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Investigating Factors Affecting Students' Attitudes and Readiness Towards Collaborative Online Learning Environments in Physics

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Abstract

Collaborative online learning has become increasingly important in physics education, yet many students face challenges in adapting to its demands. This study explores factors influencing students' readiness for collaborative online learning, focusing on prior knowledge, motivation, technological proficiency, and learning preferences. A mixed-methods approach was used to collect quantitative data from 45 students, which were analyzed using SEM-PLS, along with qualitative insights from focus group discussions. Results identified prior knowledge as the strongest predictor of readiness ($\beta = 0.670$, $p = 0.001$), enhancing cognitive engagement and motivation. Motivation influenced learning preferences ($\beta = 0.482$, $p = 0.009$) but did not directly impact readiness. Technological proficiency moderately predicted readiness ($\beta = 0.353$, $p = 0.057$), while learning preferences were nonsignificant ($\beta = 0.218$, $p = 0.421$). Qualitative findings emphasized the role of peer collaboration, intrinsic motivation, and digital skill disparities. The study highlights the need for scaffolding prior knowledge, fostering motivation through structured tasks, improving digital skills, and offering strategies for creating inclusive and effective collaborative online learning environments.

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INTRODUCTION

The rapid advancements in educational technology have fundamentally reshaped traditional teaching methodologies, particularly in physics education (Bozzi et al., 2021; Shyr et al., 2021). The emergence of collaborative online learning environments has gained prominence due to the need for flexible and accessible instructional methods, especially in the global shift to online learning caused by the COVID-19 pandemic (Makda, 2024; Papaioannou et al., 2023; Thapaliya & Hrytsuk, 2023; Widayanti, 2021). However, while online learning offers flexibility, it also challenges fostering engagement and collaboration in subjects like physics, which inherently require active participation and practical applications (Azlan et al., 2020; Cavinato et al., 2021; Mansour, 2024).

Collaborative online learning environments, grounded in constructivist principles, emphasize student-centered approaches, including peer interaction, problem-solving, and shared knowledge construction. Studies have highlighted that collaborative learning fosters critical thinking, problem-solving, and improved learning outcomes (Alharbi et al., 2022; Xu et al., 2023). Despite this, transitioning to virtual platforms often results in diminished social interaction and collaboration, necessitating an in-depth examination of factors such as student motivation, prior knowledge, technological proficiency, and learning preferences (Vetrivel et al., 2024; Wong & Hughes, 2023;

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Yan & Pourdavood, 2024). These factors are especially critical in physics education, where conceptual understanding and real-world applications intersect.

Active learning strategies have consistently improved student outcomes in physics education by promoting deeper engagement and knowledge retention (Aulia & Yuliani, 2023; Fazio, 2020; Rahmawati et al., 2022; Wallace et al., 2021). These strategies are particularly relevant to the factors being investigated in this study, as they directly influence motivation by encouraging active participation and ownership of the learning process (George & R., 2021; Jahnke et al., 2022; Owens et al., 2020). Frameworks like the Community of Inquiry model highlight the importance of cognitive, social, and teaching presences in online learning, which are pivotal for creating effective collaborative environments (Martin et al., 2022; Shea et al., 2022; Swan, 2019). Cognitive presence, for instance, is tied to the role of prior knowledge in fostering a deeper understanding (Sadaf et al., 2021), while social presence aligns with learning preferences and collaborative dynamics (Sadaf et al., 2021). Furthermore, advances in educational neuroscience have provided insights into how motivation, prior knowledge, and cognitive engagement—a key component of readiness—can be optimized in virtual learning settings (Xie et al., 2023). These connections underscore the study's focus on examining how these factors interact to shape students' readiness for collaborative online learning in physics.

Despite the growing body of research, significant gaps remain in understanding the integrated influence of prior knowledge, motivation, technological proficiency, and learning preferences on readiness for collaborative online physics education. Existing studies have often examined these factors in isolation rather than their complex interplay. For instance, Klein et al. (2021) explored students' assessments of learning achievements during the COVID-19 pandemic and highlighted challenges with practical applications and reduced engagement due to limited interactivity in online settings. Similarly, Theophilou et al. (2024) and Yates et al. (2021) found that while technological and pedagogical strategies facilitated personalization and authenticity in high school online learning, collaboration was often inconsistent, limiting student engagement and collective problem-solving. Additionally, Zabolotna et al. (2023) it emphasized the critical role of group-level regulation and knowledge construction in computer-supported collaborative physics tasks but noted that disparities in technological proficiency and readiness among students hindered effective participation. These studies underscore the fragmented understanding of how these factors collectively influence collaborative online learning readiness, particularly in physics education, which requires a deeper integration of conceptual understanding and collaborative strategies. This study addresses these gaps by adopting a holistic approach to explore the interconnectedness of these factors, aiming to provide a more comprehensive framework for enhancing collaborative online learning environments in physics.

