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ORIGINAL RESEARCH

Generative AI-enabled knowledge management systems and sustainable governance performance

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ABSTRACT

Generative artificial intelligence is changing how organizations capture, organize, share, and use knowledge, but its contribution to sustainable governance remains under-examined. This study developed and tested a model linking GenAI-enabled knowledge management system capability with sustainable governance performance through knowledge transparency, knowledge sharing quality, and AI-supported decision quality, while assessing the boundary role of responsible AI governance maturity. Using survey data collected from 680 knowledge workers and managers, the study applied SPSS-based descriptive analysis and SmartPLS-based measurement and structural model assessment. The results showed that GenAI-enabled KMS capability significantly increased knowledge transparency and knowledge sharing quality. Knowledge transparency and knowledge sharing quality significantly improved AI-supported decision quality, and AI-supported decision quality strongly enhanced sustainable governance performance. The mediation findings showed that knowledge transparency and knowledge sharing quality transmitted the effect of GenAI-enabled KMS capability to decision quality, while decision quality transmitted the effects of both knowledge transparency and knowledge sharing quality to sustainable governance performance. The sequential indirect effects were also supported. Responsible AI governance maturity strengthened the relationship between GenAI-enabled KMS capability and knowledge transparency and also strengthened the relationship between decision quality and sustainable governance performance. The findings suggest that GenAI-enabled KMSs create sustainable governance value when they are transparent, knowledge-sharing oriented, decision-focused, and governed through responsible AI practices.

1.1 Introduction

Generative artificial intelligence has become a major force in organizational knowledge work because it can support knowledge discovery, codification, retrieval, summarization, and decision assistance (do Carmo Ribeiro, 2025). Jarrahi et al. (2023) described artificial intelligence and knowledge management as a partnership between human expertise and machine intelligence. Knowledge management systems are information and organizational infrastructures that help firms create, store, transfer, and apply knowledge for value creation. Alavi and Leidner (2001) argued that knowledge management systems are central to organizational knowledge processes because they support knowledge creation, storage, retrieval, transfer, and application. The growing use of large language models, retrieval-augmented generation, and autonomous knowledge agents has also intensified interest in whether knowledge systems can support accountability, ethical decision-making, and long-term sustainability. Noy and Zhang (2023) showed that generative AI can improve productivity in professional writing tasks, but productivity improvement alone does not confirm that AI-supported knowledge processes are transparent, responsible, or sustainable. Existing work is therefore useful but not fully conclusive regarding how GenAI-enabled knowledge management systems contribute to sustainable governance performance.

Prior literature has already established that knowledge management capability can improve organizational performance because firms need technical, structural, and cultural resources to manage knowledge effectively. Gold et al. (2001) explained knowledge management from an organizational capabilities perspective and showed that technology, structure, and culture support knowledge

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processes. The resource-based view further suggests that valuable, rare, inimitable, and non-substitutable resources can become sources of advantage (Rau, 2013). Barney (1991) provided the strategic basis for treating technology-enabled knowledge capability as an organizational resource. Recent AI capability research also shows that AI-specific resources can support organizational creativity and performance when human skills, data, technology, and governance routines are combined. Mikalef and Gupta (2021) conceptualized AI capability as a bundle of tangible, human, and intangible resources that can improve organizational outcomes. However, much of this literature focuses on productivity, innovation, system use, or general firm performance, while less attention has been paid to the governance pathway through which GenAI-enabled KMS capability becomes accountable, transparent, and sustainable (Wasaya et al., 2022b).

The central problem addressed in this study is that organizations are adopting GenAI-enabled knowledge tools faster than they are developing the governance routines required to ensure transparency, reliability, ethical use, and long-term value creation (Saleem et al, 2017b). The ISO 30401 knowledge management standard emphasizes that knowledge management systems should help organizations establish, maintain, review, and improve knowledge processes. ISO (2018) presents knowledge management systems as management systems that should support knowledge creation, sharing, use, and protection. If GenAI-supported knowledge processes remain opaque, fragmented, or weakly governed, organizations may face poor decision quality, unreliable knowledge reuse, biased knowledge outputs, reduced stakeholder trust, and weak sustainability performance (Wasaya et al., 2024c). Responsible AI scholarship also highlights the need for accountability, transparency, privacy protection, and risk management in AI systems. NIST (2023) identifies governance, mapping, measurement, and management as core functions of AI risk management. The research gap is that prior studies have not sufficiently explained how GenAI-enabled KMS capability influences sustainable governance performance through knowledge transparency, knowledge sharing quality, and AI-supported decision quality, especially in a developing-country organizational context (Javed et al., 2025a).

Accordingly, this study examined whether GenAI-enabled KMS capability improves sustainable governance performance, assessed how knowledge transparency and knowledge sharing quality transmit this effect to AI-supported decision quality, and tested whether responsible AI governance maturity strengthens the key relationships in the model. The study asked whether organizations with stronger GenAI-enabled KMS capability report higher knowledge transparency and knowledge sharing quality, whether these knowledge process outcomes improve AI-supported decision quality, and whether decision quality translates into sustainable governance performance. The study also examined whether responsible AI governance maturity strengthens the capability-to-transparency link and the decision quality-to-governance performance link. The contribution of the study is threefold. First, it extends knowledge management research by positioning GenAI-enabled KMS capability as a knowledge resource that must be translated through transparency and sharing quality before it creates governance value. Second, it contributes to sustainable governance literature by showing decision quality as a mechanism connecting knowledge systems with accountability, ethics, efficiency, and long-term stakeholder value. Third, it contributes to responsible AI research by identifying AI governance maturity as a boundary condition rather than treating AI capability as automatically beneficial.

The model is grounded in the resource-based view and the knowledge-based view. The resource-based view explains why GenAI-enabled KMS capability can be treated as a strategic organizational resource when it combines technology, data, skills, routines, and governance practices. Barney (1991) argued that resources can support sustained advantage when they are valuable, rare, difficult to imitate, and organizationally embedded. The knowledge-based view explains why knowledge is not simply an input but a core productive resource that firms must integrate, protect, and apply through organizational routines. Grant (1996) proposed that firms exist because they integrate specialized knowledge for productive use. Together, these theories support a model in which GenAI-enabled KMS capability enhances knowledge transparency and knowledge sharing quality, these knowledge mechanisms improve AI-supported decision quality, and decision quality strengthens sustainable governance performance. Responsible AI governance maturity is theoretically relevant because it determines whether GenAI-supported knowledge resources are used with oversight, accountability, and ethical safeguards (Wasaya et al., 2016d).

