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Peer and tutor interaction effects on collaborative learning: The role of learning self-efficacy

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Abstract: This study delves into the intricate relationships among individual work performance, learning self-efficacy, and collaborative learning within the context of online distance learning in higher education institutions. Quantitative research methodology, focusing on students enrolled in online distance-learning programs at higher education institutions in Thailand. Data was primarily collected through a survey questionnaire, using established measurement instruments to assess key constructs includes 16 variables from 223 samples. The Structural Equation Modeling (SEM) was employed to examine complex relationships between variables then analysed by the Smart-PLS 4 software. Findings reveal significant positive associations, supported by robust statistical evidence and effect size analyses. The study contributes to theoretical frameworks by emphasizing the sequential impact of individual work factors on collaborative learning, mediated by learning self-efficacy. Practical implications are evident for educators, administrators, and instructional designers, highlighting the importance of fostering a sense of community, leveraging technology, and building students' self-efficacy beliefs. For future research, including longitudinal studies and investigations into contextual influences. Overall, this study enhances our understanding of the dynamics in online education, offering valuable insights with implications for both theory and practice in the evolving landscape of virtual higher education.
Keywords: *Collaborative learning, Learning self-efficacy, ODL (Open distance learning, Peer, Tutor learning pedagogy,*

1. Introduction

Collaborative learning in the global context signifies a transformative approach to education, reflecting the interconnected nature of today's society (Qureshi et al., 2023). Collaborative learning becomes a cornerstone for fostering cross-cultural understanding and innovation in a world marked by diverse cultures, perspectives, and technological advancements (Haataja et al., 2022). This pedagogical paradigm encourages students to actively engage with peers, transcending geographical boundaries through virtual collaboration (Yang, 2023). By embracing collaborative learning on a global scale, educational institutions can prepare students for the complexities of an interconnected world, promoting teamwork, cultural awareness, and the exchange of ideas (Ng et al., 2022). In the context of Thailand's open distance learning education, collaborative learning emerges as a pivotal strategy to address the challenges of remote instruction (Kanawapee et al., 2022). Leveraging technology and virtual platforms, collaborative learning fosters student engagement and knowledge exchange, transcending geographical constraints (Chantarasiri et al., 2022 and Kamolrat et al., 2024). The Thai open distance

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learning system benefits significantly from collaborative approaches, promoting interactive discussions among students and with tutors (Rattanaarun et al., 2023). This method enhances academic understanding and cultivates a sense of community among learners (Rupavijetra et al., 2022). As Thailand navigates the evolving landscape of open distance education, exploring collaborative learning practices becomes crucial for optimizing the effectiveness of remote instruction and ensuring a robust educational experience (Ratanasanguanvongs et al., 2022). In Thailand's open distance learning education, collaborative learning faces challenges intertwined with the dynamics of peer and tutor interaction. Disparities in technological access and communication barriers among students hinder seamless collaboration (Rattanaarun et al., 2023). Varied cultural and linguistic backgrounds further complicate effective interaction within collaborative groups. Ensuring equitable participation becomes imperative to bridge these gaps (Phadungphatthanakoon et al., 2021). The nuanced nature of peer and tutor engagement is pivotal for overcoming these challenges, demanding a thoughtful integration of technology and culturally sensitive pedagogical approaches (Praimee et al., 2022 and Kamolrat Intaratat, et al. 2024). Addressing these issues holistically is essential for optimizing collaborative learning experiences, emphasizing the role of meaningful interactions with both peers and tutors in fostering a robust open-distance learning environment in Thailand (Kitjaroonchai et al., 2023). This study holds paramount significance for policymakers, open distance learning higher education institutions, and students in Thailand. It offers insights crucial for refining policies, guiding institutions in optimizing virtual learning environments, and enhancing student experiences. Policymakers can shape inclusive strategies, institutions can refine their collaborative learning frameworks, and students can benefit from improved access and interaction. The findings underscore the importance of tailored approaches, fostering a more effective, equitable, and culturally sensitive open distance learning landscape in Thailand. This study aims to assess the direct and indirect relationships between interaction with peers, interaction with tutors, and collaborative learning with learning self-efficacy as a mediator.

