The Role of Artificial Intelligence in Building a Culture of Knowledge Sharing among Students and University Students

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Abstract: This study examines the role of Artificial Intelligence (AI) in fostering a culture of knowledge sharing and enhancing knowledge management among students and university learners in the digital learning environment. Using a quantitative explanatory approach, data were collected from 100 respondents who actively used AI-based applications such as ChatGPT, Grammarly, and Copilot in their academic activities. The data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The results reveal that AI has a significant direct effect on knowledge management ($\beta = 0.316$, $p = 0.000$) and a strong positive influence on knowledge sharing behavior ($\beta = 0.851$, $p = 0.000$). Furthermore, knowledge sharing significantly mediates the relationship between AI and knowledge management ($\beta = 0.611$, $p = 0.000$), indicating that AI's greatest impact occurs through the enhancement of collaborative knowledge exchange among learners. The model explains 80.3% of the variance in knowledge management and 72.3% in knowledge sharing, demonstrating strong predictive power. These findings highlight AI's potential as a collaborative catalyst that strengthens human-centered learning ecosystems. The study contributes both theoretically by extending the understanding of AI-mediated knowledge processes—and practically by providing insights for educators to integrate AI ethically and effectively into knowledge-based learning systems.

Keywords: Artificial Intelligence, Knowledge Sharing, Knowledge Management, Digital Learning, PLS-SEM.

I. INTRODUCTION

Over the past decade, artificial intelligence (AI) has transformed the educational landscape, enabling intelligent systems to analyze, organize, and disseminate information automatically [1]. At the heart of this transformation is the integration of AI into knowledge management processes, where AI systems organize, store, and distribute knowledge more efficiently than traditional approaches [2] [3]. In this context, AI offers substantial opportunities to support adaptive, personalized, and data-driven learning, while simultaneously raising critical questions about ethics, responsibility, and the meaning of learning in an era of instant information access [4].

From a knowledge management perspective, AI assists in identifying knowledge patterns, facilitating collaboration, and supporting the dissemination of relevant and targeted information [4]. However, the widespread availability of AI-driven tools often leads students to prioritize quick answers over critical and reflective thinking, weakening the very cognitive processes that constitute genuine learning. This paradox highlights the need to examine how AI can be leveraged not only as an automation tool, but as a catalyst for meaningful knowledge sharing and knowledge transfer in educational settings [5] [6]. To clarify the theoretical foundations of this study, the distinction between explicit and tacit knowledge is adopted as a core lens for understanding how AI interacts with human knowledge processes (see Figure 1).

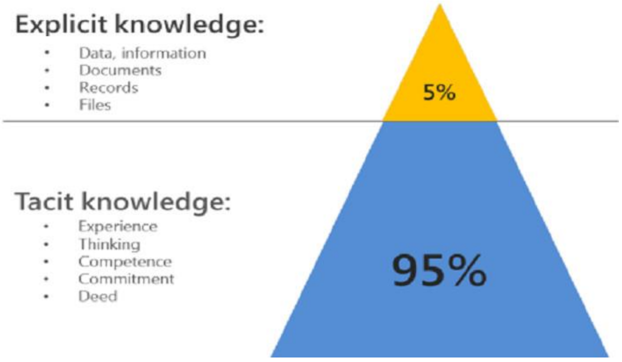

Figure 1. Fenomena Tacit & Explicit Knowledge

In this view, AI is positioned as a technological mediator that can codify and disseminate explicit knowledge, while also potentially supporting the articulation and sharing of tacit insights within learning communities. This dual role frames AI as both a knowledge repository and a facilitator of social learning dynamics. A bibliometric analysis was first conducted using VOSviewer on 58 Scopus-indexed articles identified through a predefined search strategy, in order to map the intellectual structure of research on AI, knowledge management, knowledge sharing, and knowledge transfer. The keyword co-occurrence network shows that "knowledge management" occupies a central position, with "artificial intelligence" and "knowledge sharing" forming strong and significant linkages to it [7] [8]. as shown in Figure 2.

