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Modeling the Impact of Social Media Usage and Interaction with Tutor on Collaborative Learning: The Mediating Role of Self-Efficacy in Distance Learning Environments

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Abstract

This study highlights the significance of acceptance of collaborative learning among students in online flexible distance learning higher education institutions. Collaborative learning is crucial as it enhances student engagement, fosters critical thinking, and improves learning outcomes, making it essential for modern educational frameworks. The study investigated how interactions with tutors and social media usage influence collaborative learning, focusing on learners' self-efficacy as a mediating factor. Purposive sampling was used to carry out the survey. A total of 388 responses were collected and deemed suitable for analysis. Data analysis was performed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) method, which allowed for comprehensive hypothesis testing and evaluation of complex variable relationships. The outcomes of the hypothesis testing demonstrated significance pathways: interactions with tutors and social media usage were both found to affect learners' self-efficacy, significantly enhancing collaborative learning positively. These insights suggest that institutions should strengthen interactions through digital platforms and effective tutor engagement to maximise collaborative learning. The study's implications are significant for educational policymakers and institutions seeking to optimise online learning environments by leveraging technology and fostering interpersonal interactions that build student confidence. Future research should encompass longitudinal studies to examine the sustained effects of these variables on collaborative learning, expanding demographic diversity to enhance the generalizability of the findings, and exploring the influence of emerging technologies, such as virtual reality, in these educational settings. By integrating these elements, future studies can further illuminate the pathways through which technology and human interaction can be harnessed to enhance learning efficacy. This study underscores the transformative potential of collaborative learning in online education and provides a valuable framework for institutions aiming to cultivate a responsive and effective digital learning experience.

Keywords: Interaction with Tutors, Social media Usage, Learners' Self-Efficacy, Collaborative Learning, Online Flexible Distance Learning

Introduction
Collaborative learning in online flexible distance learning higher education institutions has gained critical importance as these institutions expand on a global scale. The significance of collaborative learning within this context is multifaceted. It enhances student engagement and promotes deeper understanding through peer interactions, fostering essential skills such as teamwork, communication, and problem-solving (Taggart & Wheeler, 2023). Collaborative learning environments encourage students to divide tasks among themselves, leading to a comprehensive understanding through reciprocal peer teaching, a method that facilitates equal participation and active learning (Samsa & Goller, 2021). These environments also break down traditional classroom barriers, allowing for multifaceted engagement across diverse student cohorts (Simanungkalit et al., 2023). Globally, trends in online collaborative learning highlight the integration of technology to facilitate group interactions and the use of digital tools to optimise learning outcomes (Yu et al., 2023). Institutions are increasingly adopting platforms and tools that support synchronous and asynchronous communication, enabling students to collaborate across distances and time zones (Kebah et al., 2019).

Problem Statement & Research Objectives
However, challenges persist, particularly in organising groups to maximise learning benefits. Creating balanced groups capitalising on diverse student strengths and backgrounds is essential but remains a critical issue (Revelo et al., 2021). Research gaps in this field are evident, particularly the need for expansive studies that explore the specific dynamics of group interactions in various cultural and institutional contexts (Kebah et al., 2019). While research has highlighted the pivotal role of collaborative learning in engaging students at rural universities (Adebola, 2022), there is limited exploration of its application in other unique settings, such as large undergraduate classes, which present distinct challenges related to scale and logistics (Frey & Lewis, 2023). Furthermore, additional research is necessary to develop instructional strategies that accommodate a global student body's diverse needs and preferences, reflecting variations in learning styles and expectations (Yang, 2023). Advancing research in collaborative learning holds profound significance for policymakers, educational institutions, and students. Policymakers can leverage insights from this research to inform educational frameworks that support effective collaborative learning strategies, promoting equitable access and engagement. For online higher education institutions, findings can inform curriculum design and teaching methods that fully harness the potential of collaborative learning, leading to improved educational outcomes and heightened student satisfaction (Abulhassan & Hamid, 2021). For students, the emphasis on collaborative learning promises more engaging and effective learning experiences, preparing them more comprehensively for collaborative work environments post-graduation and equipping them with skills vital for today's globalised workforce (Davidson, 2021). This study examines the direct and indirect relationship between social media usage and interaction with tutors with collaborative learning and learners' self-efficacy as a mediator among students in online flexible distance learning higher education institutions.

