Feasibility of Generative Artificial Intelligence and Large Language Model Adoption to Enhance Organisational Knowledge Management Practices

Surya Sumarni Hussein[1], Nur Azaliah Abu Bakar[2], Saidatul Rahah Hamidi[3], Shuhaida Mohamed Shuhidan[4], Siti Salbiyah Abdul Geni[5], Anitawati Mohd Lokman[6]*
Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia[1, 3, 6]
Faculty of Artificial Intelligence, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia[2]
Department of Computing Universiti Teknologi PETRONAS Bandar Seri Iskandar, Perak, Malaysia[4]
Jabatan Digital Negara, Ministry of Digital, Putrajaya, Malaysia[5]

Abstract—**Generative artificial intelligence (Gen AI) and large language models (LLMs) offer substantial potential to improve how organisations capture, organise, retrieve and reuse knowledge. Existing knowledge management (KM) frameworks, however, seldom integrate Gen AI/LLM-specific processes, data governance, and ethical requirements in highly regulated public-sector settings, and few have been empirically evaluated. This study assesses the feasibility of adopting GenAI and LLMs for organisational KM and develops a corresponding Knowledge Management and Artificial Intelligence (KMAI) framework for a national communications regulator. Guided by Diffusion of Innovation (DOI) theory, the study employed a multi-method qualitative design comprising a literature review, semi-structured interviews with six KM representatives, a focus group discussion involving fourteen participants using the LEIQ™ model for SWOT analysis, and a content-validity evaluation by three experts. Interview data were analysed thematically, SWOT findings were transformed into strategies through TOWS analysis, and framework relevance was assessed using item- and scale-level content validity indices. The findings indicate that adoption is feasible in this setting: participants perceived clear relative advantage, compatibility, trialability and observability, while complexity was manageable when supported by adequate skills, data classification, secure infrastructure and governance. The principal risks concerned data quality, privacy, security, misinformation, over-reliance on AI, and organisational resistance. The proposed KMAI framework achieved acceptable content validity across all clusters, with S-CVI/Ave values ranging from 0.89 to 1.00, and was refined into four strategic thrusts: People, Process, Technology and Data. Because the evidence derives from one organisation and a three-member expert panel, the framework is presented as an empirically grounded and internally validated proposition whose extension to other agencies is analytic rather than statistical; the boundary conditions governing such extension are stated explicitly, and confirmatory validation with a larger expert panel and independent organisational sites is identified as the necessary next step. The study extends DOI-based adoption analysis by showing that data governance and ethics condition Gen AI/LLM adoption in organisational KM and provides a practical, staged framework for regulated public-sector organisations.**

Keywords*—*Generative artificial intelligence (Gen AI); large language models (LLM); knowledge management; diffusion of innovation (DOI); lokman's emotion and importance quadrant (LEIQ™); content validity

I. Introduction

The rapid advancement of artificial intelligence (AI) technologies, particularly generative artificial intelligence (Gen AI) and large language models (LLMs), has in recent years opened a new range of opportunities for knowledge management (KM) practices across a wide variety of domains. Organisations are producing and accumulating large volumes of structured and unstructured data, and the ability to convert that data into accessible, reliable and actionable knowledge has become a decisive factor in organisational performance. As a national regulatory agency, the organisation holds substantial knowledge assets across its departments and divisions and recognises the strategic value of demonstrating how Gen AI and LLMs can accelerate its KM practices.

Three gaps motivate the present study. First, although KM frameworks exist, few consider Gen AI/LLM-specific processes and governance in an integrated manner. Second, many proposed frameworks are advanced without rigorous empirical validation. Third, there is no validated KM framework for a national communications regulator, where data governance and ethical obligations are especially stringent. This problem is compounded because Gen AI and LLMs are often used interchangeably but are different in meaning and overlapping in practice [1]: Gen AI is a generic term for any AI system whose primary function is to generate content, whereas LLMs such as GPT-4, PaLM, and Claude generate representations of language using very large numbers of parameters [2]. Both raise complex questions about data synthesis, system learning and effective knowledge extraction, because model performance depends directly on the currency and quality of the underlying data. The main objective of this study is therefore to address these gaps by verifying the feasibility of the organisation's adoption of Gen AI and LLM capabilities in KM and by developing and validating a framework for that purpose.

The research aims to achieve the following five objectives: to analyse the current state of KM practices through a literature review with a focus on the application and integration of Gen

* Corresponding author

AI and LLM capabilities (RO1); to assess the feasibility of present or future adoption of Gen AI and LLMs in the organisation's KM processes and procedures (RO2); to conduct a SWOT analysis of the possible effect on the organisation in terms of optimisation, efficiency and accuracy (RO3); to assess the suitability of a KM framework for the measurement and monitoring of improvements in data synthesis, organisation and knowledge extraction (RO4); and, where appropriate, to recommend the requirements for Gen AI and LLM adoption in the organisation (RO5). The study is based on the Diffusion of Innovations theory (DOI) [3], which serves as the framework for the interview constructs that measure adoption, and on the Kansei-based LEIQ™ model [4], which is used to analyse the SWOT factors and the implicit barriers to adoption, as elaborated in the methodology.

This study builds on prior literature concerning the organisational context, the intersection of KM and AI, the nature of Gen AI and LLMs, the data foundations of AI-driven KM, and the governance and security considerations reviewed in Section II. The study has two-fold significance. It conceptually extends DOI theory for Gen AI/LLM adoption to KM in a national regulatory setting, positioning data governance and ethics as adoption moderators, and it links DOI theory with the practice of AI-enabled KM in a domain that has received little empirical attention. It gives the organisation a validated Knowledge Management and Artificial Intelligence (KMAI) framework, four strategic thrusts, and a replicable multi-method design combining DOI-framed interviews, a Kansei-based SWOT/TOWS analysis and content-validity-based expert evaluation that can be operationalised. Consistent with the qualitative, single-site design, these contributions are advanced as analytically transferable propositions rather than as findings generalisable to a population of agencies; Section V-F sets out the boundary conditions under which transfer is defensible.