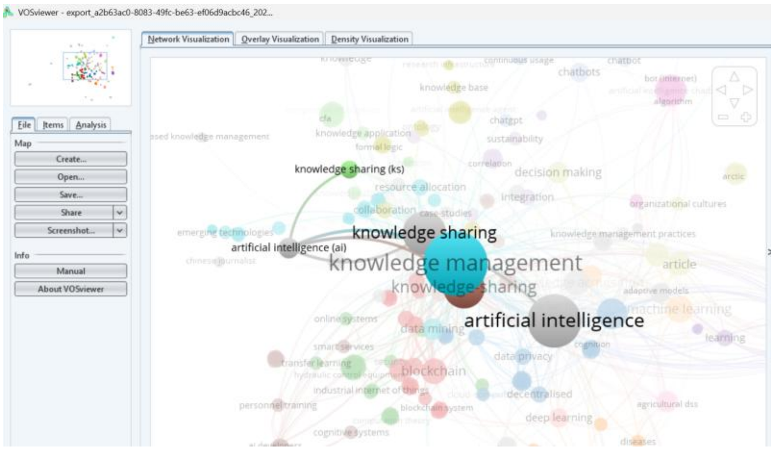

Figure 2. VOSviewer Analysis Results

These patterns indicate that AI-enabled knowledge management is an emerging and rapidly consolidating theme in the academic literature, particularly in relation to mechanisms of knowledge sharing and transfer [9] [10]. Based on these bibliometric insights, this study proposes a conceptual model in which AI exerts a direct influence on knowledge management and an indirect influence through knowledge sharing, Figure 3.

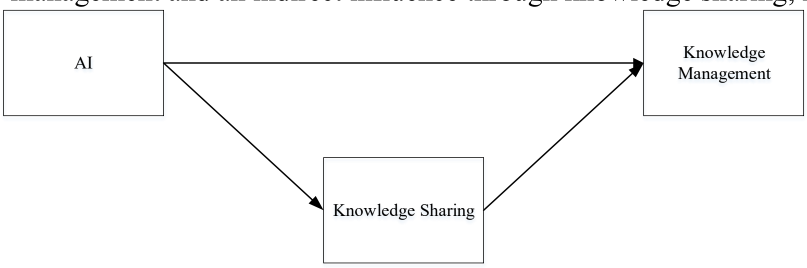

Figure 3. Conceptual Article Model

In this model, AI's capacity to manage and process information is expected to strengthen knowledge sharing practices, thereby enhancing the overall effectiveness of knowledge management systems in educational contexts [11] [12]. At the same time, the literature also points to a persistent gap between the technological potential of AI and the way students actually use it, often as a shortcut to complete tasks rather than as a medium for deeper understanding and collaborative learning [13]. This gap is particularly evident in higher education, where AI tools are widely accessible but are frequently used in a passive, instrumental manner. Students may rely on AI-generated outputs without engaging with the underlying reasoning, which risks undermining critical thinking, creativity, and epistemic responsibility in the long term. Consequently, there is a need to empirically examine how AI can be positioned as a learning partner that stimulates active knowledge sharing and knowledge transfer, rather than merely providing ready-made answers.

To address this gap, the present study employs a quantitative approach involving 100 student respondents, with the sample size determined using the Lemeshow formula for survey research. Data were collected through a Likert-scale questionnaire measuring three main variables: knowledge transfer (X_1), knowledge sharing (X_2), and artificial intelligence (Y). The data were analyzed using Partial Least Squares (PLS) structural equation modeling, following the procedures recommended by Hair et al. [14], in order to test the proposed conceptual model and provide an objective empirical basis for the arguments advanced in this article.

The findings of this study are expected to enrich the growing body of knowledge on AI-based knowledge management and offer practical insights for educational institutions seeking to implement AI in more ethical, effective, and sustainable ways. By positioning AI as a partner that supports knowledge sharing and knowledge transfer, digital education can move towards a learning ecosystem that is not only intelligent and collaborative, but also grounded in human values and ethical awareness at every stage of the learning process.

II. LITERATURE REVIEW

The integration of artificial intelligence (AI) into Knowledge Management must be accompanied by strong ethics and governance. A lack of transparency in AI algorithms can erode user trust: when AI systems provide recommendations that cannot be explained, employees find it difficult to trust them [15]. [16] emphasize that "black-box" AI triggers skepticism, so AI adoption for KM is hampered by resistance. Therefore, organizations must ensure the ethical use of data and knowledge to protect privacy, prevent bias, and avoid misuse of information [17]. Failure in this aspect not only results in legal sanctions, but also damages reputation and discourages employees from sharing knowledge. Thus, AI-KM governance should not be merely formal compliance, but must build a shared ethical understanding throughout the organization [18].