Literature Review
Underpinning Theory
Albert Bandura formulated Social Cognitive Theory, offering an extensive framework for comprehending the interaction between personal environmental influences and behavioral on learning and development (Bandura, 1986). This theory is particularly relevant for

examining the influence of social media and tutor interaction on collaborative learning, with learner self-efficacy as a mediator in online distance education. An individual's self-efficacy, defined as their belief in their capacity to succeed in particular circumstances, is an essential component of Social Cognitive Theory (Bandura, 1997). In online distance education, self-efficacy plays a vital role in determining how students engage with learning activities, interact with peers, and respond to instructional support from tutors. Bandura contends that individuals with high self-efficacy are more inclined to confront challenges and persevere in overcoming obstacles, which can significantly enhance collaborative learning experiences. Social media platforms facilitate observational learning and modeling, critical components of Social Cognitive Theory, by enabling students to observe and emulate successful behaviours exhibited by peers and tutors. These interactions can boost self-efficacy by providing opportunities for feedback, reinforcement, and social support (Sung & Yang, 2018).

Similarly, tutor interactions contribute to cognitive and emotional engagement by offering guidance, encouragement, and validation, further strengthening students' belief in their learning capabilities. According to Social Cognitive Theory, integrating social media and tutor interaction in online education can foster a dynamic learning environment in which self-efficacy mediates and enhances collaborative learning processes. This perspective helps elucidate how digital interactions and perceived competence contribute to effective learning outcomes in modern educational contexts.

Relationship between Interaction with Tutors, Learners' Self-Efficacy & Collaborative Learning
Learners ' self-efficacy significantly influences interaction with tutors and collaborative learning, an essential mediator. Tutor interactions offer guidance, feedback, and encouragement, creating an environment that promotes collaborative learning (Intaratat et al., 2024). These interactions provide academic support and bolster students' confidence in their abilities, which is crucial for successful collaboration. Learners with high self-efficacy, or the belief in their capability to execute tasks successfully, tend to engage more actively in collaborative learning settings (Li et al., 2020). This involvement is often a result of their increased confidence derived from supportive tutor interactions (Zhao & Qin, 2021). Self-efficacy empowers learners to take initiative and contribute meaningfully to group activities, thus enhancing the overall effectiveness of collaborative learning.

Moreover, self-efficacy is a bridge linking tutor support to deeper learning engagement, as students who feel capable are more likely to participate and persist in challenging tasks (Liu, Du, & Lu, 2023). This mediating role is critical, as it transforms the potential of tutor interactions into actualised collaborative learning experiences. Such dynamics underscore how educational frameworks that emphasise tutor support and learner self-efficacy can catalyse collaborative learning (Pan, 2023). Additionally, fostering a collaborative environment through tutor interactions benefits individual learners and supports collective educational goals (Osman et al., 2018). When tutors facilitate a supportive and interactive atmosphere, learners perceive heightened autonomy and engagement, leading to improved collaborative outcomes (Pan, 2022). Therefore, leveraging tutor interactions to enhance self-efficacy can significantly optimise collaborative learning strategies in educational settings. Therefore, the following hypotheses were proposed for this study:

H1: There is a relationship between interaction with tutors and collaborative learning among students in online flexible distance learning higher education institutions.
H2: There is a relationship between interaction with tutors and learners' self-efficacy among students in online flexible distance learning higher education institutions.
H3: There is a mediating effect of learners' self-efficacy on the relationship between interaction with tutors and collaborative learning among students in online flexible distance learning higher education institutions.

Relationship between Social Media Usage, Learners' Self-Efficacy, Collaborative Learning
Learners' self-efficacy significantly mediates the relationship between social media usage and collaborative learning. Social media platforms facilitate informal learning environments where students can easily connect, share resources, and collaborate on academic tasks (Almogren, 2023). This digital connectivity fosters community and active participation, which is crucial for effective collaborative learning. Self-efficacy plays a critical mediating role by influencing students' confidence in their ability to engage and succeed in collaborative tasks. Learners who believe in their capabilities are likelier to engage in social media-enhanced learning activities, enriching the collaborative learning experience (Bailey & Rakushin-Lee, 2021). Students who actively use social media for educational purposes often exhibit higher levels of self-efficacy, leading to increased engagement and participation in collaborative endeavours (Rfeqallah, 2023).

