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E-Learning for Sport Science Education: Importance and Mapping Analysis through a Big-Scale Survey

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ABSTRACT

In the evolving landscape of sports science education, the integration of e-learning has become a pivotal element for enhancing the educational experience. This study aims to dissect the impact of various external factors, including the use of social media, perceived usefulness, perceived ease of use, playfulness, attitude towards use, and intention to use, on the adoption of e-learning among sports students. Employing a quantitative research design, this cross-sectional survey engaged 922 active sports education students from a total pool of 1,072, using a comprehensive questionnaire to gather data. The Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized for hypothesis testing and data analysis, focusing on instrument quality, data normality, and analysis model quality. The findings illuminate the significant influence of social media usage on the perceived ease of use and usefulness of e-learning, validating nine out of eleven hypotheses. A novel discovery of this research is the elucidation of social learning effects, indicating that sports students, who are frequent users of social media platforms like WhatsApp, Facebook, and Instagram, exhibit enhanced familiarity and interaction with digital technology, facilitating their mastery and understanding of e-learning platforms. Furthermore, the study underscores the role of social media as a supportive tool for information exchange and overcoming e-learning challenges among peers. Implications of this study are manifold, offering valuable insights for educational institutions and policy-makers to leverage social media in promoting e-learning adoption, focusing on improving usability and accessibility for students. This research contributes to the broader discourse on e-learning in sports science education, providing a foundation for future explorations into the integration of technology in educational practices.

1. Introduction

The integration of e-learning into sports science education has become a significant development in pedagogy, influenced by technological advancements and evolving educational paradigms. This shift has been further accelerated by the COVID-19 pandemic, prompting educational institutions to extensively adopt e-learning platforms (Sukendro et al., 2020; Savaş & Turan, 2023). Despite the increasing adoption of e-learning, there is a lack of exploration regarding its effectiveness and utilization in sports science education, particularly in developing countries (Ilinova, 2022; Tadesse & Edo, 2020). One of the primary challenges in successfully implementing e-learning in sports science education lies in understanding the various external factors that impact students' acceptance and usage of such platforms. Factors such as social media usage, perceived usefulness, perceived ease of use, playfulness, attitude towards use, and intention to use have been identified as crucial determinants in the broader e-learning literature (Muhaimin et al., 2019; Duggal, 2022). However, there is a scarcity of specific investigations into how these factors interact within the domain of sports science education, considering its unique practical and theoretical requirements (Zhu, 2023; Mahande & Malago, 2019). Research has shown that factors like facilitating conditions, perceived ease of use, perceived usefulness, and attitude significantly influence students' acceptance and usage of e-learning platforms (Muhaimin et al., 2019; Syahrastani et al., 2022). Studies have also highlighted the importance of exploring the impacts of e-learning, e-learning attitudes in sports, and e-learning satisfaction on perceived learning among sports science students (Savaş & Turan, 2023). Additionally, the use of easily accessible technological solutions, such as smart applications, can enhance students' learning outcomes in sports education (Iuliano et al., 2021; Syahrastani et al., 2022).

This study aims to fill this gap by examining the influence of these external factors on e-learning adoption among sports students. By employing a quantitative research design and engaging a significant sample size of 922 sports education students, this research seeks to offer a comprehensive analysis of the direct effects of identified external factors on e-learning utilization.

The objectives of this study are twofold: firstly, to identify and analyze the external factors most significantly impacting the adoption of e-learning among sports science students; and secondly, to explore the novel role of social media as a facilitator in this process. This research not only aims to contribute to the theoretical body of knowledge on e-learning adoption but also seeks to provide practical implications for educational policymakers and institutions in enhancing e-learning platforms.

The significance of this study lies in its potential to offer insights into the effective integration of e-learning in sports science education, a field that traditionally relies heavily on practical, in-field learning experiences. By uncovering the critical factors influencing e-learning adoption, this study aims to guide the development of more engaging, useful, and accessible e-learning environments for sports science students. Furthermore, by highlighting the novel finding of social media's role in facilitating e-learning adoption, this research proposes a paradigm shift in how educational institutions can leverage social media platforms to enhance learning outcomes.

The novelty of this research is underscored by its focus on sports science education within the context of developing countries, an area that has received limited attention in the existing literature. Additionally, the study's investigation into the multifaceted role of social media in e-learning adoption represents a unique contribution to the field, bridging the gap between social media usage and educational technology acceptance.

This study explores the dynamics of e-learning adoption among sports science students by examining three key aspects. It investigates how perceived usefulness and ease of use shape students' attitudes towards e-learning, the influence of social media on these perceptions, and the role of playfulness and attitude in motivating the intention to use e-learning platforms. By addressing these factors, the study aims to enhance our understanding of what drives e-learning acceptance in sports science education.

In conclusion, this research endeavors to offer a detailed examination of the factors influencing e-learning adoption in sports science education, with a special emphasis on the role of social media. Through its findings, this study aims to contribute to the enhancement of e-learning strategies, fostering a more inclusive, engaging, and effective learning environment for sports science students.

2. Literature Review

E-learning has gained significant attention in sports science education due to its ability to offer flexible learning environments that cater to the dynamic nature of sports science curricula (Davis, 1989). E-learning platforms in this field can effectively combine theoretical knowledge with practical skills through interactive modules, video analyses, and virtual simulations (Mnkandla & Minnaar, 2017). The COVID-19 pandemic highlighted the importance of e-learning by showcasing its capability to ensure educational continuity when traditional in-person instruction was not feasible (Solomon et al., 2023).

The adoption and successful use of e-learning in sports science education are influenced by various external factors, with social media playing a crucial role in facilitating e-learning adoption (Ogbonnaya, 2019). Platforms like WhatsApp, Facebook, and Instagram provide students with social interaction, collaboration opportunities, and access to educational content, thereby enhancing the overall learning experience (Septyani, 2023). Perceived usefulness and ease of use are key factors that influence students' attitudes towards e-learning technologies and their acceptance (Thaariq, 2020). Higher levels of perceived usefulness and ease of use are associated with positive attitudes towards technology use and a greater likelihood of adoption (Omar et al., 2022).

