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Influential knowledge management factors in the acceptance of mobile learning among university students

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Abstract

The accelerated integration of mobile technologies in higher education has fostered the adoption of Mobile Learning (M-learning) as a flexible, accessible, and student-centered pedagogical model. However, the successful acceptance and sustained use of these platforms require the interplay of various factors. This study aims to examine the influence of key knowledge management processes—specifically, knowledge application, sharing, and protection—along with constructs from the Technology Acceptance Model (TAM), on M-learning acceptance among university students. A quantitative, cross-sectional research design was employed, involving 150 undergraduate students from a private university in Peru. Data were collected using a validated polychoric Likert-scale questionnaire and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicate that perceived ease of use, perceived usefulness, and knowledge sharing positively affect the application of knowledge within M-learning environments, confirming the relevance of integrating knowledge management principles with TAM. Notably, the relationship between knowledge application and actual system use, as well as between behavioral intention and knowledge application, was not statistically significant, suggesting the presence of unmeasured contextual factors. The model demonstrated strong explanatory power for knowledge application ($R^2 = 0.739$), while the explanatory power for actual system use was moderate ($R^2 = 0.243$). Findings underscore the need for educational institutions to design user-friendly M-learning platforms, promote collaborative knowledge exchange, and consider institutional and motivational variables that may enhance the sustained adoption of mobile learning technologies.

Keywords: Knowledge management, knowledge sharing, mobile learning, perceived ease of use, perceived usefulness, PLS-SEM, technology acceptance model, and university students.

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1. Introduction

In recent decades, the rapid advancement of Information and Communication Technologies (ICT) has profoundly transformed educational environments, fostering the adoption of new pedagogical models. Among these, Mobile Learning (M-learning) stands out due to its ability to offer flexible and accessible learning through mobile devices such as smartphones and tablets, enabling students to access content and resources anytime and anywhere [1]. Various studies have demonstrated that M-learning not only improves accessibility but also promotes active, student-centered methodologies, increasing motivation and knowledge retention [2, 3].

Mobile Learning (M-learning) is defined as an educational model based on the use of mobile devices—such as smartphones, tablets, and laptops—that facilitates flexible access to learning content and resources anytime and anywhere [1]. Unlike other modalities, M-learning integrates features inherent to mobility and connectivity, providing ubiquitous and personalized learning environments.

M-learning not only allows for the constant availability of information, but also supports active, student-centered methodologies such as microlearning, gamification, augmented reality, and collaborative learning [4]. These elements enhance motivation, engagement, and knowledge retention [3].

In parallel, Knowledge Management (KM) has emerged as a key approach in academic environments, promoting systematic processes for the creation, acquisition, storage, sharing, application, and protection of knowledge [5]. Its integration into digital educational platforms has shown positive results, enabling not only the accumulation of knowledge but also its effective transfer between students and instructors [6, 7].

Knowledge Management (KM) is a systematic process encompassing the creation, acquisition, storage, sharing, application, and protection of knowledge within an organization or educational community [5]. Its purpose is to maximize the value of available knowledge and improve decision-making, organizational learning, and performance.

In the educational field, knowledge management has gained significant relevance as a key facilitator for collaborative learning and competency development. Four fundamental knowledge management processes are highlighted within the university context: knowledge acquisition, sharing, application, and protection [8]. These processes enable not only the accumulation of knowledge but also its effective transfer and utilization among students, faculty, and institutions.

Despite these advances, there remains a need to deepen the understanding of how knowledge management factors specifically influence the acceptance and actual use of M-learning. While recent research has addressed this relationship [8, 9] empirical evidence is still scarce in Latin American contexts and in post-pandemic scenarios, where the intensive use of mobile platforms has revealed new dynamics of interaction and learning. Particularly, studies suggest that processes such as knowledge application and sharing, as well as perceived ease of use and perceived usefulness, play key roles in the effective adoption of these technologies [2]. However, research conducted in Peru has shown mixed results regarding the influence of behavioral intention on knowledge application, raising questions about the consistency of these findings across different contexts [9, 10].

Moreover, recent studies in technical and health education [11-13] have demonstrated that M-learning not only enhances theoretical knowledge but also improves students' self-efficacy and practical skills. However, there are still gaps regarding which specific factors enhance these benefits, particularly from a knowledge management perspective.

Additionally, bibliometric reviews [14] show sustained growth in M-learning research but also highlight the need for new studies that incorporate integrative approaches and evaluate the effects of key variables such as ease of use, perceived usefulness, and behavioral intention to use.

Given this context, the present study aims to analyze the knowledge management factors that influence the acceptance and actual use of M-learning among university students. A conceptual model is proposed based on the integration of knowledge management processes with the components of the Technology Acceptance Model (TAM), evaluating their relationships through a quantitative approach.

This study seeks to contribute to the existing body of knowledge by providing updated and contextualized empirical evidence on the impact of knowledge management on the acceptance and use of M-learning in higher education settings.

2. Theoretical Basis and Hypothesis Development

2.1. Theoretical Foundation

2.1.1. Knowledge Application

Knowledge application constitutes an essential component within knowledge management processes, as it enables students to practically utilize the knowledge acquired through mobile learning (M-learning) systems. Effective knowledge application not only facilitates the internalization of content but also promotes the real and sustained adoption of the system [8]. Moreover, students who successfully apply what they have learned show a greater willingness to use the system in real academic contexts, thus consolidating the effective use of M-learning [9].