Additionally, social media platforms contribute to a heightened sense of social presence, enhancing learners' ability to engage deeply with collaborative tasks (Wu, 2023). This environment supports self-efficacy by providing immediate feedback and social reinforcement opportunities essential for developing collaborative skills. Furthermore, the multitasking capabilities typically associated with social media usage allow students to engage in various learning activities simultaneously, bolstering self-efficacy and academic performance (Mohammed et al., 2021). Ultimately, as learners navigate social media spaces, their self-efficacy influences how effectively they can leverage these platforms for collaborative learning, thus reinforcing the pivotal role of social media usage in modern educational settings. Therefore, the following hypotheses were proposed for this study:

H4: There is a relationship between social media usage and collaborative learning among students in online flexible distance learning higher education institutions.
H5: There is a relationship between social media usage and learners' self-efficacy among students in online flexible distance learning higher education institutions.
H6: There is a relationship between learners' self-efficacy and collaborative learning among students in online flexible distance learning higher education institutions.
H7: There is a mediating effect of learners' self-efficacy on the relationship between social media usage and collaborative learning among students in online flexible distance learning higher education institutions.

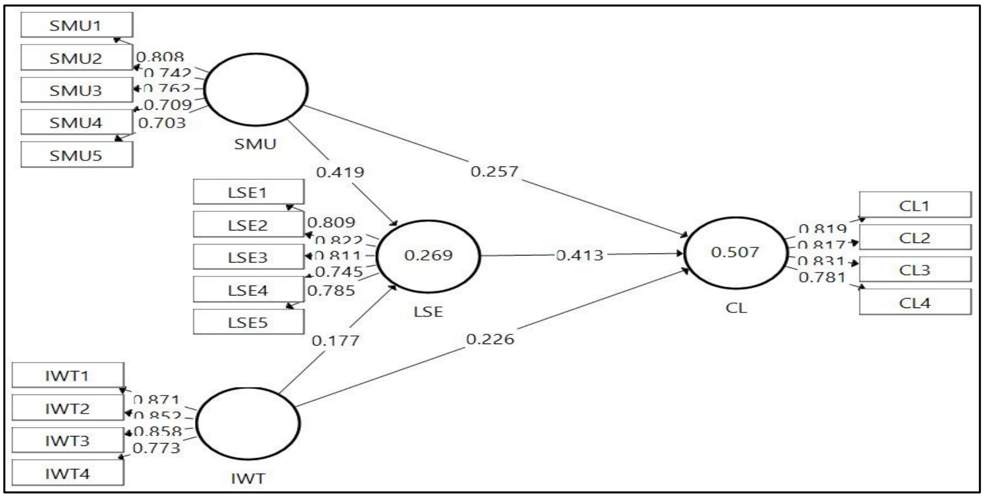

Figure 1: Research Framework

Notes: SMU=Social media Usage; IWT=Interaction with Tutors; LSE=Learning Self-Efficacy; CL=Collaborative Learning

Methodology

This study discovered the direct and indirect influences of peer interaction and social presence on collaborative learning within online flexible distance education at higher education institutions, with learners' self-efficacy as a mediating factor. Researchers collected primary data using validated and reliable measures identified through a comprehensive literature review to achieve this. The survey questionnaires, crafted based on purposive sampling due to the lack of a complete list of the population, were distributed via email to selected participants. The analysis included 18 observed variables. Among these were independent variables such as interaction with tutors (4 items) (Abrantes et al., 2007) and social media usage (5 items) (Sarwar et al., 2019), the mediating variable of learners' self-efficacy (5 items) (Kang et al., 2019), and the dependent variable of collaborative learning (4 items) (Al-Rahmi & Othman, 2013). Participants rated these variables using a five-point Likert scale, providing a detailed dataset. Out of 507 surveys distributed, 412 were returned, yielding a response rate of 81.2%, which is adequate for structural equation modeling (SEM) analysis. A total of 388 responses were considered suitable for analysis. Smartpls4 software was employed for this analysis due to its strength in handling SEM techniques, as Ringle et al. (2022) recommended. This software facilitated rigorous hypothesis testing and multivariate data analysis, enabling an in-depth examination of the measurement and structural models.