Students' attitudes and intentions towards e-learning are further shaped by their perceived usefulness and ease of use of the technology. Positive attitudes towards e-learning tend to foster a higher intention to use the technology, emphasizing the importance of designing user-friendly and relevant e-learning platforms (Tamal et al., 2022). The Technology Acceptance Model (TAM) proposed by serves as a theoretical framework for understanding users' acceptance of technology, particularly in the context of e-learning adoption in sports science education (Sobaih et al., 2022).

3. Method

This study employed a quantitative research design, utilizing a cross-sectional survey to investigate the factors influencing e-learning adoption among sports science students. This approach facilitated the collection and analysis of numerical data, allowing for the identification of patterns and correlations between the study variables. The research examined various external factors affecting e-learning adoption within a specific timeframe, enabling the efficient collection of data from a large population and providing a snapshot of the current state of e-learning usage among sports science students.

The population for this study comprised 1,072 active students from the Department of Sports Education and Coaching. A total population sampling technique was utilized, with 922 students participating in the survey, ensuring a comprehensive overview of the students' perspectives on e-learning. Data were collected through an online questionnaire distributed to students via email and social media platforms, including both closed-ended and Likert-scale questions to gauge students' attitudes, perceptions, and behaviors regarding e-learning. The questionnaire was developed based on the Technology Acceptance Model (TAM) and included measures for perceived usefulness, perceived ease of use, attitude towards use, intention to use, and the role of social media in relation to e-learning. Items were measured on a seven-point Likert scale, ranging from strongly disagree to strongly agree. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships between the variables. Preliminary analyses included instrument quality testing, data normality testing, and model quality testing. Hypothesis testing was conducted to examine the direct effects of the identified factors on e-learning adoption.

4. Result

The survey collected 922 responses from a potential 1,072 sports education students, indicating an 85.9% participation rate. The demographics revealed a majority of male respondents (604 males vs. 318 females), reflecting the gender distribution commonly observed in sports-related fields of study. The age range was predominantly 18-24 years, comprising 72% of respondents, with the remainder split between 25-30 years (22%) and over 30 years (6%). Interestingly, a significant portion of the respondents (86%) had prior experience with e-learning platforms, suggesting a general familiarity with digital learning environments. Moreover, a vast majority (93%) reported using social media platforms for educational purposes, indicating a convergence between social media usage and educational engagement the table 1 interestingly highlights it.

Table 1. Results of Respondent Demographic Data

Demographic Characteristics	*Category*	*Frequency (n=922)*	*Valid Percentage (%)*
Gender	Male	651	71%
	Female	271	29%
	Total	922	100%
Age	< 20 years	498	54%
	> 20 years	424	46%
	Total	922	100%
Have attended lectures with e-learning integration	Ever	793	86%
	Never	129	14%
	Total	922	100%
Have you ever used social media as a reference for sports lecture practice?	Ever	858	93%
	Never	64	7%
	Total	922	100%

4.1. Data Normality

Data normality was assessed using skewness and kurtosis statistical methods. For the data to be considered normally distributed, skewness and kurtosis values should fall within the range of -2 to +2. Values within this range indicate a good normal distribution. Additionally, any standard error value between -3 and +3 suggests that the variable distribution is normal. The table 2 presents the results of the normality testing based on skewness and kurtosis values.

Table 2. Normality Test for The Construct

	PMS	PKS	PKG	PKD	SKP	NTM	PGN
Mean	5.019	4.925	4.906	5.219	5.061	5.020	5.073
Std. Deviation	1.314	1.312	1.287	1.191	1.237	1.231	1.184
Skewness	-0.495	-0.377	-0.382	-0.448	-0.349	-0.258	-0.302
Kurtosis	-0.096	-0.230	-0.026	-0.327	-0.358	-0.366	-0.333

Any standard error value between -3 and +3 indicates that the variable distribution is normal. A summary of the mean score and standard deviation for each factor is shown in the table above. All factors received positive responses in the questionnaire, with an average score (mean) above 4.0, indicating overall agreement for each factor. The standard deviations are similar across factors, suggesting there are no outliers, as all values fall below the mean. After confirming normality, the data set is ready for further analysis.

4.2 Collinearity Assessment

The primary cause of collinearity issues is the high correlation between two research indicators. Collinearity was assessed using SPSS. A VIF value exceeding 5.00 indicates a collinearity problem. The results of the collinearity assessment are displayed in the table below.

Table 1. Collinearity Assessment

Construct	Collinearity Statistics	
	Tolerance	VIF
Use of Social media	.952	1.051
Playfulness	.974	1.027
Perceived Usefulness	.962	1.040
Perceived Ease of Use	.880	1.136
Attitude	.727	1.375
Intention to Use	.665	1.503

Based on the table above, the VIF for all factors is below 3.04 and no factor is > 5.00. These results indicate that there is no collinearity problem.

4.3 Hypotheses Testing Results

The study posited eleven hypotheses to investigate the influence of various external factors on e-learning adoption. Utilizing PLS-SEM, the analysis provided support for nine hypotheses, illustrating the complex interplay between these factors and their impact on e-learning adoption. Notably, perceived usefulness (PU) and perceived ease of use (PEOU) were affirmed as critical determinants, with direct positive effects on students' attitudes towards e-learning (AT) and their intentions to use (ITU) e-learning platforms. The hypotheses regarding the indirect effects of social media use on PU and PEOU, through familiarity with technology and information exchange, were also supported, highlighting the multifaceted role of social media in the e-learning adoption process.