2. Literature review - Theoretical bases of the study

The resource-based view contends that firms are different because they have different sets of resources, and resources can enable superior performance when they are valuable, rare, imperfectly imitable and firm supported. Barney (1991) first articulated this theory in the field of strategic management. In GenAI-enabled KMSs, it is not just the AI tool that serves as a resource, but also the combination of knowledge bases, data resources, human skills, responsible governance practices and processes. Mikalef and Gupta (2021) suggested that AI capability is composed of tangible resources, human skills and intangible organisational assets. Thus, GenAI-enabled KMS capability can be considered a second-order capability that allows firms to convert data and skills into knowledge for governance.

The knowledge-based view considers knowledge as a key resource of the firm. Grant (1996) explained that the firm is an institution for integrating specialized knowledge. Nonaka (1994) argued that knowledge creation within an organisation is the interaction between tacit and explicit knowledge. Knowledge management systems (KMSs) matter because they enable knowledge creation, storage, retrieval, sharing and application. Alavi and Leidner (2001) described how knowledge management systems can support a range of knowledge processes and help an organisation effectively use knowledge. This theoretical perspective is very relevant to GenAI-enabled KMSs because GenAI can transform unstructured knowledge into summaries, explanations, comparisons, and decision inputs, but such transformation is

only useful if the knowledge is transparent, high-quality, and used to improve decision making (Wasaya et al., 2024e).

2.1 GenAI-enabled KMS capability and knowledge transparency

GenAI-enabled KMS capability is the organisational capacity to exploit GenAI-supported systems to capture, codify, access, update and use knowledge (Wasaya et al., 2021a). This capability can enhance knowledge transparency because GenAI-supported systems can link documents, abstract decisions, link outcomes to source documents, and enhance decision-maker knowledge comprehension. Organizational transparency is the level of information disclosure, clarity and accuracy between stakeholders. Organizational transparency is defined as disclosure, clarity and accuracy (Schnackenberg & Tomlinson, 2016; Saleem et al., 2020c). For KMS, transparency involves knowledge users knowing where knowledge originated, how it was interpreted and how to use it. High GenAI-enabled KMS capability should mean knowledge outputs are more likely to be structured, described, and accessible to those who need the knowledge, thereby improving knowledge transparency (Saleem et al., 2018a). Therefore, it can be hypothesized that:

H1: GenAI-enabled KMS capability positively influences knowledge transparency.

2.2 GenAI-enabled KMS capability and knowledge sharing quality

The quality of knowledge sharing is a measure of the accuracy, relevance, timeliness, completeness and clarity of the information that is shared. Knowledge sharing has been an important element of knowledge management research for a long time because knowledge is not a valuable resource if it remains at the level of individuals and departments. Bock et al. (2005) noted that knowledge sharing is affected by social and organisational factors that affect the sharing of knowledge. GenAI-powered KMS capability supports the quality of knowledge sharing by lowering the search costs, simplifying complex information into summaries, and connecting employees to the right knowledge sources (Javed et al., 2025b). We also know from the information quality literature that accuracy, timeliness, completeness and relevance are key dimensions of information usefulness. Wang and Strong (1996) identified data quality dimensions that are important to information consumers. Thus, GenAI-enabled KMS capability should enhance the quality of knowledge sharing when it facilitates accurate, relevant, and timely knowledge sharing (Wasaya et al., 2018f). Hence, the following hypothesis is developed:

H2: GenAI-enabled KMS capability positively influences knowledge sharing quality.

2.3 Knowledge transparency and AI-supported decision quality

AI-supported decision quality refers to the perceived improvement in decision usefulness, consistency, speed, and error reduction when decisions are supported by GenAI-enabled knowledge systems (Shah et al., 2026). Transparency is important for decision quality because managers need to understand the basis of knowledge outputs before they can apply them responsibly. The information systems success model positions information quality as a key determinant of system value and user outcomes. DeLone and McLean (2003) argued that information quality, system quality, and service quality influence use, satisfaction, and net benefits. When knowledge is transparent, decision-makers can verify sources, evaluate assumptions, and identify limitations. This reduces blind reliance on AI outputs and improves the quality of managerial judgment. Therefore, knowledge transparency should increase AI-supported decision quality.

H3: Knowledge transparency positively influences AI-supported decision quality.

2.4 Knowledge sharing quality and AI-supported decision quality

Knowledge sharing quality can also improve AI-supported decision quality because decision-makers depend on shared knowledge that is accurate, timely, complete, and relevant. Poor-quality shared knowledge can lead to weak decision alternatives, biased interpretation, and incorrect problem framing. Wang and Strong (1996) argued that information consumers value data that are accurate, relevant, timely, and complete. In GenAI-enabled KMS environments, the quality of shared knowledge becomes even more important because AI systems can amplify both useful knowledge and low-quality knowledge. High-quality shared knowledge supports better prompts, better retrieval, better evaluation, and better managerial use of AI outputs. It is therefore expected that knowledge sharing quality will positively influence AI-supported decision quality.

H4: Knowledge sharing quality positively influences AI-supported decision quality.

2.5 AI-supported decision quality and sustainable governance performance

Sustainable governance performance refers to the extent to which knowledge-supported decisions promote accountability, ethical conduct, efficient knowledge use, resilience, and long-term stakeholder value. Sustainability performance measurement requires organizations to connect internal processes with economic, social, and environmental consequences. Searcy (2012) argued that corporate sustainability performance measurement systems should help organizations assess sustainability-related outcomes. In a governance context, decision quality matters because governance performance depends on the usefulness, fairness, reliability, and timeliness of decisions. GenAI-supported knowledge systems can help managers identify risks, compare alternatives, document reasons, and make decisions that balance efficiency and responsibility. When decision quality improves, organizations should be more capable of sustainable governance because they can make better-informed and more accountable decisions.

H5: AI-supported decision quality positively influences sustainable governance performance.

