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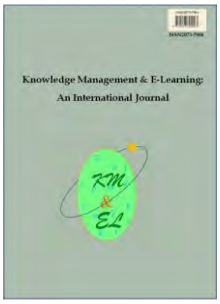
Sashi Ranjan
V. P. Joshith
K. Kavitha
Shana Chittakath
Central University of Kerala, India



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The AI-knowledge management nexus for sustainable learning: A PLS-SEM study

Sashi Ranjan

Department of Education
Central University of Kerala, India
E-mail: sashiranjan.2301607019@cukerala.ac.in

V. P. Joshith*

Department of Education
Central University of Kerala, India
E-mail: joshith@cukerala.ac.in

K. Kavitha

Department of Education
Central University of Kerala, India
E-mail: kavithakrishnan229@gmail.com

Shana Chittakath

Department of Education
Central University of Kerala, India
E-mail: shanachittakath@gmail.com

*Corresponding author

Abstract: Integrating artificial intelligence (AI) with knowledge management (KM) practices presents a promising avenue for advancing sustainable learning in higher education. However, empirical research exploring this synergy remains limited, particularly in developing countries. This study aimed to investigate the impact of AI-enhanced KM practices on sustainable learning outcomes in Indian higher education institutions. A proposed model was tested using a sample of 401 student responses, analysed through partial least square equation modelling (PLS-SEM) using SmartPLS 4. The findings revealed that AI-driven knowledge creation, storage, discovery, and prediction significantly contribute to sustainable learning when implemented ethically. Conversely, AI-based knowledge capture practices and tailored knowledge delivery did not significantly influence sustainable learning environments. The model exhibited substantial explanatory power regarding sustainable learning outcomes. This study contributes to the "*knowledge-based view*" and "*absorptive capacity*" theory by exploring the integration of AI and KM in education. Furthermore, it advances the "responsible AI paradigm" by addressing ethical considerations in AI-enhanced educational systems. The results provide a foundation for future research on the interplay between AI, KM, and sustainable learning, offering valuable insights for transforming educational practices and promoting lifelong learning in higher education.

Keywords: AI-based knowledge management; Sustainable learning; PLS-SEM; Knowledge sharing; Higher education

Biographical notes: Sashi Ranjan is a doctoral candidate in the Department of Education at the Central University of Kerala. His research interests include knowledge management in education, focusing on AI and socio-technical perspectives. He holds Master's degrees in Education and Sociology.

Prof. (Dr.) V. P. Joshith, Professor and Head, Department of Education, Central University of Kerala, holds Master's degrees in Education and Chemistry and a PhD in education. With 20 years of experience, he has authored two books and over 50 research papers, coordinated MOOCs, received the UGC Post-Doctoral Award, and contributed extensively to Technology and Sustainable Education.

K. Kavitha is a doctoral candidate in the Department of Education at the Central University of Kerala. Her research interests include AI in education and science education. She holds Master's degrees in Education and Physics.

Shana Chittakath is a doctoral candidate in the Department of Education at the Central University of Kerala. Her research interests include sustainable learning and SDGs in education. She holds Master's degrees in Education and English Literature.

1. Introduction

In the rapidly evolving landscape of the 21st century, sustainable learning has emerged as a critical imperative for educational institutions worldwide (Dube et al., 2023). This concept encompasses cultivating a capacity for continuous growth through learning that benefits individuals and contributes positively to society. As the socio-technological environment transforms, the need for individuals to adapt becomes increasingly pressing (Alam et al., 2021; De Angelis, 2023). Sustainable learning is closely aligned with the United Nations' Sustainable Development Goals (SDGs), particularly Goal 4, which advocates for quality education and lifelong learning opportunities for all (Zhao et al., 2023). Higher education institutions face many challenges as work and life become progressively dynamic. In response to these challenges, there is an urgent requirement for educational institutions to establish lifelong and adaptable learning frameworks that equip students with the requisite knowledge and skills for success in a rapidly changing world (Rehm, 2023). This necessitates a fundamental shift from traditional educational models, which often favour rote memorisation and standardised testing, towards more agile and responsive systems capable of effectively managing and leveraging knowledge within the institution (Kang et al., 2024; Sedziuviene & Vveinhardt, 2009). Knowledge Management (KM) has emerged as a vital factor in organisational success in this context. KM encompasses capturing, organising, storing, transferring, and applying knowledge within an organisation (Nonaka, 2009). Concurrently, the rapid advancement of artificial intelligence (AI) technologies presents unprecedented opportunities to enhance and optimise KM practices. AI is commonly defined as a system's ability to interpret external data correctly, learn from it, and use that learning to achieve specific goals and tasks through flexible adaptation (Haenlein & Kaplan, 2019). With its capacity to process vast amounts of data, recognise patterns, and generate insights, AI can revolutionise how knowledge is created, shared, and applied within educational institutions (Chen, 2023).

Despite the promising prospects of integrating KM and AI to advance sustainable learning, significant research gaps persist in the context of higher education. First, the application of KM in educational settings, particularly within higher education institutions, remains limited and underexplored (Omerzel et al., 2011; Singh et al., 2022; Usmani, 2023). This gap is especially pronounced in developing countries like India, where the potential benefits of structured KM practices in education are not fully realised (Bharadwaj et al., 2015; Khatun & Dar, 2021). Furthermore, there is a notable lack of research into the synergistic application of AI and KM, which conceals the potential benefits that could be derived from data-driven insights (Jarrahi et al., 2023). Understanding how AI can enhance knowledge management is crucial for maximising the sustainability benefits of these integrated approaches (Kamruzzaman et al., 2023). A further limitation in this field of study is the conceptual gaps regarding the role of KM in nurturing adaptive learning ecosystems. The absence of sufficient empirical evidence makes it challenging to align KM practices with the evolving pedagogical objectives that are increasingly necessary in contemporary education (Forbes et al., 2023). Consequently, the absence of comprehensive guidance on integrating AI and KM in educational contexts hampers the development of effective frameworks that consider cultural factors and technological considerations for educational objectives (Leoni et al., 2022).

This study develops and tests a conceptual framework examining the influence of AI-enhanced KM on sustainable learning in Indian higher education, as shown in Fig. 1. It offers insights for scholars and practitioners in education, AI, and KM fields, exploring how AI-driven KM can facilitate sustainable learning environments. The research contributes to educational technology and sustainable development discussions by investigating the synergy between AI and KM. It addresses aligning KM practices with evolving pedagogical goals, providing a framework for educational reform. Through empirical testing, the study aims to fill literature gaps and offer practical guidance on optimising learning processes through AI-driven KM, supporting long-term educational outcomes in the Indian higher education context. The theoretical underpinnings of this study are grounded in an integrated theoretical lens that seeks to bridge the gaps in the integration of AI and KM to support sustainable learning. At its core, the model is founded on the organisation's knowledge-based view (KBV) (Grant, 1996), which posits that knowledge is the most strategically valuable resource. This perspective is extended to view educational institutions as knowledge-intensive entities aiming to achieve sustained learning outcomes within higher education. Further, the KBV foundation is complemented by theories of "*knowledge creation*" (Gourlay, 2008) and "*absorptive capacity*" (Carayannis, 2012; Cohen, 2013). Both theories inform the processes of generating new knowledge and the ability to recognize, absorb, and apply external knowledge. Additionally, the integration of AI into these processes is informed by "predictive analytics theory" (Shmueli & Koppius, 2011), which explains how AI can enhance decision-making and personalized learning experiences (Tapalova & Zhiyenbayeva, 2022). Notably, the ethical dimension of AI integration is founded on responsible AI principles, underlining the significance of ethical considerations in educational technology deployment (Nguyen et al., 2023). Finally, the proposed framework assumes that AI technologies can optimise every stage of the knowledge management cycle, from generation to application, in an educational setting. It also asserts that AI-enhanced knowledge management approaches can directly contribute to long-term learning outcomes. Following the literature assessment, a set of hypotheses with a theoretical base is generated to build on the proposed theoretical model.