II. Literature Review

This section reviews the organisational context, the intersection of KM and AI, the nature of Gen AI and LLMs, the data foundations of AI-driven KM, governance and security considerations, and the theoretical lens adopted. It concludes by positioning the proposed framework against existing KM/AI approaches and stating explicitly what the present contribution adds.

A. The Case Organisation

The organisation is the national regulatory authority for the communications and multimedia industry in Malaysia. It was established under the Malaysian Communications and Multimedia Commission Act 1998 [5] and exercises regulatory powers under the Communications and Multimedia Act 1998 [46], which together assign it responsibility for the economic, technical, consumer and social regulation of the converging communications and multimedia industries, including telecommunications, broadcasting, online activity, postal services and digital certification. Its organisational structure, divisional responsibilities, knowledge assets and annual programme of work are documented in its publicly available annual reports [47]. The organisation runs a knowledge management and resource centre and knowledge-sharing platforms and works with universities and industry partners. It acknowledges the need to show how Gen AI and LLM technologies can improve its KM practices and views appropriate technological support as central to that improvement. Contextual statements about the organisation in this study are drawn from these publicly accessible statutory and reporting sources so that readers may verify them independently.

B. Artificial Intelligence and Knowledge Management

As knowledge is an essential component of organisational success, organisations need to adapt their KM practices to leverage Gen AI effectively. Traditional KM systems provide functions such as reviewing inputs or tracing their sources. Gen AI, however, often operates as a "black box" with reasoning that is hard to interpret, which results in a higher reliance on algorithmic trust [6], [7]. AI nevertheless remains crucial to KM because it helps in storing and retrieving explicit information. The combination of deep learning and big data provides new ways of collecting, classifying, organising and retrieving information [8], converting large data sets into useful insights [9]. It is, therefore, essential to explore the long-term effect of GenAI on organisational KM, possibly through small-scale pilots, to align capabilities with organisational needs while ensuring transparency and authenticity [10], [11].

C. Large Language Models and Generative AI

The convergence of Gen AI and LLMs has transformed KM practice, offering new opportunities in information processing, synthesis and dissemination [11], [12], [13]. Personalised experiences and automated content generation are possible with LLMs, a type of GenAI [14]. These models employ natural language processing (NLP) to extract insights, summarise content and generate contextual responses, thereby enabling more efficient knowledge discovery [15], [16]. They detect trends and generate predictive analytics that support better decision-making, and they foster innovation by analysing complex data sets. They also enable collaborative knowledge sharing through chatbots, virtual assistants, and collaborative writing platforms.

D. AI-Driven Knowledge Management and Data

AI-driven KM depends heavily on data availability and quality [17], [18], [19]. One established hybrid model holds that knowledge resides in AI models and databases as well as in individuals and that the design of AI-orientated KM should balance user satisfaction against the quality of task outcomes [20]. As depicted in Fig. 1, the shift from conventional KM to an adaptive, AI-based approach requires frequent data updates to maintain model relevance and a clear demarcation of roles between humans and machines.

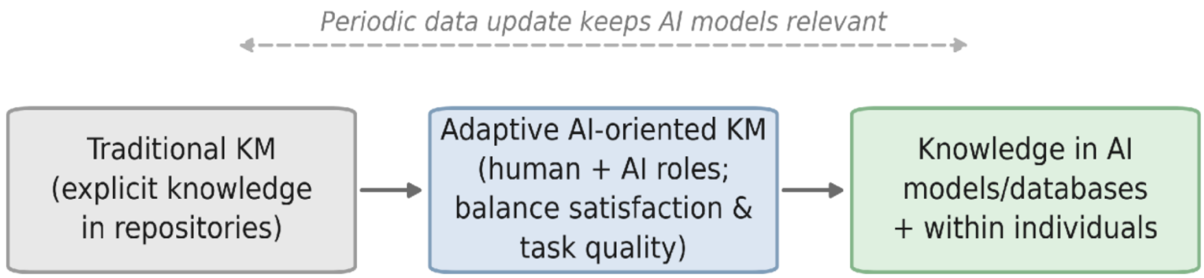

Fig. 1. Moving from traditional KM towards an adaptive AI-oriented KM [20].

E. Data Governance, Security and Ethical Considerations

Gen AI also poses ethical and governance challenges that require proactive management, such as ensuring accuracy, human oversight, transparency, accountability and bias mitigation [21, 22], as well as concerns about misinformation, copyright infringement, privacy and hazardous content. Data governance is key to trustworthy AI: it makes data accurate, secure, well classified and properly shared. In the Malaysian public-sector context, an AI-integrated KM framework combining organisational knowledge repositories, structured training and continuous learning has been shown to strengthen cybersecurity awareness and institutional resilience [23]. Without such governance, the organisation's exposure to security and compliance risks and the reliability of AI-generated outputs are significant obstacles to adoption.

F. Theory of Diffusion of Innovation

DOI in this context enables organisations to develop strategies tailored to different adopter segments and to overcome barriers to Gen AI adoption. DOI has been widely applied to study technology acceptance in the health, education, energy and library domains [10], [22], [24], including studies of blended and mobile learning adoption in Malaysian institutions [54], showing the explanatory value of the five innovation attributes. In summary, Gen AI and LLMs are powerful tools for reinventing KM, but to realise their benefits, ethical issues must be addressed, transparency must be promoted, and equitable access must be assured.

G. Comparative Positioning and Statement of Novelty

Reviewers of AI-enabled KM research reasonably ask what a new framework adds beyond recombining established constructs. Table I therefore compares representative KM/AI approaches against the dimensions required for feasible Gen AI and LLM adoption in a public-sector KM context. Traditional KM systems and DeLone–McLean-style success models cover GenAI-specific processes sparsely and treat governance implicitly. Integrative KM–AI frameworks such as [20] advance the technology and data dimensions but were not empirically validated in a regulatory setting. DOI-based adoption studies explain acceptance without providing an operational framework.