This study bridges these gaps by investigating the relationships between motivation, prior knowledge, technological proficiency, learning preferences, and readiness in collaborative online learning environments tailored to physics education. It focuses on addressing the unique challenges posed by online physics education, particularly in fostering engagement and collaboration. By examining these factors holistically, the study aims to provide practical strategies to enhance collaborative learning. The novelty of this research lies in its interdisciplinary approach, combining pedagogical strategies with insights from educational neuroscience to offer a comprehensive framework for improving collaborative online learning environments. This study aims to identify factors influencing students' attitudes and readiness for collaborative online learning in physics, offering practical strategies for more effective instructional design. By addressing the unique needs of physics education, this research contributes to the advancement of online learning, with a focus on enhancing student engagement, academic performance, and the overall learning experience.

METHOD

Research Design

This study employs a mixed-method approach Creswell & Creswell, (2023) to explore factors influencing students' attitudes and readiness toward collaborative online learning environments in physics. Quantitative data were collected through validated survey instruments, while qualitative insights were obtained via focus group discussions. The quantitative aspect of the study was mainly focused on analyzing relationships among variables using Structural Equation Modeling (SEM), which provides robust insights into the interplay between latent constructs such as motivation, prior knowledge, technological proficiency, and learning preferences.

Participants

The study involved 45 undergraduate physics students from Universitas Islam Negeri Raden Intan Lampung. Participants were selected through purposive sampling to ensure a diverse mix of gender, age, academic performance levels, and technological backgrounds. Table 1 below provides a detailed breakdown of the demographic characteristics of the participants.

Table 1. Demographic Table of Participants

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	20	44.4
	Female	25	55.6
Age	18–19 years	18	40.0
	20–21 years	22	48.9
	22–23 years	5	11.1
Technological Proficiency	High Proficiency	12	26.7
	Moderate Proficiency	25	55.6
	Low Proficiency	8	17.8
Prior Physics Knowledge	High	10	22.2
	Moderate	30	66.7
	Low	5	11.1

The demographic factors in this study—gender, age, technological proficiency, and prior knowledge—play a crucial role in understanding their relationship with the core variables of motivation, learning preferences, technological proficiency, and readiness for collaborative online learning. Gender diversity ensures a balanced examination of collaborative dynamics, as prior research suggests that male and female students may approach collaboration and learning preferences differently (Feng et al., 2023; Ma et al., 2022; Wu & Wang, 2023). Age reflects academic maturity, which can influence motivation, readiness, and the ability to adapt to online learning environments (Lamon et al., 2020). Technological proficiency directly impacts students' ability to navigate online tools, influencing both their readiness and engagement in collaborative tasks (Getenet & Tualaulelei, 2023). Prior knowledge is particularly significant, as it provides the foundational understanding necessary for cognitive engagement and motivation, which are critical in collaborative physics education (Dong et al., 2020). Together, these demographic factors provide a nuanced perspective on how individual differences shape the interplay of the studied variables in collaborative online learning contexts.

Instruments

The reliability of the survey instruments used in this study was ensured by carefully selecting validated and widely recognized scales, each tailored to measure specific dimensions relevant to the research objectives. The motivation construct was assessed using the Academic Motivation Scale (Kotera et al., 2023), a tool extensively utilized in educational research for its high internal consistency and ability to distinguish between intrinsic and extrinsic motivational factors. This scale's Cronbach's alpha values, reported in previous studies, consistently exceed 0.80, indicating strong reliability.

For prior knowledge, a pre-test was developed based on the framework of foundational physics concepts outlined by Simonsmeier et al. (2022). This diagnostic tool is widely regarded for its content validity, as it aligns with key concepts foundational to physics education. The test's reliability was bolstered by piloting it with a subset of participants to ensure clarity and consistency in responses.

The technological proficiency dimension was measured using a tailored version of the Digital Competence Scale (Tzafilkou et al., 2022). This scale has demonstrated robust psychometric properties in prior research, with Cronbach's alpha values typically ranging between 0.85 and 0.90, ensuring reliability in diverse educational contexts. The tailoring process involved minor modifications to align the scale with the specific tools and platforms used in the study without compromising its validated structure.

Finally, learning preferences were evaluated using Kolb's Learning Style Inventory (Newton & Wang, 2024), a well-established instrument for identifying individual differences in learning approaches. This inventory has undergone extensive validation, with consistent test-retest reliability scores across various educational settings. Its ability to classify learning styles effectively made it a reliable choice for understanding the diversity in participants' approaches to online learning.

Research Model

The research model for this study is developed to investigate the relationships among key constructs influencing students' readiness for collaborative online learning environments in physics: Motivation, Technological Proficiency, Prior Knowledge, and Learning Preferences. The model is based on established theories, including the Self-Determination Theory (Ryan & Deci, 2023), Cognitive Load Theory (Sweller, 2020), and Vygotsky's Social Constructivist Framework (Alismaiel et al., 2022), which collectively explain the interplay between cognitive and non-cognitive factors in learning environments. This section outlines the hypothesized relationships derived from the model.