2. Literature Review

2.1. Underpinning Theory

Social Cognitive Theory, as developed by Bandura (1986), provides a robust theoretical foundation for the study of individual work performance, learning self-efficacy, and collaborative learning in online distance education. This theory posits that individuals learn by observing others, modeling behaviors, and assessing the consequences of those behaviors. In the context of online learning, the study aligns with Social Cognitive Theory by examining how individual work performance serves as a model influencing the development of learning self-efficacy beliefs. Bandura's theory emphasizes the role of self-regulation, where learners monitor and adjust their behavior based on internal standards, shaping the study's exploration of how self-efficacy mediates the relationship between individual work performance and collaborative learning outcomes. Moreover, Social Cognitive Theory underscores the reciprocal determinism among personal factors, behavior, and the environment. The study, focusing on interactions with peers and tutors in an online setting, resonates with this concept, as it delves into how these social interactions influence individual learning experiences. By adopting Social Cognitive Theory, the study gains a theoretical lens to understand the dynamic interplay between individual actions, observational learning, and the collaborative learning environment in the context of online higher education.

2.2. Relationship between Interaction with Peers, Learning Self-Efficacy, and Collaborative Learning

Previous studies have consistently highlighted the intricate relationship between interaction with peers, collaborative learning, and learning self-efficacy in education (Liu et al., 2022). Research indicates that peer interaction plays a fundamental role in the collaborative learning process, facilitating knowledge construction through shared experiences, discussions, and diverse perspectives (Zhao et al., 2023). Collaborative learning environments, enriched by meaningful peer interactions, not only contribute to academic achievement but also enhance the development of social and cognitive skills (De Backer et al., 2022). Learning self-efficacy, defined as an individual's belief in their capability to accomplish a specific learning task, emerges as a crucial mediator in this dynamic. Studies suggest that positive peer interactions positively influence learning self-efficacy (Dehbozorgi et al., 2021). When students engage in collaborative endeavors, share insights, and collectively overcome challenges, they experience a boost in their confidence regarding their ability to master academic content (Yadav et al., 2021). Conversely, challenges in peer interactions or limited collaboration may negatively impact learning self-efficacy. Individuals who struggle to engage with peers or face barriers in collaborative learning settings may exhibit lower confidence levels in their academic abilities (Hsu et al., 2021). Understanding this relationship is pivotal for educators and institutions seeking to design effective collaborative learning environments that not only foster academic achievement but also promote the development of students' self-efficacy beliefs, ultimately contributing to a more positive and empowering educational experience (Chan et al., 2021). *Therefore, the following hypotheses were proposed for this study:*

H_1: There is a relationship between interaction with peers and collaborative learningamong students of open distance learning higher education institutions.

H_2: There is a relationship between interaction with peers and learning self-efficacy among students of open distance learning higher education institutions.

H_3: There is a mediating effect of learning self-efficacy on the relationship between interaction with peers and collaborative learning among students of open distance learning higher education institutions.

2.3. Relationship between Interaction with Tutors, Learning Self-Efficacy, and Collaborative Learning

Previous studies underscore the significant relationship between interaction with tutors, collaborative learning, and learning self-efficacy in the educational context. Interactions with tutors play a crucial role in guiding and facilitating collaborative learning experiences (Wang et al., 2022) Tutors, as facilitators of knowledge, contribute to the creation of a supportive learning environment that encourages collaboration among students (Tan et al., 2023). Research suggests that positive interactions with tutors enhance the effectiveness of collaborative learning (Chan et al., 2023). Tutors can provide guidance, feedback, and scaffolding that are instrumental in promoting meaningful collaboration among students. When tutors actively engage with learners, fostering a participatory and constructive atmosphere, students are more likely to develop a sense of competence and mastery over the learning material (Bećirović et al., 2023). Learning self-efficacy acts as a mediator in this relationship. Studies indicate that the quality of interaction with tutors influences students' beliefs in their ability to succeed in academic tasks. Supportive tutor-student interactions correlate positively with learning self-efficacy, influencing students' confidence in their capacity to grasp and apply complex concepts within a collaborative framework (Guo et al., 2023). Conversely, limited or ineffective interactions with tutors may impede collaborative learning experiences and subsequently impact learning self-efficacy negatively (Ng et al., 2022). A lack of guidance or unclear communication from tutors may leave students feeling