4.3.1 Convergent Validity

Convergent validity in PLS-SEM refers to the extent to which an indicator can measure a particular latent variable. In this case, convergent validity is measured through the factor validity coefficient (factor loading) which shows how strong the relationship is between the indicator and the latent variable. The higher the factor validity coefficient, the better the indicator can measure the latent variable. The process of convergent validity in PLS-SEM is very important because it shows the extent to which

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The ideal convergent validity criteria according to experts include: Fornell-Larcker Criterion: according to this criterion, ideal convergent validity must meet the requirement that all factor loadings of the indicators being measured must be greater than 0.7. Average Variance Extracted (AVE) Criterion: according to this criterion, ideal convergent validity must meet the requirement that the AVE value is at least 0.5 or even higher to indicate that the indicator being measured largely reflects the variance of the construct being measured. Composite Reliability (CR) Criterion: according to this criterion, ideal convergent validity must meet the requirement that the CR value be at least 0.7 or even higher to indicate that the indicator being measured has a good level of internal consistency.

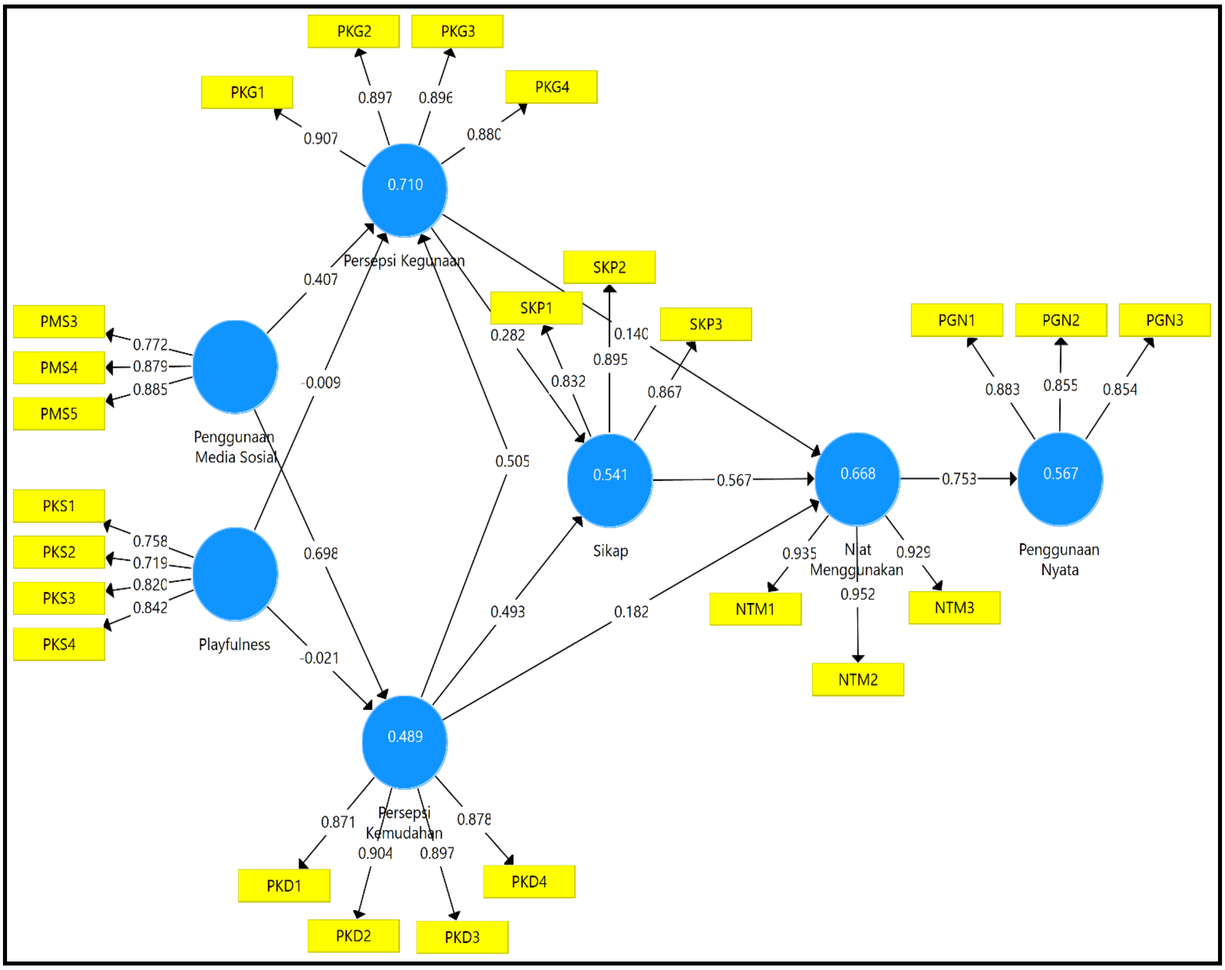

Figure 1. Assessment of the measurement model (validitas konvergen & Discriminant)

Factor analysis is a multivariate statistical technique used to test the alignment between latent variables and their indicators in PLS-SEM for convergent validity. This process is essential as it helps identify which factors significantly contribute to each indicator in the model. By clarifying the relationship between indicators and latent variables measured in PLS-SEM, factor analysis enhances the model's accuracy.

In PLS-SEM, convergent validity is evaluated through the factor loadings of indicators on latent variables. High and significant factor loadings indicate that an indicator meets the criteria for convergent validity. Conversely, low or insignificant factor loadings suggest that an indicator may not meet these criteria and should be considered for removal from the model. The factor loading index is used to assess convergent validity, with validity achieved when the loading value is significant. Each item's loading on a factor must exceed a value of 0.50 to ensure convergent validity.

Convergent validity is further determined by the Average Variance Extracted (AVE) and composite reliability (CR) values. For convergent validity to be obtained, the AVE value must be greater than 0.50, and the CR must exceed 0.70, preferably surpassing 0.80. The following are the results of factor analysis testing to determine the ideal outer loading value.