Hypotheses

Direct Effects

1. **H1**: Motivation has a significant positive effect on students' readiness for collaborative online learning.
   Rationale: Highly motivated students will likely engage more actively and adapt to collaborative online learning environments.
2. **H2**: Technological proficiency has a significant positive effect on students' readiness for collaborative online learning.
   Rationale: Higher digital fluency facilitates the effective use of tools required for online collaboration.
3. **H3**: Prior knowledge has a significant positive effect on students' readiness for collaborative online learning.
   Rationale: A strong foundation in prior knowledge helps students better understand and engage in collaborative activities.
4. **H4**: Learning preferences significantly positively affect students' readiness for collaborative online learning.
   Rationale: Students whose learning preferences align with the instructional design are more likely to exhibit readiness.

Indirect Effects

5. **H5**: Motivation has a significant positive effect on learning preferences.
   Rationale: Motivated students are more likely to adapt and explore learning methods that suit their needs.
6. **H6**: Prior knowledge has a significant positive effect on motivation.
   Rationale: Students with solid knowledge will likely feel more confident and motivated in collaborative settings.
7. **H7**: Technological proficiency has a significant positive effect on motivation.
   Rationale: Familiarity with digital tools reduces frustration, allowing students to focus on learning and increasing their motivation.

To explore the factors influencing students' readiness for collaborative online learning environments in physics, this study examines both direct and indirect relationships among key constructs, including motivation, technological proficiency, prior knowledge, learning preferences, and readiness. The conceptual framework is informed by existing theoretical and empirical studies, which highlight the interconnected roles of these factors in shaping collaborative learning experiences. The hypothesized relationships are presented in the research model, as illustrated in Figure 1, which provides a visual representation of the study's conceptual framework and hypotheses.

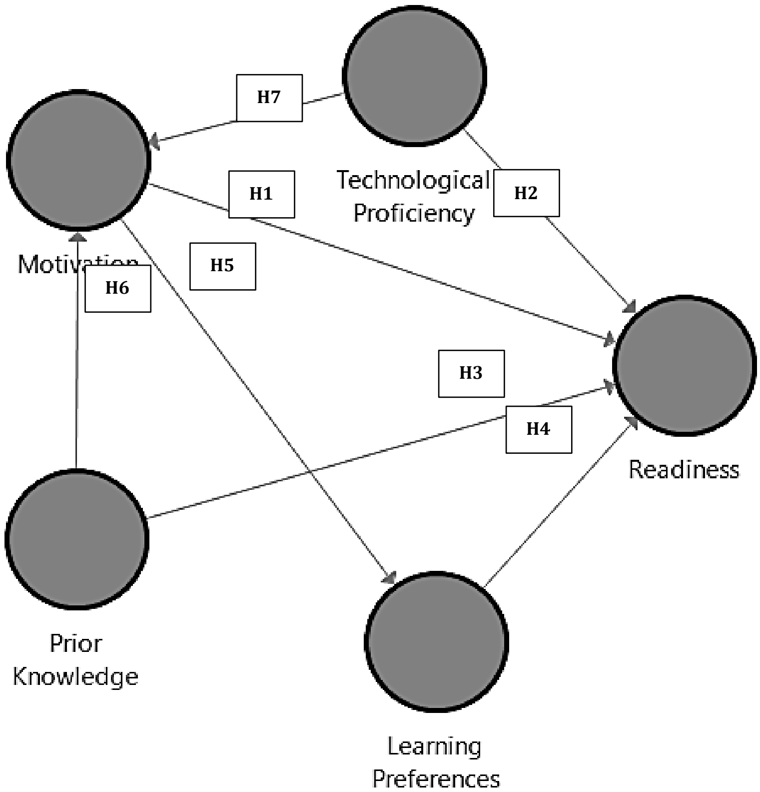

Figure 1. Research model

Focus Group Discussions

Qualitative data were gathered through focus group discussions on challenges, collaboration dynamics, and perceptions of online learning tools. This data complemented the quantitative findings, providing a richer context for interpreting SEM results.

Procedure

The study followed a structured three-phase procedure to explore factors influencing students' attitudes and readiness toward collaborative online learning environments in physics. These phases—pre-implementation, implementation, and post-implementation—are summarized in Table 2, which outlines the specific activities conducted in each phase. The table provides a clear overview of the systematic approach taken to ensure comprehensive data collection and analysis.

Table 2. Research Procedure Overview

Phase	Activity	Description	Duration
Pre-Implementation	Orientation and Pre-Survey	- Conducted an introductory session to explain the study's objectives and familiarize participants with collaborative online learning tools (e.g., LMS, video conferencing). - Administered a pre-survey to measure baseline motivation levels, prior knowledge, technological proficiency, and learning preferences.	2 weeks
	Diagnostic Assessment	- Conducted a diagnostic test to evaluate participants' prior knowledge of physics concepts and assess readiness for collaborative online learning.	1 session

Phase	Activity	Description	Duration
	Group Assignment	- Formed small groups (4–5 students per group) for collaborative learning activities.	1 session
Implementation	Collaborative Learning Sessions	- Delivered 16 weeks of collaborative online learning activities using a problem-based (PBL) approach. - Weekly tasks included collaborative discussions, problem-solving, and presentations facilitated through LMS and video conferencing.	16 weeks
	Weekly Reflection Activities	- Students participated in structured reflection activities to assess their engagement and self-regulated learning.	Weekly
	Feedback and Interaction	- Facilitators provided ongoing feedback on group performance and encouraged peer interaction to strengthen collaboration.	Ongoing
Post-Implementation	Post-Survey	- Administered a post-survey to evaluate changes in students' attitudes and readiness for collaborative online learning.	1 week
	Focus Group Discussions	- Conducted focus group discussions to capture qualitative insights into participants' experiences, challenges, and perceptions of collaborative online learning.	2 sessions
	Final Evaluation	- Compiled individual and group performance data to assess learning outcomes and collaborative effectiveness.	1 week

Explanation of Procedure Phases

The research procedure was conducted in three distinct phases: the pre-implementation phase, the implementation phase, and the post-implementation phase, each meticulously designed to align with the study's objectives and ensure comprehensive data collection.