2. Literature review and hypotheses development

2.1. AI's role in knowledge management

Effective knowledge management impacts organisational performance (Kocjancic & Gricar, 2023). Artificial intelligence is one of the essential keys to constructing blocks for the development, improvement, and advancement of knowledge management (Pai et al., 2022). AI has increasingly permeated KM practices due to its potential to enhance knowledge discovery, sharing, and application in organisations (Majumder & Dey, 2022). Techniques in AI like natural language processing, machine learning, and deep learning can improve KM (Jarrahi et al., 2023). Also, case studies discuss AI's role in "*enhancing knowledge discovery, sharing, and utilisation*" through recommendations and insights (Manuti & Monachino, 2020). AI has also been known to enhance administrative decision-support systems by utilising knowledge management, focusing on private college administration, highlighting the need to digitise and implement strong decision-making support to improve governance and efficiency in educational institutions (Alshadoodee et al., 2022).

AI advancements have transformed computer-based education through learning analytics and educational data mining, improving knowledge management by forecasting student trajectories, assessing learners holistically, and enhancing support strategies (Baker, 2021). The deployment of AI also intersects with sustainability in knowledge-based development (KBD) initiatives (Leoni et al., 2022). Knowledge-based development fuels progress towards social and environmental goals, and technology can facilitate sustainable KBD practices (Laszlo & Laszlo, 2007). Building knowledge communities and accessing resources through advanced AI tools is one avenue that structures organisational knowledge assets to facilitate sustainability-oriented consulting and training (Rehm, 2023). New AI techniques promoting transparency, evidence, and security could bolster trust in technology applications (Hsieh et al., 2020).

2.2. AI's role in sustainable learning

Within education, the synergy between AI and KM has become increasingly crucial for advancing sustainable development goals (SDGs) (Klašnja-Milićević & Ivanović, 2021). Universities are preparing students for future industrial needs by assessing current curricula in AI, IoT, and edge computing (Dec et al., 2022). Such innovative technologies enable humans to continue their activities, like teaching and learning effectively, remotely or in a blended environment. It is understood that personalised e-learning powered by AI boosts access to education, facilitates training, and empowers people to address sustainability challenges (Chanyawudhiwan & Mingsiritham, 2023; Klašnja-Milićević & Ivanović, 2021). Moreover, AI can improve learning management systems, monitor student knowledge, provide personalised feedback and create immersive training simulations through AI-augmented virtual reality (Mehriddin et al., 2021). Studies also strengthen AI's potential to enhance e-learning during the COVID-19 pandemic (Ara Shaikh et al., 2022). AI Explainable AI (XAI) algorithms in education play a role in detecting emotions, predicting dropouts and providing assistance (Lin et al., 2023). Similarly, when AI chatbots are used for education, finding knowledge factors like acquisition, sharing, and perception significantly influences sustainable usage (Al-Sharafi et al., 2023). A comparable "*rule-based expert system*" in higher education supports academic advising and knowledge sharing, highlighting issues that technological solutions can address (Bilquise & Shaalan, 2022). Also, AI supports sustainable learning outcomes with evidence of the positive impact of e-learning services on sustainability and performances among Saudi university students (Alam et al., 2021). At the same time, combining AI and virtual reality enhances online education by creating more realistic and immersive training simulations for learners (Mehriddin et al., 2021). Conclusively, implementing a predictive model with theoretical support is feasible, allowing adaptation of variables through artificial intelligence, thus creating an AI-based framework for sustainable learning.

2.3. Challenges

Challenges include a lack of understanding of AI and KM in the context of technological, cultural, social, financial, ethical and political challenges. Integrating AI technologies in KM systems can lead to ethical issues surrounding privacy, security, and accountability (Pai et al., 2022). However, integrating educational technology like AI presents benefits and risks that require prudent consideration (Zhang & Aslan, 2021). AI applications in education require a comprehensive overview while emphasising the need for ethical practices and informed decision-making regarding AI adoption. Key issues are privacy, bias, transparency, and AI's humane and responsible development (Akgun & Greenhow, 2022). Artificial intelligence presents both challenges and opportunities for future teaching and teacher education. Despite uncertainties about future educational demands, schools have to adapt to digitalisation and AI to offer practical learning opportunities; therefore, regulatory oversight of the development and implementation of artificial intelligence is necessary to address these challenges (Zeinz, 2019).

2.4. Hypotheses generation

2.4.1. Knowledge creation (KC)

Using AI-powered solutions, educational institutions can create new knowledge and insights supporting sustainable learning initiatives. Additionally, AI-powered systems have been found to support sustainable education by improving access to education, academic and professional training and empowering individuals to address sustainability challenges (Klašnja-Milićević & Ivanović, 2021). Grant's (1996) Knowledge-Based View theory suggests that knowledge is vital for firms to obtain a long-term competitive advantage. Educational institutions can improve learning outcomes and promote long-term sustainability goals by maximising their knowledge resources (Olan et al., 2022). Also, the literature has highlighted the potential of AI in enhancing knowledge discovery, sharing, and utilisation in organisations (Kocjancic & Gricar, 2023; Majumder & Dey, 2022). AI significantly enhances knowledge creation, promoting sustainable learning through its capabilities in data analysis, optimisation, and decision-making (Vinuesa et al., 2020).

Thus, hypothesis 1 (H1) is proposed:

H1: Knowledge creation through AI-powered tools enhances sustainable learning.

2.4.2. Knowledge capture practice (KCP)

An organisation's ability to perceive the value of new knowledge, absorb it, and use it to accomplish desired outcomes is referred to as absorptive capacity theory (Cohen, 2013). In the context of AI-KM integration, this theory suggests that AI systems can help organisations capture diverse knowledge sources and facilitate sustainability (Rohde et al., 2024). The reviewed studies have shown the ability of AI to integrate various knowledge sources and facilitate knowledge exchange, supporting the second hypothesis (Manuti & Monachino, 2020; Olan et al., 2022).

Thus, hypothesis 2 (H2) is proposed:

H2: AI systems capture diverse knowledge sources and support sustainable learning.

2.4.3. Maximised knowledge storage (KS)

Knowledge management capabilities, competitive advantage, and sustainable performance depend heavily on an organisation's capacity to manage its knowledge resources (Gold et al., 2001). This demands AI-driven repositories to optimise information storage and retrieval, promoting knowledge exchange and ongoing development in sustainable learning (Venkatachalam & Venkatachalam, 2024). Also, the literature has highlighted the potential of AI-powered systems in optimising knowledge storage and retrieval processes (Kocjancic & Gricar, 2023). Combining AI-driven personalised learning, continual learning principles, and knowledge storage algorithms supports knowledge acquisition and retention efficiency and effectiveness in educational settings (Salo-Lahti et al., 2023). Additionally, AI algorithms facilitate the storage and retrieval of knowledge through intelligent systems that understand every professional's learning needs, helping them excel in their skills (Cossu et al., 2021).