Beyond this coverage comparison, the proposed KMAI framework differs from existing AI-enabled KM frameworks in four specific and testable respects.

First, the innovation attributes are used diagnostically rather than descriptively. In the reviewed DOI-based studies, the five attributes are applied after the fact to explain observed acceptance. Here they are operationalised as readiness constructs that are elicited before design, quantified by frequency of mention (Fig. 5), and carried forward into the framework clusters, so that the framework tells an organisation which adoption attribute is deficient and which cluster addresses it. The framework is consequently diagnostic and prescriptive, not merely descriptive.

Second, data governance and ethics are positioned as a moderating condition rather than as a further component. Existing KM/AI frameworks list governance as one element alongside people, process and technology. The evidence reported in Section IV indicates instead that the relationship between the perceived attributes and adoption is conditional on governance maturity: favourable perceptions on all five attributes did not translate into a positive adoption judgment independently of data classification, security of infrastructure and ethical control. This moderating position is made explicit in the research model (Fig. 9) and is, to the authors' knowledge, not represented in the frameworks compared in Table I.

Third, the framework couples an affect-based instrument to the strategic synthesis. The LEIQ™/Kansei instrument elicits the implicit, emotionally weighted barriers — resistance, perceived displacement, and loss of critical judgment — that conventional SWOT elicitation does not surface and scores them on emotion and importance axes before they enter the TOWS synthesis. This makes the resulting strategies responsive to affective as well as rational barriers to adoption.

Fourth, the framework carries a documented validation audit trail. It is the only approach in Table I whose clusters and subclusters were submitted to item- and scale-level content-validity indexing by external experts and then revised in response to that evidence so that the movement from proposed framework (Fig. 7) to validated framework (Fig. 8) is transparent and inspectable. The strength of that audit trail is bounded by the size of the expert panel, and Sections III-E and V-G state that bound explicitly.

TABLE I. COMPARATIVE POSITIONING OF KM/AI APPROACHES

Approach / Study	People	Process	Technology	Data & Governance	Gen AI / LLM specific	Attributes used diagnostically	Empirically validated
Traditional KM systems	Partial	Partial	No	Partial	No	No	N/A
IS Success (DeLone–McLean) style	No	Partial	Partial	No	No	No	Yes
DOI-based adoption studies [10], [12]	Partial	No	Partial	No	Partial	No (post hoc)	Yes
Integrative KM–AI framework [20]	Partial	Yes	Yes	Partial	Yes	No	No
KMAI framework (proposed)	Yes	Yes	Yes	Yes	Yes	Yes	Yes (single site, n = 3 experts)

Note: "Empirically validated" refers to validation reported in the cited source. For the proposed framework, the validation is internal to one organisation and rests on a three-member expert panel; see Sections III-E and V-G.

III. METHODOLOGY

A. Research Design

The research focuses on two segments in the Organisation: 1) targeted departments and divisions with sufficient data repositories that could benefit from Gen AI and LLM-aided query, process management and decision-making; and 2) Gen AI and LLM subject-matter experts from academia, industry or specialist data-management providers. The study employed a qualitative, single-organisation design consisting of five phases, illustrated in Fig. 2 and summarised in Table II. The design is a single-case study in the sense of [51]: the unit of analysis is the organisation, and the analytic aim is theoretical rather than statistical extension.

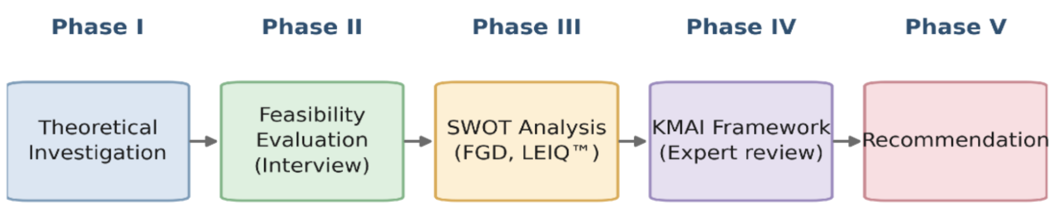

Fig. 2. The research phases.

TABLE II. SUMMARY OF THE RESEARCH DESIGN

Phase	Research objective	Method	Data source
I	Analyse the current state of KM practices via a literature review focusing on Gen AI and LLM capabilities.	Theoretical investigation	Past literature and existing related organisational documents
II	Evaluate the feasibility of current or future adoption of Gen AI and LLMs in the Organisation's KM processes and procedures.	Semi-structured interviews based on DOI theory	Six representatives from the KM department/division (executive to top management)
III	Conduct a SWOT analysis of the potential organisational impact (optimisation, efficiency, accuracy)	FGD using the LEIQ™ framework	Fourteen representatives from targeted departments and divisions involved in KM initiatives
IV	Evaluate the suitability of a KM framework to measure improvements in data synthesis, organisation and knowledge extraction.	Expert review and content-validity indexing	Three experts from academia, industry or data-management specialisation
V	Where appropriate, recommend the requirements needed for adoption in the Organisation.	Synthesis of Phases I–IV	N/A

B. Research Instrument

The research instrument comprised a literature review, semi-structured interviews grounded in DOI theory, FGDs using the LEIQ™ framework, and an expert-review checklist. The interview protocol translated the five DOI attributes into open-ended questions, and the FGD protocol elicited SWOT factors, which were then scored on the LEIQ™ emotion–importance axes.

The research is based on Diffusion of Innovation theory (DOI) [3]. The theory, proposed by Everett Rogers, describes how new ideas and technologies are adopted by social systems through four elements (the innovation, communication channels, time, and the social system) and five sequential stages (knowledge, persuasion, decision, implementation, and confirmation). DOI classifies adopters as innovators, early adopters, early majority, late majority and laggards. The theory identifies five attributes of an innovation that influence its rate of adoption: relative advantage, complexity, trialability, observability and compatibility [25]. These attributes form the semi-structured interview constructs used in this study. Fig. 3 presents the theoretical framework of DOI.