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less capable or unsure about their academic abilities. Understanding and leveraging the dynamic interplay between interaction with tutors, collaborative learning, and learning self-efficacy are crucial for educational practitioners (In'am & Sutrisno, 2021). This knowledge can inform instructional strategies, emphasizing the pivotal role tutors play in cultivating a positive collaborative learning environment that contributes to the enhancement of students' self-efficacy beliefs (Li & Yang, 2021). *Hence, the following hypotheses were proposed for this study:*

H[4]: There is a relationship between interaction with tutors and collaborative Learning among students of open distance learning higher education institutions.

H[5]: There is a relationship between interaction with tutors and learning self-efficacy among students of open distance learning higher education institutions.

H[6]: There is a relationship between learning self-efficacy and collaborative Learning among students of open distance learning higher education institutions.

H[7]: There is a mediating effect of learning self-efficacy on the relationship between interaction with tutors and collaborative learning among students of open distance learning higher education institutions.

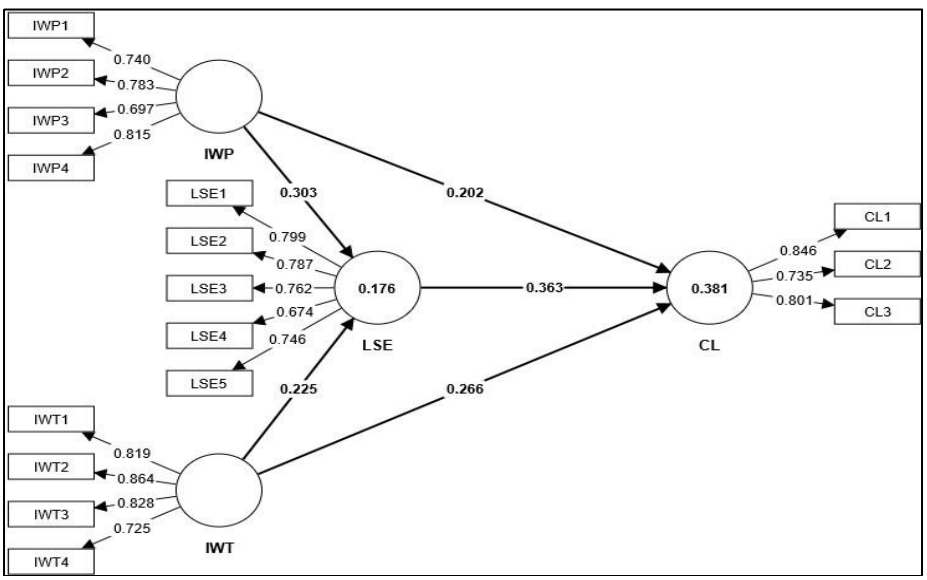

Figure 1.
Research model.
Note: IWP=Interaction with peers IWT=Interaction with tutors LSE=Learning self-efficacy.