Data Analysis

Respondents Profile

The respondent profile for this study reveals a balanced gender distribution, with female respondents slightly outnumbering their male counterparts at 51.3% (199 individuals) compared to 48.7% (189 individuals). This near-equal representation provides a robust foundation for capturing perspectives across genders. Regarding age distribution, the largest group comprises those aged 31-40, representing 44.6% (173 respondents), indicating active participation from mid-career or mature students. This is followed by individuals under 30, comprising 39.7% (154 respondents), highlighting significant engagement from younger learners. Participants aged 41-50 and 51-60 make up 12.4% (48 individuals) and 3.4% (13 individuals), respectively, suggesting lesser involvement from older age brackets, possibly due to completion commitments or other life responsibilities. Examining the year of study, Year 3 students account for the highest frequency at 24.7% (96 participants), suggesting these students possess valuable insights into the learning system. Year 2 and Year 1 students contribute substantially, with 20.9% (81 participants) and 18.6% (72 participants), respectively, indicating robust participation from early-stage learners. Conversely, the percentage decreases as students approach the final years, with Year 4 at 16.2% (63), Year 5 at 11.6% (45), and Year 6 at 8.0% (31), possibly reflecting graduation trends. Regarding academic programs, the data is dominated by Diploma students, who constitute 65.7% (255 respondents) of the sample, illustrating a strong preference or institutional offering for this qualification. Certificate programs engage 21.4% (83 participants), while Bachelor's, Master's, and Doctorate programs represent smaller portions at 7.0% (27), 4.9% (19), and 1.0% (4), respectively, indicating diverse but limited engagement in higher degrees. Remarkably, when considering the likelihood of recommending collaborative learning to peers, 99.2% (385 participants) of respondents affirm they would recommend it, reflecting overwhelming satisfaction or positive perceptions. Only a minimal 0.8% (3 respondents) would not recommend it, pointing to rare cases of dissatisfaction.

Common Method Bias

In assessing common method bias using the full collinearity test as recommended by Kock (2015) and Kock & Lynn (2012), we observe the variance inflation factor (VIF) values across the constructs of collaborative learning, social media usage, interaction with tutors, and learner self-efficacy. All VIF values presented in Table 1 are lower than the recommended threshold of 3.3, indicating that common method bias is unlikely to compromise the results of this study. Specifically, VIF values for collaborative learning as a dependent variable are 1.837 and 1.847 for influences from social media usage and interaction with tutors, respectively. Similarly, social media usage and interaction with tutors show VIF values ranging from 1.256 to 1.499 against other constructs, confirming the absence of significant multicollinearity. This suggests robust and reliable measurements for the constructs in question, ensuring that the examined relationships are not artefacts of measurement bias.

Table 1
Full Collinearity Test

	CL	SMU	IWT	LSE
CL		1.837	1.847	1.592
SMU	1.439		1.499	1.493
IWT	1.256	1.302		1.356
LSE	1.353	1.621	1.695	

Measurement Model

The study utilised the measurement evaluation approach Hair et al. (2017) suggested, conducting first- and second-order assessments to pinpoint items with loadings lower than 0.7. An evaluation of construct reliability and validity revealed that all constructs' Average Variance Extracted (AVE) values surpassed the 0.5 benchmark, ranging from 0.556 to 0.705, affirming convergent validity (Hair et al., 2017). Additionally, composite reliability scores for all constructs were above 0.7, ranging between 0.801 and 0.862, and Cronbach's alpha values also exceeded 0.7, ranging from 0.800 to 0.860 (see Table 2). Cross-loadings were initially examined to verify discriminant validity and ensure an accurate representation of the constructs (see Table 3). Following this, the Heterotrait-Monotrait (HTMT) ratio was applied, in line with the recommendations of Henseler, Ringle, and Sarstedt (2015), to further assess discriminant validity within the Variance-Based Structural Equation Modeling (VB-SEM). The HTMT ratios for the constructs were all below the 0.85 threshold, as shown in Table 4, confirming satisfactory discriminant validity.