Although promising, the implementation of AI in KM faces complex challenges that can trigger a "knowledge crisis" if not addressed. One of the main challenges is employee resistance. Fears of being replaced by AI can lead to knowledge hoarding and rejection of AI-KM initiatives [16]. Gelashvili-Luik, Vihma, and Pappel (2025) describe a "spiral of resistance" in which concerns about job loss and skepticism about automation reinforce the reluctance to share knowledge. As a result, tacit knowledge is difficult to capture and innovation is hampered. Furthermore, technical skill gaps within organizations and high costs are barriers to AI adoption [17]. Aljuwaiber (2025) found that despite its benefits, the implementation of AI for KM is often hampered by a lack of experts, costly technology investments, and a culture resistant to change. This is in line with the findings of Hu et al. (2025) that although AI adoption can increase employee knowledge sharing, its success is greatly influenced by contextual factors such as leadership support and pro-technology attitudes [18]. Without leadership that encourages learning and positive attitudes towards technology, AI integration tends to fail to trigger knowledge sharing behavior.

AI offers great opportunities to revolutionize KM practices and knowledge sharing in organizations. First, AI can automate routine knowledge management tasks, allowing professionals to focus on strategic work. For example, AI systems can search for and retrieve information in real time, speeding up the retrieval of knowledge needed by employees [19] shows that cognitive computing can detect barriers to collaboration and facilitate the flow of knowledge across teams. Second, AI facilitates knowledge sharing without the constraints of time and space. Technologies such as intelligent chatbots, NLP-based platforms, and recommendation systems make it easier for employees in different locations to communicate and share knowledge instantly [17]. This creates a real-time flow of knowledge within the organization, which was previously difficult to achieve with traditional methods. AI is also capable of identifying knowledge gaps and providing personalized learning recommendations. Thus, employee continuous learning can be accelerated through AI recommendations, which ultimately enriches the company's collective knowledge base.

III. RESEARCH METHODS

This study uses a quantitative approach with an explanatory survey method. This approach was chosen because the study aims to explain the causal relationship between the variables of Artificial Intelligence (AI), Knowledge Sharing, and Knowledge Management through empirical hypothesis testing. According to Sugiyono (2022), explanatory quantitative research is used to test theories by measuring the relationship between variables through systematic and measurable statistical analysis.

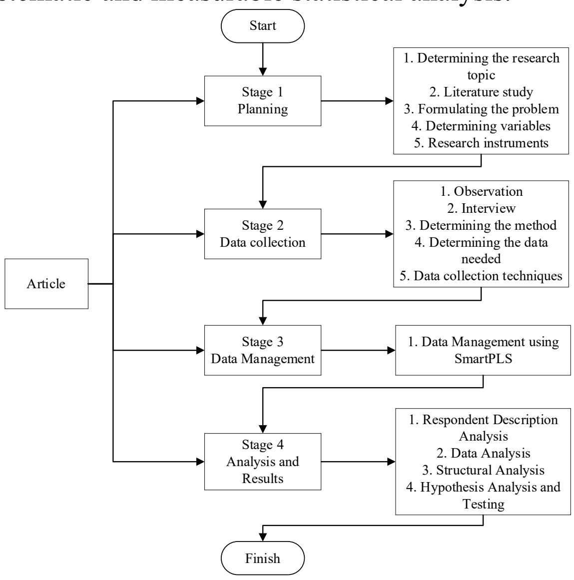

Figure 4. Research Stages

Tabel 1 Summary of Research Stages

Research stage	Main activities	Output
Planning	Topic identification; literature review on AI, knowledge sharing, and knowledge management; formulation of research questions and hypotheses; operationalization of constructs and indicators; questionnaire design (Likert 1–5).	Validated constructs and questionnaire draft.
Data collection	Defining population and inclusion criteria; applying Lemeshow formula; purposive sampling of high school and university students using AI tools; online survey distribution via Google Forms.	100 completed questionnaires suitable for analysis.
Data management	Data cleaning, screening, transformation, and grouping; preparation of dataset in the required format; importing data into SmartPLS 4.0.	Final dataset ready for PLS-SEM analysis.
Analysis and results	Descriptive statistics; evaluation of measurement model (reliability and validity); evaluation of structural model (path coefficients, hypothesis testing) using PLS-SEM.	Empirical evidence on the effects of AI Use on Knowledge Sharing and Knowledge Management.