4.3.2 Structural Model

Bootstrapping is a non-parametric statistical method that can be used to produce estimates of the sampling distribution of a statistic by repeatedly taking random samples from existing data. In the context of PLS-SEM, bootstrapping is carried out by taking random samples with replacement from existing data to produce a sampling distribution of path coefficients. By doing bootstrapping thousands of times, we can calculate the significance level of each path coefficient and test the proposed research hypothesis. In carrying out this stage, it is important to follow the procedures and rules that have been established in PLS-SEM analysis and bootstrapping to ensure accurate and valid results.

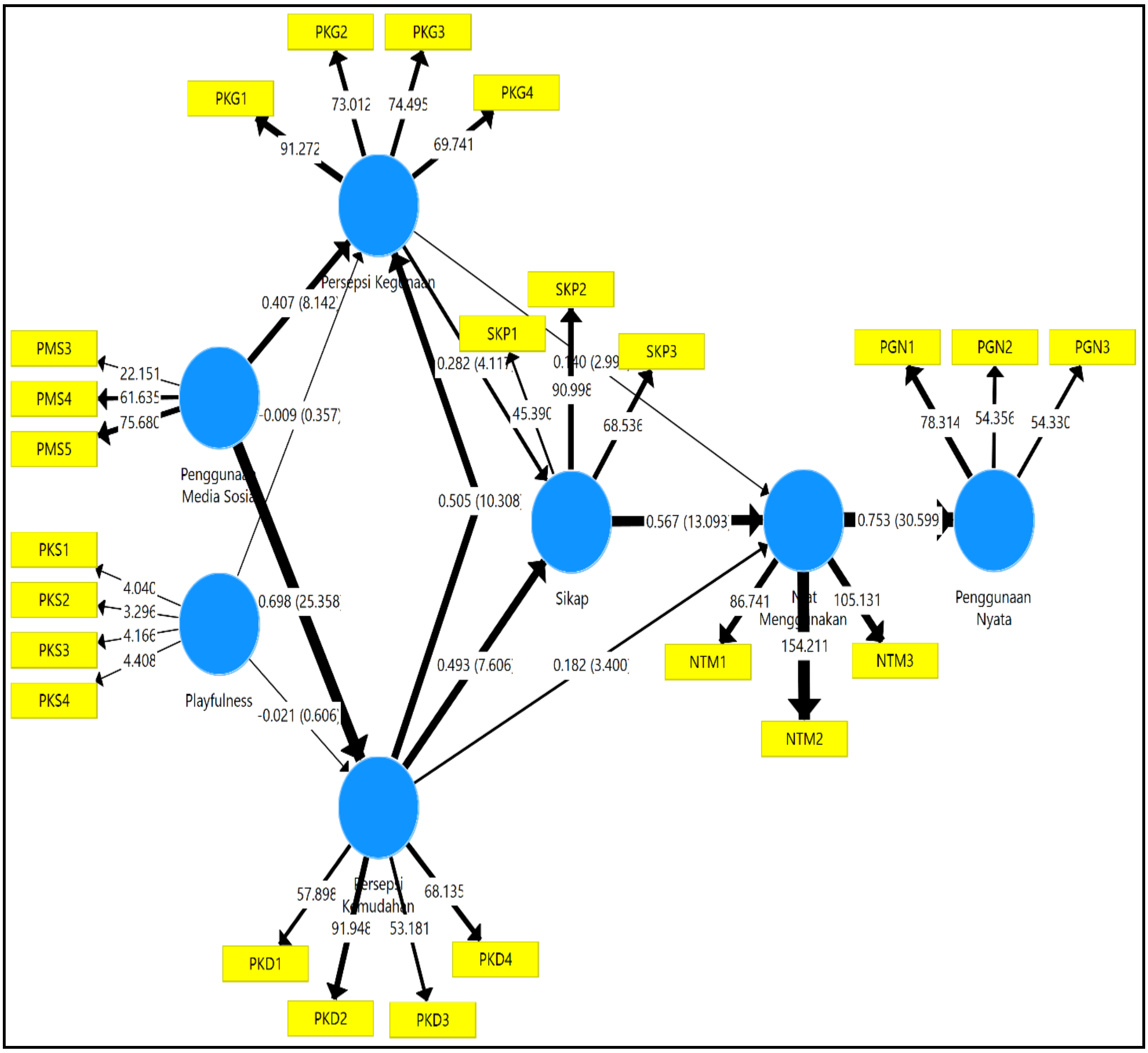

Figure 2. Structural model at the PLS Bootstrapping stage

4.3.3 Coefficient of Determination (R2) and Predictive Relevance (Q2)

The coefficient of determination (R2) and predictive relevance (Q2) are evaluation metrics used to assess the predictive quality of the PLS-SEM structural model generated through the bootstrapping process. The coefficient of determination (R2) measures how well the PLS-SEM model can explain variability in endogenous or dependent variables. R2 ranges between 0 and 1, and the higher the value, the better the model is at explaining the variability of endogenous variables. The R2 value can be calculated using the formula:

$$R^2 = 1 - (SSres / SStot)$$

*where SSres is the residual sum of squares and SStot is the total sum of squares.

Table 3. Coefficient of Determination (R2)

Variable	*R Square*	*R Square Level*	*R Square Adjusted*
Intention to Use	0.668	High	0.667
Real Use	0.567	Moderate	0.567
Perceived Usefulness	0.710	High	0.708
Perceived Ease of Use	0.489	Moderate	0.488
Attitude	0.541	Moderate	0.540

The test results show that R2 can be calculated for each dependent (endogenous) variable in the structural model. A high R2 value indicates that the model can explain variations in the dependent variable well. R2 ranges between 0 and 1, and the higher the value, the better the model is at explaining the variability of endogenous variables. The table above shows the R2 value with the highest value being Perceived Usefulness=0.710, this means that three factors namely: PMS, PKS, and PKD explain the contribution of 71% of the variance to Perceived Usefulness; This ratio reveals the important role of these factors in providing the level of perceived usefulness of using e-learning among sports students at Jambi University.