2.1.2. Behavioral Intention to Use

Behavioral intention to use refers to the degree to which a student is predisposed to use a technology in the future [15]. A positive intention directly affects the willingness to apply the acquired knowledge, as students motivated to use the system tend to transfer their learning to practical situations [2, 16]. However, this relationship is not always direct, as contextual factors and institutional support may mediate the impact of behavioral intention on knowledge application [10].

2.1.3. Behavioral Intention to Use and Perceived Usefulness

Behavioral intention is also closely linked to perceived usefulness, understood as the degree to which a user believes that using a system will improve their academic performance. According to the Technology Acceptance Model (TAM), this relationship is crucial [15] since when students exhibit a strong intention to use, it is largely because they perceive the system as useful and beneficial for their learning, which reinforces the acceptance of M-learning [8].

2.1.4. Knowledge Sharing

Knowledge sharing involves interaction and communication among students to exchange experiences and learning. An environment that fosters knowledge sharing facilitates the practical application of learned content, as it allows students to access different perspectives and resources [4, 9]. Likewise, collaborative mobile learning formats such as videos and forums promote this exchange, strengthening the effective application of knowledge [17].

2.1.5. Knowledge Sharing and Behavioral Intention

Knowledge sharing not only enriches the learning experience but also has a positive impact on behavioral intention to use. When students actively participate in knowledge exchange, their predisposition to continue using the system increases [8]. Social interaction acts as an incentive that reinforces the use of M-learning, creating a virtuous circle of participation and adoption.

2.1.6. Perceived Ease of Use

Perceived ease of use is a central element of the TAM, defined as the degree to which a student perceives the system as effort-free [15]. A system perceived as easy to use not only encourages adoption but also facilitates knowledge application by reducing technical and cognitive barriers [3, 8]. Thus, an intuitive and accessible design enables students to focus their efforts on applying the learned content.

2.1.7. Perceived Ease of Use and Knowledge Sharing

Perceived ease of use also has a direct impact on knowledge sharing [6, 17]. When students find it easy to interact with the system and access collaborative tools, they are more likely to share information and experiences. This is particularly evident in environments where multimedia resources or discussion forums integrated into mobile platforms are used, removing obstacles to participation.

2.1.8. Perceived Ease of Use and Actual Use

Perceived ease of use is a fundamental predictor of the actual use of the system [8, 10]. As perceived complexity decreases, students show a greater willingness to integrate M-learning into their daily activities. Easy navigation, content accessibility, and system adaptability promote sustained use of the platform [3].

2.1.9. Perceived Usefulness → Knowledge Application

Perceived usefulness, understood as the belief that the system contributes to improving academic performance, has been widely recognized as a key factor for knowledge application [8]. When students perceive that M-learning provides practical and relevant tools, they are more inclined to transfer this knowledge to real-world contexts. This finding is consistent with recent research in health education [11, 12] which showed that perceived usefulness facilitates practical application in clinical settings.

2.1.10. Perceived Usefulness and System Adoption

The greater the perception of usefulness, the higher the likelihood that students will adopt and continuously use the system [8, 13]. The perception of concrete benefits, such as time-saving, accessibility, and improved learning, motivates the recurrent use of M-learning, even beyond the formal academic environment.

2.2. Research Hypothesis

In this study, ten hypotheses were proposed to explore the relationships between knowledge management factors and the acceptance of M-learning among university students. These hypotheses were evaluated through a structural model validated using PLS-SEM. The hypotheses are detailed as follows:

- H1: The correct application of knowledge leads to greater use of the M-learning system.
- H2: Behavioral intention does not show a significant direct impact on knowledge application.
- H3: The greater the intention to use, the higher the perceived usefulness of the M-learning system.
- H4: There is a strong relationship between active knowledge sharing and the effective application of knowledge in the M-learning system.
- H5: A higher level of knowledge sharing enhances students' predisposition to continue using the M-learning system.
- H6: Perceived ease of use has a positive impact on knowledge application, facilitating practical learning.
- H7: The perception of a simple system fosters a favorable environment for collaborative knowledge sharing.
- H8: Perceived ease of use is a key determinant for the effective and sustained use of the M-learning system.
- H9: Students who perceive the M-learning system as useful are more likely to apply the acquired knowledge in practical scenarios.
- H10: There is no statistically significant direct relationship between perceived usefulness and the actual use of the M-learning system.

3. Methodology

To validate the proposed model in this research, the PLS-SEM (Partial Least Squares Structural Equation Modeling) methodology was used. This is a second-generation multivariate approach widely recognized for its ability to analyze complex structural models. This method, also known as Structural Equation Modeling using Partial Least Squares, has been recommended for its effectiveness in estimating causal relationships between latent variables, especially in contexts where sample sizes are small or the data do not follow normal distributions [18].

One of the practical advantages of the PLS algorithm is its flexibility to handle variance-based models, allowing researchers to work with small samples without compromising the robustness of the analysis [19]. Moreover, it offers the possibility of simultaneously evaluating the reliability and validity of the measurement model (through factor loadings analysis, internal consistency, and discriminant validity), as well as the structural relationships proposed between constructs. This feature has increased its popularity in the field of social sciences, particularly in studies on technology acceptance in higher education, where models often incorporate multiple unobservable variables.

As a direct precedent, the present research takes reference from the study conducted by Al-Emran and Mezhuyev [8]. In that study, the authors proposed a conceptual model that integrates knowledge management factors—such as knowledge acquisition, sharing, application, and protection—with variables from the Technology Acceptance Model (TAM), using PLS-SEM to validate their hypotheses. Following this approach, the present research designed a new structural model adapted to the Peruvian context, including an adaptation and validation of the measurement instrument.