A. Planning Stage

This stage began with identifying the research topic regarding the impact of Artificial Intelligence (AI) utilization on knowledge sharing and knowledge management within educational environments. A comprehensive literature review was conducted to examine prior studies and theoretical frameworks relevant to technology adoption, collaborative learning, and organizational knowledge processes. Based on this review, research questions were formulated to explore how AI tools such as ChatGPT, Grammarly, and Copilot influence students' knowledge-sharing behavior and their ability to acquire, store, and apply knowledge effectively. This stage concluded with the operationalization of research variables, the determination of indicators, and the development of a structured questionnaire instrument using a five-point Likert scale.

B. Data Collection Stage

The population of this study consists of high school and university students who have used AI-based learning tools such as ChatGPT, Grammarly, or Copilot. The sample was determined using purposive sampling, a non-probability technique that selects respondents based on specific inclusion criteria aligned with the research objectives. The criteria include: (1) respondents are active high school students or university students, (2) have used AI-based applications for at least one month, and (3) are willing to complete the research questionnaire in full. To ensure an adequate sample size without requiring exact population data, the Lemeshow formula was applied, which is appropriate for studies with unknown populations and ensures statistical representativeness at a specified confidence level [20] (Naing et al., 2022). Based on the calculation, the minimum required sample was 97 respondents. In this study, a total of 100 respondents were collected, which also satisfies the minimum sample recommendation for Partial Least Squares (PLS) analysis as suggested by Hair et al. [14]), i.e., between five to ten times the number of indicators in the research model. Data were gathered using an online questionnaire distributed via Google Form, consisting of closed-ended items measured with a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

C. Data Management Stage

Data obtained from the questionnaires were processed through several stages, including data cleaning, data transformation, data grouping, and testing data to ensure consistency and completeness. The processed dataset was then analyzed using SmartPLS version 4.0, which is suitable for predictive modeling and the analysis of latent constructs with relatively small samples.

D. Analysis and Result Stage

At this stage, descriptive statistical analysis was first performed to summarize respondent characteristics and response distributions. Subsequently, Partial Least Squares–Structural Equation Modeling (PLS-SEM) was employed to assess both the outer model (validity and reliability testing of indicators) and the inner model (hypothesis testing among latent constructs). PLS was chosen due to its robustness in handling non-normally distributed data, small to moderate sample sizes, and complex model structures [14].

The analysis results are expected to provide empirical evidence regarding how AI usage influences knowledge sharing and knowledge management in educational settings. These findings are anticipated to offer both theoretical contributions by reinforcing the understanding of AI's role in educational knowledge ecosystems and practical implications for developing more collaborative, adaptive, and sustainable AI-integrated learning systems.

IV. RESULT AND DISCUSSION

A. Respondent Description Analysis

The data in this study were collected using a structured questionnaire that first underwent a pre-test phase involving ten academic experts to evaluate the clarity, relevance, and consistency of the questionnaire items. Feedback from this stage was used to refine the wording and structure of several indicators to ensure validity and reliability before full distribution. After revision, the finalized questionnaire was distributed online via Google Forms to respondents who met the inclusion criteria. From this distribution, a total of 110 responses were received. A subsequent data cleaning process was conducted to eliminate incomplete, invalid, or duplicate entries, resulting in 100 valid datasets that met the criteria for statistical analysis. The detailed demographic and descriptive characteristics of the respondents are presented in Table 1 below.