Table 2
Construct Reliability & Validity

	CA	CR	AVE
CL	0.828(0.795, 0.857)	0.832(0.797, 0.859)	0.660(0.619, 0.699)
IWT	0.860(0.831, 0.886)	0.862(0.825, 0.885)	0.705(0.666, 0.746)
LSE	0.854(0.824, 0.879)	0.858(0.826, 0.881)	0.632(0.587, 0.675)
SMU	0.800(0.758, 0.832)	0.801(0.755, 0.832)	0.556(0.509, 0.599)

Notes: 95% Confidence Interval Bootstrapping; CA=Cronbach Alpha; CR=Composite Reliability; AVE=Average Variance Extracted

Table 3
Cross Loadings

	CL	IWT	LSE	SMU
CL1	**0.819**	0.413	0.549	0.535
CL2	**0.817**	0.392	0.464	0.411
CL3	**0.831**	0.393	0.499	0.454
CL4	**0.781**	0.356	0.494	0.390
IWT1	0.456	**0.871**	0.285	0.405
IWT2	0.400	**0.852**	0.268	0.347
IWT3	0.356	**0.858**	0.282	0.303
IWT4	0.388	**0.773**	0.344	0.343
LSE1	0.556	0.313	**0.809**	0.452
LSE2	0.494	0.253	**0.822**	0.403
LSE3	0.465	0.283	**0.811**	0.357
LSE4	0.477	0.266	**0.745**	0.337
LSE5	0.459	0.283	**0.785**	0.398
SMU1	0.404	0.303	0.376	**0.808**
SMU2	0.416	0.278	0.374	**0.742**
SMU3	0.349	0.317	0.330	**0.762**
SMU4	0.480	0.325	0.409	**0.709**
SMU5	0.397	0.339	0.331	**0.703**

Table 4
Hetrotrait-Monotrait (HTMT) Ratios

	CL	IWT	LSE
IWT	0.563(O.451, 0.662)		
LSE	0.730(0.649, 0.803)	0.409(0.287, 0.519)	
SMU	0.669(0.580, 0.753)	0.502(0.386, 0.610)	0.587(0.488, 0.681)

Notes: 95% Confidence Interval Bootstrapping

Structural Model

This study's evaluation of the structural model followed the methodology established by Hair et al. (2017), focusing on a detailed examination of pathway coefficients (β) and the coefficients of determination (R^2). The study employed the Partial Least Squares (PLS) method, using 5,000 sub-samples to evaluate the significance of the path coefficients. Table 5 provides a comprehensive account of the hypothesis testing results, including confidence intervals for the path coefficients (beta), t-statistics, and p-values. This meticulous approach sheds light on the strength and significance of the relationships between variables in the structural model. Table 5 reviews each hypothesis concerning the beta coefficients, T-statistics, P-values, and the support or lack thereof for each hypothesis. This methodology enhances the study's findings, offering a refined and detailed understanding of the variable interactions examined.

Table 5 strongly supports all seven hypotheses tested in this study, reflecting significant relationships among the examined variables. For *Hypothesis 1*, which posits that interaction with tutors influences collaborative learning, the beta value of 0.226 coupled with a t-statistic of 4.816 and a p-value of 0.000 demonstrate a significant positive effect, leading to its acceptance. This indicates that students who frequently interact with tutors are more likely to engage collaboratively with peers. Hypothesis 2 explores the link between interaction with tutors and learning self-efficacy, showing a beta of 0.177, a t-statistic of 3.506, and a p-value of 0.000, confirming its acceptance. This suggests that tutor interactions significantly boost students' confidence in their learning abilities.

Further, *Hypothesis 3* examines the mediating role of learning self-efficacy between interaction with tutors and collaborative learning. With a beta of 0.073, a t-statistic of 3.242, and a p-value of 0.001, the hypothesis is accepted, highlighting that learning self-efficacy partly mediates this relationship, enhancing collaborative learning outcomes. For *Hypothesis 4*, concerning the influence of social media usage on cooperative learning, a beta of 0.257, a t-statistic of 5.069, and a p-value of 0.000 confirm a significant positive effect, validating the hypothesis. This illustrates that students engaging with social media are more inclined towards collaborative learning scenarios.

