, A., Tuominen, H., Molnár, G., & Niemivirta, M. (2021). Mutual relationships between the levels of and changes in interest, self-efficacy, and perceived difficulty during task engagement. *Learning and Individual Differences*, 92, 102090. <https://doi.org/10.1016/j.lindif.2021.102090>
- Owusu-Fordjour, C., Koomson, C. K., & Hanson, D. (2020). The impact of COVID-19 on learning: The perspective of the Ghanaian student. *European Journal of Education Studies*, 7(3), 88–101. <https://doi.org/10.5281/zenodo.3753586>
- Pala, Ş. M., & Başbüyük, A. (2023). The predictive effect of digital literacy, self-control and motivation on the academic achievement in the science, technology and society learning area. *Technology, Knowledge and Learning*, 28(1), 369–385. <https://doi.org/10.1007/s10758-021-09538-x>
- Pavlov, A., Duhon, G., & Dawes, J. (2021). Examining the impact of task difficulty on student engagement and learning rates. *Journal of Behavioral Education*, 32(3), 527–542. <https://doi.org/10.1007/s10864-021-09465-y>
- Perry, B., & Edwards, M. (2019). Innovative arts-based learning approaches adapted for mobile learning. *Open Praxis*, 11(3), 303. <https://doi.org/10.5944/openpraxis.11.3.967>
- Pintrich, P. R. (2000). Issues in self-regulation theory and research. *The Journal of Mind and Behavior*, 21(1/2), 213-219. <https://www.jstor.org/stable/43853917>



- Pogorskiy, A., Kovanis, M., Wang, J., & Renz, K. (2018). Utilising a virtual learning assistant as a measurement and intervention tool for self-regulation in learning. In *Proceedings of the International Conference on Teaching, Assessment, and Learning for Engineering* (pp. 1–5). <https://doi.org/10.1109/TALE.2018.8615327>
- Prasetya, R. (2023). The interplay between self-regulated learning behavioral factors and students' performance in English language learning through Moodle. *ELT Forum: Journal of English Language Teaching*, 12(3), 145–156. <https://doi.org/10.15294/elt.v12i3.66613>
- Puzziferro, M. (2008). Online technologies self-efficacy and self-regulated learning as predictors of final grade and satisfaction in college-level online courses. *The American Journal of Distance Education*, 22(2), 72–89. <https://doi.org/10.1080/08923640802039024>
- Rafi, M., JianMing, Z., & Ahmad, K. (2019). Technology integration for students' information and digital literacy education in academic libraries. *Information Discovery and Delivery*, 47(4), 203–217. <https://doi.org/10.1108/IDD-07-2019-0049>
- Ramsden, P. (1991). A performance indicator of teaching quality in higher education: The course experience questionnaire. *Studies in Higher Education*, 16(2), 129–150. <https://doi.org/10.1080/03075079112331382944>
- Ramsden, P. & Entwistle, N.J. (1981) Effects of Academic Departments on Students' Approaches to Studying. *British Journal of Educational Psychology*, 51(3), 368–383. <https://doi.org/10.1111/j.2044-8279.1981.tb02493.x>
- Rongrong, L., Onen, D. J., Nuwagaba, G., Saeed, H., & Sumbeiywo, F. (2022). Evaluating the effectiveness of online teaching in architecture courses. *Architectural Science Review*, 65(2), 89–100. <https://doi.org/10.1080/00038628.2021.2023869>
- Safdari, S., & Maftoon, P. (2017). The development of motivation research in educational psychology: The transition from early theories to self-related approaches. *Advanced Education*, 7, 95–101. <https://doi.org/10.20535/2410-8286.93906>
- Sarstedt, M., Radomir, L., Moisescu, O. I., & Ringle, C. M. (2022). Latent class analysis in PLS-SEM: A review and recommendations for future applications. *Journal of Business Research*, 138, 398–407. <https://doi.org/10.1016/j.jbusres.2021.08.051>
- Scasserra, D. (2008). *The influence of perceived task difficulty on task performance*. Doctoral dissertation. Retrieved from <https://rdw.rowan.edu/etd/756/>
- Shahrol, S. S. M., Suhaili, S., & Mohd, H. (2020). A systematic literature review on teaching and learning English using mobile technology. *International Journal of Information and Education Technology*, 10(9), 709–714. <https://doi.org/10.18178/ijiet.2020.10.9.1430>
- Solem, R. (2015). Limitation of a cross-sectional study. *American Journal of Orthodontics and Dentofacial Orthopedics*, 148(2), 205. <https://doi.org/10.1016/j.ajodo.2015.05.006>
- Spector, P. (2019). Do not cross me: Optimizing the use of cross-sectional designs. *Journal of Business and Psychology*, 34(2), 125–137. <https://doi.org/10.1007/s10869-018-09613-8>
- Suan, A. (2023). Self-regulation as an antecedent of academic achievement: A mixed method study. *British Journal of Multidisciplinary and Advanced Studies*, 4(4), 20–43. <https://doi.org/10.37745/bjmas.2022.0246>