Table 2. Respondent Description Analysis

Item	Frequency (f)	Percentage (%)
Gender		
Male	56	56%
Female	44	44%
Education Level		
High School Student (or equivalent)	32	32%
Undergraduate Student	61	61%
Postgraduate Student	7	7%
Age		
< 18 Years	22	22%
18–22 Years	57	57%
23–26 Years	18	18%
> 26 Years	3	3%
Frequency of AI Use for Learning		
Every Day	35	35%
3–4 Times/Week	33	33%
1–2 Times/Week	22	22%
Rarely (<1 Time/Week)	10	10%
Main Purpose of Using AI		
Completing Academic Assignments	42	42%
Searching for Additional Learning Materials	27	27%
Discussion and Knowledge Sharing	19	19%
Experimenting/Practicing AI Programming	12	12%
Perception of AI in Learning		
Very Helpful in Understanding Materials	39	39%
Helpful but Requires Ethical Guidance	41	41%
Neutral (Depends on Usage Context)	14	14%
Less Helpful	6	6%
Knowledge Sharing Behavior		

Often Share Ideas and Results with Friends	36	36%
Share Only When Asked	44	44%
Rarely Share Knowledge	20	20%
Ethical Awareness in AI Usage		
High (Understand Boundaries and Copyright)	48	48%
Moderate (Sometimes Cite without Sources)	33	33%
Low (Ignore Ethical Considerations)	19	19%

As shown in Table 1, this study involved 100 respondents who participated through an online questionnaire distributed via Google Forms. Based on gender distribution, 56 respondents (56%) were male and 44 respondents (44%) were female, indicating a relatively balanced representation between male and female participants. Regarding educational background, the majority were undergraduate students, totaling 61 respondents (61%), followed by high school students with 32 respondents (32%), and a smaller proportion of postgraduate students amounting to 7 respondents (7%).

In terms of age, most respondents were in the 18–22 years category, totaling 57 respondents (57%), while 22 respondents (22%) were below 18 years old. The 23–26 years age group accounted for 18 respondents (18%), and only 3 respondents (3%) were above 26 years of age. Based on the frequency of AI use for learning, 35 respondents (35%) reported using AI every day, 33 respondents (33%) used it three to four times per week, 22 respondents (22%) used it once or twice a week, and 10 respondents (10%) indicated rare use (less than once per week).

When viewed from the main purpose of AI utilization, the majority of respondents, 42 respondents (42%), used AI to complete academic assignments, followed by 27 respondents (27%) who used it for searching additional learning materials, 19 respondents (19%) for discussion and knowledge sharing, and 12 respondents (12%) for experimenting with AI programming. Regarding respondents' perception of AI in learning, 39 respondents (39%) considered AI very helpful in understanding learning materials, 41 respondents (41%) viewed it as helpful but requiring ethical guidance, 14 respondents (14%) maintained a neutral stance, and 6 respondents (6%) found it less helpful.

From the perspective of knowledge sharing behavior, 36 respondents (36%) often shared ideas and results with friends, 44 respondents (44%) shared only when asked, and 20 respondents (20%) rarely shared knowledge. Lastly, in terms of ethical awareness in AI usage, 48 respondents (48%) demonstrated high ethical awareness understanding boundaries and respecting copyright while 33 respondents (33%) were categorized as moderate, and 19 respondents (19%) showed low ethical awareness, indicating that they tended to ignore ethical considerations in AI use.

B. Data Analysis

In this study, outer model measurements were used with Structural Equation Modeling-Partial Least Square (SEMPLS) for reliability, convergent validity, and discriminant validity. The criteria for assessing convergent validity and discriminant validity between constructs to ensure acceptable results are as follows: factor loadings and Cronbach's alpha (CA) must have a minimum value of 0.7, composite reliability (CR) must have a value greater than 0.8, and Average Variance Extracted (AVE) must have a minimum value of 0.5.

Tabel 3. Results of Reliability and Convergent Validity Analysis

Construct	Item	Loading	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Artificial Intelligence (AI)	AI1	0.846	0.915	0.936	0.746
	AI2	0.842			
	AI3	0.897			
	AI4	0.880			
	AI5	0.852			
Knowledge Management (KM)	KM1	0.875	0.917	0.938	0.751
	KM2	0.893			
	KM3	0.872			
	KM4	0.809			
	KM5	0.881			
Knowledge Sharing (KS)	KS1	0.855	0.863	0.907	0.710
	KS2	0.776			
	KS3	0.877			
	KS4	0.858			

Based on Table 2, reliability and convergent validity analyses for various constructs have been conducted. The analysis results show that all indicators have outer loading values above 0.70, which means they meet the convergent validity criteria (Hair et al., 2021). Cronbach's Alpha (CA) values ranged from 0.863 to 0.917 and Composite Reliability (CR) from 0.907 to 0.938, both exceeding the threshold of 0.70, which indicates excellent internal consistency. In addition, the Average Variance Extracted (AVE) value for all constructs is above 0.50 (range 0.710–0.751), indicating that each construct is able to explain more than 71% of the variance of its indicators. Thus, the measurement model in this study can be declared reliable and valid, supporting the feasibility of further analysis to test the relationship between Artificial Intelligence (AI), Knowledge Sharing (KS), and Knowledge Management (KM) variables in the conceptual model of the article.