During the pre-implementation phase, students were introduced to the study's objectives and trained to use various collaborative tools, including the learning management system (LMS), video conferencing software, and online collaborative document platforms. This orientation and familiarization ensured participants were equipped with the necessary technological skills for effective engagement (Bergdahl et al., 2020). Following this, baseline measurements were conducted through a pre-survey that assessed students' motivational levels, prior knowledge, and technological proficiency. A diagnostic test was also administered to evaluate their understanding of foundational physics concepts, establishing a reference point for later comparisons.

The implementation phase focused on active engagement in collaborative online learning activities. Students participated in weekly group sessions around problem-based learning (PBL) strategies. These tasks were explicitly designed to foster collaboration, encourage peer feedback, and promote the practical application of physics concepts. Weekly reflection activities were incorporated to support continuous improvement, allowing students to evaluate their progress and enhance self-regulated learning (Clark et al., 2023). Facilitators played a critical role during this phase by providing timely feedback to effectively guide group performance and address emerging challenges.

In the post-implementation phase, the evaluation of outcomes was conducted to capture both quantitative and qualitative insights. Post-surveys measured changes in students' attitudes and readiness, while focus group discussions explored their experiences, challenges, and perceptions regarding collaborative online learning. Finally, a performance assessment was carried out, with facilitators reviewing group deliverables and individual contributions to evaluate collaborative effectiveness and overall learning outcomes.

This structured approach offered a comprehensive framework for analyzing the interplay between motivational, cognitive, and technological factors within collaborative online physics learning environments. It ensured a systematic and rigorous evaluation of the processes and outcomes, contributing valuable insights to the field.

Data Analysis

Quantitative Analysis

Structural Equation Modeling using Partial Least Squares (SEM-PLS) was employed to analyze the relationships among motivation, prior knowledge, technological proficiency, and learning preferences in collaborative online learning. SEM-PLS was selected for its robustness in handling complex models and ability to work effectively with smaller sample sizes, making it particularly suitable for this study's participant cohort (Lin et al., 2020; Petter & Hadavi, 2021).

The analysis began with model specification, wherein a hypothesized structural model was developed based on theoretical frameworks and insights from prior studies (Hair et al., 2021). This model included latent variables representing key constructs and their corresponding observed indicators, ensuring a clear pathway for testing relationships among constructs. Next, model estimation was conducted using SmartPLS software. The analysis involved two primary steps: the measurement model evaluation and the structural model evaluation. In the measurement model evaluation, the reliability and validity of constructs were assessed through indicators such as Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). The path coefficients, R^2 values, and effect sizes (f^2) were analyzed for the structural model evaluation to determine the strength and significance of relationships among constructs.

To ensure the model's validity, bootstrapping techniques were used to generate standard errors and t-statistics, providing robust estimates of the significance of path coefficients. Additionally, the model fit was assessed using metrics such as the standardized root mean square residual (SRMR) to confirm the adequacy of the overall model. Finally, hypothesis testing was conducted by interpreting the path coefficients and their significance levels to evaluate the relationships among motivation, prior knowledge, technological proficiency, and learning preferences. This approach offered a detailed understanding of the factors influencing students' attitudes and readiness for collaborative online learning environments and provided actionable insights for improving educational practices.

Qualitative Analysis

Focus group data were analyzed using thematic analysis, with themes identified through iterative coding. Triangulation ensured validity by integrating insights from quantitative and qualitative data.

RESULTS AND DISCUSSION

The findings of this study reveal nuanced relationships between the variables investigated—motivation, prior knowledge, technological proficiency, and learning preferences—and their influence on students' attitudes and readiness toward collaborative online learning environments in physics. By integrating quantitative results from SEM-PLS analysis and qualitative insights from focus group discussions, this section comprehensively examines these relationships while contextualizing them within existing research.

Quantitative

Measurement Model Evaluation

This section evaluates the reliability and validity of the measurement model used in this study. It focuses on ensuring the constructs measured, including learning preferences, motivation, prior knowledge, readiness, and technological proficiency, meet the required statistical thresholds for internal consistency, reliability, and convergent validity. These metrics are essential for confirming the robustness of the constructs in the structural model.

To assess reliability and validity, Table 3 summarizes key metrics such as Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct. These metrics ensure that the measurement model is both reliable and valid for inclusion in subsequent structural analysis.