Hypothesis 5, which states that social media usage enhances learning self-efficacy, is strongly supported by a beta of 0.419, an outstanding t-statistic of 9.350, and a p-value of 0.000, representing a robust influence. *Hypothesis 6* highlights the direct impact of learning self-efficacy on collaborative learning, reflected by a beta of 0.413, a t-statistic of 9.016, and a p-value of 0.000, further validating its acceptance. This underscores the crucial role of self-efficacy in promoting collaborative learning among students.

Lastly, *Hypothesis 7* demonstrates the mediating effect of learning self-efficacy in the relationship between social media usage and collaborative learning, with a beta of 0.173, a t-statistic of 6.502, and a p-value of 0.000 supporting its acceptance. This suggests that enhanced self-efficacy gained from social media usage significantly contributes to students' collaborative learning. Overall, these findings affirm the integral role of tutor interactions, social media usage, and self-efficacy in fostering collaborative learning in educational settings.

Table 5
Hypotheses Testing Results

Hypotheses	Beta	T-Statistics	P-Values	2.50%	97.50%	Decision
H1: IWT -> CL	0.226	4.816	0.000	0.123	0.310	*Accepted*
H2: IWT -> LSE	0.177	3.506	0.000	0.077	0.276	*Accepted*
H3: IWT -> LSE -> CL	0.073	3.242	0.001	0.032	0.120	*Accepted*
H4: SMU -> CL	0.257	5.069	0.000	0.162	0.360	*Accepted*
H5: SMU -> LSE	0.419	9.350	0.000	0.327	0.503	*Accepted*
H6: LSE -> CL	0.413	9.016	0.000	0.321	0.501	*Accepted*
H7: SMU -> LSE -> CL	0.173	6.502	0.000	0.124	0.230	*Accepted*

Effect Sizes (f^2) & Variance Inflation Factor (VIF)

Table 6 presents a comprehensive analysis of effect sizes (f^2) following Cohen's (1992) criteria, which classify them as small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 and above). In this study, the effect sizes span from small (0.035) to medium (0.253), highlighting the varying impacts of the examined variables. Moreover, the Variance Inflation Factor (VIF) values, also shown in Table 6, are significantly below the conservative threshold of 5, with the highest value recorded at 1.454, indicating negligible concerns regarding collinearity. This affirms that the structural model's interpretation of effect sizes and coefficients is reliable. The endogenous construct demonstrates a considerable explained variance, with an R^2 value of 0.507, as depicted in Figure 1. Regarding the mediator, the model elucidates approximately 26.9% of its variance, evidenced by an R^2 value of 0.269. This emphasises the model's efficacy in capturing mediation effects and accurately representing the underlying processes.

Table 6
Effect Sizes (f^2) & Variance Inflation Factor (VIF)

	f2		VIF	
	CL	LSE	CL	LSE
IWT	0.082	0.035	1.257	1.214
LSE	0.253		1.368	
SMU	0.092	0.198	1.454	1.214

PLSpredicts & Cross-Validated Predictive Ability Test (CVPAT)

The model's inferences and managerial implications were rigorously assessed using out-of-sample predictive analysis via the PLSpredict approach, as suggested by Shmueli et al. (2016, 2019). According to Table 7, the application of PLS-SEM produced significantly better Q^2 predictions (>0) than naive mean predictions, consistently displaying lower Root Mean Square Error (RMSE) values in comparison to linear model (LM) benchmarks. This underscores the robust predictive capabilities of the model. Specifically, PLS-SEM predictions exceeded those of the LM prediction benchmark in seven cases, as detailed in Table 7, demonstrating the model's strong predictive power. The adoption of the Cross-Validated Predictive Ability Test (CVPAT) by Hair et al. (2022), in conjunction with its integration into PLSpredict analysis by Liengaard et al. (2021), has significantly advanced predictive modeling techniques. Furthermore, as shown in Table 8, the PLS-SEM approach offers superior predictive performance, indicated by lower average loss values than indicator averages and LM benchmarks, providing persuasive evidence of its enhanced predictive capabilities.