3. Methodology

This study employs a quantitative research methodology, focusing on students enrolled in online distance-learning programs at higher education institutions in Thailand. Data was primarily collected through a survey questionnaire, adapted from previous studies, using established measurement instruments to assess key constructs. The study includes 16 observed variables, contributing to specific constructs: 'interaction with tutors' (4 items), 'interaction with peers' (4 items), 'learning self-efficacy' (5 items), and 'collaborative learning' (3 items). The survey achieved a 74.3% response rate, with 223 returned questionnaires out of 300 distributed. Following data collection, rigorous data cleaning and screening procedures were implemented to ensure data integrity and quality. This process resulted in a final dataset of 205 meticulously prepared samples for in-depth analysis. To examine complex relationships between variables, the study employed structural equation modeling (SEM), a sophisticated statistical technique known for exploring intricate patterns within research data. SEM allows for assessing both measurement and structural relationships within the research framework. For the analysis, Smart-PLS 4 software (Ringle et al., 2022), a well-established tool for SEM, was chosen. This selection highlights the commitment to robust data analysis and modeling, providing valuable insights into intricate relationships and patterns within the context of online distance learning in Thailand's higher education institutions. The methodology reflects a systematic and comprehensive approach to understanding the complexities of the chosen research constructs and their interrelationships within the specific context of online distance learning in the higher education landscape of Thailand.

4. Data Analysis

4.1. Common Method Bias

In management research, a prevalent concern is common method bias, where the variance in a study intended to reflect constructs but may be influenced by the measurement method used. To mitigate this issue, this study employed Harman's one-factor test method to assess the measurement items. The test results revealed that the primary factor accounted for only 36.9% of the variance, indicating that common method bias did not significantly impact the study. This aligns with Podsakoff and Organ's (1986) suggestion that common method bias is generally not a concern when the principal component explains less than 50% of the variance.

4.2. Measurement Model

In this study, the assessment of measurements, both in the first-order and second-order contexts, followed the methodology proposed by Hair et al. (2017). The objective was to identify items with loadings below the 0.7 threshold. The scrutiny of construct reliability and validity revealed that all constructs achieved Average Variance Extracted (AVE) values exceeding 0.5, ranging from 0.570 to 0.657 (Table 1), confirming the establishment of convergent validity as per Hair et al. (2017). Furthermore, composite reliability for all constructs surpassed 0.7, ranging from 0.845 to 0.884, and Cronbach's alpha values were also above 0.7, ranging from 0.711 to 0.826 (Table 1), indicating strong internal consistency and reliability. To ascertain discriminant validity, researchers initially examined cross-loadings to ensure each item effectively represented and measured its respective construct (Table 2). Subsequently, the Hetrotrait-Monotrait (HTMT) ratio, a recommended criterion for assessing discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler, Ringle & Sarstedt, 2015), was employed. The HTMT ratios for the constructs, along with the original sample and 95% confidence intervals (two-tailed), were presented in Table 3. The HTMT values were below the 0.85 threshold, and the bias-corrected and accelerated bootstrap confidence intervals remained below 1, confirming adherence to discriminant validity. This thorough analysis instills confidence in the distinctiveness of the constructs and their effective measurement of different aspects of the phenomenon under investigation. Overall, the robust evaluation of measurements and validity in this study establishes a solid foundation for subsequent data analysis and interpretation.

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Table 1.
Construct reliability & validity.

	CA	CR	AVE
CL	0.711	0.837	0.632
IWP	0.756	0.845	0.578
IWT	0.826	0.884	0.657
LSE	0.811	0.868	0.570

Table 2.
Cross loadings.

	CL	IWP	IWT	LSE
CL1	0.846	0.359	0.376	0.512
CL2	0.735	0.331	0.328	0.305
CL3	0.801	0.252	0.304	0.383
IWP1	0.236	0.740	0.171	0.253
IWP2	0.337	0.783	0.169	0.225
IWP3	0.310	0.697	0.205	0.306
IWP4	0.316	0.815	0.204	0.298
IWT1	0.363	0.268	0.819	0.188
IWT2	0.430	0.221	0.864	0.272
IWT3	0.296	0.126	0.828	0.272
IWT4	0.264	0.188	0.725	0.239
LSE1	0.458	0.343	0.246	0.799
LSE2	0.379	0.316	0.176	0.787
LSE3	0.339	0.221	0.201	0.762
LSE4	0.358	0.190	0.219	0.674
LSE5	0.390	0.257	0.284	0.746

Table 3.
Hetrotrait-Monotrait (HTMT) ratios.