The questionnaire employed was of a polychoric type, structured using a five-point Likert response scale, where the value 1 represents "strongly disagree" and the value 5 represents "strongly agree." This instrument was initially subjected to an exploratory factor analysis to refine and validate the items, ensuring the adequacy of the indicators for each construct. Subsequently, a confirmatory analysis was carried out using PLS-SEM, evaluating both the measurement model and the structural model. The choice of the reflective approach for the common factor items is based on the fact that the included constructs (e.g., perceived ease of use, knowledge sharing, perceived usefulness) are considered latent variables that cannot be directly observed but are inferred from valid and reliable indicators.

A key aspect in applying the model was the evaluation of the strength of the factor loadings, which indicate the degree of correlation between each indicator and its respective factor. Loadings above 0.7 were considered acceptable, ensuring the convergent validity of the model [20].

The study sample consisted of 150 students from the Political Science program at a private university located in the city of Arequipa, Peru. The population was predominantly male (60.7%), while females accounted for 39.3%. The ages of the participants ranged from 16 to 23 years, with a mean age of 18.17 years (SD = 1.686). Data collection was conducted online during July 2024, ensuring participant confidentiality and informed consent.

The use of PLS-SEM was fundamental in addressing the objectives of the study, allowing validation of the relationships between knowledge management factors and M-learning acceptance, as well as analyzing the applicability of the model in a local context. This not only provides updated empirical evidence but also offers a relevant methodological contribution for future research in the educational and technological fields.

4. Results

To ensure the reliability and validity of the instrument used in this research, two complementary phases of analysis were implemented: an exploratory factor analysis and a confirmatory analysis, both aimed at validating the structure of the proposed model.

First, the internal reliability of the instrument initially composed of 36 items was evaluated using IBM-SPSS software version 27. The Cronbach's Alpha coefficient yielded a value of 0.967 [21] is considered an excellent level of reliability ($\alpha \geq 0.90$). This result suggests a high internal consistency among the items, indicating a strong correlation between the questions measuring each construct, which allows us to affirm that the instrument is reliable for measuring the proposed variables.

Subsequently, Exploratory Factor Analysis (EFA) was conducted to identify and reduce the underlying dimensions in the data, condensing the information contained in the original variables into a smaller set of meaningful components. To ensure the adequacy of EFA, two essential tests were applied:

- Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy: The result obtained was 0.938, far exceeding the minimum recommended threshold of 0.70. This value indicates that the data are suitable for factor analysis, showing a high degree of correlation among the items.
- Bartlett's Test of Sphericity: This test, which evaluates whether the correlation matrix is significantly different from an identity matrix, yielded an approximate Chi-square value of 4357.783, with 630 degrees of freedom and a significance level of $p = 0.000$. These results confirm that there is a significant relationship among the variables, justifying the applicability of factor analysis.

The factor reduction process was carried out using the Principal Component Analysis (PCA) method, which identifies the factors that explain most of the total observed variance in the data. The communalities analysis showed values ranging from 0.640 to 0.879, meaning that each item explained between 64.0% and 87.9% of the variance associated with the corresponding construct—results considered highly satisfactory. These levels indicate that the selected items have strong explanatory power within the model.

Regarding total variance explained, after factor reduction, five principal components were identified, which together accounted for 76.705% of the accumulated variance. This percentage exceeds the recommended threshold of 50% [20] and approaches the optimal level (above 70%), reinforcing the robustness of the model and validating the grouping of the items into their respective factors.

The second phase consisted of validating the model through Structural Equation Modeling (PLS-SEM) using SmartPLS software version 3.3.3, a tool widely recognized for its ability to estimate complex models with relatively small sample sizes and non-normal data distributions. This method is particularly useful when working with latent constructs represented through observed indicators, as in the present research.

The first criterion evaluated in this phase was the individual reliability of the indicators, determined by the outer loadings, which reflect the contribution of each item to the definition of its corresponding factor. The results showed that all external loadings exceeded the recommended threshold of $\lambda \geq 0.707$, ranging from 0.773 to 0.933, confirming that the indicators present adequate individual reliability and are consistent with the constructs to which they belong.

Furthermore, the internal consistency of each construct was verified through three complementary metrics:

- Cronbach's Alpha: The values ranged from 0.839 to 0.914, exceeding the minimum threshold of 0.70, indicating satisfactory internal reliability.
- Rho_A coefficient: Values obtained ranged from 0.839 to 0.915, confirming the stability and consistency of the measurements.
- Composite Reliability (ρc): The results ranged between 0.892 and 0.941, meeting acceptable levels (≥ 0.70).

Convergent validity was also assessed through the Average Variance Extracted (AVE). The values obtained ranged from 0.674 to 0.842, all exceeding the minimum threshold of 0.50, confirming that the indicators share a high degree of common variance, validating the internal cohesion of the model.

Finally, discriminant validity was evaluated using two criteria:

- Fornell-Larcker Criterion: The square roots of the AVE of each construct were greater than the correlations with other factors, confirming adequate discrimination among them. HTMT (Heterotrait-Monotrait Ratio): Although some values approach the suggested limit of ≤ 0.85, overall, acceptable discrimination is achieved.

These results confirm the robustness of the instrument in terms of reliability and validity, ensuring the strength of the conclusions drawn from the proposed model.

Table 1.
External Loadings Matrix: Individual reliability of each indicator.