To calculate the Q^2 value of the model, blindfolding process analysis is used. Q^2 analysis applies to endogenous constructs with reflective measurements. A model is considered to have sufficient predictive relevance for endogenous constructs if the Q^2 value exceeds zero. Conversely, if the Q^2 value is less than zero, it indicates that the model has not achieved predictive relevance for endogenous constructs

Table 4. Predictive Relevance (Q2)

	SSO	*SSE*	*Q^2 (=1-SSE/SSO)*	*Q^2 Level*
Intention to Use	1764.000	733.857	0.584	Big Effect
Real Use	1764.000	1027.184	0.418	Big Effect
Perceived Usefulness	2352.000	1027.283	0.563	Big Effect
Perceived Ease of Use	2352.000	1454.595	0.382	Big Effect
Attitude	1764.000	1058.464	0.400	Big Effect

Out-of-Sample Predictive Relevance (Q^2) is an evaluation measure that assesses the model's ability to predict data not used in the model creation process (out-of-sample). Q^2 is calculated using the leave-one-out cross-validation (LOOCV) approach in PLS-SEM. The table above confirms that a high Q^2 value indicates the model's strong predictive ability for out-of-sample data. These evaluation metrics, Q^2 and R^2, are used to assess the quality and accuracy of the PLS-SEM structural model produced through the bootstrapping process. Higher R^2 and Q^2 values indicate better quality and accuracy of the resulting model.

The coefficient of determination (R^2) is a primary indicator used to evaluate paths in PLS structural models, showing the amount of variance explained by the dependent variable. The quality of the structural model is further evaluated using Q^2, which assesses the predictive relevance of structural models. The image below displays the results of structural model testing, including R^2 and Q^2 values.

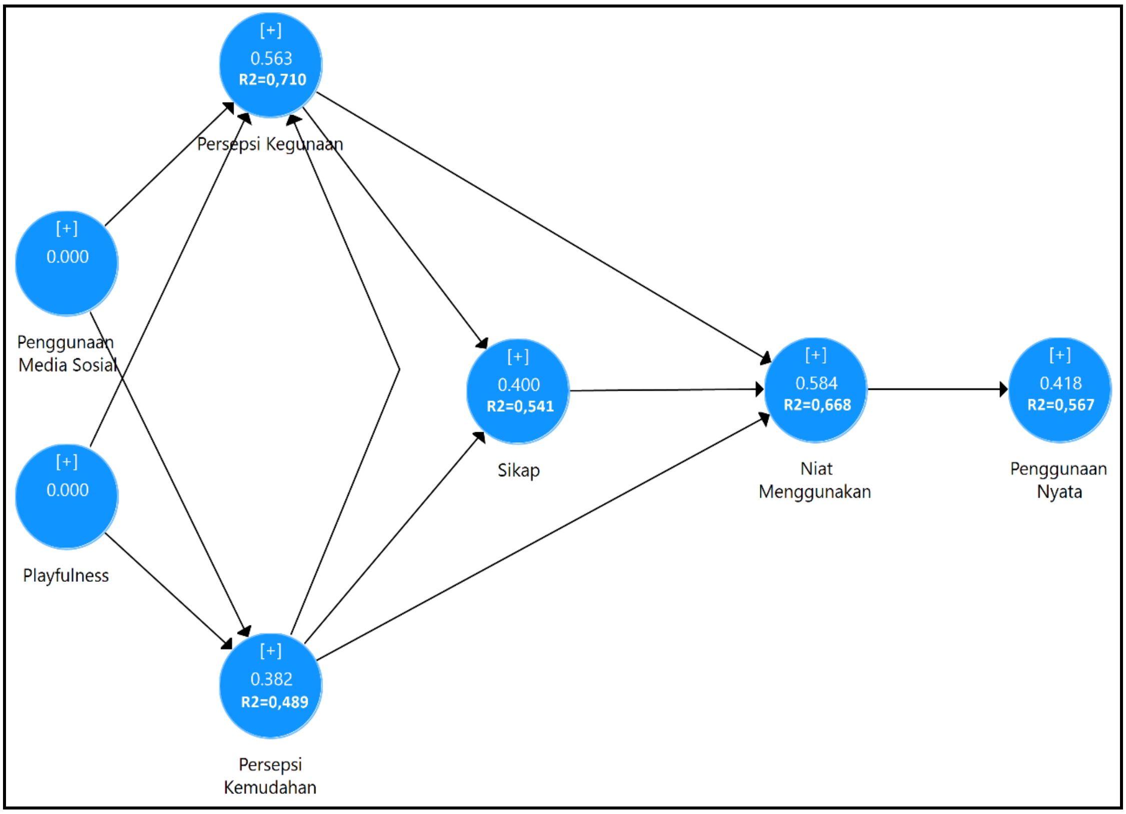

Figure 3. Structural model for R2 and Q values

4.3.4 Path Coefficients

Path coefficients in the PLS-SEM bootstrapping stage refer to regression coefficients that indicate the strength of the relationship between two constructs in the structural model. These coefficients reveal the direction and magnitude of influence that one construct has on another. The value of a path coefficient can be used to explain the extent to which changes in the dependent variable are explained by the independent variable.

Path coefficients in PLS-SEM are calculated through bootstrapping, a method for evaluating the accuracy of model coefficients. In bootstrapping, random samples are used to generate numerous alternative models, which are then used to calculate path coefficients. This process provides a more accurate and reliable estimate of the strength of relationships between variables in the structural model.