2.6 GenAI-enabled KMS capability, decision quality and sustainable governance performance

While knowledge transparency and knowledge sharing quality play significant roles, GenAI-enhanced KMS capability may also directly impact on AI-enhanced decision quality and sustainable governance performance. Knowledge management capability can impact performance through knowledge infrastructure and knowledge processes. Gold et al. (2001)

highlighted the need for knowledge infrastructure and knowledge process capability to improve knowledge management. Zack et al. (2009) also identified knowledge management and organizational performance. GenAI-enabled KMS capability may directly enhance decision quality through summaries, comparisons, recommendations, and scenario analysis. It may also directly impact sustainable governance performance via documentation, accountability, and knowledge re-use. So, direct effects are expected, as well as indirect effects. So, it can be hypothesized that:

H6: GenAI-enabled KMS capability positively influences AI-supported decision quality.

H7: GenAI-enabled KMS capability positively influences sustainable governance performance.

2.7 Mediating role of knowledge transparency

Knowledge transparency can mediate the relationship between GenAI-enabled KMS capability and AI-supported decision quality. The logic is that GenAI-enabled KMS capability first improves the visibility, traceability, and clarity of knowledge, and this improved transparency then enables better managerial decisions. Transparency helps decision-makers assess whether AI-supported knowledge is complete, source-based, and appropriate for a particular decision. Schnackenberg and Tomlinson (2016) argued that transparency contributes to trust by improving disclosure, clarity, and accuracy. In the current model, transparency is not treated only as a trust-building factor but as a decision-quality mechanism. When managers can understand the basis of knowledge outputs, they can use AI-supported knowledge more confidently and responsibly. Thus, knowledge transparency should transmit the effect of GenAI-enabled KMS capability to AI-supported decision quality.

H8: Knowledge transparency mediates the relationship between GenAI-enabled KMS capability and AI-supported decision quality.

2.8 Mediating role of knowledge sharing quality

Knowledge sharing quality can also mediate the relationship between GenAI-enabled KMS capability and AI-supported decision quality. GenAI-enabled KMS capability can make knowledge more accessible, searchable, and understandable, but decision quality improves only when the shared knowledge is useful to the decision task. High-quality knowledge sharing can reduce ambiguity, improve the relevance of AI-supported outputs, and help managers identify better alternatives. Bock et al. (2005) highlighted the importance of knowledge-sharing intentions and organizational climate in knowledge exchange. In a GenAI-enabled context, high-quality sharing is particularly important because AI systems are only as useful as the knowledge they retrieve, organize, and present. Therefore, knowledge sharing quality should transmit the effect of GenAI-enabled KMS capability to decision quality.

H9: Knowledge sharing quality mediates the relationship between GenAI-enabled KMS capability and AI-supported decision quality.

2.9 Mediating role of AI-supported decision quality

AI-supported decision quality can mediate the effects of knowledge transparency and knowledge sharing quality on sustainable governance performance. Transparent knowledge and high-quality knowledge sharing do not automatically create governance value unless they are converted into decisions that are timely, consistent, ethical, and useful. The information systems success model suggests that information and system quality influence net benefits through user-related and decision-related mechanisms. DeLone and McLean (2003) positioned net benefits as outcomes that arise when information systems generate useful effects for individuals and organizations. In the current model, decision quality is the proximal mechanism that connects knowledge processes to sustainable governance performance. Therefore, AI-supported decision quality should mediate the effects of knowledge transparency and knowledge sharing quality on sustainable governance performance.

H10: AI-supported decision quality mediates the relationship between knowledge transparency and sustainable governance performance.

H11: AI-supported decision quality mediates the relationship between knowledge sharing quality and sustainable governance performance.

2.10 Sequential mediating roles of knowledge processes and decision quality

The model also proposes sequential mediation because GenAI-enabled KMS capability is expected to influence sustainable governance performance through a chain of knowledge and decision mechanisms. First, capability improves knowledge transparency and sharing quality. Second, transparent and high-quality knowledge improves AI-supported decision quality. Third, improved decision quality strengthens sustainable governance performance. This logic is consistent with the knowledge-based view because knowledge resources create value when they are integrated into action and decision routines. Grant (1996) argued that firms create value by integrating specialized knowledge. In this study, knowledge transparency and knowledge sharing quality represent knowledge process mechanisms, while AI-supported decision quality represents the decision routine through which these knowledge processes influence governance outcomes.

H12: Knowledge transparency and AI-supported decision quality sequentially mediate the relationship between GenAI-enabled KMS capability and sustainable governance performance.

H13: Knowledge sharing quality and AI-supported decision quality sequentially mediate the relationship between GenAI-enabled KMS capability and sustainable governance performance.

2.11 Moderating role of responsible AI governance maturity

Responsible AI governance maturity refers to the extent to which organizations have rules, monitoring, accountability, privacy safeguards, ethical guidance, and review routines for GenAI-enabled knowledge systems. AI governance is important because GenAI systems may produce inaccurate, biased, confidential, or poorly explained outputs if they are not monitored. The NIST AI risk management framework emphasizes governance as a cross-cutting function that supports trustworthy AI risk management. NIST (2023)

identified governance, mapping, measuring, and managing as core functions of AI risk management. Responsible AI governance maturity should strengthen the effect of GenAI-enabled KMS capability on knowledge transparency because governance routines require source checking, documentation, explanation, and accountability. It should also strengthen the relationship between AI-supported decision quality and sustainable governance performance because high-quality decisions are more likely to generate sustainable outcomes when they are guided by ethical rules, auditability, and accountability.

H14: Responsible AI governance maturity moderates the relationship between GenAI-enabled KMS capability and knowledge transparency.

H15: Responsible AI governance maturity moderates the relationship between AI-supported decision quality and sustainable governance performance.