Thus, hypothesis 3 (H3) is proposed:

H3: AI-driven repositories facilitate sustainable learning through maximised knowledge storage.

2.4.4. Smart knowledge discovery (KD)

AI enhances knowledge discovery through techniques like natural language processing and machine learning (Lin et al., 2023; Majumder & Dey, 2022). The notion of intelligent information processing is centred on creating computational models and methods that imitate the cognitive functions of humans, including learning, reasoning, and solving problems (Newell & Simon, 2019). In the context of AI-KM integration, this idea suggests that AI-powered tools can enhance knowledge discovery processes by identifying relevant information, extracting insights, and uncovering patterns or connections (Safder et al., 2018). Additionally, AI enables brilliant knowledge discovery for sustainable learning by anchoring novel machine learning methods, reasoning, and search techniques (Shehzadi et al., 2022).

Thus, hypothesis 4 (H4) is proposed:

H4: AI-powered tools for brilliant knowledge discovery facilitate sustainable learning.

2.4.5. Predictive knowledge (PK)

AI develop predictive models for sustainable learning by using machine learning algorithms to predict students' difficulties while using e-learning management systems, ultimately supporting decision-making and contributing to sustainable learning (El Koshiry et al., 2023). The predictive analytics approach uses statistical methods and machine learning algorithms to examine historical and present data to forecast future behaviours or events (Shmueli & Koppius, 2011). Taking this as a base in the context of AI-KM integration suggests that the predictive competency of AI-KM systems can augment sustainable learning by identifying potential dropouts, detecting emotions, and providing tailored interventions (El Koshiry et al., 2023). The studies have explored the potential of AI in predicting student performance and providing personalised support (Hori et al., 2020; Lin et al., 2023).

Thus, hypothesis 5 (H5) is proposed:

H5: Predictive competency of AI-KM systems augments sustainable learning.

2.4.6. Tailored knowledge delivery/sharing (TKD)

The idea of personalized learning places significant emphasis on customising educational experiences to cater to individual students' distinct requirements, preferences, and aptitudes (Pane et al., 2017). AI can support sustained learning in AI-KM integration by offering personalised information delivery and exchange methods (Mehriddin et al., 2021). The extent to which AI can disseminate tailored knowledge is supported by research that has demonstrated the capability of AI in assisting individualised e-learning, offering customised feedback and guidance (Al-Sharafi et al., 2023; Klašnja-Milićević & Ivanović, 2021; Mehriddin et al., 2021).

Thus hypothesis 6 (H6) is proposed:

H6: AI promotes sustainable learning through tailored knowledge delivery/sharing.

2.4.7. Ethical AI-KM integration (E)

The responsible AI paradigm strongly emphasises the necessity of creating and implementing AI systems that are accountable, transparent, and consistent with moral standards (Floridi et al., 2018). This paradigm indicates that an ethical approach to AI-KM integration is essential for developing trust, defending the rights of learners, and advancing fair access to resources and information (Nguyen et al., 2023). Establishing ethical principles and guidelines for AI in education is essential to guide the development and deployment of trustworthy AI systems, which benefit students, teachers, developers, policymakers, and decision-makers in educational institutions (Holmes et al., 2023). It becomes imperative for ethical issues in AI-KM integration to guarantee responsible and reliable implementation (Akgun & Greenhow, 2022; Pai et al., 2022).

Thus, hypothesis 7 (H7) is proposed:

H7: An ethical AI-KM integration support sustainable learning.

2.5. Conceptual framework

Fig. 1 illustrates the conceptual framework linking AI-driven knowledge management (AI-KM) practices to sustainable learning. The framework highlights seven pathways (H1–H7), representing key AI-KM practices: knowledge creation, knowledge capture practices, maximised knowledge storage, smart knowledge discovery, predictive knowledge, tailored knowledge delivery/sharing, and ethical AI-KM integration. Each pathway demonstrates how these AI-KM practices collectively support sustainable learning by enhancing knowledge processes and promoting responsible AI use. This framework visually synthesizes the hypotheses discussed earlier, emphasizing the central role of AI in transforming knowledge management to achieve sustainable and equitable learning outcomes.

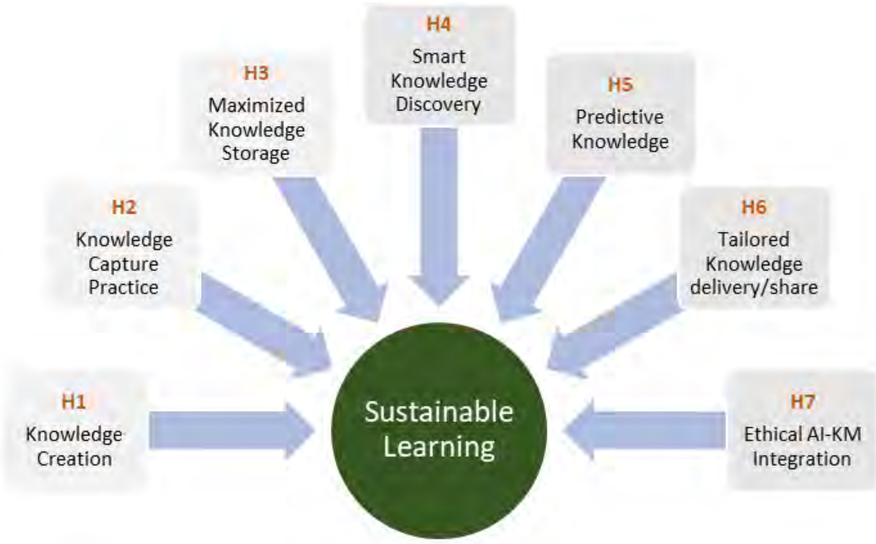

Fig. 1. Conceptual framework

3. Research method

3.1. Research sample and design

This research was carried out on students enrolled in higher education institutes in India. The target population included institutions under central, private, aided and state affiliations. Educational levels of the sample varied from undergraduate, postgraduate and research scholars. Academic disciplines involved arts, humanities, science, social science and others as an option. The study involved a convenience sampling method wherein a Google survey form was shared with individuals and groups over two months in March-April 2024. This method helped in a way that participants could fill in their responses at their availability and convenience. This method encourages individuals to complete the questionnaire based on their availability and willingness to participate (Al-Adwan et al., 2021). Respondents were from different places around India. The adoption of the convenience sampling method in this research was driven by its convenience and efficiency, as it proved to be more accessible and quicker in survey administration compared to alternative methods. The final number of valid sample responses collected was 401, considered apt for statistical analyses (Al-Adwan et al., 2021; Gravetter & Forzano, 2011; Lakens, 2022).

The authors identified sustainable learning as an endogenous construct with 5 items (Choudhury, 2018; Malunga & Holcombe, 2014). Exogenous constructs: knowledge creation (4 items); knowledge capture practice (KCP) 4 items; maximized knowledge storage (KS) 4 items; smart knowledge discovery (KD) 5 items, predictive knowledge (PK) 5 items; tailored knowledge delivery/share (TKD) 5 items, ethical AI-KM integration (E) 5 items totalling to 37 items. The authors reviewed the literature extensively and existing scales to construct and validate the tool (Conchado et al., 2015; Manohar Singh & Gupta, 2014).