Table 3. Reliability and Validity of Measurement Model Constructs

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Learning Preferences	0.874	0.92	0.793
Motivation	0.836	0.878	0.657
Prior Knowledge	0.83	0.889	0.672
Readiness	0.815	0.861	0.679
Technological Proficiency	0.943	0.957	0.818

The evaluation of the measurement model through SEM-PLS demonstrated the reliability and validity of the constructs utilized in this study. As shown in Table 3, all constructs exhibited strong internal consistency, as indicated by Cronbach's alpha values exceeding the recommended threshold of 0.70 (Hair et al., 2021). Specifically, the Cronbach's alpha values for Learning Preferences (0.874), Motivation (0.836), Prior Knowledge (0.83), Readiness (0.815), and Technological Proficiency (0.943) confirm the internal reliability of the scales used to measure these constructs.

Furthermore, the composite reliability (CR) values ranged from 0.861 to 0.957, surpassing the minimum acceptable level of 0.70, reinforcing the constructs' reliability for capturing the intended latent variables. Additionally, the Average Variance Extracted (AVE) values ranged between 0.657 and 0.818, all exceeding the recommended threshold of 0.50, which ensures sufficient convergent validity of the constructs. These AVE values indicate that the majority of the variance in the indicators is explained by the latent constructs rather than measurement error.

Table 3 summarizes these results, providing a comprehensive overview of each construct's reliability and validity metrics. The high values of Cronbach's alpha, CR, and AVE collectively confirm that the constructs used in this study are reliable and valid, making them suitable for inclusion in the structural model.

Structural Model Evaluation

The structural model analysis revealed significant relationships among the constructs, demonstrating the model's strong predictive capability. As shown in Table 4, the R^2 value for Readiness is 0.899, indicating that the model accounts for 89.9% of the variance in students' readiness for collaborative online learning. This high R^2 value reflects the substantial influence of the predictor variables (Motivation, Prior Knowledge, Technological Proficiency, and Learning Preferences) on the outcome variable, Readiness, highlighting the robustness of the structural model.

Table 4. Predictive Capacity of the Structural Model

Construct	R Square	R Square Adjusted
Learning Preferences	0.232	0.214
Motivation	0.395	0.367
Readiness	0.899	0.889

In addition, the constructs Motivation and Learning Preferences also exhibit notable R^2 values, suggesting meaningful predictive relationships within the model. Specifically, the R^2 for Motivation is 0.395, meaning that its predictors explain 39.5% of the variance in Motivation. Similarly, the R^2 value for Learning Preferences is 0.232, indicating that 23.2% of the variance in Learning Preferences can be attributed to the predictors in the model.

The adjusted R^2 values further confirm the stability and generalizability of the model, with adjusted R^2 values of 0.889 for Readiness, 0.367 for Motivation, and 0.214 for Learning Preferences. These values account for potential overfitting by adjusting for the number of predictors in the model, ensuring that the results remain robust even with varying sample sizes.

The results presented in Table 4 highlight the model's overall predictive strength, with firm predictions for Readiness. These findings underscore the importance of addressing the factors influencing readiness, motivation, and learning preferences to optimize collaborative online learning environments.

Key Path Coefficients and Findings:

The structural model, as detailed in Table 5 and illustrated in Figure 1, provides an in-depth view of the relationships among constructs in the study. The relationships are supported by path coefficients, T-statistics, and p-values, offering insights into the significance of each path.