	Knowledge application	**Behavioral intention to use**	**Knowledge sharing**	**Perceived ease of use**	**Actual system use**	**Perceived usefulness**
AU1					0.933	
AU2					0.918	
AU3					0.877	
BI1		0.902				
BI2		0.916				
BI3		0.935				
KAP1	0.828					
KAP2	0.840					
KAP3	0.880					
KAP4	0.779					
KS1			0.823			
KS2			0.819			
KS3			0.799			
KS4			0.842			
PE1				0.889		
PE2				0.844		
PE3				0.790		
PE4				0.918		
PE5				0.870		
PU1						0.838
PU2						0.870
PU3						0.773
PU4						0.836

The evaluation of construct reliability and validity is an essential step to ensure the internal consistency and quality of the proposed measurement model. In this study, such evaluation was conducted using various statistical indicators widely accepted in methodological literature.

First, Cronbach’s Alpha was calculated, a coefficient that measures the internal consistency of the items comprising each of the constructs. This coefficient ranges between 0 and 1, with a recommended threshold of 0.70 to be considered acceptable [22]. In the present analysis, the results obtained for the six constructs ranged from 0.839 to 0.914, demonstrating that each set of items possesses adequate internal homogeneity; that is, all items contribute coherently to measuring the same underlying concept. Values above 0.90, as observed, are interpreted as excellent reliability, which strengthens confidence in the consistency of the scales used.

Additionally, the rho_A coefficient was evaluated, recommended by Dijkstra and Henseler [23] as a more precise measure of composite reliability, especially in the context of PLS-SEM modeling. The acceptable minimum value for rho_A is also 0.70. In this study, the results ranged from 0.839 to 0.915, fully meeting the required standards and confirming the robustness of the measurement model.

Furthermore, Composite Reliability (ρc) was calculated, which assesses internal reliability considering individual factor loadings and associated errors. Similar to the previous coefficients, a value of $\rho c \geq 0.70$ is considered acceptable [20]. The results obtained showed values between 0.892 and 0.941, supporting the appropriate consistency and quality of the instrument, indicating that the indicators accurately reflect the latent constructs.

To establish convergent validity, the Average Variance Extracted (AVE) was calculated. This indicator measures the proportion of variance that a construct captures from its indicators relative to the variance attributed to measurement error. A minimum acceptable AVE value is 0.50 [24] implying that at least 50% of the variance is explained by the underlying construct. In the present research, AVE values ranged from 0.674 to 0.842, surpassing the required threshold. These results demonstrate that the indicators used for each construct share a significant amount of common variance, thus confirming the model's convergent validity.

Overall, the consistency and quality of the measurement model are supported by the robustness of the reported indicators in terms of internal reliability and convergent validity. These results ensure the relevance of the instrument used to measure the proposed factors, guaranteeing the accuracy and significance of the findings obtained in the subsequent structural analysis (See Table 2).

Table 2.
Construct Reliability and Validity.

	Cronbach's Alpha	rho_A	Composite reliability	Average Variance Extracted (AVE)
Knowledge application	0.852	0.857	0.900	0.693
Behavioral intention to use	0.906	0.908	0.941	0.842
Knowledge sharing	0.839	0.839	0.892	0.674
Perceived ease of use	0.914	0.916	0.936	0.745
Actual system use	0.897	0.915	0.935	0.828
Perceived usefulness	0.849	0.849	0.898	0.689

Discriminant validity is a fundamental criterion to ensure that each construct included in the model measures distinct concepts and that there is no significant overlap between them. In other words, it verifies that the latent variables are conceptually different from each other and that the items associated with each construct do not exhibit excessive correlations with other factors in the model.

To assess discriminant validity in this study, two of the most recognized and robust methods in methodological literature were applied: the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT) index.

The criterion proposed by Fornell and Larcker establishes that, in order to confirm discriminant validity, the square root of the Average Variance Extracted (AVE) of each construct must be greater than the correlations between that construct and any other construct in the model [24]. This implies that a construct should share more variance with its own indicators than with the indicators of other constructs.

The results obtained, presented in Table 3, confirm that all constructs meet this requirement. In each case, the square roots of the AVE (shown in the main diagonal of the table) exceed the off-diagonal correlations. For example, for the construct Knowledge Application, the value is 0.833, which is higher than its correlations with other factors, such as 0.608 with Behavioral Intention to Use or 0.759 with Knowledge Sharing.

This pattern is consistently observed for the other constructs: Behavioral Intention to Use (0.918), Knowledge Sharing (0.821), Perceived Ease of Use (0.863), Actual System Use (0.910), and Perceived Usefulness (0.830), allowing us to conclude that the model exhibits adequate discriminant validity according to the Fornell-Larcker criterion. This ensures that each construct captures unique phenomena within the model without redundancy with the other factors.

Table 3.
Discriminant Validity According to the Fornell-Larcker Criterion.

	Knowledge application	Behavioral intention to use	Knowledge sharing	Perceived ease of use	Actual system use	Perceived usefulness
Knowledge application	0.833					
Behavioral intention to use	0.608	0.918				
Knowledge sharing	0.759	0.599	0.821			
Perceived ease of use	0.751	0.648	0.689	0.863		
Actual system use	0.333	0.382	0.347	0.49	0.91	
Perceived usefulness	0.766	0.68	0.635	0.694	0.333	0.83

Complementarily, the HTMT index, proposed by Henseler, et al. [25] was used. This index is considered a stricter and more sensitive criterion for detecting issues related to discriminant validity. This method compares the mean of the heterotrait-heteromethod correlations (i.e., between different constructs) with the mean of the monotrait-heteromethod correlations (within the same construct). An HTMT value below 0.85 indicates adequate discriminant validity between constructs.