3.2. Data analyses

This study adopted PLS-SEM to analyse the research model. SmartPLS 4 software was used to test the model justified for its ability to maximise explained variance in educational research. PLS-SEM's flexibility in modelling complex relationships with observable variables and its capability to account for measurement error, as highlighted by Hair and Alamer (2022). It is a reliable and valuable tool for explaining and predicting outcomes in educational settings. This method is preferred for its focus on both in-sample and out-of-sample prediction, and its suitability for handling formative (composite) constructs without imposing specific constraints. The software's user-friendly interface and functionality have made it particularly popular among researchers due to its ease of use and robust capabilities. SmartPLS facilitates various aspects of PLS-SEM analysis, including measurement model evaluation, structural model evaluation, handling multicollinearity, second-order latent variables, mediation, moderation with numerical and categorical variables, and multi-group analysis (Hanna et al., 2018; Purwanto & Sudargini, 2021; Silaparasetti et al., 2017).

4. Results

4.1. PLS-SEM model

The first step in checking how well a PLS study measures the validity and reliability of items is to look at the outer model. The model is evaluated depending on whether they are measuring things that directly reflect a concept (reflective measures) or things that contribute to a concept (formative measures), as well as the overall structure of the measurement model itself (Davcik, 2014). Before putting a model to hypothesis testing, it is crucial to confirm the validity and reliability of a suggested measurement model. Before moving on to the structural model, the convergent and discriminant validity of the models' measurements must be assessed to meet this goal (Hair & Alamer, 2022; Sarstedt Marko & Ringle, 2020).

4.2. Item reliability

For the reliability assessment, the factor loading of each item was checked. The suggested loading is expected to exceed 0.708, although a threshold of 0.50 is also in an acceptable range (Hair & Alamer, 2022). As shown in Table 1 and Fig. 2, all items' standardised factor loading estimates were acceptable, ranging from 0.521 to 0.770.

Table 1
Constructs, item, CA, rho_a, rho_c and AVE

Constructs	Item	No of items	Outer loadings	CA(α)	rho_A	rho_c	AVE	VIF
E		5		0.659	0.670	0.784	0.423	
	E1		0.655					1.233
	E2		0.682					1.230
	E3		0.694					1.224
	E4		0.683					1.273
	E5		0.521					1.145
KC		4		0.706	0.708	0.819	0.532	
	KC1		0.690					1.256
	KC2		0.719					1.314
	KC3		0.762					1.412
	KC4		0.745					1.375
KCP		4		0.684	0.683	0.808	0.513	
	KCP1		0.697					1.246
	KCP2		0.742					1.394
	KCP3		0.732					1.290
	KCP4		0.692					1.259
KD		5		0.766	0.772	0.842	0.516	
	KD1		0.760					1.449
	KD2		0.736					1.461
	KD3		0.708					1.396
	KD4		0.699					1.387
	KD5		0.686					1.361
KS		4		0.745	0.748	0.839	0.566	
	KS1		0.770					1.443
	KS2		0.725					1.391
	KS3		0.752					1.443
	KS4		0.762					1.431
PK		5		0.764	0.766	0.841	0.514	
	PK1		0.705					1.428
	PK2		0.693					1.355
	PK3		0.755					1.497
	PK4		0.738					1.473
	PK5		0.692					1.310
SL		5		0.707	0.716	0.810	0.463	
	SL1		0.562					1.145
	SL2		0.749					1.409
	SL3		0.713					1.406
	SL4		0.715					1.329
	SL5		0.646					1.251
TKD		5		0.732	0.735	0.824	0.484	
	TKD1		0.659					1.254
	TKD2		0.711					1.377
	TKD3		0.663					1.281
	TKD4		0.757					1.495
	TKD5		0.682					1.383

Note. E: Ethical AI-KM integration; KC: Knowledge creation; KCP: Knowledge capture ; KD: Smart knowledge discovery; KS: Maximised knowledge storage; PK: Predictive knowledge; SL: Sustainable learning; TKD: Tailored knowledge delivery/sharing

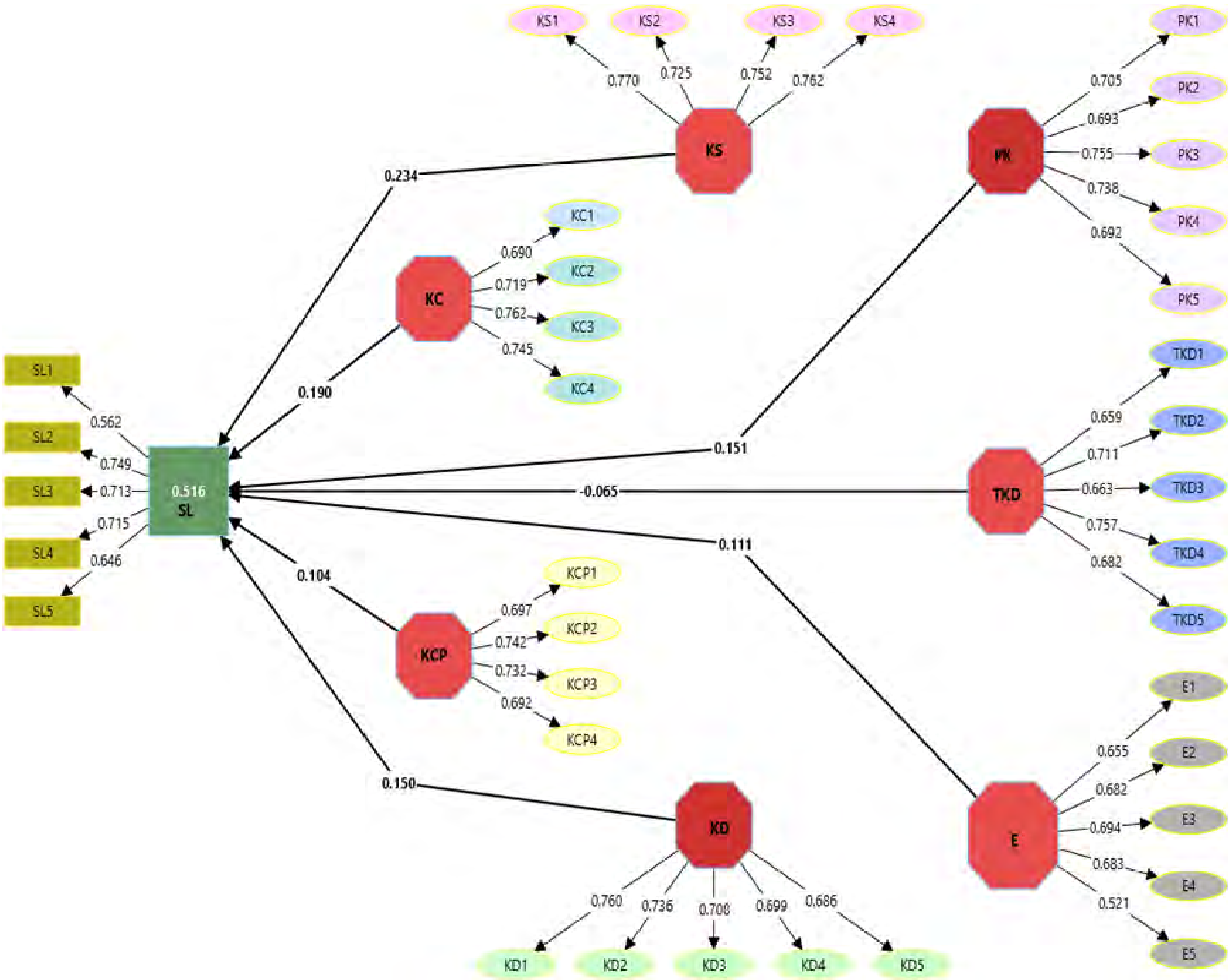

Fig. 2. PLS-SEM algorithm

4.3. Composite (scale) reliability

The study's internal consistency reliability/scale reliability was assessed by examining composite reliability (rho_c) and Cronbach's alpha (α), consistent with the recommendation by (Arkorful et al., 2024). Table 1 shows six of the constructs displayed a CR (rho_c) and CA(α) > 0.7, thus maintaining internal consistency. Two of the constructs, E and KCP, have CR < 0.7. This can be considered acceptable, indicating moderate internal consistency. While Cronbach's alpha can underestimate reliability, especially with non-parallel items, it remains essential for assessing internal consistency. Research shows that Cronbach's alpha increases with more items, improving reliability. Therefore, a value of