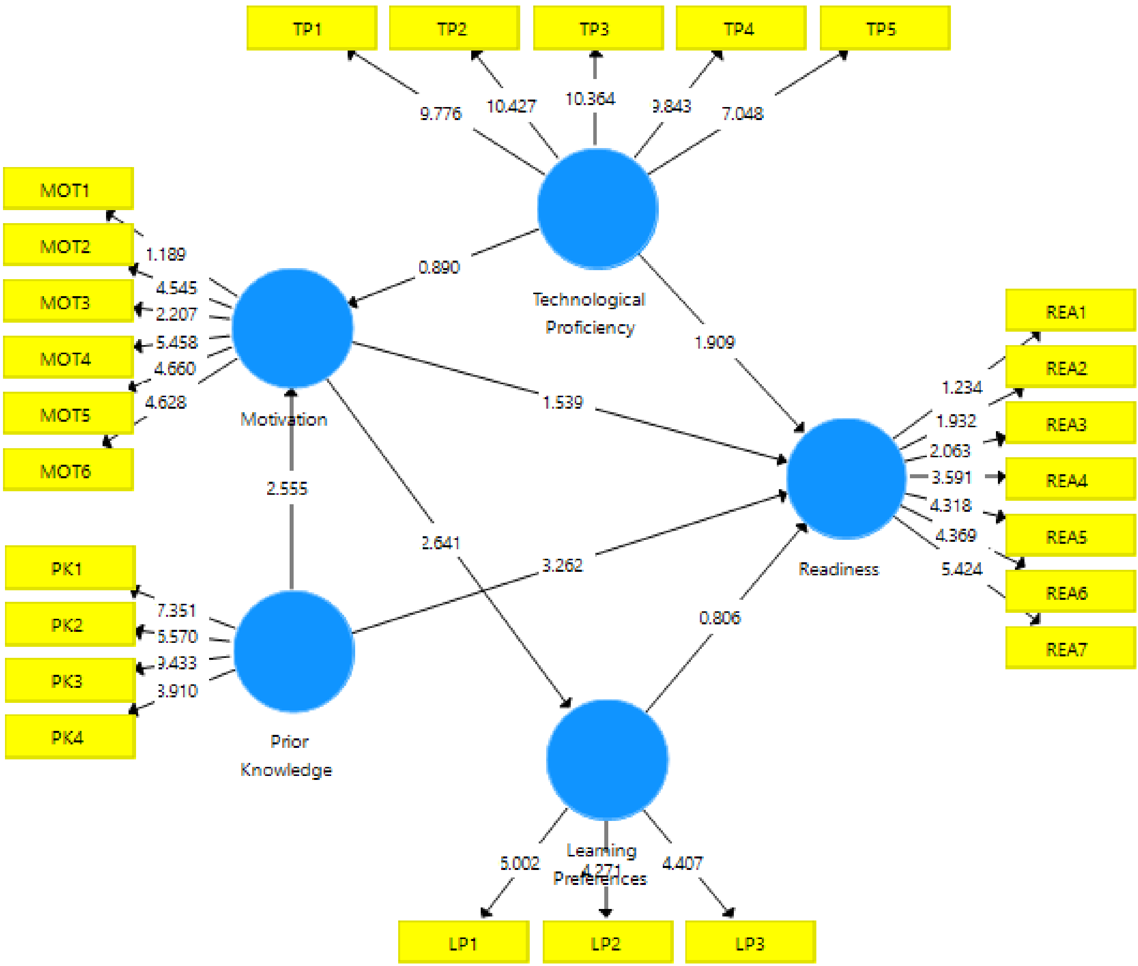

Figure 2. Measurement model evaluation results

The structural model analysis provides important insights into the relationships between the constructs and their influence on students' readiness for collaborative online learning. Among the predictors, prior knowledge emerged as the strongest determinant of readiness, with a path coefficient of $\beta = 0.670$ ($p = 0.001$) and a T-statistic of 3.262. This finding underscores the critical role of foundational understanding in preparing students for successful engagement in collaborative online learning environments (ElSayary, 2023). Students with a solid knowledge base are better equipped to navigate the complexities of collaborative tasks, contributing to higher readiness levels (Retnowati et al., 2018). These results align with Sweller's Cognitive Load Theory, which emphasizes the importance of prior knowledge in reducing extraneous cognitive load during complex tasks (Sweller, 2020). Similar findings have been reported in recent studies, where foundational knowledge was shown to significantly predict success in collaborative settings by facilitating more efficient problem-solving and peer interactions (Haataja et al., 2022; Kim & Tawfik, 2023). This strong relationship supports H3 (Prior Knowledge → Readiness) and highlights the need for pre-learning interventions to bridge knowledge gaps in online environments.

Furthermore, prior knowledge significantly influenced motivation ($\beta = 0.772$, $p = 0.011$, $T = 2.555$), suggesting that students who feel competent in their subject area are more likely to exhibit intrinsic and extrinsic motivation to participate in collaborative learning. This finding is consistent with Deci and Ryan's Self-Determination Theory, which posits that competence is a core psychological need driving motivation (Ryan & Deci, 2023). Recent empirical studies corroborate this relationship, demonstrating that students with higher prior knowledge are more likely to perceive tasks as achievable and meaningful, which enhances their engagement and persistence in learning activities (McDaniel & Einstein, 2020; Mihalca & Mengelkamp, 2020; Wong & Liem, 2022). These findings confirm H6 (Prior Knowledge → Motivation) and underscore prior knowledge's central role in fostering readiness and motivation.

Motivation demonstrated an interesting pattern of effects. It significantly impacted learning preferences ($\beta = 0.482$, $p = 0.009$, $T = 2.641$), suggesting that motivated students are more adaptable in selecting learning approaches to enhance engagement. This supports H5 (Motivation → Learning Preferences) and highlights the dynamic interplay between motivation and self-directed learning. Similar findings were reported by Yu (2022), who noted that motivated learners tend to experiment with diverse learning strategies to optimize their performance in online environments. However, the direct effect of motivation on readiness was negative and nonsignificant ($\beta = -0.201$, $p = 0.124$). This unexpected result suggests that motivation alone may not be sufficient to drive readiness and may exert its influence indirectly through constructs such as learning preferences. This finding contradicts earlier studies emphasizing the direct role of motivation in online learning readiness (Çebi, 2023) and suggests that the interplay of motivation with other factors, such as cognitive resources or task design, warrants further exploration.