The results obtained, presented in Table 4, show that although some HTMT correlations approach the suggested upper limit, the values generally meet the recommended standards. For example, the relationship between Knowledge Application and Knowledge Sharing reaches a value of 0.896, which is slightly elevated. This suggests a strong conceptual relationship, yet still within acceptable margins given the interrelated nature of these constructs. For other pairs of constructs, such as Perceived Ease of Use → Actual System Use (0.533) and Behavioral Intention to Use → Knowledge Sharing (0.686), the values remain within normal parameters.

This result suggests that, although some factors maintain a close relationship—which is to be expected in studies on technology acceptance and knowledge management, where theoretical dependencies exist—there is no evidence of collinearity or lack of discriminant validity that would compromise the validity of the model.

Table 4.
Discriminant Validity According to the Heterotrait-Monotrait Ratio (HTMT) Criterion.

	Knowledge application	**Behavioral intention to use**	**Knowledge sharing**	**Perceived ease of use**	**Actual system use**	**Perceived usefulness**
Knowledge application						
Behavioral intention to use	0.693					
Knowledge sharing	0.896	0.686				
Perceived ease of use	0.850	0.712	0.785			
Actual system use	0.373	0.427	0.394	0.533		
Perceived usefulness	0.896	0.77	0.745	0.785	0.370	

Figure 1 graphically represents the results of the reliability and validity analysis of the structural model, focusing particularly on the coefficient of determination R^2, also known as the Pearson coefficient. This coefficient is a key measure in the context of structural equation modeling, as it evaluates the explanatory power of the model—that is, the percentage of variance in the dependent variables explained by the exogenous constructs included in the model.

In this study, the calculation of the R^2 values was carried out using SmartPLS software (v.3.3.3), which applies the Partial Least Squares (PLS) algorithm, suitable for complex models and small sample sizes. The PLS algorithm is based on an iterative partial least squares approach that optimizes the explained variance of the dependent variables. To ensure result stability, the algorithm was executed with a total of 300 iterations, setting a convergence or stopping criterion at 10^{-7}, thus ensuring the model reached an optimal and precise solution.

Regarding the obtained results, the R^2 value of 0.739 stands out for the endogenous/mediator variable Knowledge Application. This value indicates that 73.9% of the variance of this variable is explained by the model's exogenous factors (specifically: Behavioral Intention to Use, Knowledge Sharing, Perceived Ease of Use, and Perceived Usefulness). According to the standards established [3, 20] an R^2 value above 0.67 is considered substantial, demonstrating an excellent level of predictive power of the model concerning the Knowledge Application variable. In practical terms, this result suggests that the factors identified in the structural model have a significant and direct influence on how students apply knowledge in M-learning environments.

On the other hand, for the endogenous variable Actual System Use, the coefficient of determination value was $R^2 = 0.243$, meaning the model explains 24.3% of the variance of this variable. Although this value is considered moderate [3] it is important to note that the remaining percentage—75.7%—could be influenced by other external factors not contemplated in the model, such as contextual, institutional, motivational, or technological aspects, which could be incorporated in future research to enhance the model's explanatory capacity.

Overall, the results reflected in Figure 1 support the relevance and robustness of the proposed model, particularly regarding the mediator variable Knowledge Application, showing that the structural relationships proposed have a significant effect. Likewise, although the explanation for Actual System Use is partial, the model provides a useful framework for understanding the underlying mechanisms that influence M-learning acceptance among university students.

These findings not only reinforce the validity of the empirical model constructed but also suggest future lines of research aimed at including additional variables to improve the explanation of the adoption and effective use of mobile technologies in educational settings (See Figure 1).