0.6 may be acceptable, but higher reliability would enhance measurement accuracy (Bonett & Wright, 2015; Hayashi & Yuan, 2022; Peterson & Kim, 2013).

4.4. Construct validation

4.4.1. Convergent validity

Convergent validity evaluates the interrelatedness among measures of the same construct (White, 2003). While evaluating convergent validity, the average variance extracted (AVE) values show that five constructs (KC, KCP, KD, KS, PK) exceed the 0.5 thresholds, demonstrating sufficient validity (Cheung et al., 2024; Chin & Yao, 2014; Hair & Alamer, 2022).

However, three constructs (ethical AI integration, sustainable learning and tailored knowledge delivery/sharing) fall below the threshold. Despite the low AVE values, it is important to consider the broader context of social science research, which usually involves complexities and reliance on grey-box models and self-reports (Bruschi, 2017). The variance inflation factor (VIF) values are below 5, indicating no significant collinearity issues (Sarstedt et al., 2020).

Additional criteria like standardised factor loading ≥ 0.5 and composite reliability ≥ 0.7, which are met in this model, further support its validity (Bonett & Wright, 2014; Hanna et al., 2018; Purwanto & Sudargini, 2021). Considering these factors together, convergent validity is demonstrated with the needed exploration of constructs having a value below the threshold.

4.5. Discriminant validity

Two criteria were used to assess discriminant validity. Fornell and Larcker's (1981) criterion was applied, showing that the square root of the AVE for each construct should exceed its correlation with any other construct in the model. Table 2 shows that the square root of the E AI-KM value of AVE (0.650) is smaller than TKD (0.686). This shows a potential issue with the discriminant validity between E AI-KM and TKD. Similarly, in the case of PK, the square root of AVE is smaller than TKD (0.721), thus having potential issues with discriminant validity between TKD and PK. The rest of the constructs come under acceptable values.

Table 2
Fornell-larcker criterion

	E	KCP	KC	KS	PK	SKD	SL	TKD
E	0.650							
KCP	0.539	0.716						
KC	0.541	0.618	0.729					
KS	0.539	0.637	0.558	0.753				
PK	0.640	0.578	0.530	0.618	0.717			
SKD	0.565	0.610	0.569	0.665	0.654	0.718		
SL	0.533	0.569	0.575	0.620	0.579	0.598	0.680	
TKD	0.686	0.615	0.551	0.610	0.721	0.628	0.526	0.696

Secondly, the Heterotrait-Monotrait ratio (HTMT) values were checked. Table 3 shows that the HTMT ratio between E AI-KM and TKD, PK and TKD is above the threshold limit of 0.85, thus lacking discriminant validity (Fornell & Larcker, 1981). The HTMT criterion values should be less than 0.85, ideally below 0.90, to ensure the absence of multicollinearity and discriminant validity among the latent variables (Ab Hamid et al., 2017). So, these two constructs require further exploration.

Table 3
Heterotrait-Monotrait ratio (HTMT) matrix

	E	KCP	KC	KS	PK	SKD	SL	TKD
E	/							
KCP	0.782	/						
KC	0.784	0.889	/					
KS	0.750	0.892	0.766	/				
PK	0.888	0.804	0.718	0.818	/			
SKD	0.781	0.844	0.774	0.875	0.860	/		
SL	0.760	0.817	0.813	0.847	0.784	0.804	/	
TKD	0.967	0.871	0.767	0.822	0.964	0.841	0.725	/

4.6. Goodness of fit

The assessment of the measurement model focussed on achieving satisfactory goodness of fit (GoF). Five principles indices, as given in Table 4, were used to understand the comprehensive model fit. SRMR (Standardised Root Mean Square Residual) measures the mean absolute correlation residual. Values < 0.8 indicate a good model fit. d_ULS (Unweighted least squares discrepancy) and d_G (geometric Mean discrepancy) also measure model fit, where low values show better fit. Here, the values are identical for both models. Chi-square tests if a model is significantly different from the saturated model. In this case, too, the values are identical, suggesting non-significant. NFI (Normed fit index) measures the proportion of co-variance in the data explained by the model. A value closer to 1 indicates a better fit, and > 0.9 is a good fit. Here, the value of 0.704 suggests improvement in the estimated model. Conclusively, most statistics show equivalence between the estimated and saturated models, showing that the model fits the data based on d statistics and SRMR. However, the Chi-Square value and relatively low NFI of 0.704 necessitate refining the model structure, and further evaluation is needed to strengthen it (Hammervold & Olsson, 2012; Perry et al., 2015; Sahoo, 2019; Sarstedt et al., 2020).

Table 4
Model fit indices

Index	Saturated model	Estimated model
SRMR	0.062	0.062
d_ULS	2.677	2.677
d_G	0.769	0.769
Chi-square	1657.751	1657.751
NFI	0.704	0.704

Note. SRMR: Standardized Root Mean Square Residual; d_ULS: Unweighted Least Squares Discrepanc;. d_G: Geometric Mean Discrepancy; Chi-Square: Chi-Square Test; NFI: Normed Fit Index

4.8. Structural model assessment

The structural model is evaluated in three stages: R2 (Coefficient of determination), showing the model's explanatory power; Q2 (Predictive relevancy) and the significance of the path coefficient (Hair et al., 2021; Sarstedt et al., 2020). Also, every path was tested through 5000 bootstrap re-samples and a blindfolding procedure to calculate Q2 estimates (Hair et al., 2021).

Fig. 3. shows the result of PLS-SEM bootstrapping, and Table 5 gives the summary.