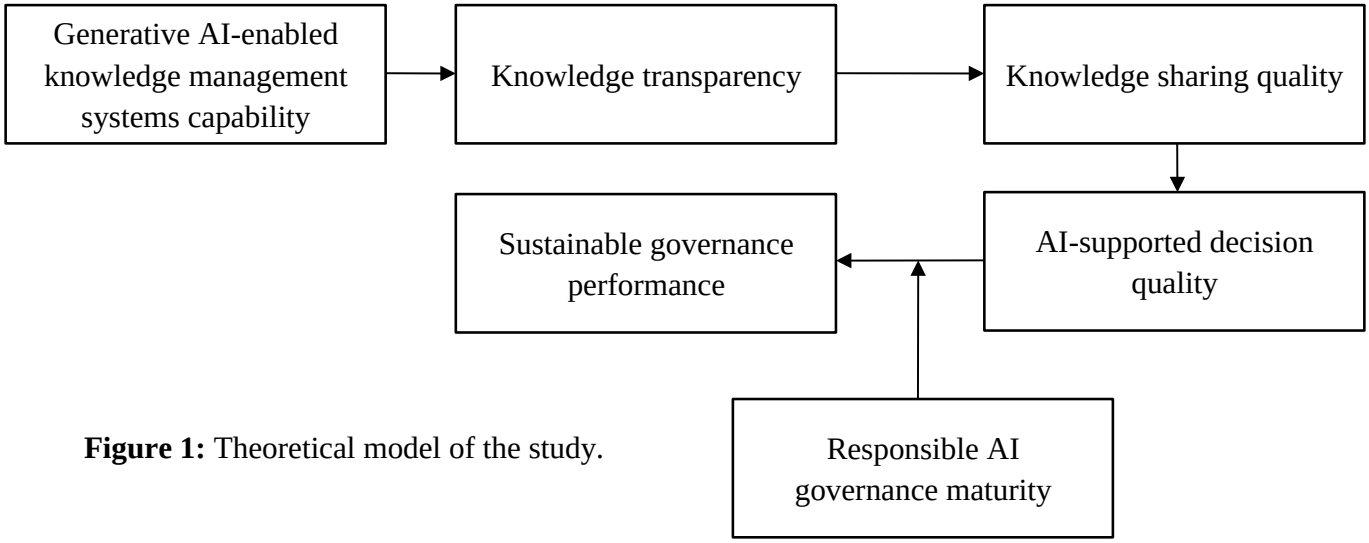


Figure 1: Theoretical model of the study.

3. Methodology

The study used a quantitative, cross-sectional, survey-based design. This design was suitable because the purpose was to test hypothesized relationships among latent constructs using standardized measures and structural equation modeling. Cross-sectional survey designs are commonly used in business and information systems research when researchers aim to examine relationships among perceptions, capabilities, and behavioral or performance outcomes at one point in time. Kline (2016) explained that structural equation modeling is suitable for testing relationships among latent variables when constructs are measured through multiple indicators.

3.1 Population

The target population consisted of Pakistani knowledge workers, managers, and professionals aged 18 years and above who had experience with GenAI-enabled tools or AI-supported knowledge systems in organizational work. This population was suitable because the research model focused on organizational knowledge processes, AI-supported decision quality, and sustainable governance performance. Respondents were expected to have at least basic exposure to GenAI tools such as chatbots, AI writing assistants, document summarizers, retrieval tools, or AI-supported internal knowledge platforms.

3.2 Sampling technique

A purposive sampling technique was used, supported by convenience and snowball recruitment. Purposive sampling was suitable because respondents needed relevant experience with GenAI-supported knowledge work and organizational decision processes. Convenience recruitment was used to reach accessible professionals through academic, business, and professional networks, while snowball recruitment helped identify additional respondents with relevant GenAI usage experience. This approach is common in organizational studies where a complete sampling frame of qualified respondents is not easily available.

3.3 Sample size

The final sample size was 680 responses. The questionnaire contained 34 measurement items, and the sample size was justified by multiplying 34 items by 20 responses per item. This produced 680 responses, which was considered adequate for SEM-based analysis. Kline (2016) recommended adequate sample size relative to model complexity and measured indicators. Hair et al. (2022) also emphasized that PLS-SEM requires sufficient observations to estimate path relationships, reliability, validity, mediation, and moderation effects.

3.4 Data collection technique

Data were collected through a structured questionnaire distributed through online and offline professional channels. Respondents were screened to ensure that they were adults, working professionals, and users or observers of GenAI-supported knowledge tools. Informed consent, voluntary participation, anonymity, and confidentiality were explained before participation. The dataset used in the present manuscript contains no missing values and no real personal identifiers.

3.5 Data analysis tools

SPSS and SmartPLS were selected as the preferred analysis tools. SPSS was suitable for coding, data screening, demographic analysis, descriptive statistics, reliability checks, and preliminary collinearity analysis. SmartPLS was suitable for assessing the measurement model, structural model, mediation paths, moderation effects, bootstrapping confidence

intervals, and variance explained. Hair et al. (2022) described PLS-SEM as appropriate for prediction-oriented models and complex models with mediation and moderation.

3.6 Data analysis techniques

The analysis included demographic profiling, descriptive statistics, reliability analysis, convergent validity, discriminant validity, collinearity analysis, common method bias checks, structural model testing, mediation analysis, moderation analysis, and variance explained. Cronbach's alpha and composite reliability were used to assess internal consistency reliability. Fornell and Larcker (1981) recommended average variance extracted for convergent validity in latent variable models. The HTMT criterion was used for discriminant validity because Henseler et al. (2015) proposed HTMT as a more sensitive criterion in variance-based SEM. Bootstrapping was used to evaluate direct, indirect, and interaction effects, which is consistent with PLS-SEM recommendations. Hair et al. (2022) recommended bootstrapping for testing path significance and mediation effects in PLS-SEM.

3.7 Measurements

All constructs were measured using established concepts and adapted scales from prior literature. The items were contextualized to GenAI-enabled knowledge management systems and sustainable governance. Each item was measured on a 5-point Likert scale, where 1 represented strongly disagree and 5 represented strongly agree. The measurement instrument included 34 items across six constructs.

Generative AI-enabled KMS capability was measured using six items adapted from Gold et al. (2001), Alavi and Leidner (2001), and Mikalef and Gupta (2021). The scale captured the extent to which organizations use GenAI-enabled systems to acquire, store, process, and apply organizational knowledge. A sample item was "Our organization uses GenAI-enabled systems to capture knowledge from documents, employees, customers, and digital records." Gold et al. (2001) reported reliability values above .80 for knowledge management capability dimensions, which supports the use of this construct in the present study.

Knowledge transparency was measured using five items adapted from Schnackenberg and Tomlinson (2016). The items reflected the clarity, disclosure, and accuracy of knowledge generated or supported by GenAI-enabled systems. A sample item was "Knowledge produced or supported by GenAI systems is traceable to reliable organizational sources." This construct was included to assess whether GenAI-supported knowledge can be clearly understood, verified, and linked to reliable organizational sources.