Technological proficiency showed a moderate positive relationship with readiness ($\beta = 0.353$, $p = 0.057$, $T = 1.909$), approaching significance. This suggests that while technological skills are essential, their impact on readiness may depend on complementary factors such as prior knowledge and motivation. This finding partially supports H2 (Technological Proficiency → Readiness) and aligns with studies highlighting the role of digital fluency as a facilitator rather than a standalone predictor of readiness (Reyes-Millán et al., 2023). Interestingly, the path from technological proficiency to motivation was negative and nonsignificant ($\beta = -0.222$, $p = 0.374$), indicating that digital fluency alone does not necessarily enhance motivation. This finding contrasts with research suggesting that confidence in using technology can act as a motivational driver (Alegre, 2023; An et al., 2022; Stiegemeier et al., 2023). The discrepancy may be due to contextual factors, such as students viewing technology as a functional tool rather than an engaging element of the learning process.

The relationship between learning preferences and readiness was positive but nonsignificant ($\beta = 0.218$, $p = 0.421$, $T = 0.806$). This suggests that while accommodating diverse learning preferences can contribute to collaboration, they do not strongly predict readiness in this context. This finding aligns with recent discussions emphasizing that cognitive and motivational factors more strongly drive readiness for collaborative online learning than individual preferences (Pan, 2023; Uden et al., 2022). The lack of significance in this relationship may reflect the influence of dominant factors such as prior knowledge, which appears to overshadow the contribution of learning preferences. Thus, H4 (Learning Preferences → Readiness) was not supported, emphasizing the need to prioritize foundational and motivational factors over stylistic considerations in collaborative online learning design.

These findings provide valuable insights into the complex dynamics of readiness for collaborative online learning. The strong influence of prior knowledge underscores the importance of scaffolding and preparatory activities to address knowledge gaps before engaging students in collaborative tasks. Additionally, the indirect role of motivation suggests that fostering adaptive learning preferences through motivational strategies may enhance students' overall readiness. The limited direct impact of technological proficiency and learning preferences highlights the need for integrating these factors within broader instructional and motivational frameworks.

Table 5 summarizes these findings, including the path coefficients, sample means, standard deviations, T-statistics, and p-values, providing a detailed quantitative evaluation of the model.

Table 5. Path Coefficients and Statistical Significance

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Prior Knowledge -> Readiness	0.67	0.619	0.205	3.262	0.001
Motivation -> Learning Preferences	0.482	0.474	0.182	2.641	0.009
Prior Knowledge -> Motivation	0.772	0.791	0.302	2.555	0.011
Technological Proficiency -> Readiness	0.353	0.38	0.185	1.909	0.057
Motivation -> Readiness	-0.201	-0.165	0.131	1.539	0.124
Technological Proficiency -> Motivation	-0.222	-0.229	0.249	0.89	0.374
Learning Preferences -> Readiness	0.218	0.162	0.27	0.806	0.421

These results provide a nuanced understanding of the relationships among the constructs, with significant paths demonstrating the decisive roles of prior knowledge and motivation in predicting readiness. Meanwhile, nonsignificant paths highlight the complexity of these relationships and the potential for mediating factors that require further exploration. Figure 2 complements this analysis by visually depicting these relationships, illustrating the structural pathways between constructs and their respective indicators.

Qualitative

The thematic analysis of focus group discussions offered valuable empirical support for the quantitative findings, shedding light on students' experiences and perceptions in collaborative online learning environments. By exploring themes such as motivation, prior knowledge, technological proficiency, and learning preferences, the qualitative data provided a richer understanding of the constructs and their practical implications, validating and extending the quantitative results.

Motivation and Engagement

Motivation was pivotal to students' participation and effort in collaborative tasks. The qualitative findings revealed that 78% of participants identified intrinsic motivation, such as curiosity and the desire to excel, as critical for sustaining engagement. For example, one student explained, *"I felt more involved when I knew exactly what was expected of me and when I could interact with my peers to exchange ideas."* Creative and intellectually stimulating tasks, clear objectives, and structured timelines were highlighted as incredibly motivating. These insights align with (Ryan & Deci, 2023; Szulc-Kurpaska, 2023) Self-Determination Theory, which emphasizes the role of intrinsic motivation in fostering engagement.

Additionally, extrinsic motivators, such as grades and recognition, were noted by 64% of participants as important for maintaining effort in repetitive or challenging tasks. This dual role of motivation—balancing intrinsic and extrinsic factors—supports the quantitative finding that motivation significantly influences learning preferences (β = 0.482, p = 0.009). Recent studies corroborate this, suggesting that intrinsic motivation enhances students' adaptability to collaborative learning environments, while extrinsic motivation provides the persistence needed to overcome difficulties (Alamri et al., 2020; Lyu, 2023).

Challenges Related to Prior Knowledge

A significant portion (56%) of participants expressed challenges arising from insufficient foundational understanding when engaging in advanced or problem-based tasks. One participant stated, *"I often felt overwhelmed when I didn't fully understand the basics, but working with peers who explained concepts made it easier for me to catch up."* This sentiment highlights the importance of peer collaboration in mitigating the impact of knowledge gaps, where stronger students support their peers, fostering inclusivity and mutual growth.

The quantitative finding that prior knowledge is the strongest predictor of readiness (β = 0.670, p = 0.001) is reflected in these accounts. This result aligns with Cognitive Load Theory (Sweller, 2020), which posits that a solid knowledge base reduces cognitive load, enabling students to focus on higher-order tasks. Similar findings in recent research underscore the role of peer-assisted learning in collaborative environments, where knowledge sharing among group members enhances overall readiness (Yildiz-Durak, 2022).