	CL	IWP	IWT
IWP	0.534		
IWT	0.54	0.311	
LSE	0.656	0.446	0.364

4.3. Structural Model

This study conducted a thorough evaluation of the structural model by simultaneously assessing pathway coefficients (β) and coefficients of determination (R2), by the methodology detailed by Hair et al. (2017). The evaluation employed the Partial Least Squares (PLS) method, utilizing 5000 subsamples to establish the significance level of path coefficients. The outcomes of hypothesis tests, encompassing confidence intervals, path coefficients (beta), associated t-statistics, and p-values, are comprehensively presented in Table 4. This meticulous analysis provides valuable insights into the significance and robustness of the relationships among the variables within the structural model. Beginning with

Hypothesis 1 (H1), which posited a link between Interaction with Peers (IWP) and Collaborative Learning (CL), the Beta coefficient of 0.202, a T-statistic of 2.894, and a P-value of 0.004 provide robust evidence supporting a positive association between Interaction with Peers and collaborative learning. Hence H1 is supported. Moving to Hypothesis 2 (H2), which explored the connection between IWP and Learning Self-Efficacy (LSE), the substantial Beta coefficient of 0.303, a T-statistic of 3.927, and a highly significant P-value of 0.000 signify strong support for the notion that higher Interaction with Peers is correlated with increased learning self-efficacy. Therefore, H2 is supported. Hypothesis 3 (H3) delved into the mediating relationships between IWP, LSE, and CL. The Beta coefficient of 0.11, a T-statistic of 2.993, and a P-value of 0.003 support the hypothesis, indicating that Interaction with Peers not only influences learning self-efficacy but also subsequently impacts collaborative learning. Thus, H3 is supported. Hypothesis 4 (H4) investigated the influence of Interaction with Tutors (IWT) on Collaborative Learning, revealing a substantial Beta coefficient of 0.266, a T-statistic of 4.840, and a P-value of 0.000. These results strongly endorse the hypothesis, providing clear evidence that increased Interaction with Tutors is positively associated with collaborative learning. Turning to Hypothesis 5 (H5), which explored the link between IWT and LSE, the Beta coefficient of 0.225, a T-statistic of 2.852, and a P-value of 0.004 affirm the hypothesis, indicating that Interaction with Tutors positively influences learning self-efficacy. Thus, H5 is supported. Hypothesis 6 (H6) examined the impact of Learning Self-Efficacy on Collaborative Learning, revealing a substantial Beta coefficient of 0.363, a T-statistic of 5.845, and a P-value of 0.000. These findings strongly support the hypothesis, emphasizing the pivotal role of learning self-efficacy in promoting collaborative learning. Therefore, H6 is supported. Hypothesis 7 (H7) extended the mediating relationship, exploring the influence of IWT on LSE and subsequently on CL. Although the results showed a statistically significant relationship with a Beta coefficient of 0.082, a T-statistic of 2.437, and a P-value of 0.015, the effect size is relatively smaller compared to other hypotheses. Despite this, the evidence supports H7, indicating a mediating impact of Interaction with Tutors on learning self-efficacy and collaborative learning. Hence, H7 is supported. The analysis of the study produced compelling evidence supporting the majority of hypotheses, confirming the relationships among the investigated variables. A detailed presentation of hypothesis testing results, inclusive of effect sizes, can be found in Table 4. Effect sizes were evaluated using Cohen's criteria (1992), categorized as small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The observed effect sizes in this study ranged from small (0.056) to large (0.175). These effect size measures offer valuable insights into the practical significance and magnitude of the observed relationships, enhancing the comprehensive interpretation of variable impacts. To ensure the reliability of the structural model, intrinsic Value Inflation Factor (VIF) values were scrutinized, all falling below the lenient threshold of 5, with the highest value being 1.214. This low collinearity level ensures meaningful comparisons and interpretation of coefficients in the model without concerns. The endogenous construct demonstrated a substantial degree of explained variance, boasting an R^2 value of 0.381 (Figure 1). Regarding the mediator, the model accounted for approximately 17.6% of the variance in the structure, evidenced by an R^2 value of 0.176. These R^2 values provide valuable insights into the extent of variance explained by the model and its predictive ability concerning observed outcomes.