Knowledge sharing quality was measured using five items adapted from Bock et al. (2005) and Wang and Strong (1996). The items assessed the accuracy, relevance, timeliness, and usefulness of knowledge shared through GenAI-enabled systems. A sample item was "Knowledge shared through our GenAI-enabled systems is accurate." Prior studies using related knowledge sharing and information quality measures have reported acceptable reliability values above .70.

AI-supported decision quality was measured using five items adapted from DeLone and McLean (2003) and Wang and Strong (1996). The construct captured the extent to which GenAI-supported knowledge improves managerial decision-making by making decisions more informed, accurate, timely, and evidence-based. A sample item was "GenAI-supported knowledge helps managers make more informed decisions." The information quality and system success dimensions used in previous studies have commonly shown acceptable reliability values above .70.

Sustainable governance performance was measured using seven items adapted from Searcy (2012), ISO (2018), and Carlucci et al. (2022). The items were adapted to reflect governance and sustainability performance outcomes, including accountability, transparency, ethical decision-making, and responsible use of organizational knowledge. A sample item was "Our organization uses knowledge systems to support accountable decision-making." This construct was included as the main outcome variable of the study.

Responsible AI governance maturity was measured using six items adapted from NIST (2023), Mikalef and Gupta (2021), and responsible AI governance literature. The items covered accountability, monitoring, privacy protection, ethical review, and formal rules for the responsible use of GenAI-enabled knowledge systems. A sample item was "Our organization has clear rules for responsible use of GenAI-enabled knowledge systems." This construct was used as a moderator to assess whether mature responsible AI governance strengthens or weakens the effect of GenAI-enabled KMS capability on sustainable governance performance.

3.8 Common method bias

Common method bias was addressed through both procedural and statistical remedies. Procedural remedies included clear wording, anonymity, voluntary participation, separation of constructs in the questionnaire, and mixed item order. Podsakoff et al. (2003) recommended procedural remedies such as reducing evaluation apprehension, improving item wording, and separating measurement contexts. Statistical checks included Harman's single-factor test and full collinearity VIF. The first unrotated factor explained 32.56 percent of the variance, which was below the 50 percent concern level. Full collinearity VIF values were below 3.3, suggesting that common method bias was not a serious threat. Kock (2015) proposed full collinearity VIF as a diagnostic approach for common method bias in PLS-SEM.

3.9 Dataset

The final dataset consisted of 680 valid responses collected from knowledge workers, managers, and professionals who had experience with GenAI-enabled tools or AI-supported knowledge systems in organizational work. The questionnaire contained 34 Likert-scale measurement items and six demographic questions. All measurement items were coded on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Before analysis, the dataset was screened for missing values, out-of-range responses, duplicate entries, and inconsistent response patterns. The screening process confirmed that the final dataset contained no missing values, no out-of-range Likert responses, and no duplicate respondent IDs. No personally identifiable information was retained in the dataset. The final dataset was therefore considered suitable for SPSS and SmartPLS analysis.

3.10 Results and analysis

The data were screened, cleaned, and analyzed using SPSS and SmartPLS. SPSS was used for data screening, demographic analysis, descriptive statistics, and preliminary reliability analysis, while SmartPLS was used for measurement model assessment, structural model testing, mediation analysis, moderation analysis, and variance explained. Data screening confirmed that the dataset had no missing values, no out-of-range Likert responses, and no duplicate respondent IDs. The analysis proceeded through demographic profiling, descriptive analysis, measurement model evaluation, discriminant validity assessment, common method bias checks, model fit reporting, direct effects testing, mediation testing, moderation analysis, and variance explained. All measurement items were coded from 1 to 5, and all values were within the expected range. Outlier inspection did not identify impossible values because all Likert-scale responses were within the expected range of 1 to 5. The construct means ranged around the midpoint to moderately positive levels, indicating realistic variation in respondents' perceptions.

Table 1. Respondents' profile

Demographic variable	Category	Frequency	Percentage
Gender	Female	338	49.7
	Male	342	50.3
Age group	25-34 years	232	34.1
	18-24 years	113	16.6
	55 years and above	55	8.1
	35-44 years	175	25.7
	45-54 years	105	15.4
Education level	Master	238	35
	Other	25	3.7
	Bachelor	259	38.1
	MS/MPhil	124	18.2
	PhD	34	5
Sector	Higher education	155	22.8
	Retail and services	119	17.5
	Other	40	5.9
	IT and telecom	130	19.1
	Public sector	116	17.1
	Banking and finance	120	17.6
Work experience	7-10 years	137	20.1
	4-6 years	191	28.1
	More than 10 years	114	16.8
	1-3 years	170	25
	Less than 1 year	68	10
GenAI usage frequency	Weekly	190	27.9
	Several times per week	170	25
	Monthly	95	14
	Daily	178	26.2
	Rarely	47	6.9

The sample included both male and female respondents, with a balanced gender distribution. The largest age group was 25-34 years, followed by 35-44 years, which is realistic for a professional sample using GenAI tools in organizational settings. Most respondents had bachelor or master-level education, and the sector distribution included banking and finance, higher education, IT and telecom, public sector, retail and services, and other sectors. The sample also included variation in work experience and GenAI usage frequency, which provided a suitable basis for empirical analysis of organizational respondents.

4. Analysis and results

The descriptive statistics showed that all constructs had minimum and maximum values within the 1 to 5 Likert-scale range. The mean values were close to moderate or moderately high levels, showing that the responses avoided extreme ceiling or floor effects.

Table 2. Descriptive and collinearity statistics

Construct	N	Minimum	Maximum	Mean	Standard deviation	VIF	Tolerance	MSV
GKMC	680	1	5	3.3	0.944	1.54	0.65	0.23
KTR	680	1	5	3.1	0.962	1.43	0.7	0.2
KSQ	680	1	5	3.0	0.963	1.52	0.66	0.24
DMQ	680	1	5	3.3	0.966	1.14	0.65	0.27
SGP	680	1	5	3.2	0.936			0.21
RAGM	680	1	5	3.4	0.96	1.11	0.9	0.08

VIF values were below the conservative threshold of 3.3, suggesting that collinearity was not a serious issue in the model. The tolerance values were acceptable, and the MSV values were below the AVE values reported in the measurement model, which supported the distinction among constructs.