C. Structural Model Results

The structural model of this study was analyzed using SmartPLS, as shown in Figure 4. The model includes Artificial Intelligence (AI) as the exogenous variable, Knowledge Sharing (KS) as the mediating variable, and Knowledge Management (KM) as the endogenous variable. The relationships among these constructs were tested using Structural Equation Modeling–Partial Least Squares (SEM-PLS) and bootstrapping procedures.

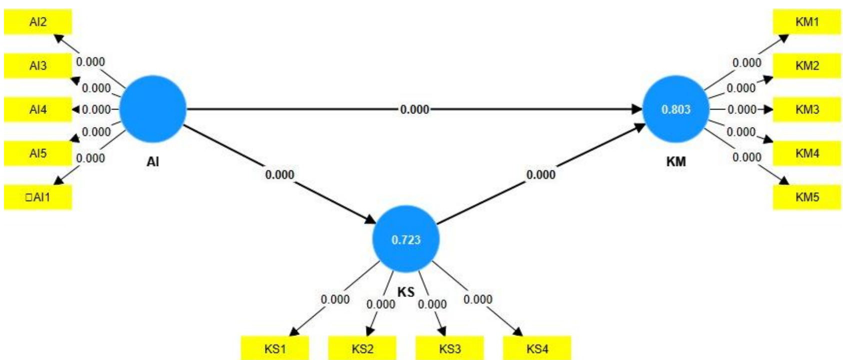

Figure 5. Structural Model Results

The Figure 5 shows the results of structural model estimation (inner model) that tests the relationship between three main constructs, namely Artificial Intelligence (AI), Knowledge Sharing (KS), and Knowledge Management (KM). This model aims to explain how the application of artificial intelligence (AI) affects the effectiveness of knowledge management (KM), both directly and through the mediation of knowledge sharing behavior (KS).

The analysis results show that AI has a direct influence on KM with a significant coefficient (p-value = 0.000). The R^2 value for the KM construct is 0.803, which means that 80.3% of the variation in Knowledge Management can be explained by AI and KS simultaneously. This indicates that the higher the use of AI in academic learning and work processes, the more effective the respondents' ability to organize and distribute knowledge. These findings are in line with Al-Qaysi et al. (2025) who assert that artificial intelligence can improve the efficiency of explicit knowledge and strengthen data-based learning in educational organizations.

AI also shows a significant direct influence on KS (p-value = 0.000) with R^2 = 0.723, which means that 72.3% of the variation in knowledge sharing behavior can be explained by the use of AI. This illustrates that students who frequently utilize AI in their learning activities are more likely to share their ideas, learning resources, and academic experiences with their peers. AI acts as a collaborative catalyst that facilitates real-time information exchange, supporting the findings of Pai et al. (2022) that the integration of AI in digital environments encourages active participation and strengthens learning collaboration.

The analysis results also show a significant influence between KS and KM (p-value = 0.000). This indicates that knowledge sharing behavior is the main mediating component that connects the influence of AI on the effectiveness of knowledge management. In other words, AI not only contributes directly to improving KM, but its greatest impact arises through increased knowledge sharing behavior among students. This finding reinforces Al-Kadi and Ali (2024) theory in the SECI model, where social processes such as sharing experiences and knowledge are at the heart of organizational knowledge formation.

The high R^2 values for the KS (0.723) and KM (0.803) constructs confirm that the model has strong predictive power. Conceptually, AI is proven to have a direct and indirect effect on KM through KS. This is in line with the previous bootstrapping results, where all relationships had a significance level of $p < 0.001$ and a t-statistic value above 1.96, reinforcing the empirical validity of the model.