To assess the model's ability to draw inferences and offer management recommendations, an out-of-sample predictive analysis was carried out using the PLSpredict method, following the approach outlined by Shmueli et al. (2016, 2019). The predictive analysis results, presented in Table 5, include Q^2 predictions, with values above 0 indicating that the predictions made by PLS-SEM surpassed the standard naive mean prediction outcomes. Moreover, in eight instances, the root mean square error (RMSE) values of the PLS-SEM predictions were lower than those of the linear model (LM) prediction benchmark, highlighting the superior predictive power of the proposed model (Table 5). These findings serve as additional evidence supporting the effectiveness of the structural model in generating precise predictions and offering valuable insights for managerial decision-making. Hair et al. (2022) introduced the Cross-Validated Predictive Ability Test (CVPAT) as an assessment tool for evaluating the predictive capabilities of PLS-SEM models. In their study, Liengaard et al. (2021) applied the CVPAT alongside the PLSpredicts analysis to evaluate the model's predictive performance. The CVPAT involved an out-of-sample prediction method to measure the model's prediction error and compute the average loss value. Two benchmarks were used for comparison: the average loss value of predictions using indicator averages (IA) as a simple benchmark and the average loss value of a linear model (LM) forecast as a more conservative benchmark. To establish the model's superior predictive capabilities compared to the benchmarks, the average loss value of PLS-SEM should be lower, resulting in a negative difference in the average loss values. The CVPAT aimed to assess whether the difference in average loss values between PLS-SEM and the benchmarks was significantly below zero. A significantly negative difference would indicate that the model exhibited enhanced predictive abilities. The results of the CVPAT, presented in Table 6, confirmed the model's superiority. The average loss value of PLS-SEM was indeed lower than that of the benchmarks, as evidenced by the negative difference in the average loss values. This provides compelling evidence of the model's robust and superior predictive capabilities compared to the benchmarks.

Ringle and Sarstedt (2016) and Hair et al. (2018) introduced the application of Importance Performance Analysis (IPMA) as a robust approach to assessing the significance and effectiveness of latent variables in explaining acceptance. The outcomes of this comprehensive analysis are thoughtfully presented in Table 7. Among the latent variables studied, learning self-efficacy emerged as the most influential factor (0.363) concerning the overall impact on collaborative learning, followed by interaction with tutors (0.348), and interaction with peers (0.312). These values elucidate the relative importance of each latent variable within the context of collaborative learning. Additionally, in terms of performance scores, interaction with tutors demonstrated the highest score (63.948) on a 0 to 100 scale, indicating its relatively robust performance. Conversely, learning self-efficacy received the lowest score (61.133), suggesting the lowest level of achievement. Intriguingly, despite its utmost significance in determining collaborative learning, learning self-efficacy exhibited the lowest performance level. Drawing on these noteworthy findings, we recommend that top management in open distance learning higher education institutions prioritize and accentuate endeavors aimed at improving students' learning self-efficacy. By strategically focusing on enhancing learning self-efficacy, overall collaborative learning can be significantly enhanced, leading to more effective and beneficial outcomes for the students.

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Table 4.
Hypotheses testing results, f^2 & VIF.

Hypotheses	Beta	T statistics	P-value s	f^2	VIF	2.50%	97.50%	Decision
H1:IWP -> CL	0.202	2.894	0.004	0.056	1.177	0.067	0.338	Supported
H2:IWP -> LSE	0.303	3.927	0.000	0.104	1.066	0.136	0.437	Supported
H3:IWP -> LSE -> CL	0.11	2.993	0.003			0.044	0.186	Supported
H4:IWT -> CL	0.266	4.840	0.000	0.101	1.127	0.154	0.367	Supported
H5:IWT -> LSE	0.225	2.852	0.004	0.058	1.066	0.053	0.367	Supported
H6:LSE -> CL	0.363	5.845	0.000	0.175	1.214	0.229	0.472	Supported
H7:IWT -> LSE -> CL	0.082	2.437	0.015			0.021	0.152	Supported

Table 5.
PLspredicts.