- Sun, J. C. Y., Oh, Y. J., Seli, H., & Jung, M. (2017). Learning behavior and motivation of at-risk college students: The case of a self-regulatory learning class. *Journal of At-Risk Issues*, 20(2), 12–24.
- Tokan, M. K., & Imakulata, M. M. (2019). The effect of motivation and learning behaviour on student achievement. *South African Journal of Education*, 39(1), 1–8. <https://doi.org/10.15700/saje.v39n1a1510>
- Tolstoukhova, I., Kryucheva, Y., Якобюк, Л., & Kulikova, S. (2019). The use of mobile technology in professional education of students. *Humanities & Social Sciences Reviews*, 7(4), 899–905. <https://doi.org/10.18510/hssr.2019.74120>
- Trautwein, U., Lüdtke, O., Nagy, G., & Lenski, A. (2015). Using individual interest and conscientiousness to predict academic effort: Additive, synergistic, or compensatory effects? *Journal of Personality and Social Psychology*, 109(1), 142–162. <https://doi.org/10.1037/pspp0000034>
- UNESCO. (2020). COVID-19 educational disruption and response. <https://en.unesco.org/covid19/educationresponse>
- Uther, M., & Ylinen, S. (2018). The role of subjective quality judgements in user preferences for mobile learning apps. *Education Sciences*, 9(1), 3. <https://doi.org/10.3390/educsci9010003>
- Vela, D., Mancheno, A., Castelo, E., & Chávez, M. (2024). Theories and applications of school motivation: Exploring the reciprocal relationship with academic achievement in Latin America. *Journal of Ecohumanism*, 3(4), 2274–2281. <https://doi.org/10.62754/joe.v3i4.3752>
- Villarreal-Lozano, R., Morales-Martinez, G., Collantes, Á., & Amador, M. (2022). Cognitive assessment of motivation to perform classroom or online math tasks among engineering students. *International Journal of Evaluation and Research in Education*, 11(4), 1903. <https://doi.org/10.11591/ijere.v11i4.22008>
- Wahyuni, S., Novitasari, Y., Suharni, S., & Reswita, R. (2023). The effect of digital literacy-based learning on student motivation and socialization ability. *Consilium: Berkala Kajian Konseling dan Ilmu Keagamaan*, 9(2), 88. <https://doi.org/10.37064/consilium.v9i2.13454>
- Wang, T., Chen, W., Kang, Y., Lin, C., Cheng, C., Suk, F., ... & Huang, W. (2021). Why do pre-clinical medical students learn ultrasound? Exploring learning motivation through ERG theory. *BMC Medical Education*, 21(1). <https://doi.org/10.1186/s12909-021-02869-4>
- Wolgast, M., Ajdahi, S., Hansson, E., & Wolgast, S. (2021). Status, pride, and educational motivation: Understanding differences in attitudes to education from the perspective of evolutionary emotion theory. *Nordic Psychology*, 74(2), 138–149. <https://doi.org/10.1080/19012276.2021.1939110>
- Wu, M., Fang, F. C., Wu, W., & Geng, W. (2021). Project-based engineering learning in college: Associations with self-efficacy, effort regulation, interest, skills, and performance. *SN Social Sciences*, 1(12), 1–16. <https://doi.org/10.1007/s43545-021-00157-y>
- Wulandari, S., & Trisnawati, A. D. (2024). Digital Literacy in the Early Childhood Islamic Education Space in Purwokerto. In *Annual Conference on Islamic Early Childhood Education (ACIECE)* (Vol. 8, pp. 77-83). <https://conference.uin-suka.ac.id/index.php/aciece/article/view/1533>
- Zheng, Y., & Xiao, A. (2024). A structural equation model of online learning: Investigating self-efficacy, informal digital learning, self-regulated learning, and course satisfaction. *Frontiers in Psychology*, 14, 1276266. <https://doi.org/10.3389/fpsyg.2023.1276266>