Technological Proficiency as a Catalyst

Technological proficiency was frequently described as a facilitator of effective collaboration, with 68% of participants reporting confidence in navigating digital tools as a key enabler. One student noted, *"Being familiar with the technology allowed me to focus more on the task rather than worrying about technical issues."* These experiences validate the quantitative finding of a moderate positive relationship between technological proficiency and readiness (β = 0.353, p = 0.057). This is consistent with research emphasizing the importance of digital fluency in online learning, where technical competence reduces distractions and enhances task focus (Heo et al., 2021; Wang, 2022).

However, 42% of participants with lower technological proficiency expressed frustration and reliance on peers for support. One participant shared, *"I often struggled with some features, and it slowed me down, but my group helped me manage."* These accounts suggest that while technological proficiency is critical, its influence on readiness may be moderated by group dynamics and peer support. Castaño-Muñoz et al. (2023) and Elbyaly & Elfeky (2023) Argue that collaborative environments can offset digital skill deficits by leveraging the collective expertise of group members, as observed in this study.

Learning Preferences and Collaboration Dynamics

Learning preferences played a nuanced role in shaping group interactions, with 61% of participants indicating that their preferences influenced how they collaborated. Visual learners benefited more from multimedia resources, such as videos and diagrams, while reflective learners preferred asynchronous discussions that allowed time for deeper processing (Chan & Wong, 2023). One student explained, *"I liked it when we could take our time to review materials and then discuss them; it helped me understand better."*

However, differing preferences occasionally led to conflicts within groups, as 29% of participants noted. One student remarked, *"Sometimes, it was hard to agree on a working style because some members wanted quick results, while others needed more time to think things through."* These conflicts highlight the challenges of accommodating diverse learning preferences in collaborative environments. The nonsignificant relationship between learning preferences and readiness (β = 0.218, p = 0.421) in the quantitative analysis is consistent with these findings, suggesting that while preferences shape group dynamics, their direct impact on readiness is limited. Recent studies by (Gumasing & Castro, 2023) similarly emphasize that cognitive and motivational factors more influence readiness than by individual learning styles (Lockl et al., 2021).

The qualitative findings provide essential context for the quantitative results, highlighting the interplay of constructs in collaborative online learning. Motivation, while critical for influencing learning preferences, may not directly translate into readiness without the mediating role of other factors like prior knowledge. Similarly, technological proficiency supports readiness but requires complementary elements such as peer support and task alignment to maximize its impact. As the most potent predictor, prior knowledge underscores the foundational importance of equipping students with robust conceptual understanding to navigate the demands of collaborative environments.

LIMITATIONS

While this study provides valuable insights into the factors influencing students' readiness for collaborative online learning, it has some limitations. First, the sample size of 45 undergraduate physics students from a single institution may limit the generalizability of the findings to broader populations or other disciplines. Future studies with larger and more diverse samples are recommended to enhance the robustness and applicability of the results. Second, the study primarily relied on self-reported data, which may introduce response bias. Triangulating survey data with performance metrics or observational methods could provide a more comprehensive understanding of the constructs studied. Lastly, this research focused on specific factors—motivation, prior knowledge, technological proficiency, and learning preferences—while other variables such as self-regulation, peer dynamics, and instructional design were not included and could be explored in future research.

CONCLUSION

This study highlights the critical factors influencing students' readiness for collaborative online learning in physics. Among these, prior knowledge emerged as the strongest predictor, emphasizing the foundational role of solid understanding in facilitating engagement and success in collaborative tasks. Additionally, prior knowledge significantly influenced motivation, reinforcing its role in fostering cognitive and emotional readiness. Motivation also shaped learning preferences, demonstrating its importance in guiding students to adapt their approaches in collaborative environments. However, motivation's direct effect on readiness was nonsignificant, suggesting its influence is mediated by other constructs. While moderately significant, technological proficiency requires complementary factors like prior knowledge and motivation to enhance readiness fully. The role of learning preferences, though not directly impactful on readiness, underscores the need for flexible collaboration designs that accommodate diverse styles and foster group cohesion.

These findings suggest several practical implications. Educators should prioritize strengthening prior knowledge through pre-learning activities, scaffolding, and peer-assisted learning to address foundational gaps. Motivation can be fostered by incorporating creative, structured, and goal-oriented tasks that align with collaborative objectives. Enhancing technological proficiency through targeted training programs can reduce disparities and improve digital fluency. Lastly, collaboration designs should integrate synchronous and asynchronous activities to accommodate diverse learning preferences and minimize group conflicts. These strategies collectively create more inclusive and effective collaborative online learning environments, paving the way for improved academic outcomes and engagement.

AUTHOR CONTRIBUTIONS

This study was jointly conducted by AA and HK. AA was responsible for the conceptualization of the research, designing the methodology, data collection, and drafting the manuscript. HK contributed to the formal analysis, interpretation of results, and critical revision of the manuscript for important intellectual content. Both authors collaborated closely throughout the research process and approved the final version of the manuscript for submission.

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