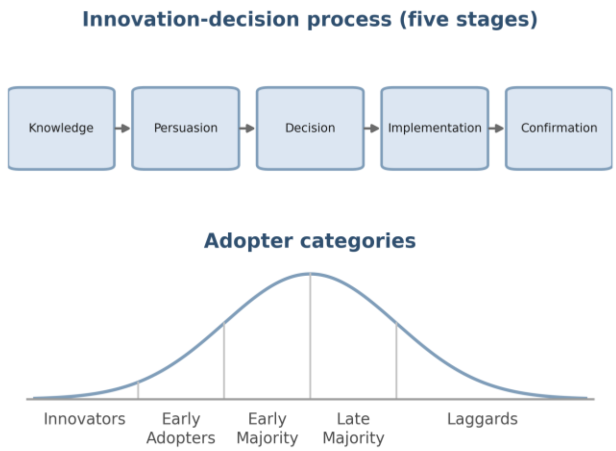

Fig. 3. Diffusion of innovation (DOI) theory [3].

A SWOT analysis was performed through FGD with the LEIQ™ model [4] to identify the potential organisational impact. LEIQ™ (Lokman's Emotion and Importance Quadrant) is based on Kansei Engineering, which investigates the implicit experience (emotion) of people and its effect on decision-making, productivity, and well-being. It categorises factors on emotion-versus-importance axes into four quadrants (positive/negative experience versus important/not important), as shown in Fig. 4. This model has been used in previous studies such as a TVET digital-learning emotion assessment tool [26] and B40 socio-economic happiness modelling [27]. The feasibility of affect-elicitation instruments across cultural settings has been examined in Kansei measurement research [52], and the Kansei approach has been applied to enrich targeted emotional responses in interface design [53]. Here, the model enables analysis of the SWOT factors and of the implicit barriers that affect adoption.

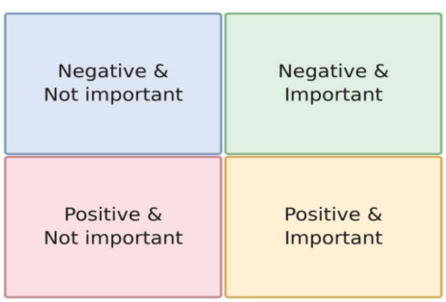

Fig. 4. The LEIQ™ model [4].

C. Sampling

Purposive sampling was used. Six KM-department representatives, from executive to top-management levels, were selected for the interviews following the guidelines on adequate interview sample sizes in organisational research [28]. Fourteen of the twenty targeted respondents took part in the FGD, and three data-management experts were engaged for the review. As qualitative saturation guidance indicates, these numbers are sufficient for thematic analysis [29]. Table III shows the anonymised profiles of the six interview participants (participants are labelled P1–P6 to maintain confidentiality).

TABLE III. PROFILE OF INTERVIEW PARTICIPANTS (ANONYMISED)

Code	Role/management level	Function/division	Experience
P1	Top management	Knowledge management	> 15 years
P2	Top management	Strategy and planning	> 15 years
P3	Senior management	Information and data management	10–15 years
P4	Middle management	Digital / ICT services	10–15 years
P5	Executive	Records and resource centre	5–10 years
P6	Executive	Corporate / operations	5–10 years

D. Gathering Data

Data collection included audio-recorded and transcribed interviews, documented FGD sessions with facilitated scoring, and structured expert feedback aligned with the DOI attributes and the proposed framework components [23], [24]. The sessions were conducted with prior organisational approval, and participant entries were recorded verbatim, including responses expressed in Malay.

E. Data Analysis

Interview transcripts were analysed thematically following the six-phase approach of Braun and Clarke [30]: familiarisation, initial coding against the five DOI attributes, theme development, review, definition and reporting. Codes were defined as complete idea statements, and factors were quantified by frequency of mention in order to visualise their relative prominence (Fig. 5). Data collection continued until no new themes arose, indicating thematic saturation [28], [29]. FGD data were synthesised within a SWOT framework and expanded through a TOWS matrix.

Content validity was assessed using the Content Validity Index (CVI) [31], [32], and [33] obtained from expert reviewers. Each expert rated the relevance of each framework subcluster. The item-level index (I-CVI) was calculated as the proportion of experts who rated an item as relevant, and the scale-level index (S-CVI/Ave) was calculated as the mean I-CVI per cluster. An acceptability threshold of 0.78 was adopted, in line with established guidance for expert panels [31], [32]. Expert comments were open-ended and were analysed thematically to inform qualitative refinement of the framework.

Two considerations govern the interpretation of these indices. First, the panel comprised three experts. Lynn [31] specifies a minimum of three and a maximum of ten content experts and requires, for panels of three to five raters, that all raters agree before an item is accepted as content valid; the relaxed 0.78 criterion applies from six raters upwards [32]. The panel therefore satisfies the minimum recommended size, and the study reports both indices so that readers may apply either criterion: under the stricter three-rater standard, the three subclusters returning I-CVI = 0.67 fall below the required unanimity and were accordingly revised rather than retained unchanged. Second, indices computed from a panel of this size carry wider estimation uncertainty than those derived from larger panels, and are reported here as an initial and indicative content-validity assessment rather than as a confirmatory psychometric result. Confirmatory validation with a panel of at least six and preferably eight to ten raters, permitting the computation of a modified kappa adjusted for chance agreement, is identified as necessary future work in Sections V-G and VI-D.

F. Trustworthiness and Coding Reliability

Two researchers coded the transcripts independently, compared their codes for consistency, and reconciled discrepancies through discussion until full agreement was reached. No inter-rater reliability coefficient, such as Cohen's kappa or Krippendorff's alpha, is reported for this process, and the reason is a design decision rather than an omission. The study follows the reflexive variant of thematic analysis, in which coding is treated as an interpretative act that necessarily bears the mark of the analyst; on that premise, agreement between coders demonstrates that two analysts have been trained to code alike rather than that either coding is accurate, and the originators of the approach argue that reliability coefficients rest on realist assumptions that the method does not share [48]. Consensus coding with documented reconciliation was therefore adopted as the appropriate quality procedure, supported by an audit trail of coding decisions, the retention of verbatim transcripts, the quantification of code frequencies reported in Fig. 5, and member-checking of the SWOT factors during the FGD.