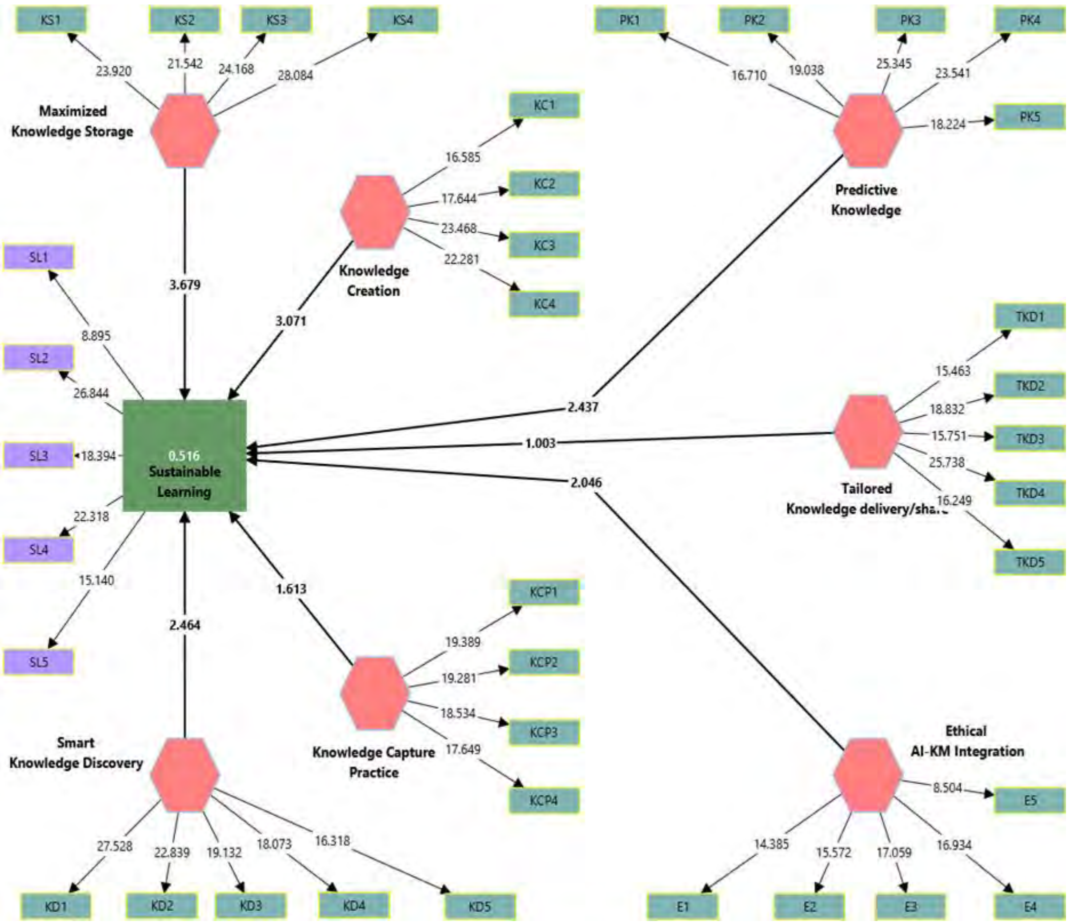

Fig. 3. PLS-SEM bootstrapping result

Results from Table 5 show that KC has a significant positive influence on SL [$\beta = 0.190$, $t = 3.071$, $p = 0.002 < 0.01$], thus confirming H1. At the same time, KCP showed a positive but insignificant effect on SL [$\beta = 0.104$, $t = 1.613$, $p = 0.107 > 0.05$]. Hence, H2 is not supported. However, H3 is supported after results revealed that maximized knowledge storage significantly influences Sustainable Learning positively (KS-SL) [$\beta = 0.234$, $t = 3.679$, $p = 0.000 < 0.001$].

Also, it is learned that smart knowledge discovery significantly influences sustainable learning positively (KD-SL) [$\beta = 0.150$, $t = 2.464$, $p = 0.014 < 0.05$], thereby confirming H4. Predictive knowledge shows a significant positive effect on sustainable learning (PK-SL) [β = 0.151, t = 2.437, p = 0.015 < 0.05], supporting H5. At the same time, H6 was not supported as tailored knowledge delivery/sharing showed an insignificant negative effect on sustainable learning (TKD-SL) [β = -0.065, t = 1.003, p = 0.316 > 0.05]. Interestingly, ethical AI-KM integration shows a significant positive influence on sustainable learning (E-SL) [β = 0.111, t = 2.046, p = 0.041 < 0.05], supporting H7.

Additionally, Table 5 displays a coefficient of determination (R2) value of 0.516 and a Q2 value of 0.484, exceeding zero, meaning that the factors collectively explain 51.6% of the variability in sustainable learning and the predictive relevance of the model, respectively (Chin, 1998; Hair et al., 2021; Hammervold & Olsson, 2012). Also, considering effect size for the significant paths, knowledge Storage, knowledge creation, smart knowledge discovery, and predictive knowledge appear to be the most important factors influencing sustainable learning, but others are insignificant due to small effect size (Cohen, 2013).

Table 5
Structural model indexes

Structural path	β	t value	p-value	SD	R^2	F^2	2.5% LLCI	97.5% ULCI	Q^2
E-SL	0.111	2.046	0.041	0.054		0.012	0.004	0.219	
KCP-SL	0.104	1.613	0.107	0.065		0.010	-0.017	0.240	
KC-SL	0.190	3.071	0.002	0.062		0.039	0.068	0.309	
KS-SL	0.234	3.679	0.000	0.064		0.049	0.109	0.356	
PK-SL	0.151	2.437	0.015	0.062		0.018	0.031	0.272	
KD-SL	0.150	2.464	0.014	0.061		0.020	0.027	0.268	
TKD-SL	-0.065	1.003	0.316	0.065		0.003	-0.192	0.065	
Overall model indices					0.516				0.484

Note. LLCI: Lower-Level Confidence Interval; ULCI: Upper-Level Confidence Interval

Table 6
Aggregate importance and performance index values for sustainable learning

Sustainable learning (SL)	Total (Importance)	Effect index value (Performance)
Ethical AI-KM integration	0.111	63.037
Knowledge capture practice	0.104	63.711
Knowledge creation	0.190	63.437
Maximized knowledge storage	0.234	64.751
Predictive knowledge	0.151	64.462
Smart knowledge discovery	0.150	63.496
Tailored Knowledge delivery/share	-0.065	64.154

4.9. Importance-performance map analysis

An importance-performance map analysis is carried out to provide additional insights by combining the importance and performance of constructs in PLS-SEM analysis (Sarstedt et al., 2020). Here, the significance and effectiveness of factors influencing sustainable learning were checked through this process. Fig. 4. shows constructs placed in different quadrants for specific improvement or performance enhancement.