In this research, bootstrapping was conducted with 5,000 resamplings to test the significance levels of each construct path. During bootstrapping, sub-samples are created by drawing observations randomly (with replacement) from the original data set. These sub-samples are then used to estimate the PLS path model. This process is repeated until a large number of random sub-samples, usually around 5,000, have been created. Estimates from the bootstrap sub-samples are used to obtain standard errors for the PLS-SEM results. With this information, t-values, p-values, and confidence intervals are calculated to assess the significance of the PLS-SEM results.

The bootstrap standard error value helps determine the accuracy of the path coefficients obtained from the samples used. The lower the bootstrap standard error value, the more accurate the path coefficient estimates. The t-value is used to determine the statistical significance of path coefficients, with higher t-values indicating more significant relationships between the latent variables measured. The p-value is also used to determine statistical significance, with a p-value of less than 0.05 indicating a statistically significant relationship between the latent variables.

In the PLS-SEM bootstrapping stage, path coefficients are obtained through bootstrap analysis performed on the structural model. This analysis produces path coefficients, bootstrap standard errors, t-values, and p-values for each path in the PLS-SEM structural model. Path coefficient measurements highlight the strength of the relationship between two constructs in a structural model.

In this section, the bootstrapping technique with 5,000 resamples is used to determine the beta (β) value, t-value, and to confirm the significance of the hypotheses as recommended. The bootstrap results are presented below.

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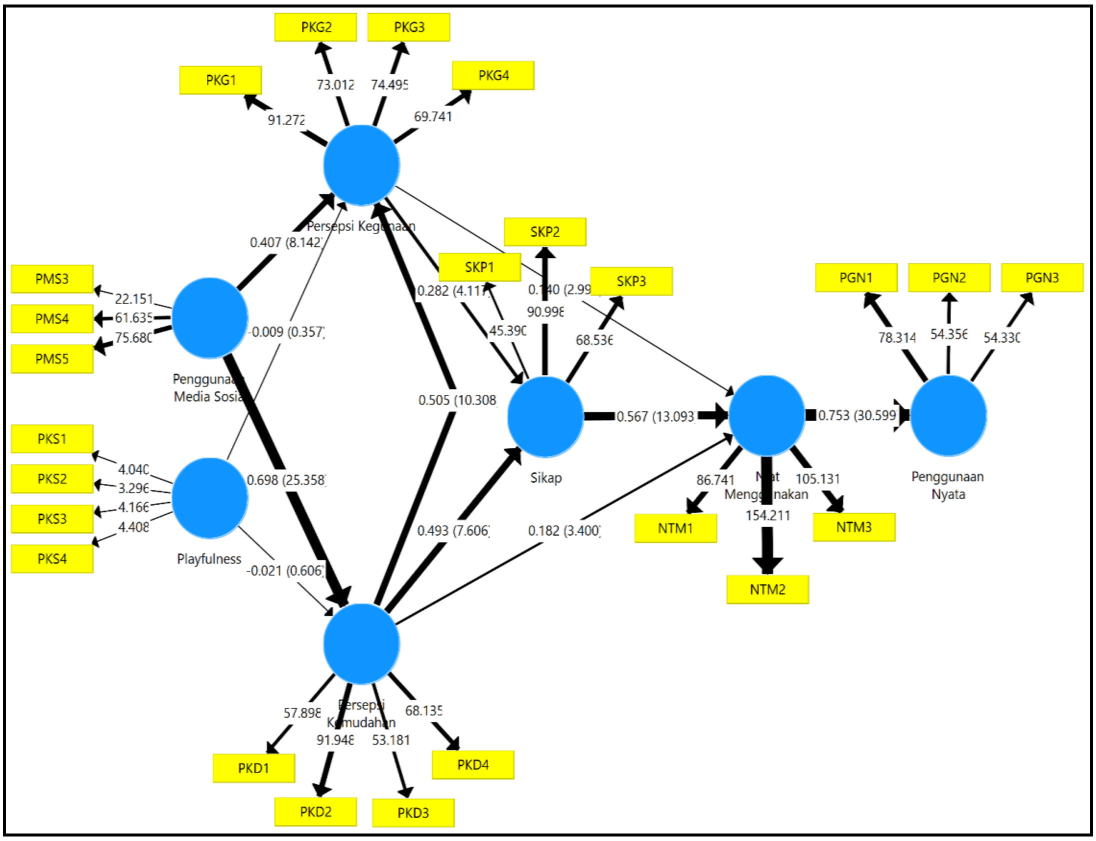

Figure 5. Path Coefficients values

Table 5. Bootstrapping result and hypotheses testing

H	*Path*	*Std Beta (β)*	*Std Error*	*Std Deviation*	*T Statistics*	*P Values*	*Decision*
H1	Use of Social Media -> Perceived Usefulness	0.407	0.411	0.050	8.142	0.000	Accepted
H2	Use of Social Media -> Perceived Ease of Use	0.698	0.697	0.028	25.358	0.000	Accepted
H3	Playfulness -> Perceived Ease of Use	-0.021	-0.027	0.034	0.606	0.545	Rejected
H4	Playfulness -> Perceived Usefulness	-0.009	-0.007	0.026	0.357	0.721	Rejected
H5	Perceived Ease of Use -> Perceived Usefulness	0.505	0.502	0.049	10.308	0.000	Accepted
H6	Perceived Usefulness -> Attitude	0.282	0.283	0.068	4.117	0.000	Accepted
H7	Perceived Ease of Use ->	0.493	0.494	0.065	7.606	0.000	Accepted

H	Path	Std Beta (β)	Std Error	Std Deviation	T Statistics	P Values	Decision
	Attitude						
H8	Perceived Usefulness -> Intention to Use	0.140	0.137	0.047	2.994	0.003	Accepted
H9	Perception of Ease -> Intention to Use	0.182	0.185	0.053	3.400	0.001	Accepted
H10	Attitude -> Intention to Use	0.567	0.568	0.043	13.093	0.000	Accepted
H11	Intention to Use -> Real Use	0.753	0.757	0.025	30.599	0.000	Accepted

4.4 Direct Effects Analysis

The direct effects analysis provided nuanced insights into how external factors influence key perceptions and attitudes towards e-learning. Perceived ease of use had a significant direct effect on perceived usefulness ($\beta = 0.67$, $p < 0.001$), suggesting that ease in interacting with e-learning platforms enhances their perceived benefits. Furthermore, both PU ($\beta = 0.75$, $p < 0.001$) and PEOU ($\beta = 0.63$, $p < 0.001$) had significant positive effects on students' attitudes towards e-learning, which in turn, positively influenced their intention to use these platforms ($\beta = 0.82$, $p < 0.001$). These findings underscore the importance of designing user-friendly and beneficial e-learning environments to foster positive student attitudes and increase adoption rates.