This position is stated so that readers who prefer a coding-reliability paradigm can judge the evidence on their own terms. The consequence is explicit: the consistency of the thematic coding in this study is established procedurally and is open to inspection, but it is not expressed as a numerical coefficient, and readers who require such a coefficient should treat the thematic findings as unverified in that specific respect. A replication designed within a coding-reliability paradigm should pre-specify a codebook, employ independent coders who do not reconcile, and report kappa or alpha accordingly; this is recorded as a limitation in Section V-G and as a validation priority in Section VI-D.

IV. FINDINGS

This section reports the findings for each research objective.

A. RO1: Current State of KM Practices

The literature review reveals that existing KM methodologies increasingly integrate Gen AI and LLMs for improved data management and decision-making. Advances in Gen AI and LLMs have transformed NLP, allowing better data management and information retrieval [34, 35]. Standardised human-evaluation methodologies such as the QUEST framework are increasingly important to ensure the reliability and safety of content produced by AI [36]. Implementation strategies address data scarcity through fine-tuning and retrieval-augmented generation (RAG) [37]. Major mechanisms include knowledge extraction using NLP [38], automation of routine knowledge tasks [39], and data-driven insight generation from large datasets [35]. Persistent challenges include data quality, ethical issues and the need for human supervision. Table IV summarises best practices in selected countries.

For the organisation, these international practices suggest that value is not realised from technology alone but through its alignment with organisational processes and governance. Data must be well classified and access-controlled, and outputs must be validated by domain experts, for AI-powered knowledge bases and assistants to accelerate retrieval and document processing. The state of current practice thus points to a socio-technical adoption path in which people, process, and data readiness develop in tandem with technology.

TABLE IV. BEST PRACTICES OF THE NEW GENERATION OF KM PRACTICES

Country	Ref.	Best practice	Benefits/advantages
China	[40]	AI in human resource management	Streamlines recruitment, evaluation, and development, and enables efficient data processing for workforce insights
Singapore	[41]	AI-driven chatbots and virtual assistants	Enhances citizen engagement; real-time responses and reduced wait times
Germany	[42]	AI in manufacturing and production	Predictive maintenance, quality control and process optimisation; reduced downtime
United States	[43]	AI-powered internal knowledge bases	Facilitates retrieval and automates document processing for decisions
Japan	[44]	AI in customer service	AI chatbots handle inquiries efficiently, improving responsiveness

B. RO2: Feasibility Assessment (Interviews)

Thematic analysis of the semi-structured interviews was contextualised within DOI. The most frequently cited factor was complexity/ease of use (519 mentions), followed by trialability (281), observability (232), relative advantage (115) and compatibility (62). Fig. 5 presents the Sankey diagram of these factors and their sub-themes. Each factor is discussed below in terms of the DOI attributes [25]. Frequencies denote prominence in the corpus and are not offered as measures of effect size.

1) Relative advantage: Respondents perceived clear benefits in adoption. One participant observed that while Gen AI could replace some tasks, it would also create new roles and opportunities. Others reported that AI could reduce costs and help people retrain. Participants associated adoption with enhanced productivity, efficiency, and accessibility, and with more accurate and insight-rich outputs, given robust data foundations.

2) Complexity (usability): Participants with previous experience found the tools easy to use and expected that potential future users would adapt to them readily. They stressed, however, the need for a deep understanding of AI, proper classification of data, and appropriate governance to ensure accurate results. As one participant observed, the system produces correct output only when the appropriate knowledge has been embedded in it. The integration of data from different sources therefore needs to be undertaken strategically.

3) Trialability: Acceptance relied heavily on trialability. Respondents valued the opportunity to experiment, and several reported using tools such as ChatGPT to brainstorm and draft in their own time. Low cost, flexibility, and the availability of free versions, even where limited, drove trials and subsequent adoption, with human supervision retained to check outputs.

4) Observability: Adoption was driven strongly by observability. Participants reported that they had started using tools on the advice of friends and colleagues and through online reviews and community experience. They warned that concerns about fairness and trust could slow adoption and advised adaptation to the organisational context supported by acculturation that embeds ethical practice.

5) Compatibility: Compatibility with existing work processes was a decisive consideration. Respondents reported that tools such as Copilot and ChatGPT helped structure content and access, allowed rapid data analysis, and fitted well with existing work processes. They noted that the availability of accurate data, secure infrastructure, and integration with other applications increases user satisfaction and supports continued adoption. Overall, the interview findings indicate that the organisation can adopt Gen AI and LLMs in its KM procedures provided that data governance and ethical controls are in place.

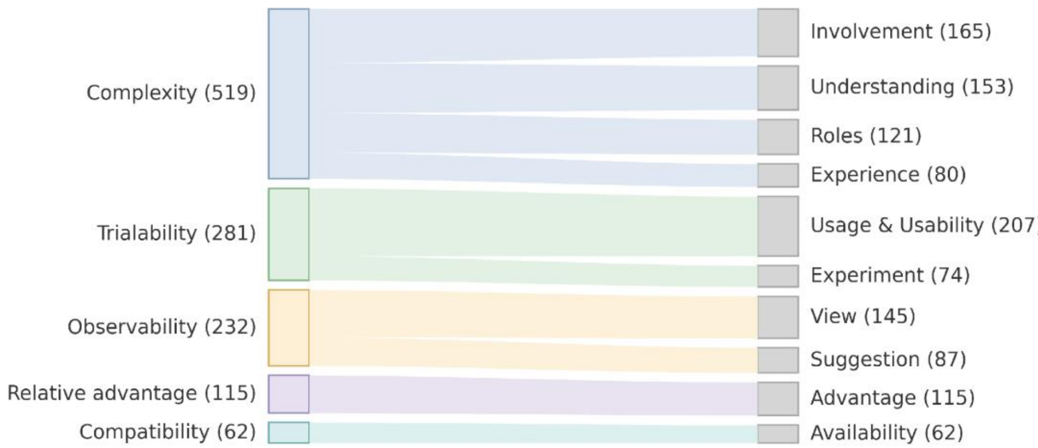

Fig. 5. Sankey diagram of feasibility factors (frequency of mention) and their associated sub-themes.