D. Hypothesis Testing Analysis

This section presents the results of testing the hypotheses proposed in the study, using the SmartPLS analysis method and bootstrapping technique to evaluate the significance of the relationship between constructs. The results of the hypothesis testing can be seen in Table 3 below.

Tabel 4. Hypotesis Testing Analysis

Hypothesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
AI → KM	0.316	0.317	0.057	5.576	0.000
AI → KS	0.851	0.850	0.023	37.791	0.000
KS → KM	0.611	0.611	0.052	11.841	0.000

The hypothesis testing results show that all relationships between variables in the model have T-statistics values > 1.96 and p-values < 0.05, so all hypotheses are declared significant.

AI → KM (β = 0.316; p = 0.000)

Artificial Intelligence has a positive and significant effect on Knowledge Management. This means that the higher the application of AI in the learning process and information management, the more effective knowledge management in the academic environment will be. AI helps organize, store, and distribute knowledge efficiently. These results are consistent with the studies by Al-Qaysi et al. (2025) which found that AI acts as a knowledge enabler in supporting data-driven digital learning.

AI → KS (β = 0.851; p = 0.000)

This relationship shows the strongest influence among all paths, indicating that AI plays a significant role in increasing knowledge sharing behavior among students. The use of AI in learning (e.g., ChatGPT, Gemini, or Copilot) encourages students to collaborate, exchange ideas, and discuss results digitally. This finding is in line with Jose Arias-Pérez and Huynh (2024) , who assert that AI enhances cognitive and collaborative interactions in knowledge-based learning processes.

KS → KM (β = 0.611; p = 0.000)

These results confirm that knowledge sharing behavior has a significant influence on the effectiveness of knowledge management. This means that the more actively learners share knowledge (whether through discussions, online forums, or digital collaboration), the better the ability of institutions or learning groups to manage and maintain collective knowledge. This finding supports Al-Kadi and Ali (2024) conceptual model regarding the importance of knowledge conversion (socialization–externalization–combination–internalization) as the foundation of knowledge management.

This structural model reinforces the main thesis of the essay that Artificial Intelligence is not merely a knowledge automation tool, but an intelligent system that strengthens collaborative networks in digital knowledge management. AI plays a role in shaping more active, systematic, and reflective knowledge-sharing behavior patterns among learners. When used ethically and collaboratively, AI functions as a knowledge enabler accelerating information flow, deepening conceptual understanding, and enhancing the ability of organizations (campuses/schools) to manage knowledge collectively.

Thus, these results not only empirically support the conceptual model but also provide evidence that AI can act as a catalyst for humanistic learning, in line with the ethical reflection of the essay: technology should be a mirror of human intelligence, not its replacement.

V. CONCLUSION

Over the past decade, Artificial Intelligence (AI) has transformed the paradigm of knowledge management in education with its ability to automatically analyze, organize, and disseminate information, creating a huge leap forward in how knowledge is managed. However, this revolutionary potential has not been optimally utilized due to passive user behavior; many students and university students use AI only as an instant tool to obtain answers, rather than as a reflective partner in the learning process. Empirical results show that knowledge sharing is the key to bridging the effectiveness of AI: the direct influence of AI on knowledge management is strengthened through increased knowledge sharing behavior, where active user participation makes AI a catalyst that accelerates knowledge transfer and improves the overall effectiveness of knowledge management. This awareness confirms that the integration of AI in education must be based on a humanistic learning framework learning that places moral and human values above technological efficiency. Modernizing education that only emphasizes productivity without considering ethics risks producing a generation that is digitally savvy but lacking in moral reflection. Therefore, AI-based education should produce ethical thinkers, digitally savvy individuals with empathy, responsibility, and critical thinking skills, as emphasized by UNESCO (2024) in its global call for the importance of digital ethics literacy. Without strong ethical guidance, dependence on AI can actually erode students' reasoning and creativity. Therefore, the development of an AI-based education ecosystem must ensure that technology functions as a tool to enlighten character, not merely to pamper convenience. Ultimately, it can be asserted that Artificial Intelligence is not merely a data management machine, but a reflection of human intelligence in managing knowledge; the future of learning is not determined by how quickly we use AI, but by how deeply we understand the meaning behind the knowledge it generates. Technology can accelerate the learning process, but only humans determine the direction, value, and meaning of knowledge itself.

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