	Q^2predict	PLS_RMSE	LM_RMSE	PLS-LM
CL1	0.197	0.637	0.656	-0.019
CL2	0.161	0.601	0.607	-0.006
CL3	0.102	0.653	0.659	-0.006
LSE1	0.122	0.624	0.632	-0.008
LSE2	0.088	0.638	0.651	-0.013
LSE3	0.051	0.675	0.685	-0.010
LSE4	0.045	0.721	0.740	-0.019
LSE5	0.094	0.606	0.609	-0.003

Table 6.
Cross validated predictive ability.

	Average loss difference	t-value	p-value
CL	-0.072	3.754	0.000
LSE	-0.036	2.080	0.039
Overall	-0.050	3.327	0.001

Table 7.
Importance-performance matrix analysis.

	Total effect	Performance
IWP	0.312	61.428
IWT	0.348	63.948
LSE	0.363	61.133

5. Discussion & Conclusion

In the realm of online distance learning within higher education institutions, optimizing the influence of interaction with peers and tutors on collaborative learning is pivotal for fostering effective educational experiences. Employing strategic approaches to enhance these interactions, with learning self-efficacy acting as a mediator, can significantly contribute to the overall success of online education.

One key strategy involves fostering a sense of community within virtual learning environments. Establishing online forums, discussion boards, or collaborative projects encourages regular interaction among peers. Facilitators can design activities that prompt students to share insights, ask questions, and collaboratively solve problems, creating an environment conducive to meaningful peer-to-peer engagement.

Similarly, enhancing interaction with tutors involves employing responsive and proactive communication channels. Virtual office hours, personalized feedback on assignments, and regular communication through messaging platforms contribute to a supportive tutor-student relationship. Clear expectations and guidelines for communication can also help students feel more comfortable reaching out to tutors, promoting a more interactive and engaging learning experience. Integrating technology tools that facilitate real-time collaboration can further amplify the impact of peer and tutor interactions. Video conferencing, collaborative document editing, and virtual group projects provide platforms for dynamic engagement, fostering a sense of collective learning. Additionally, incorporating gamification elements or interactive simulations can make the learning experience more engaging, encouraging students to actively participate in collaborative activities. In tandem with these strategies, promoting and developing students' learning self-efficacy plays a crucial role. Providing resources such as self-assessment tools, goal-setting activities, and constructive feedback helps students build confidence in their ability to navigate and succeed in the online learning environment. Ultimately, a holistic approach that intertwines effective peer and tutor interactions with the cultivation of learning self-efficacy can significantly enhance collaborative learning in online distance education. These strategies contribute to creating a vibrant and supportive online learning community, where students feel empowered to collaborate, learn from one another, and succeed in their educational pursuits.

5.1. Theoretical Implications

The theoretical implications derived from the above study are substantial and contribute significantly to the existing body of knowledge in online distance learning. The study elucidates the intricate relationships among individual work performance, learning self-efficacy, and collaborative learning, establishing a comprehensive theoretical framework. By employing structural equation modeling and assessing multiple pathways, the study enriches theoretical perspectives on the sequential impact of individual work factors on collaborative learning through the mediating role of learning self-efficacy. These findings expand our understanding of the dynamics in online higher education, providing a nuanced model that emphasizes the interconnectedness of individual efforts, self-efficacy beliefs, and collaborative learning outcomes. The theoretical implications underscore the importance of considering multifaceted relationships and mediator variables in conceptualizing and refining theoretical frameworks for online distance learning in higher education institutions. Furthermore, the study contributes theoretical insights by incorporating Cohen's effect size analysis, providing a nuanced understanding of the practical significance and magnitude of the observed relationships. This inclusion enriches the theoretical framework by emphasizing not only statistical significance but also the real-world impact of individual work performance, learning self-efficacy, and collaborative learning. Additionally, the study's examination of intrinsic Value Inflation Factor (VIF) values contributes to the theoretical underpinnings by addressing potential collinearity issues in structural models, enhancing the robustness of theoretical constructs. Moreover, the theoretical implications extend to the realm of virtual education and highlight the significance of fostering a sense of community among online learners. The study underscores the importance of technological tools, such as collaborative platforms and interactive simulations, in shaping the dynamics of online distance learning environments. These theoretical insights have broader implications for instructional design and pedagogical strategies in the evolving landscape of digital education. Overall, the study's theoretical contributions offer a holistic and nuanced understanding of the complex relationships in online higher education, laying a foundation for future theoretical development and refinement in this rapidly evolving field.