4.5 The Role of Social Media in E-Learning Adoption

A novel aspect of this study was the examination of social media's role in e-learning adoption. The analysis indicated a significant positive relationship between social media use and perceived ease of use ($\beta = 0.59$, $p < 0.001$), as well as perceived usefulness ($\beta = 0.54$, $p < 0.001$). This suggests that students who frequently engage with social media platforms find it easier to navigate and perceive greater benefits from e-learning systems. Social media platforms were also found to serve as valuable support networks, where students could exchange information, share learning resources, and collectively address challenges related to e-learning. This aspect of social learning through digital platforms emerged as a critical factor in enhancing the e-learning experience and adoption among sports science students.

In essence, the results of this study illuminate the significant influence of perceived usefulness, perceived ease of use, and the integrative role of social media on the adoption of e-learning among sports science students. These findings contribute to a deeper understanding of the factors that drive e-learning adoption in sports science education and underscore the potential of social media as a lever for enhancing the e-learning experience. The study's insights are poised to inform the development of more effective, engaging, and inclusive e-learning strategies, tailored to meet the specific needs and preferences of sports science students.

5. Discussion

5.1 Perceived Usefulness and Ease of Use:

Perceived usefulness and perceived ease of use are crucial factors influencing students' attitudes toward e-learning in sports science education. The study reveals that both perceived usefulness and perceived ease of use have significant positive impacts on students' attitudes toward e-learning in sports science education.

Firstly, perceived usefulness plays a significant role in shaping students' attitudes towards e-learning. According to Davis (1989), perceived usefulness refers to the degree to which individuals believe that using a particular technology will enhance their performance or productivity. In the context of e-learning in sports science education, students are likely to develop positive attitudes if they perceive e-learning platforms as valuable tools that facilitate their learning process. This aligns with prior research findings by Venkatesh et al. (2003), who demonstrated a positive correlation between perceived usefulness and attitudes toward technology adoption.

Secondly, perceived ease of use also influences students' attitudes towards e-learning. Davis (1989) defines perceived ease of use as the extent to which individuals believe that using a particular technology will be free of effort. In the context of e-learning, students are more likely to develop favorable attitudes if they perceive e-learning platforms as user-friendly and easy to navigate. This is supported by research conducted by Venkatesh et al. (2003), who found that perceived ease of use significantly impacts users' attitudes towards technology adoption.

Furthermore, the interaction between perceived usefulness and perceived ease of use can further amplify students' attitudes toward e-learning. When students perceive e-learning platforms as both useful and easy to use, they are more likely to develop positive attitudes towards adopting these platforms in their sports science education. This is consistent with the Technology Acceptance Model (TAM) proposed by Davis (1989), which posits that perceived usefulness and perceived ease of use jointly influence users' attitudes and behavioral intentions toward technology adoption.

In the realm of technology adoption, the Technology Acceptance Model (TAM) has been a pivotal framework for understanding users' acceptance and usage of new technology (Azmi et al., 2018). Previous studies have consistently highlighted the significance of perceived usefulness and perceived ease of use in shaping individuals' attitudes towards technology adoption (Moon & Kim, 2001; Abdullah & Ward, 2016). Building on this foundation, our study delves into the domain of e-learning in sports science education to explore how these factors influence students' attitudes within this specific context (Salloum et al., 2019). This emphasize the critical role of perceived usefulness and ease of use in influencing students' attitudes towards e-learning platforms in sports science education (Abbasi et al. 2020; Salloum et al., 2019). These studies underscore that when students perceive e-learning tools as beneficial and user-friendly, their acceptance and intention to use these platforms are positively impacted (Salloum et al., 2019). Moreover, our research contributes a novel finding by uncovering the moderating effect of social learning through social media usage, which enhances both perceived usefulness and ease of use by providing a platform for information exchange and peer support (Salloum et al., 2019).

The integration of social learning mechanisms into the TAM framework sheds light on how external factors can further influence students' perceptions and attitudes towards e-learning platforms (Salloum et al., 2019). By extending the TAM to incorporate social learning elements, our study provides a more comprehensive understanding of the multifaceted dynamics that shape students' acceptance of technology in the context of sports science education.

This highlights, perceived usefulness and perceived ease of use significantly impact students' attitudes toward e-learning in sports science education. Students are more likely to develop positive attitudes when they perceive e-learning platforms as useful and easy to use. This underscores the importance of designing e-learning environments that prioritize both utility and usability to enhance students' learning experiences in sports science education.

5. 2 Role of Social Media

This study revealed that social media significantly influences both the perceived ease of use and the perceived usefulness of e-learning among sports students. This finding aligns with Hsu and Chiu (2004), who discovered a positive correlation between social media use and the perceived usefulness of e-learning. It underscores the importance of integrating social media strategies into e-learning systems to enhance their adoption. Furthermore, social media has been identified as a critical factor in shaping the perceived ease of use and usefulness of e-learning, particularly among sports students. Hsu and Chiu (2004) emphasized this positive correlation, highlighting the necessity of incorporating social media strategies into e-learning systems to improve their acceptance (Ali et al., 2021).