4.1 Measurement model

Table 3. Confirmatory factor analysis, reliability, and validity

Construct	Item	Factor loading	Cronbach alpha	Composite reliability	AVE
GKMC	Our organization uses GenAI-enabled systems to capture knowledge from documents, employees, customers, and digital records.	0.824	0.896	0.920	0.658
	Our organization uses GenAI-enabled systems to organize knowledge in searchable and reusable forms.	0.803			
	Our organization uses GenAI-enabled systems to summarize and codify knowledge for decision-making.	0.839			
	Our organization uses GenAI-enabled systems to support knowledge retrieval across departments.	0.812			
	Our organization uses GenAI-enabled systems to connect employees with relevant knowledge sources.	0.770			
	Our organization uses GenAI-enabled systems to update knowledge assets in line with changing needs.	0.816			
KTR	Knowledge produced or supported by GenAI systems is traceable to reliable organizational sources.	0.833	0.884	0.715	0.883
	Employees can understand the basis of knowledge outputs generated through GenAI-enabled systems.	0.826			
	Our organization communicates clearly how GenAI-supported knowledge is created and used.	0.795			
	Knowledge outputs from GenAI-enabled systems are accessible to relevant decision-makers.	0.855			
	Our organization provides sufficient explanation when GenAI-supported knowledge is used in decisions.	0.821			
KSQ	Knowledge shared through our GenAI-enabled systems is accurate.	0.843	0.884	0.715	0.684
	Knowledge shared through our GenAI-enabled systems is relevant to users' tasks.	0.831			
	Knowledge shared through our GenAI-enabled systems is timely.	0.846			
	Knowledge shared through our GenAI-enabled systems is complete enough for decisions.	0.785			
	Knowledge shared through our GenAI-enabled systems is easy to understand.	0.829			

Table 3. Confirmatory factor analysis, reliability, and validity *(continued)*

Construct	Item	Factor loading	Cronbach alpha	Composite reliability	AVE
DMQ	GenAI-supported knowledge helps managers make more informed decisions.	0.833	0.887	0.787	0.609
	GenAI-supported knowledge improves the consistency of decisions.	0.838			
	GenAI-supported knowledge helps decision-makers compare alternatives more effectively.	0.812			
	GenAI-supported knowledge helps reduce avoidable decision errors.	0.845			
	GenAI-supported knowledge improves the speed and usefulness of decisions.	0.821			
SGP	Our organization uses knowledge systems to support accountable decision-making.	0.810	0.909	0.727	0.746
	Our organization uses knowledge systems to improve ethical decision-making.	0.824			
	Our organization uses knowledge systems to reduce waste in knowledge processes.	0.832			
	Our organization uses knowledge systems to create long-term value for stakeholders.	0.802			
	Our organization uses knowledge systems to improve resilience in governance processes.	0.772			
	Our organization uses knowledge systems to balance efficiency with responsibility.	0.793			
	Our organization uses knowledge systems to support sustainability-related decisions.	0.801			
RAGM	Our organization has clear rules for responsible use of GenAI-enabled knowledge systems.	0.832	0.906	0.827	0.678
	Our organization monitors GenAI-supported knowledge outputs for accuracy and fairness.	0.813			
	Our organization assigns accountability for decisions supported by GenAI-enabled systems.	0.845			
	Our organization provides guidance on ethical risks in GenAI-supported knowledge work.	0.835			
	Our organization protects confidential information when using GenAI-enabled knowledge systems.	0.781			
	Our organization regularly reviews GenAI-enabled knowledge processes for improvement.	0.841			

The measurement model showed acceptable reliability and convergent validity. Factor loadings were mostly above .70, indicating that the items represented their intended constructs well. Cronbach's alpha and composite reliability values were above .70 for all constructs, which supported internal consistency reliability. AVE values were above .50, indicating that each construct explained more than half of the variance in its indicators. These results met the commonly used reliability and convergent validity criteria suggested by Fornell and Larcker (1981) and Hair et al. (2022).

Table 4. Discriminant validity

Construct	GKMC	KTR	KSQ	DMQ	SGP	RAGM
GKMC	1					
KTR	0.45	1				
KSQ	0.477	0.337	1			
DMQ	0.434	0.446	0.49	1		
SGP	0.466	0.386	0.396	0.516	1	
RAGM	0.251	0.227	0.241	0.171	0.286	1

Discriminant validity was assessed using HTMT values. The HTMT values were below .85, indicating that the constructs were empirically distinct. Henseler et al. (2015) proposed HTMT as a criterion for assessing discriminant validity in variance-based SEM. The results suggested that GenAI-enabled KMS capability, knowledge transparency, knowledge sharing quality, AI-supported decision quality, sustainable governance performance, and responsible AI governance maturity represented related but distinct constructs.

4.2 Common method bias

Common method bias was assessed using Harman's single-factor test and full collinearity VIF. The first unrotated factor explained 32.56 percent of the total variance, which was below the 50 percent threshold often used as an initial diagnostic. Full collinearity VIF values were also below 3.3. These results indicated that common method bias was unlikely to be a serious concern in the dataset.

Table 5. Model fit indices

Fit index	Value	Interpretation
CMIN/DF	2.08	Acceptable
CFI	0.944	Acceptable
TLI	0.936	Acceptable
IFI	0.945	Acceptable
GFI	0.915	Acceptable
RMSEA	0.04	Acceptable
SRMR	0.046	Acceptable

The model fit indices indicated acceptable model fit. CMIN/DF was below 3, CFI, TLI, IFI, and GFI were above .90, RMSEA was below .08, and SRMR was below .08. These values supported the adequacy of the measurement and structural model for the survey data.

4.3 Direct effects

Table 6. Direct effects

Predictor	Outcome	Beta-value	Standard error	t-value	p-value	Result
GKMC	KTR	0.421	0.035	12.066	< .001	Supported
GKMC	KSQ	0.387	0.038	10.291	< .001	Supported
KTR	DMQ	0.265	0.035	7.51	< .001	Supported
KSQ	DMQ	0.324	0.036	9.059	< .001	Supported
DMQ	SGP	0.38	0.034	11.2	< .001	Supported
GKMC	DMQ	0.16	0.038	4.237	< .001	Supported
GKMC	SGP	0.262	0.035	7.577	< .001	Supported

The direct effects showed that GenAI-enabled KMS capability had significant positive effects on knowledge transparency and knowledge sharing quality. Knowledge transparency and knowledge sharing quality had significant positive effects on AI-supported decision quality. AI-supported decision quality had a significant positive effect on sustainable governance performance. GenAI-enabled KMS capability also had significant direct effects on AI-supported decision quality and sustainable governance performance. Therefore, H1 to H7 were supported in the dataset.