5.2. Practical Implications

The practical implications arising from the above study hold significant value for educators, instructional designers, and administrators in the realm of online distance learning in higher education institutions. The identification of key relationships among individual work performance, learning self-efficacy, and collaborative learning offers practical guidance for enhancing the effectiveness of virtual learning environments. Educators can leverage these findings to design targeted interventions that foster meaningful interactions among students, promoting collaborative learning experiences. Practitioners can utilize the study's insights to develop strategies aimed at building students' learning self-efficacy. Providing resources such as self-assessment tools, goal-setting activities, and personalized feedback aligns with the study's emphasis on bolstering individual beliefs in one's capacity to succeed in an online learning context. Administrators can use the study's findings to inform decision-making regarding technological infrastructure and support services. Integrating collaborative tools and creating spaces for peer-to-peer and tutor-student interactions aligns with the study's emphasis on the importance of fostering a sense of community in virtual learning environments. Additionally, the study's practical implications extend to professional development initiatives for online educators, emphasizing the significance of proactive communication, constructive feedback, and clear expectations in facilitating effective interactions. Overall, the study provides actionable insights that can inform the design and implementation of online education programs, enhancing the practical effectiveness of virtual learning experiences in higher education.

5.3. Limitation of the Study

While the study provides valuable insights, certain limitations should be acknowledged. The reliance on self-reported data through survey questionnaires introduces the potential for response bias and social desirability. Additionally, the study's focus on a specific context, such as online distance learning in higher education institutions, may limit the generalizability of findings to other educational settings. Furthermore, the cross-sectional nature of the study design restricts the establishment of causality among variables. Despite these limitations, the study lays a solid foundation for future research and opens avenues for exploring nuanced relationships in the dynamic landscape of online education.

5.4. Suggestions for Future Study

For future research, it is recommended to employ diverse research methods, such as longitudinal studies, to establish causal relationships among variables. Exploring the influence of contextual factors and demographic variables on the observed relationships could provide a more comprehensive understanding. Additionally, investigating the impact of interventions designed to enhance interaction with peers, tutors, and learning self-efficacy would offer practical insights for educational practitioners. Comparative studies across various online learning platforms and institutions could further broaden the generalizability of findings. Lastly, exploring the perspectives of both students and educators on their online learning experiences may contribute to a more holistic understanding of the dynamics in virtual higher education settings.

5.5. Conclusion

This study delves into the intricate relationships among individual work performance, learning self-efficacy, and collaborative learning within the context of online distance learning in higher education institutions. The findings reveal significant positive associations, supported by robust statistical evidence and effect size analyses. The study contributes to theoretical frameworks by emphasizing the sequential impact of individual work factors on collaborative learning, mediated by learning self-efficacy. Practical implications are evident for educators, administrators, and instructional designers, highlighting the importance of fostering a sense of community, leveraging technology, and building students' self-efficacy beliefs. Acknowledging limitations, such as reliance on self-reported data, the study suggests avenues for future research, including longitudinal studies and investigations into contextual influences. Overall, this study enhances our understanding of the dynamics in online education, offering valuable insights with implications for both theory and practice in the evolving landscape of virtual higher education.

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