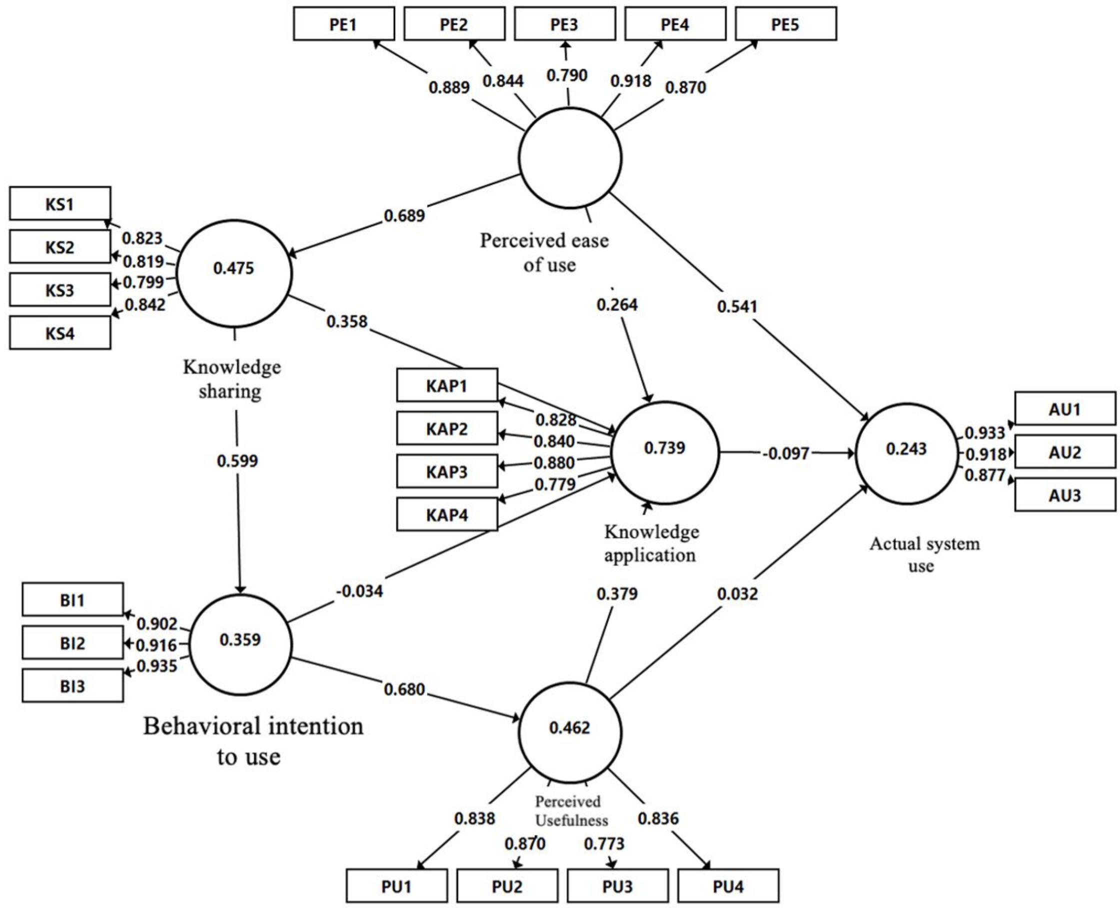

Figure 1.
R^2 of the SmartPLS model for the communication area.

Table 5 presents the results obtained from the statistical procedure known as Bootstrapping, which is essential within the PLS-SEM approach to assess the statistical significance of the path coefficients in the structural model.

Bootstrapping is a non-parametric method that estimates the precision and robustness of the model parameters by creating multiple subsamples randomly drawn from the original sample, with replacement. In this study, 10,000 bootstrap samples were generated, ensuring adequate stability and reliability in parameter estimation, particularly in contexts where normal distribution cannot be guaranteed—a typical characteristic of the PLS methodology.

The procedure allowed for the calculation of the following statistics for each relationship proposed in the model:

- The mean of the bootstrap sample (M),
- The standard error (STDEV),
- The t-statistic, obtained by dividing the original coefficient by the standard error,
- And the associated p-value, which determines statistical significance.

The criterion adopted to establish significance was a 95% confidence level ($p < 0.05$). In other words, relationships with p-values lower than 0.05 were considered statistically significant, implying a Type I error risk below 5%.

The results reveal that 7 out of the 10 proposed hypotheses were accepted, while three hypotheses did not reach statistical significance:

- Hypothesis H1: Knowledge Application → Actual System Use ($p = 0.252$)
- Hypothesis H2: Behavioral Intention to Use → Knowledge Application ($p = 0.303$)
- Hypothesis H10: Perceived Usefulness → Actual System Use ($p = 0.372$)

In these cases, the p-values exceed 0.05, and therefore, it cannot be affirmed with sufficient statistical evidence that a significant relationship exists between the variables proposed in those hypotheses. This finding suggests that, although knowledge application and perceived usefulness may theoretically be linked to actual system use, other external factors not considered in the model might be conditioning this relationship.

In contrast, the remaining hypotheses—H3, H4, H5, H6, H7, H8, and H9—show significant path coefficients with p-values below 0.001, displaying highly robust results. Among the most notable, we find:

- H3: Behavioral Intention to Use → Perceived Usefulness ($p = 0.000$, $t = 11.607$): Indicates that students' predisposition to use the system has a direct and significant effect on their perception of usefulness.
- H4: Knowledge Sharing → Knowledge Application ($p = 0.000$, $t = 5.392$): Confirms that sharing knowledge among students favors the practical application of what has been learned.
- H7: Perceived Ease of Use → Knowledge Sharing ($p = 0.000$, $t = 10.696$): Highlights how the perception of a simple and intuitive system facilitates interactions and knowledge exchange.

- H8: Perceived Ease of Use → Actual System Use ($p = 0.000$, $t = 4.982$): Supports the relevance of usability for the effective adoption of M-learning.
- H9: Perceived Usefulness → Knowledge Application ($p = 0.000$, $t = 4.601$): Underscores the importance of students perceiving concrete benefits in applying acquired knowledge.

The Bootstrapping test not only adds statistical robustness to the model but also helps identify which relationships are stronger and more stable within the context of M-learning acceptance and knowledge management.

Table 5.
Hypothesis Testing – Bootstrapping.

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-Statistics (|O/STDEV|)	P Values
H1	-0.097	-0.098	0.146	0.667	0.252
H2	-0.034	-0.034	0.066	0.516	0.303
H3	0.68	0.68	0.059	11.607	0.000
H4	0.358	0.358	0.066	5.392	0.000
H5	0.599	0.599	0.063	9.465	0.000
H6	0.264	0.261	0.073	3.598	0.000
H7	0.689	0.686	0.064	10.696	0.000
H8	0.541	0.541	0.109	4.982	0.000
H9	0.379	0.379	0.082	4.601	0.000
H10	0.032	0.04	0.098	0.326	0.372

5. Discussion

The results obtained in this research on the acceptance of M-learning and knowledge management among university students reveal findings consistent with the reviewed literature, providing significant empirical evidence that complements and expands previous studies.

Firstly, the high internal reliability of the instrument used (Cronbach's Alpha = 0.967) and the robustness of the Exploratory Factor Analysis results (KMO = 0.938; total variance explained = 76.705%) align with studies Al-Emran, et al. [2]; Chicana-Huanca, et al. [9] and Chicana-Huanca, et al. [10] who also validated robust instruments to measure M-learning acceptance and its associated factors through factor analysis and structural equation modeling.