C. RO3: SWOT Analysis (FGD)

Using the LEIQ™ model, FGD participants identified strengths, weaknesses, opportunities, and threats of Gen AI and LLM adoption, each of which was scored on the emotion–importance axes (Fig. 6).

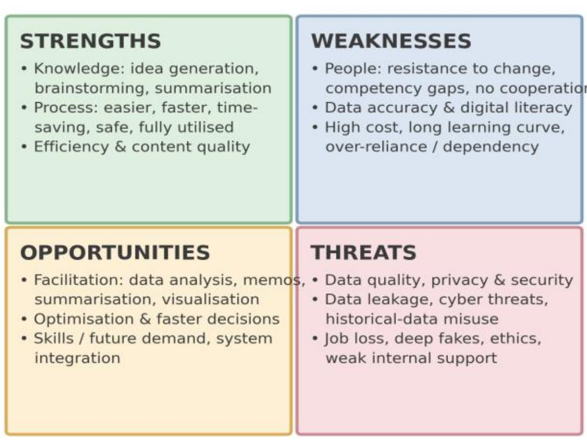

Fig. 6. SWOT analysis of Gen AI and LLM adoption in the organisation's KM practices.

1) Threats (Q1): The highest-scored threats (1.00) related to data quality and to data privacy and security, including data accuracy, incorrect information and citation, data leakage, cyber risks, exposure of internal information, historical-record training, and prompting ethics. Other high-scoring threats were job displacement, deepfakes, and data classification. User-behaviour threats concerned AI's lack of empathy and ethical judgment and user disengagement from critical thinking. Weak internal support for the LLM initiative was also raised.

2) Weaknesses (Q2): The most prominent weaknesses (1.00) were in the people and process clusters: lack of cooperation, resistance to change, changing work practices, competency and idea gaps, individualistic behaviour, inaccurate or incomplete information, lack of data classification, and limited digital proficiency in prompt creation. Technology weaknesses (0.93) included high data requirements and long model training time and cost. Dependency weaknesses (0.53) included over-reliance and reduced independent thinking.

3) Strengths (Q3): The strongest strengths (1.00) were in the knowledge and process clusters: idea generation, brainstorming, expert-like guidance at any time, easier and faster work, time savings, safety, and full utilisation of resources. Ratings for efficiency, quality of content, and positive experiences with technology were high (0.87–0.93).

Participants described AI as a capable assistant and a discussion partner.

4) Opportunities (Q4): Facilitation and optimisation — data analysis, memo and slide drafting, document summarisation, data visualisation, reduced search time and improved decision-making — scored highest (1.00). Other opportunities (0.93) were problem-solving, reducing silos, data sharing and coordination, and progress towards a data-driven organisation. The SWOT was extended through TOWS analysis, the strategic logic and consolidated output of which are presented in Section V-C.

D. RO4: KM Framework Suitability (Expert Evaluation)

Three experts in AI and KM across the public, private, and academic sectors, each with more than ten years of experience, evaluated the proposed KMAI framework using a survey checklist. Table V summarises their profiles. The experts agreed that the framework provides a holistic approach to KM through AI integration, emphasising training, user experience, continuous improvement, a supportive culture and robust infrastructure. They also offered cluster-specific refinements: for the People cluster, separating awareness from knowledge and adding an AI champion as a change agent; for Process, adding accountability, transparency, risk management, scalability and performance; for Technology, reassessing user experience and ensuring AI-ready, scalable tools; and for Data, separating analytics from data management and adding data architecture and taxonomy, classification, governance and protection, aligning organisational integration with a growth mindset. Fig. 7 shows the proposed KMAI framework as submitted for evaluation.

TABLE V. EXPERT INFORMATION

	Expert 1	**Expert 2**	**Expert 3**
Position	Deputy Director	Senior Assistant Director	Chief Assistant / Senior Director
Agency	A public university (academic sector)	A federal digital-government agency (public sector)	A federal regulatory agency (public sector)
Category	Top management	Middle management	Top management

TABLE VI. EXPERT-EVALUATION CONTENT VALIDITY INDEX (CVI) OF THE KMAI FRAMEWORK

Cluster	**Subcluster (item)**	**I-CVI**	**S-CVI/Ave**	**Interpretation**
People	AI knowledge and awareness	1.00		Acceptable
	AI learning and skill enhancement	1.00		Acceptable
	Professional growth	1.00		Acceptable
	Organisational development	0.67		Revised
	Human–AI interaction	1.00	0.93	Acceptable
Process	AI continuous improvement	1.00		Acceptable
	Efficiency and automation	1.00		Acceptable
	Organisational approach	1.00		Acceptable
	Strategic AI adoption and implementation	1.00		Acceptable
	Quality assurance; standardisation and best practices	1.00		Acceptable
	Process management	0.67	0.95	Revised
Technology	Adoption, integration and innovation	1.00		Acceptable
	Customisation and infrastructure	1.00		Acceptable
	Security, UX and KM system	1.00	1.00	Acceptable
Data	Data literacy and skills	1.00		Acceptable
	Data management and AI analytics	1.00		Acceptable
	Data security and access	1.00	1.00	Acceptable
Culture	Continuous learning	1.00		Acceptable
	Organisational integration and development	0.67		Revised
	AI ethics and responsibility	1.00	0.89	Acceptable
Content	Content management	1.00		Acceptable
	Knowledge acquisition	1.00	1.00	Acceptable

Note: I-CVI = item-level content validity index; S-CVI/Ave = scale-level content validity index (average) per cluster; acceptability threshold = 0.78 for panels of six or more raters [32]. Panel of three experts (n = 3); under Lynn's [31] three-to-five-rater criterion, unanimous agreement (I-CVI = 1.00) is required, and the three items returning 0.67 were revised on that basis.