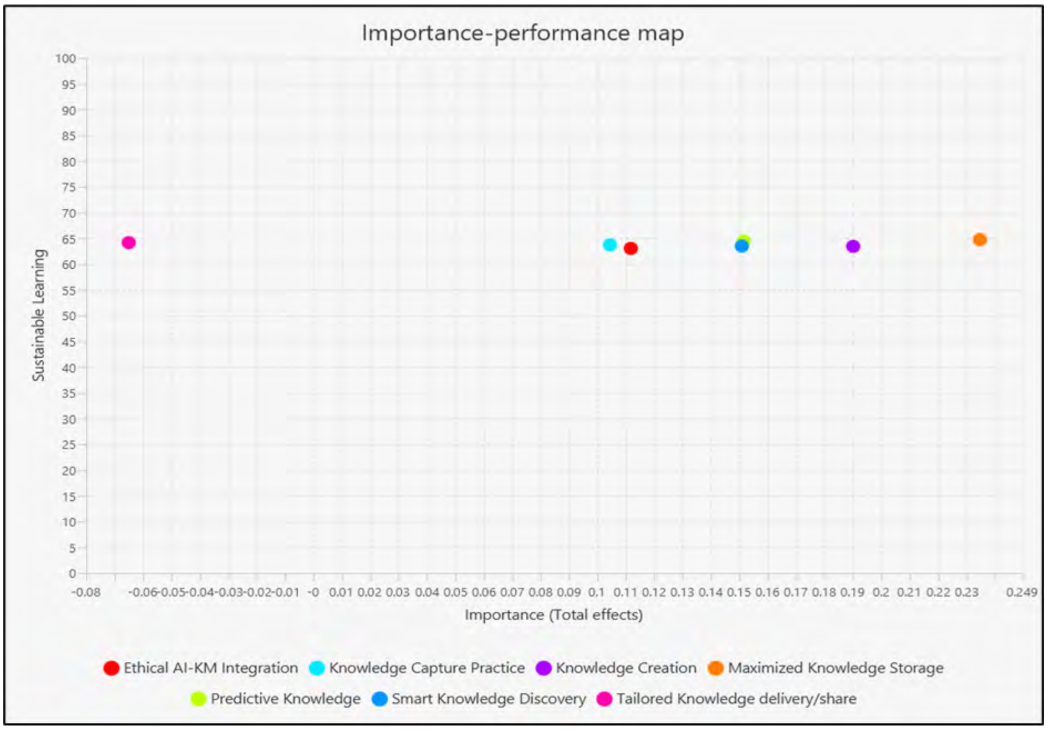

Fig. 4. The Importance-Performance map

The standardised total effect (importance) and the latent variable scores (Performance) are given in Table 6. Among the constructs, maximised knowledge storage has the highest positive impact on sustainable learning, with a total effect of 0.234 and the highest performance index value of 64.751, showing that storing knowledge is important for sustainable learning outcomes. Similarly, knowledge creation shows a strong positive influence with a total effect of 0.190 and a performance index of 63.437, highlighting the importance of generating new ideas and perspectives through AI tools. Predictive knowledge and smart knowledge discovery demonstrate positive impacts with total effects of 0.151 and 0.150, respectively and performance values of 64.462 and 63.496. These results highlight their role in enhancing learning by anticipating future knowledge demands and relevant information. On the other hand, ethical AI-KM integration and knowledge capture practice show moderate positive effects with total effects of 0.111 and 0.104 and performance values of 63.037 and 63.711, respectively, indicating their support but critically fewer roles to play.

However, tailored knowledge delivery/sharing has a negative total effect of -0.065 despite a high-performance index of 64.154, suggesting non-contribution towards sustainable learning.

The performance of latent variables is in Fig. 5.

4.10. Revised conceptual framework

An updated conceptual framework consisting of research hypotheses is illustrated in Fig. 6.

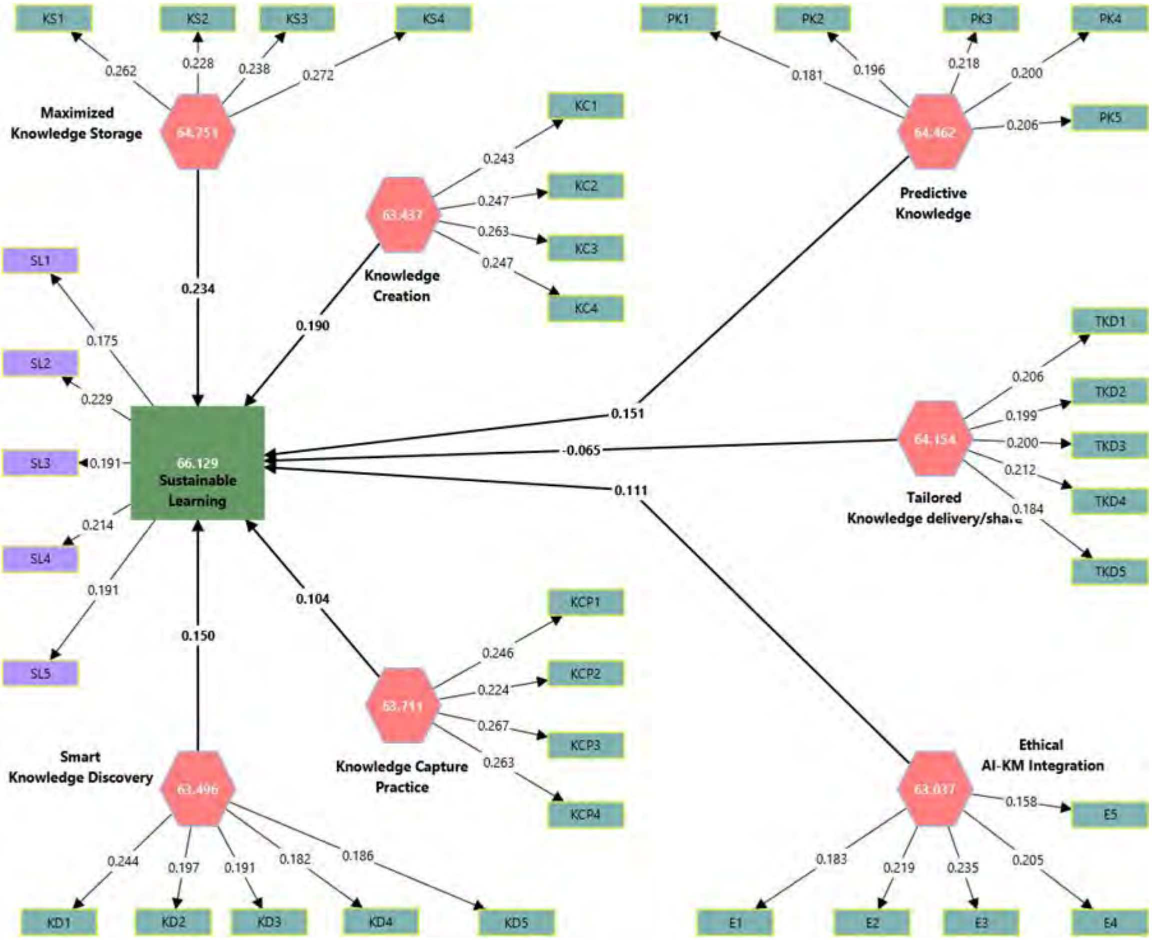

Fig. 5. Latent variable performance

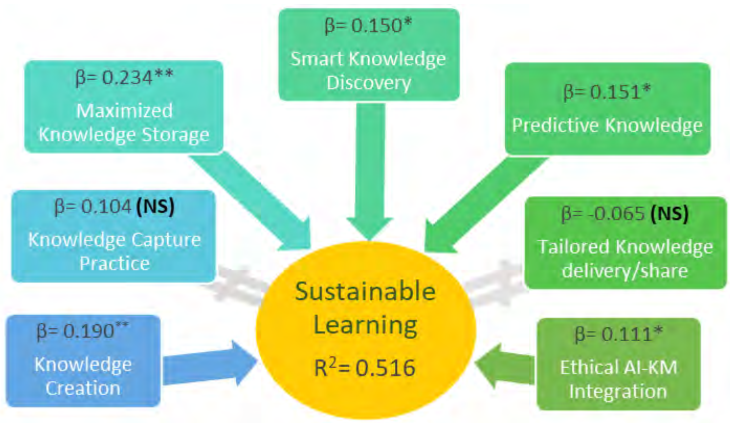

Fig. 6. Revised conceptual framework

Table 7 shows the key results for the assumptions made at the beginning of the study.