Regarding the impact of M-learning on knowledge application, the results show that constructs such as knowledge sharing (H4: $\beta = 0.358$, $p < 0.001$), perceived ease of use (H6: $\beta = 0.264$, $p < 0.001$), and perceived usefulness (H9: $\beta = 0.379$, $p < 0.001$) have a positive and significant influence. These findings are in line with other studies Al-Emran, et al. [2] and Chicana-Huanca, et al. [9] who identified ease of use and perceived usefulness as key determinants in the adoption of M-learning.

In particular, the positive relationship between perceived ease of use and knowledge sharing (H7: $\beta = 0.689$, $p < 0.001$) reinforces what was found by other studies [11, 12] who highlighted that user-friendly design and mobile platform accessibility not only facilitate knowledge acquisition but also encourage collaborative information exchange.

However, one of the most relevant and divergent findings is the lack of significance in the relationship between knowledge application and actual system use (H1: $p = 0.252$), as well as between behavioral intention and knowledge application (H2: $p = 0.303$). Unlike studies where M-learning-based training improved the application of skills in clinical settings [26] our results suggest that intention and acquired knowledge do not necessarily translate into greater effective use of the system. This may be explained by contextual, institutional, or motivational barriers not considered in the model, which coincides with the limitations mentioned in studies [23].

The substantial R^2 value for knowledge application (0.739) supports the strong explanatory power of the model, well above established standards [20]. However, the moderate R^2 value for actual system use (0.243) reaffirms the need to include additional variables, as suggested other studies [14, 17, 27] who emphasize that contextual factors, such as technological infrastructure or institutional support, may play a crucial role in the effective adoption of M-learning.

Finally, the consistency of our results with the propositions of the TAM model [15] is evident, as both ease of use and perceived usefulness proved to be significant predictors of behavioral intention and knowledge sharing. This finding aligns with recent studies [9, 10, 28] which highlight the continued relevance of the TAM model in explaining technological acceptance in mobile educational environments [23].

In summary, the present study confirms the relevance of ease of use, perceived usefulness, and knowledge sharing as key factors in strengthening the application of knowledge on M-learning platforms. At the same time, it highlights the need to further explore the elements limiting actual system use, opening new avenues for future research aimed at optimizing the adoption of these technologies in university contexts.

6. Conclusions

The present study demonstrated that perceived ease of use, perceived usefulness, and knowledge sharing are key factors that positively influence the application of knowledge in M-learning environments, validating the integration of the knowledge management model with the Technology Acceptance Model (TAM). These results confirm that when students perceive the platform as easy to use and recognize practical benefits in its use, not only does their predisposition to adopt it increase, but collaboration and knowledge sharing among them are also enhanced.

However, one of the most relevant findings is the lack of a statistically significant relationship between knowledge application and actual system use, as well as between behavioral intention and knowledge application. These results suggest that although students may have a positive perception of M-learning and apply the knowledge acquired, this does not always translate into sustained use of the system, possibly due to contextual, motivational, or institutional factors not considered in the model. Likewise, the model showed substantial explanatory power regarding knowledge application ($R^2 = 0.739$), though moderate in explaining actual system use ($R^2 = 0.243$), leaving open the possibility of incorporating new variables in future research to strengthen its predictive capacity.

Based on the findings, it is recommended that educational institutions prioritize the design of M-learning platforms with intuitive, accessible, and user-friendly interfaces, as these promote both practical learning and collaborative knowledge sharing. Additionally, it is essential that the content offered demonstrates clear practical value for students, increasing their perception of usefulness and, consequently, their motivation to apply what they have learned.

Furthermore, it is suggested to implement strategies that encourage collaboration and active knowledge sharing among students, through tools such as forums, chats, and group projects. To improve the sustained adoption of the system, it is also recommended that future research incorporate additional factors such as technological infrastructure, institutional support, motivational aspects, or contextual barriers that may be limiting the actual use of M-learning.

Finally, it would be advisable for universities to complement the implementation of M-learning with support programs, tutoring, and technical assistance, as well as longitudinal studies that allow the observation of the evolution of the use and acceptance of these technologies over time, in order to develop more effective strategies tailored to the real needs of students.

References

[1] J. Traxler, "Defining, discussing and evaluating mobile learning: The moving finger writes and having writ..." *International Review of Research in Open and Distance Learning*, vol. 8, no. 2, pp. 1–12, 2007. https://doi.org/10.19173/irrodl.v8i2.355

[2] M. Al-Emran, V. Mezhuyev, and A. Kamaludin, "Is M-learning acceptance influenced by knowledge acquisition and knowledge sharing in developing countries?," *Education and Information Technologies*, vol. 26, no. 3, pp. 2585–2606, 2021. https://doi.org/10.1007/s10639-020-10378-y

[3] K.-Y. Chin and C.-S. Wang, "The effectiveness of a VR-based mobile learning system for university students to learn geological knowledge," *Interactive Learning Environments*, vol. 32, no. 8, pp. 4281–4296, 2024. https://doi.org/10.1080/10494820.2023.2196790

[4] M. Al-Emran, V. Mezhuyev, and A. Kamaludin, "An innovative approach of applying knowledge management in m-learning application development: A pilot study," *International Journal of Information and Communication Technology Education*, vol. 15, no. 4, pp. 94–112, 2019. https://doi.org/10.4018/IJICTE.2019100107

[5] I. Nonaka and H. Takeuchi, *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. New York, USA: Oxford University Press, 1995.