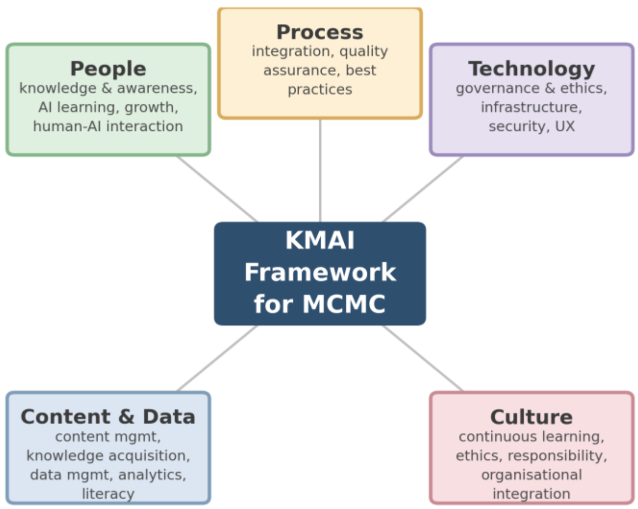

Fig. 7. Proposed KMAI framework submitted for expert evaluation.

Table VI reports the content-validity results. Item-level indices were 1.00 where all three experts agreed and 0.67 where two of three agreed. Scale-level indices (S-CVI/Ave) exceeded the 0.78 threshold for every cluster: People 0.93, Process 0.95, Technology 1.00, Data 1.00, Culture 0.89 and Content 1.00. Three subclusters — organisational development (People), process management (Process) and organisational integration and development (Culture) — returned I-CVI values of 0.67. Under Lynn's three-to-five-rater criterion, these values do not meet the required unanimity, and the corresponding subclusters were therefore revised rather than retained unchanged. The framework was updated accordingly (Fig. 8): awareness was separated from knowledge, and an AI champion was added (People); risk management, scalability, and performance were added (Process); AI integration and user interfaces were added (Technology); and AI analytics was separated from data management, with data architecture and taxonomy, classification, governance, and protection added (Data). These indices are indicative and require confirmation with a larger panel, as set out in Sections III-E and V-G.

E. RO5: The Validated KMAI Framework

The evaluated and revised KMAI framework (Fig. 8) comprises five components. People covers knowledge, awareness, AI learning, professional development, human–AI interaction, and the AI champion role. The process covers AI integration and optimisation, quality assurance, best practices, risk management, scalability and performance. Technology covers AI governance and the ethical framework, infrastructure, security, user experience and user interfaces. Content and Data covers content management, knowledge acquisition, data management, AI analytics, data architecture and taxonomy, classification, governance and protection, security, literacy and access. Culture covers continuous learning, ethical responsibility, organisational integration and a growth mindset. Because the framework is described once here, Section VI does not restate its components and instead sets out how they are to be implemented.

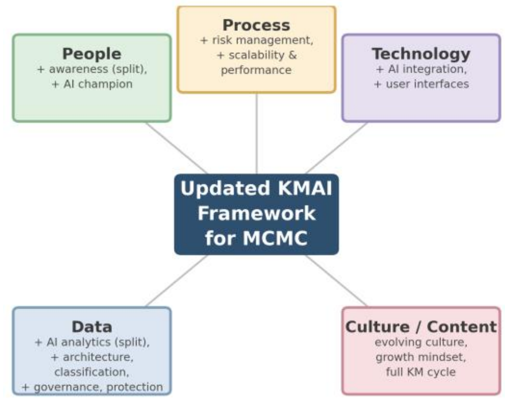

Fig. 8. Updated KMAI framework based on expert recommendations.

V. Analysis and Discussion

This section interprets the findings reported in Section IV in relation to the research objectives and prior literature. It does not restate the framework components, which are given in Section IV-E, nor the TOWS strategy statements, which are consolidated in Table VII; it addresses instead what the evidence means, what it establishes, and what it does not.

A. Interpreting Feasibility Against the DOI Attributes

The interview evidence is positive on all five DOI attributes, but the attributes are not equally weighted, and the distribution is itself informative. Complexity dominated the corpus (519 mentions), yet the substance of those mentions was not that the tools are difficult to operate; participants with prior exposure described them as easy to use. The complexity discussed was organisational rather than interfacial — understanding what the tools do, defining roles, and classifying data so that outputs are accurate. Prominence in the corpus therefore reflects where uncertainty is concentrated, not where resistance is greatest. Trialability (281) and observability (232) were the mechanisms through which that uncertainty was reduced: free or low-cost versions permitted low-risk experimentation, and peer recommendation and visible results converted experimentation into use. Relative advantage (115) and compatibility (62) attracted fewer mentions not because they were unimportant but because they were largely uncontested; participants treated the productivity benefits and the fit with existing work processes as settled.

This pattern qualifies the classical DOI account in one respect relevant to Gen AI. Rogers's formulation treats complexity as a property of the innovation that retards adoption. In this setting, complexity was relocated to the organisation: the innovation was simple to use and difficult to govern. The implication for practice is that adoption efforts should be directed at data classification, role definition and competence rather than at usability, and this is reflected in the weighting of the People, Process and Data clusters of the framework.

B. Data Governance and Ethics as a Moderating Condition

The most consequential finding is that positive perceptions of all five attributes did not, on their own, yield an unqualified adoption judgment. Across the interviews and the FGD, participants attached a condition to their support: outputs must be accurate, data must be classified, infrastructure must be secure, and use must be ethically bounded. The FGD reinforced this, with the highest-scored threats (1.00) concentrated in data quality and data privacy and security. Governance therefore does not act as a further antecedent alongside the five attributes; it acts on the relationship between those attributes and adoption. Where governance maturity is low, favourable perceptions of relative advantage and trialability produce uncontrolled experimentation rather than institutional adoption — a pattern visible in the reported individual use of public tools outside organisational channels. Fig. 9 states this moderating relationship as the study's research model [3], [23].