Table 7
PLSpredicts

	PLS-RMSE	LM-RMSE	PLS-LM	Q^2_predict
CL1	0.627	0.630	-0.003	0.316
CL2	0.624	0.626	-0.002	0.216
CL3	0.684	0.697	-0.013	0.246
CL4	0.714	0.711	0.003	0.187
LSE1	0.620	0.622	-0.002	0.212
LSE2	0.630	0.638	-0.008	0.160
LSE3	0.678	0.675	0.003	0.138
LSE4	0.693	0.700	-0.007	0.123
LSE5	0.624	0.633	-0.009	0.166

Table 8
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-value	p-value
CL	-0.130	6.110	0.000
LSE	-0.076	4.518	0.000
Overall	-0.100	6.195	0.000

Importance-Performance Map Analysis (IPMA)

The Importance-Performance Map Analysis (IPMA), as recommended by Ringle and Sarstedt (2016) and Hair et al. (2018), provides insightful guidance on enhancing educational outcomes by focusing on the importance and performance of contributing constructs. In this analysis, "Social Media Usage" shows the highest importance (0.430) and good performance (67.430), while "Learners' Self-Efficacy" also holds significant significance (0.413) but the lowest performance (60.765). Given its critical role, boosting learners' self-efficacy is imperative for improving collaborative learning. Strategies might include offering personalised feedback to enhance confidence, implementing goal-setting with progress tracking to bolster a sense of achievement, and nurturing a supportive learning environment through peer mentoring and forums. Additionally, resources on self-regulation skills could empower students to manage their learning effectively. Enhancing these areas can substantially uplift self-efficacy, thus amplifying its impact on collaborative learning outcomes, ultimately fostering a more engaging and effective online educational experience.

Table 9
Importance-Performance Map Analysis

Constructs	Total Effect	Performance
IWT	0.299	66.670
LSE	0.413	60.765
SMU	0.430	67.430

Discussions

To effectively enhance interaction with tutors and the use of social media for improving collaborative learning outcomes in online flexible distance learning environments, higher education institutions need to adopt a set of strategic interventions that underscore the role of self-efficacy as a mediator. According to the data analysis, interaction with tutors significantly impacts learning self-efficacy, with a beta value of 0.177. At the same time, social media usage shows a robust influence with a beta of 0.419, both of which contribute to improved collaborative learning marked by a beta of 0.413. These statistics suggest that by enhancing self-efficacy, educational institutions can substantially boost students' collaborative learning experiences (Liu, Du, & Lu, 2023). A primary strategy is to strengthen tutor-student interaction through structured engagement frameworks. Institutions should consider training tutors to facilitate active, interactive sessions that encourage student participation and provide timely feedback, which supports self-efficacy development (Intaratat et al., 2024). Employing technologies such as virtual office hours, chat functions, and interactive webinars can help maintain open communication channels and foster a supportive learning atmosphere.

Additionally, as social media wields significant potential to enhance collaborative learning, institutions must effectively integrate these platforms into their learning ecosystems. Creating official social media study groups where students exchange ideas and resources can cultivate a vibrant learning community, promoting continuous engagement beyond the traditional classroom. This aligns with the beta value of 0.257 for the influence of social media usage on collaborative learning, emphasising its pivotal role (Wu, 2023). Further boosting the mediation effect of self-efficacy can involve peer-assisted learning programs where more experienced students serve as mentors, aiding others in navigating course material and developing stronger competencies. This approach fosters peer collaboration and reinforces the students' belief in their academic capabilities (Bailey & Rakushin-Lee, 2021). Workshops focused on developing self-regulation strategies and effective time management are essential, as they empower learners to take charge of their educational progress and enhance their self-efficacy in parallel (Pan, 2022). Through these initiatives, online flexible distance learning institutions can create a holistic educational model that prioritises academic achievement and instils confidence and collaborative skills for student success in a digital learning environment. By leveraging these strategies, institutions can redefine student interactions and social engagement into a powerful catalyst for superior collaborative learning outcomes.