Table 7
Hypotheses summary

Hypotheses	Statements	Result
H1	Knowledge creation through AI-powered tools positively contributes toward sustainable learning. (KC-SL)	Fail to reject
H2	AI systems capture diverse knowledge sources and support sustainable learning. (KCP-SL)	Reject
H3	AI-driven repositories facilitate sustainable learning through maximised knowledge storage. (KS-SL)	Fail to reject
H4	AI-powered tools for smart knowledge discovery contribute toward sustainable learning. (KD-SL)	Fail to reject
H5	Predictive competency of AI-KM systems augments sustainable learning. (PK-SL)	Fail to reject
H6	AI facilitates sustainable learning through tailored knowledge delivery/sharing. (TKD-SL)	Reject
H7	An ethical AI-KM integration supports sustainable learning (E-SL)	Fail to reject

5. Discussion

The studied conceptual model offers a valuable framework for understanding the role of artificial intelligence in knowledge management practices facilitating sustainable learning in higher education. The results align with and challenge existing literature, offering novel insights into integrating AI and KM in educational contexts. The findings support the positive impact of AI-powered knowledge creation on sustainable learning (H1), extending the work of Kocjancic and Gricar (2023), and Majumder and Dey (2022) in the specific context of higher education. While previous studies focused on organisational settings, this study demonstrates that AI-enhanced knowledge creation principles can be effectively applied to promote sustainable learning in educational environments. This finding further bridges the gap between organisational KM theory and educational practice, suggesting a new avenue for conceptualising knowledge construction in technology-enhanced learning environments.

However, the notion that artificial intelligence systems could capture diverse knowledge sources and support sustainable learning (H2) lacked statistical significance. This result differs from the assumptions made by Manuti and Monachino (2020) and Olan et al. (2022) regarding AI's role in knowledge capture and integration. Moreover, findings highlight the complexity of knowledge capture in educational contexts, suggesting that AI's mere aggregation of diverse knowledge sources may not directly translate to improved learning outcomes. This calls for re-evaluating how we conceptualise knowledge capture in educational settings and points to the need for more nuanced theories that account for the unique challenges of integrating diverse knowledge sources in learning environments. Additionally, this study supports the positive impact of AI-driven repositories on sustainable learning through maximised knowledge storage with the highest significant path (H3), extending the work of Kocjancic and Gricar (2023) and Olan et al. (2022). This finding bridges organisational KM theories with educational practice, suggesting that AI-enhanced knowledge storage principles can effectively support sustainable learning in higher education.

The positive relationship between AI-powered smart knowledge discovery tools and sustainable learning (H4) aligns with and extends the work of Lin et al. (2023) and Majumder and Dey (2022). The study provides empirical evidence of how AI-enhanced knowledge discovery approaches can support higher education's critical thinking and problem-solving skills, extending existing knowledge discovery theories by highlighting AI's unique benefits in educational settings. Also, with a significant path, H5 support that AI-KM systems with predictive capabilities augment sustainable learning, extending the work of Hori et al. (2020). This finding supports the conceptual model and strengthens the application of predictive analytics in education for personalised learning. Furthermore, as anticipated, the research did not corroborate the theory that AI facilitates sustainable learning through tailored knowledge delivery/sharing (H6). This result differs from the assumptions put forth by Klašnja-Milićević and Ivanović (2021) regarding the effectiveness of AI-driven personalised content delivery in educational contexts. The finding here also highlights the complexity of personalised knowledge delivery in educational settings, calling for re-evaluating the personalisation theories in education and pointing to the need for more nuanced models that account for the multifaceted nature of learning (Wang, 2024). Finally, the result endorses that ethical AI-KM integration promotes the proposed model of sustainable learning (H7), aligning with and extending the earlier studies (Akgun & Greenhow, 2022; Pai et al., 2022). This finding connects ethical AI frameworks with educational theory and practice, emphasizing that ethical implementation of AI-KM systems is not just a regulatory concern but a critical factor in fostering sustainable learning outcomes.

6. Implications and future research scope

This study has significantly enriched theoretical knowledge regarding the intersection of AI, KM, and sustainable learning in educational settings. Testing an integrated conceptual model provided valuable insights into AI-based knowledge creation, storage, discovery, and prediction processes. The study enhances the theoretical landscape by providing empirical support for five of the seven hypotheses proposed in the theoretical model while challenging assumptions regarding knowledge capture and tailored delivery/sharing. This outcome underscores the complexity of learning environments and calls for more sophisticated theoretical frameworks. The positive impact of AI on knowledge creation and storage extends existing theories of knowledge construction and repositories, necessitating new conceptualisations that integrate AI capabilities. Similarly, AI's effectiveness in discovery and predictive abilities provides grounds to expand learning analytics and KM theories into pedagogical domains. Notably, the endorsement of ethical AI-KM integration emphasises its fundamental importance in theoretical and practical educational contexts. These findings collectively suggest the need to develop holistic models that combine insights from KM, AI, pedagogical realities, and educational perspectives to facilitate sustainable learning. From a practical standpoint, considering all stakeholders, these findings can guide strategic decision-making regarding AI integration for knowledge optimisation and learner support in educational institutions. Also, recognising ethical AI integration as a critical success factor underscores the importance of responsible development and robust oversight mechanisms in educational technology initiatives. In the future, conceptual and operational refinement through more thorough studies, including varied multi-dimensional realities over longer durations, seems necessary to generate truly sustainable learning on a global scale. Despite current contributions, further progressive re-evaluation guided by empirical evidence has the potential to optimise AI-KM synergy and achieve significant educational agendas.

Pointing to limitations, the study ignored important stakeholder perspectives, such as those of educators who are major players in the use of technology. Given that learning is a collaborative process, future studies can assess the opinions of all relevant participants. Furthermore, the study's generalizability is limited due to its single-country focus and snapshot design. Although not investigated, differing socioeconomic and cultural dynamics across lines may impact the outcomes.

7. Conclusion

This study's exploration of the nexus between AI and KM in higher education updates our understanding of sustainable learning. The mismatch between expectation and results underscores the complexity of learning environments and calls for a fundamental reimagining of how we conceptualise knowledge dynamics in AI-augmented educational ecosystems. At the same time, the positive correlations between AI-driven knowledge creation, storage, and discovery with sustainable learning outcomes signal a transformative potential that extends beyond mere technological integration. Therefore, the results suggest a recalibration of educational strategies, where AI becomes a tool and a catalyst for promoting adaptive, lifelong learning competencies. Perhaps most significantly, this study elevates the discourse on ethical AI integration from a peripheral concern to a central tenet of sustainable learning. This finding reframes the narrative around AI in education, positioning ethical considerations as foundational to the AI-KM system's success rather than post-hoc regulatory measures. Thanks to this work, interdisciplinary research at the nexus of AI, KM, and education now has additional directions to pursue. It invites us to envision learning environments where AI does not simply augment existing practices but fundamentally reshapes how knowledge is created, shared, and applied. Further, this vision pushes to create more comprehensive, context-sensitive frameworks that may represent the dynamic interaction between instructional realities and technology affordances. The real test will come from our capacity to use these findings to build technologically sophisticated, morally sound, and naturally sustained learning ecosystems.

Author Statement

The authors declare that there is no conflict of interest.

ORCID

Sashi Ranjan https://orcid.org/0009-0000-3188-1013

V. P. Joshith https://orcid.org/0000-0002-5573-2335

K. Kavitha https://orcid.org/0009-0001-5628-0270

Shana Chittakath https://orcid.org/0009-0000-1672-4394

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