Appendix A

Questionnaire for Tertiary Students of Clay Courses in Ghana

This questionnaire aims to explore students' experiences with studio-based clay courses in higher education. There are no right or wrong answers; please answer honestly. Participation is voluntary, and all responses are anonymous. The survey will take approximately 10 minutes.

Section 1: Sociodemographic Information

- Age: _____
- Gender: ☐ Female ☐ Male
- Academic Level: _____
- Institution: _____
- Institutional Index Number: _____
- Cumulative Weighted Average (CWA): _____

Section 2: Questionnaire Items

Please indicate your level of agreement with the following statements using the scale below:

1 = Strongly Disagree 2 = Disagree 3 = No Opinion 4 = Agree 5 = Strongly Agree

Motivation Factors

1. I really like learning studio-based clay courses.
2. Studying clay is necessary to me because it will enable me to produce clay works.
3. Studying clay is significant to me because I would like to make as many works as possible.
4. Studying clay is notable to me because a student is supposed to show what they have learnt.
5. Studying clay is important to me so that I can be a more knowledgeable person.
6. Studying clay is valuable to me so that I can broaden my outlook.
7. Studying clay is necessary to me because I may need it later (for job, studies).
8. Studying clay is useful to me so that I can understand clay terminologies.
9. Studying clay is meaningful to me so that I can produce clay works on my own.
10. Studying clay is important to me because I would like to become an expert.

Digital Literacy Factors

11. I know how to use digital tools to find information.
12. I am competent in using technology to collaborate and share work.
13. Instructors provide digital literacy training at the university.
14. Exposure to digital tools at university encourages continuous learning.
15. Gaps in digital skills arise when clay courses do not include applied learning with technology.

Task Difficulty Factors

16. There is a clearly defined body of knowledge to guide my work.
17. There is an understandable sequence of steps I can follow during my work.
18. I often encounter specific problems I cannot solve immediately.
19. I spend a lot of time trying to solve such specific problems.
20. In some studio practicals, things are predictable; in others, outcomes are uncertain.
21. It takes a long time before I know whether my work effort was successful.



Course Interest Factors

22. The course developed my problem-solving skills.
23. The course improved my logical skills.
24. The course helped me develop teamwork ability.
25. The course made me confident in facing unfamiliar problems.
26. The course improved my written communication skills.
27. The course helped me plan and manage my own work.

Self-Regulatory Learning Factors

28. I choose study locations to avoid distractions.
29. I choose study times with minimal distractions.
30. I take thorough notes in online courses as they are essential for learning.
31. I monitor my own learning development.
32. I seek help from knowledgeable individuals when needed.
33. I do not compromise work quality because it is online.
34. I communicate with classmates to assess my progress.
35. I communicate with classmates to compare learning experiences.
36. When I make mistakes, I adjust my behavior.
37. I plan and organize well to succeed in academic tasks (e.g., group presentations, oral work, research).
38. I summarize what I've learned in online courses to reflect on my understanding.