Suggestions for Future Study

Future research should explore the long-term impacts of enhanced self-efficacy through tutor interactions and social media usage on collaborative learning outcomes in online flexible distance education. A longitudinal study design could provide insights into how sustained involvement in these interactive environments influences students' academic and professional trajectories. Additionally, expanding the demographic scope beyond current populations to include diverse age groups, cultural backgrounds, and educational settings could validate the generalizability of the findings. Investigating the specific social media interactions that most effectively contribute to self-efficacy and collaborative learning would offer more nuanced guidance for educational strategies. Additionally, new technology like virtual and augmented reality could be studied in future research to enhance interactive learning experiences, thereby extending the application of Social Cognitive Theory in digital learning contexts. Finally, comparing the effectiveness of tutor-led versus peer-led interventions in boosting self-efficacy could provide valuable insights into optimising collaborative learning strategies across various educational platforms, thus enriching the pedagogical approaches in online education systems.

Conclusions

This study underscores the significant role of self-efficacy as a mediator in enhancing collaborative learning through interactions with tutors and the use of social media within online flexible distance learning environments. The results demonstrate that tutor engagement and social media integration are vital components that boost students' self-belief in their learning capabilities, positively impacting their collaborative learning experiences. By leveraging these tools, educational institutions can establish a more vibrant and encouraging classroom atmosphere that promotes involvement, increases student involvement, encourages active participation, and deepens student engagement. These findings highlight the importance of adopting strategic measures incorporating human interaction and technological advancements to foster a holistic educational experience. This method improves students' learning abilities and provides them with essential skills to succeed in a progressively digital and interconnected environment. Future research should explore these interactions' sustained effects and expand the study's demographic and technological scope, providing a broader understanding of effective online learning mechanisms.

Implications

The theoretical implications of this study are deeply rooted in the framework of Social Cognitive Theory, as proposed by Albert Bandura (Bandura, 1986), which provides a detailed explanation of the interplay between self-efficacy, student interactions and learning outcomes in online flexible distance education. This theory highlights how personal belief systems, such as self-efficacy, mediate the relationship between environmental influences like social media interactions and tutor engagement on students' collaborative learning processes (Zhao & Qin, 2021; Liu, Du, & Lu, 2023). The empirical findings align with this theory by demonstrating significant beta values where social media usage and tutor interactions enhance learner self-efficacy, improving collaborative learning. The significant pathway coefficients underscore the mediating role of self-efficacy in transforming technological and interpersonal interactions into effective collaborative learning experiences (Intaratat et al., 2024; Wu, 2023). This suggests that when students are confident in their abilities, they engage more deeply, thus maximising the educational potential of digital and interactive platforms.
Furthermore, the study expands on Social Cognitive Theory by incorporating the technological dimension of social media (Bailey & Rakushin-Lee, 2021), offering new insights into how digital environments can be structured to bolster student efficacy and collaborative engagement. This integration supports the proposed research model and provides a theoretical bridge that connects traditional educational paradigms with modern digital learning practices, highlighting the multifaceted impacts of self-efficacy as a mediator in educational settings (Pan, 2022). Through these implications, the study reinforces the applicability and adaptability of Social Cognitive Theory in understanding complex educational dynamics in the digital age.

The practical implications of this study emphasise the strategic role of self-efficacy in enhancing collaborative learning through improved interactions with tutors and the integration of social media in online flexible distance learning environments. By recognising the significant influences where tutor interactions and social media usage markedly enhance self-efficacy (Bailey & Rakushin-Lee, 2021; Intaratat et al., 2024), educational institutions can implement targeted initiatives to boost learners' confidence and collaborative skills. Tutors should be trained to provide regular, structured feedback and foster an engaging learning atmosphere, strengthening students' self-belief and willingness to participate actively in learning activities (Zhao & Qin, 2021). Moreover, leveraging social media platforms can create collaborative spaces where students interact, share resources, and learn from peers in a supportive community. This study underscores the need for institutions to integrate technology-driven learning approaches that align with Social Cognitive Theory principles, thereby enhancing educational outcomes in digital settings. By adopting these strategies, institutions enhance their programs' efficacy and prepare students more effectively for dynamic, collaborative work environments. These efforts ultimately support the development of more robust, interactive, and successful online learning models.

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