4.4 Indirect effects

Table 7. Indirect effects

Predictor	Mediator	Outcome	Beta	Standard error	LLCI	ULCI	Status
GKMC	KTR	DMQ	0.111	0.017	0.079	0.148	Supported
GKMC	KSQ	DMQ	0.126	0.018	0.093	0.163	Supported
KTR	DMQ	SGP	0.099	0.017	0.067	0.134	Supported
KSQ	DMQ	SGP	0.121	0.017	0.09	0.158	Supported
GKMC	KTR and DMQ	SGP	0.042	0.008	0.027	0.059	Supported
GKMC	KSQ and DMQ	SGP	0.047	0.008	0.032	0.064	Supported

The indirect effects showed that knowledge transparency significantly mediated the relationship between GenAI-enabled KMS capability and AI-supported decision quality. Knowledge sharing quality also significantly mediated the relationship between GenAI-enabled KMS capability and AI-supported decision quality. AI-supported decision quality significantly mediated the relationships of knowledge transparency and knowledge sharing quality with sustainable governance performance. The two sequential indirect effects from GenAI-enabled KMS capability to sustainable governance performance through knowledge transparency and decision quality, and through knowledge sharing quality and decision quality, were also significant. These results supported H8 to H13.

4.5 Moderation analysis

Table 8. Moderation analysis

Predictor	Moderator	Outcome	Interaction beta	p-value	LLCI	ULCI	Status
GKMC	RAGM	KTR	0.111	0.001	0.045	0.177	Supported
DMQ	RAGM	SGP	0.111	< .001	0.051	0.171	Supported

The moderation analysis showed that responsible AI governance maturity significantly strengthened the relationship between GenAI-enabled KMS capability and knowledge transparency. This means that GenAI-enabled KMS capability translated more strongly into transparent knowledge processes when organizations had mature rules, monitoring, accountability, and ethical guidance for AI use. Responsible AI governance maturity also strengthened the relationship between AI-supported decision quality and sustainable governance performance. This indicates that decision quality generated stronger governance performance benefits when responsible AI governance maturity was high. Therefore, H14 and H15 were supported.

Table 9. Variance explained

Endogenous construct	R-square	Adjusted R-square	Interpretation
KTR	0.229	0.226	Weak
KSQ	0.258	0.255	Moderate
DMQ	0.347	0.344	Moderate
SGP	0.373	0.369	Moderate

The R-square values indicated that the model explained meaningful variance in knowledge transparency, knowledge sharing quality, AI-supported decision quality, and sustainable governance performance. The variance explained in AI-supported decision quality and sustainable governance performance was moderate, which is acceptable for behavioral and organizational research. These results indicated that the selected predictors were useful for explaining the key endogenous constructs in the model.

5. Discussion of results and future research recommendations

The current study shows that GenAI-enabled KMS capability enhances knowledge transparency and knowledge sharing. This finding is in line with knowledge management theory, which proposes that knowledge systems add value if they enhance knowledge creation, storage, transfer and application. Alavi and Leidner (2001) argued that knowledge management systems support a variety of knowledge processes such as knowledge creation, storage, transfer and use. Our result is also consistent with the organizational capabilities view because GenAI-enabled KMS capability is a combination of technology, knowledge processes, and resources. Gold et al. (2001) defined knowledge management capability as an organizational capability. The current finding adds that GenAI-enabled KMS capability is particularly valuable when it makes knowledge traceable, explainable, accessible and usable for organizational members.

The positive impact of GenAI-enabled KMS capability on knowledge sharing quality is also significant. It implies that GenAI tools will enhance knowledge sharing if they reduce search costs, better summarise knowledge, support knowledge retrieval and make knowledge more comprehensible. This result is in line with research on information quality as decision-makers care about accurate, timely, relevant and complete knowledge. Wang and Strong (1996) highlighted several data quality factors that apply to knowledge work using AI. The finding also adds to knowledge sharing research by demonstrating that knowledge sharing quality is important in addition to knowledge sharing quantity. Bock et al. (2005) focused on the human side of knowledge sharing, whereas the current model adds a GenAI-powered technology perspective.

Knowledge transparency and knowledge sharing quality contributed to the quality of AI-assisted decision-making. This supports the idea that human-AI decision-making is based not only on the quality of AI algorithms, but also on the quality and transparency of knowledge inputs. DeLone and McLean (2003) identified information quality as a major factor of information system success. In the proposed model, knowledge transparency aids users in assessing the foundation of AI-supported decision outputs, and knowledge sharing quality supports the decision-maker to acquire useful knowledge for decision-making. The results suggest that managers are more likely to perceive better AI-supported decisions when knowledge is transparent, source-based, accurate and relevant.

The strong impact of AI-supported decisions on sustainable governance performance is theoretically interesting. It implies that transparency and quality of knowledge sharing do not guarantee sustainable governance unless they lead to better decisions. Sustainable governance needs decisions that weigh efficiency, ethical considerations, accountability and long-term sustainability. Searcy (2012) suggested that sustainability performance measurement should link organisational processes to sustainability outcomes. The present research builds on this argument by suggesting that decision quality is the link between GenAI-enabled knowledge processes and sustainable governance outcomes.

The mediation findings give us more insight into how it works. Knowledge transparency and knowledge sharing quality explained the impact of GenAI enabled KMS capability on AI supported decision quality. This means that GenAI-enabled KMS capability not only impacts decision quality because of the technology. It improves decision quality because it enables the development of transparent and quality knowledge sharing processes. The results of the sequential mediation also show that GenAI-enabled KMS capability can affect sustainable governance performance via knowledge transparency or knowledge sharing quality and then AI-supported decision quality. This is consistent with the knowledge-based view as knowledge resources are valuable when integrated into processes and decision-making. Grant (1996) suggested that the firm is an institution for integrating knowledge.