[6] M. Al-Emran, V. Mezhuyev, and A. Kamaludin, "Students' perceptions towards the integration of knowledge management processes in M-learning systems: A preliminary study," *International Journal of Engineering Education*, vol. 34, no. 2, pp. 371-380, 2018. https://doi.org/10.1007/s10639-018-2149-1

[7] H. S. Al Sagri and N. Zemirli, "Toward knowledge management approach to enhance the mobile learning management systems. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)," vol. 9228, pp. 74-83, 2015. https://doi.org/10.1007/978-3-319-23144-0_7

[8] M. Al-Emran and V. Mezhuyev, "Examining the effect of knowledge management factors on mobile learning adoption through the use of importance-performance map analysis (IPMA)," *Advances in Intelligent Systems and Computing*, vol. 1058, pp. 449-458, 2020. https://doi.org/10.1007/978-3-030-31129-2_41

[9] S. Chicana-Huanca, A. Duche-Perez, Y. Tomaylla-Quispe, and O. Gutierrez-Aguilar, "Factors that influence the acquisition, application and protection of knowledge through m-learning," presented at the 2022 17th Latin American Conference on Learning Technologies (LACLO). https://doi.org/10.1109/LACLO56648.2022.10013415, 2022.

[10] S. Chicana-Huanca, O. Gutierrez-Aguilar, F. Ticona-Apaza, G. Calliñaupa-Quispe, and B. Chicana-Huanca, "Influential factors in knowledge management in the acceptance of M-learning in university students," presented at the 2022 17th Iberian Conference on Information Systems and Technologies (CISTI) IEEE, 2022.

[11] F. A. HajiAbad, F. Keshmiri, F. Jabinian, and S. M. Shiryazdi, "Micro-learning and mindtools in mobile-learning (M-Learning): Effects on knowledge and self-efficacy in laparoscopy education for surgical nursing students," *BMC Nursing*, vol. 24, no. 1, p. 202, 2025. https://doi.org/10.1186/s12912-025-02841-3

[12] L. Shamsi, M. Janighorban, and S. Mohamadirizi, "The effect of educational intervention based on mobile learning on the knowledge and self-efficacy of healthcare providers in vaccination," *Journal of Education and Health Promotion*, vol. 14, no. 1, p. 7, 2025. https://doi.org/10.4103/jehp.jehp_1426_23

[13] E. K. Sari and D. P. Sari, "The effect of mobile learning application in enhancing students' knowledge of caring sepsis patients," *International Journal of Public Health Science*, vol. 12, no. 2, pp. 787–793, 2023. https://doi.org/10.11591/ijphs.v12i2.22206

[14] G. Kaisara and K. J. Bwalya, "Mobile learning in higher education: Insights from a bibliometric analysis of the body of knowledge," *International Journal of Learning, Teaching and Educational Research*, vol. 22, no. 6, pp. 152–174, 2023. https://doi.org/10.26803/ijlter.22.6.9

[15] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989. https://doi.org/10.2307/249008

[16] B. R. Alhamad and S. Agha, "Comparing knowledge acquisition and retention between mobile learning and traditional learning in teaching respiratory therapy students: A randomized control trial," *Advances in Medical Education and Practice*, vol. 14, pp. 333-342, 2023. https://doi.org/10.2147/AMEP.S390794

[17] G. Kaisara and K. J. Bwalya, "Preferred knowledge formats in mobile learning in Namibian public universities: A students' perspective," *Development and Learning in Organizations*, vol. 39, no. 1, pp. 36-38, 2025.

[18] K. K.-K. Wong, "Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS," *Marketing Bulletin*, vol. 24, no. 1, pp. 1-32, 2013.

[19] W. W. Chin and P. R. Newsted, "Structural equation modeling analysis with small samples using partial least squares," *Statistical Strategies for Small Sample Research*, vol. 1, no. 1, pp. 307-341, 1999.

[20] J. F. Hair, R. E. Anderson, R. L. Tatham, and W. C. Black, *Análisis multivariante*. Madrid: Prentice Hall, 2019.

[21] D. George and P. Mallery, *SPSS for Windows step by step: A simple guide and reference*, 4th ed. Boston, MA: Allyn & Bacon, 2003.

[22] J. Nunnally and I. Bernstein, *Psychometric theory*, 3rd ed. New Delhi: Tata McGraw-Hill, 2010.

[23] T. K. Dijkstra and J. Henseler, "Consistent partial least squares path modeling," *MIS Quarterly*, vol. 39, no. 2, pp. 297–316, 2015. https://doi.org/10.25300/MISQ/2015/39.2.02

[24] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981. https://doi:10.1177/002224378101800104

[25] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, no. 1, pp. 115–135, 2015. https://doi.org/10.1007/s11747-014-0403-8

[26] M. Abdollahi, G. A. Valizadeh, L. Bazrafkan, M. Dehghani, and M. Bijani, "A comparative study on effectiveness of workshop education versus education via mobile learning (M-Learning) in developing medical students' knowledge and skill about cardiopulmonary resuscitation," *Disaster and Emergency Medicine Journal*, vol. 7, no. 2, pp. 83-89, 2022. https://doi.org/10.5603/DEMJ.a2022.0014

[27] D. Yu, Z. Yan, and X. He, "Capturing knowledge trajectories of mobile learning research: A main path analysis," *Education and Information Technologies*, vol. 27, no. 5, pp. 7257–7280, 2022. https://doi.org/10.1007/s10639-021-10869-6

[28] A. A.-F. Karasneh, "On the mediating role of M-learning between social capital and knowledge sharing: Students' perspectives during COVID-19 pandemic," *European Journal of Educational Research*, vol. 11, no. 2, pp. 1197–1207, 2022. https://doi.org/10.12973/eu-jer.11.2.1197