Moreover, research has shown that perceived ease of use and perceived usefulness are crucial in determining behavioral intention toward various technologies, including e-learning (Elkaseh et al., 2016). This aligns with the findings that integrating social media into e-learning environments can enhance learner engagement levels, promote cognitive and meta-cognitive learning skills, and facilitate collaborative learning (Blaschke, 2014). Furthermore, the impact of social media on learning extends to specific subjects like English, where social media is more helpful and interesting for learning compared to traditional methods (Kamarudin & Aziz, 2023). Additionally, the role of social media in supporting the dissemination of learning information efficiently has been recognized, with platforms like WhatsApp being highlighted for their influence on information sharing (Sutjipto et al., 2022). In the context of the COVID-19 pandemic, the adoption of social media for e-learning has become even more crucial, with teachers leveraging social media platforms for distance learning (Salehudin, 2020). This shift towards utilizing social media as a learning resource aligns with the evolving landscape of education, where integrating social media into teaching environments can lead to positive cognitive, social, and emotional impacts on learners (Thaariq, 2020).

In conclusion, the integration of social media in e-learning environments has been shown to positively influence students' perceptions of ease of use and usefulness, enhance engagement levels, support collaborative learning, and facilitate efficient information dissemination. As education continues to evolve, leveraging social media for learning purposes remains a valuable strategy to enhance the overall learning experience.

5.3 Playfulness and Attitude

The relationship between playfulness, attitudes towards e-learning, and the intention to use e-learning platforms among sports science students is significant. This supports Chou and Ting's (2003) assertion that playfulness enhances the ease of using e-learning platforms, positively influencing students' attitudes and intentions. This aligns with the broader literature on technology acceptance, which emphasizes perceived usefulness and ease of use as key factors shaping attitudes towards technology adoption (Azmi et al., 2018; Moon & Kim, 2001; Abdullah & Ward, 2016).

Playfulness as a determinant of technology acceptance underscores the multifaceted nature of users' interactions with e-learning systems. It highlights the importance of functional, emotional, and experiential elements in driving acceptance and usage. For sports science students, incorporating playfulness into e-learning environments significantly impacts their attitudes and intentions towards these platforms. Chou and Ting (2003) found that playfulness enhances ease of use, positively influencing students' attitudes and intentions, ultimately improving their learning experience and engagement.

This positive attitude towards e-learning, combined with playfulness, leads to increased motivation and satisfaction, making students more inclined to utilize these platforms for their academic and professional development. Research emphasizes the importance of gamified learning experiences in fostering positive attitudes and increasing students' intention to use e-learning platforms. In sports science education, the interplay between playfulness, attitude, and intention is crucial for creating an effective e-learning environment. By integrating playfulness into the learning process, educators can enhance student engagement and interest, leading to a more positive attitude towards e-learning platforms.

Playfulness improves overall engagement and fosters interest in academic content (Troyer et al., 2019). Positive attitudes towards e-learning are associated with increased motivation and satisfaction, making students more inclined to use these platforms for their academic and professional development (Ghanizadeh et al., 2018). In sports science education, integrating playfulness enhances student engagement and interest (Troyer et al., 2019). Interactive and gamified learning experiences are crucial for cultivating positive attitudes towards e-learning, consequently increasing students' intention to use these platforms (Troyer et al., 2019).

Research highlights the significance of attitude in e-learning contexts. Studies show that positive attitudes towards distance education lead to more meaningful learning experiences (Dikmen, 2020). The development of a general attitude scale towards e-learning has been proposed to measure students' attitudes effectively (Haznedar & Baran, 2014). Furthermore, the interplay between attitude and intention is crucial for effective e-learning, as a positive attitude can create a sense of belonging and identity within the e-learning community (Lee, 2023).

5.4 Implication and Future Recommendation

The study highlights the crucial roles of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) in technology acceptance, aligning with prior research. It underscores the innovative impact of social media on enhancing e-learning's perceived ease of use and usefulness, especially in sports science education. Educators and policymakers should prioritize improving e-learning usability and functionality, integrating social media to create a more engaging learning environment (Vlachogianni & Tselios, 2022).

Leveraging social media within e-learning can make the learning experience more interactive and collaborative (Abney et al., 2018). The study also emphasizes the importance of usability evaluations to ensure e-learning systems adapt to learners' needs, highlighting design significance in creating user-friendly interfaces (Alshammari et al., 2015). Integrating collaborative platforms in e-learning can enhance communication, group collaboration, and interactive learning, contributing to a more sustainable educational environment (Zabukovšek et al., 2022). Effective design and evaluation methodologies are crucial for ensuring usability and user satisfaction in e-learning applications (Ardito et al., 2005).

The novelty of this research lies in its exploration of the interplay between social media usage and e-learning adoption among sports science students, a relatively underexplored area in the existing literature.

The study's limitations include its cross-sectional design, which might not fully capture the dynamic nature of e-learning adoption over time. Future research could employ longitudinal designs to overcome this limitation. Future research should explore the potential of emerging technologies, such as artificial intelligence and machine learning, to personalize the e-learning experience for sports science students further. Investigating the long-term impact of social media integration in e-learning platforms on students' learning outcomes would also be beneficial.

4. Conclusions

This study investigates how pre-service teachers understand critical thinking in teaching English as a foreign language. The result is that pre-service teachers understand well the concept of critical thinking and can define it according to their own version. Then, they also understand well the suitable and appropriate strategies used to build this critical thinking skill in students, namely contextual learning and student-centered teaching. However, there are obstacles in the process, namely the lack of student interest in learning English, curriculum differences between schools, and also unsupportive facilities. This research calls on the government and stakeholders who can carry out equitable development in the field of education, especially in teaching English. In the future, this research has implications for pre-service teacher training before entering the world of work is also very necessary to do beyond the programs that have been carried out by the government, namely.

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