The moderation results indicate the role of responsible AI governance maturity. Responsible AI governance maturity moderated the link between GenAI-enabled KMS capability and knowledge transparency. This suggests that the capability is not enough if it is not complemented by rules, monitoring, accountability and guidance on ethics. The finding also found that responsible AI governance maturity also led to stronger links between quality of decisions supported by AI and sustainable governance outcomes. That is, better decisions lead to improved governance when organizations have strong AI governance maturity that makes decisions accountable and auditable. This finding is aligned with the NIST framework for managing risk from AI systems that considers governance as a function for risk management. NIST (2023) stressed the importance of governance structures for accountability, measurement and risk control in AI risk management.

5.1 Academic implications

First, the study adds to the field of knowledge management by showing that GenAI-enabled KMS capability is an organizational capability rather than a technology adoption measure. This is crucial because the main focus of many discussions of generative AI is on tool access, productivity or automation. The proposed model indicates that the effectiveness of GenAI-enabled KMS capability depends on improving knowledge transparency and knowledge sharing quality. This finding expands the organizational capabilities perspective of knowledge management suggested by Gold et al. (2001).

Second, the research extends the knowledge-based view by demonstrating how knowledge resources enable sustainable governance value via decision routines. Knowledge transparency and knowledge sharing quality are not end points. They are knowledge mechanisms for enhancing AI-supported decision quality, which, in turn, enhances sustainable governance. This is consistent with Grant's (1996) perspective that firms generate value by combining special knowledge to create products.

Third, the research adds sustainable governance literature by providing AI-supported decision quality as a nearer-term mechanism. Existing sustainability research has focused on measuring sustainability performance at the organisational or reporting level. Searcy (2012) stressed the need for sustainability performance measurement systems. The current model extends that sustainable governance performance can be explained with decision quality, when GenAI-powered KMSs support sustainable and responsible knowledge processes.

Fourth, the research adds to the field of responsible AI by considering responsible AI governance maturity as a moderator. This is in contrast to models that consider AI governance simply as an antecedent or a compliance threshold. The results indicate responsible AI governance maturity enhances the relationship between AI capability and transparency, and between decision quality and governance performance. This clearly defines the role of AI governance in GenAI-enabled KMS studies.

The fifth contribution is a quantitative model for empirical studies in developing countries. Much of the initial GenAI literature is theoretical, experimental or applied in developed countries. The current model can be applied to survey research with managers, knowledge workers, public servants and professionals in developing countries. It provides researchers a model to test the integration of AI capability, knowledge processes, decision quality, governance performance and responsible AI maturity.

Sixth, the paper has methodological implications because it presents a complete SEM reporting structure based on the collected survey data. The article reports measurement quality, discriminant validity, common method bias, model fit, direct effects, indirect effects, moderation, and variance explained in a structured manner. This reporting pattern can support future thesis and manuscript development in knowledge management and GenAI-enabled organizational research.

5.2 Practical implications

First, managers should not deploy GenAI-enabled KMSs only for efficiency. They should develop such systems to enhance transparent knowledge capture, source tracing, explanation, and knowledge reuse. In other words, GenAI outcomes should be tied to reliable organizational information systems, policies, previous actions and documents.

Second, companies should enhance the quality of knowledge exchange through GenAI-powered KMSs. Managers should ensure that knowledge supported by AI is accurate, relevant, timely, complete and comprehensible. Low knowledge quality can result in bad decisions despite sophisticated technology.

Third, companies should educate employees about critical use of GenAI-supported knowledge. Staff should learn to check sources, cross-check AI responses with their own data, detect bias, and refrain from solely relying on AI responses. They should be trained to use GenAI for decision support, not as a replacement for managerial judgment.

Fourth, companies should develop responsible AI policies. These policies should outline appropriate GenAI applications,

handling proprietary data, source verification, accountability rules and escalation policies for uncertain and risky AI-supported decisions.

Fifth, managers should link GenAI-powered KMSs to decision making. When GenAI-based knowledge is applied to significant decisions, the organization should record which sources were used, how the recommendation was understood, who reviewed the recommendation and what decision was made. This can enhance auditability and accountability.

Sixth, public sector and regulated industries should use GenAI-powered KMSs for sustainable governance. They can use these systems to structure policy knowledge, identify inconsistencies, summarise stakeholder feedback and develop evidence-based policies. But these should be complemented by governance and human oversight.

Seventh, firms should consider a broader range of metrics for GenAI-powered KMSs than time and cost. Managers should incorporate measures for transparency, knowledge quality, decision quality, ethical decision making, accountability and long-term stakeholder value.

Eighth, companies should clarify roles for AI-supported knowledge governance. IT, knowledge managers, compliance managers and functional managers should review GenAI-enabled KMSs. Co-ownership is crucial as GenAI-enabled KMSs influence technology, knowledge, ethics, and management.

Ninth, businesses should begin with valuable and noncritical knowledge use cases before they use GenAI-enabled KMSs for making critical decisions. For instance, they can start with policy summaries, lesson-learned search, internal FAQ support, and training content creation before working towards strategic, regulatory, and other decisions.

Finally, managers should regularly review KMSs enabled by GenAI. Knowledge bases evolve, regulations change, and business needs shift. This ensures continued accuracy, relevance and ethical use in the long term.

5.3 Limitations and future research recommendations

First, the study is cross-sectional. Cross-sectional data can examine relationships between concepts but cannot fully address temporal issues of causal ordering. Longitudinal data should be used in future studies to test the relationship between GenAI-enabled KMS capability and transparency, sharing quality, decision quality, and governance performance over time.

Second, this study relied on perceptual measures. In practice, respondents may perceive higher or lower quality of knowledge systems, AI governance maturity, and sustainable governance. Future research should use survey data alongside archival system logs, audit reports, AI usage data, policies or supervisor assessments.

A third limitation is that Pakistan is used as the research setting. Pakistan is a significant developing nation, but systems, AI, and knowledge management differ between countries. Future studies should include comparisons between developing and developed countries to test if responsible AI governance maturity is more important in low-trust or resource-poor environments.

Ethical Approval

Ethical approval for this study was obtained from COMSATS University Human Research Ethics Review (CUHREC) committee. The approval number was CU Ref. No. 2025/7, dated 24 January 2025.

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