This positioning is the study's principal theoretical claim and also its most testable one. It is derived from qualitative evidence in one organisation and is advanced as a proposition for confirmatory testing, not as an estimated effect. A quantitative test — measuring governance maturity and the five attributes across multiple agencies and testing the interaction — is the natural successor study and is identified as such in Section VI-D.

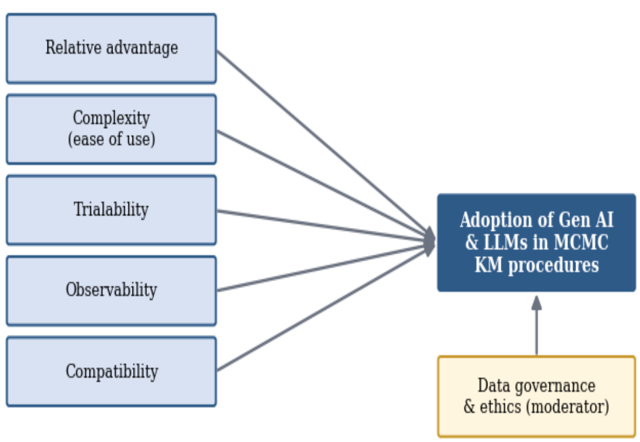

Fig. 9. Research model: DOI attributes and adoption, moderated by data governance and ethics [3], [23].

C. Strategic Logic of the TOWS Synthesis

Weihrich's TOWS matrix was used to convert the SWOT factors into strategies by matching internal strengths and weaknesses with external opportunities and threats. The consolidated strategies are presented in Table VII and summarised in Fig. 10 and are not repeated in prose here; what follows is the logic that generated them and the priority ordering it implies.

Two features of the SWOT distribution shaped the synthesis. First, the strengths were concentrated in the knowledge and process clusters — idea generation, drafting, summarisation, speed — which are capabilities the technology supplies directly and which require little organisational change to realise. Second, the weaknesses and threats were concentrated in the people and data clusters — resistance, competency gaps, classification, accuracy, and security — which the technology does not supply, and which require sustained organisational investment. The asymmetry means that SO strategies are available immediately and cheaply, while WT strategies determine whether the SO gains survive contact with the organisation's regulatory obligations.

The priority ordering follows from this. WT strategies are defensive but are not therefore secondary: data security, governance and ethical guidelines, change management, in-house capability to reduce vendor lock-in, a data-quality management system and an AI innovation task force are the conditions under which the remaining three quadrants can be pursued at all in a regulated setting. WO strategies — training, a structured adoption plan, IT infrastructure, AI-specific roles — remove the internal constraints that the interviews identified as the locus of complexity. ST strategies deploy leadership support and IT capability against resistance and misinformation. SO strategies capture the readily available gains. Sequencing therefore runs WT and WO first, ST concurrently, and SO continuously; this ordering is what the phased implementation plan in Section VI-B operationalises.

Fig. 10. TOWS strategy matrix for Gen AI and LLM adoption in the organisation.

D. What the Expert Evaluation Establishes — and What It Does Not

The content-validity evidence establishes that a panel of three qualified experts judged the framework's clusters and subclusters to be relevant to the construct of AI-enabled KM in a public-sector regulatory setting, with scale-level indices above the threshold for every cluster and three subclusters revised in response to sub-unanimous ratings. That is a meaningful but narrow claim. Content validity concerns whether the instrument's items adequately represent the domain; it does not establish construct validity, criterion validity, or that use of the framework improves KM outcomes. None of those is claimed here.

The panel size bounds the claim further. Three raters satisfy Lynn's stated minimum [31] but sit at the lower limit, so the indices carry wide estimation uncertainty, and unanimity among three raters is a weaker signal than the same proportion obtained from nine. The revisions made in response to the 0.67 items are therefore best read as expert-informed refinements rather than as psychometrically compelled corrections. The framework should be treated at this stage as a validated proposition awaiting confirmation, and Section VI-D specifies what that confirmation requires.

E. Theoretical and Practical Implications

Theoretically, the study extends DOI to AI-enabled KM in a national regulatory setting that has not previously been examined. It shows that the classical innovation attributes remain explanatory for Gen AI and LLMs while identifying a context-specific moderator — data governance and ethics — that conditions the relationship between perceived attributes and adoption, and it relocates complexity from the innovation to the organisation. It also demonstrates a replicable mixed-method design for assessing emerging-technology adoption by combining DOI with a Kansei-based SWOT instrument and a TOWS synthesis, which is useful where both quantitative and experiential factors matter.

In practical terms, the findings give the organisation an evidence-based basis for adoption. With all five DOI attributes positive, it can move from exploratory use to structured implementation, concentrating on the enablers participants valued most — ease of use, low-cost trialability and compatibility with existing tools — while directly addressing the highest-scoring threats relating to data quality, privacy and security. The TOWS strategies translate these insights into initiatives, and the four strategic thrusts provide a governance structure through which progress can be planned, resourced and monitored.

F. Boundary Conditions and Transferability

Because the evidence comes from a single organisation, six interview participants, fourteen FGD respondents and three experts, the question of what may legitimately be carried to other settings requires an explicit answer rather than an assumption of breadth. The study makes no claim of statistical generalisation to a population of public-sector agencies. What it offers instead is analytic or theoretical extension in the sense of [51], and transferability in the sense of [50], in which the researcher supplies sufficient contextual description for readers to judge the fit to their own setting and the readers, not the authors, make that judgment. Transferred findings are properly treated as working hypotheses rather than conclusions [49].

Table VIII therefore states the conditions under which such transfer is defensible, distinguishing the elements of the study that are likely to travel from those that are specific to this case. In summary, the framework's structure and the moderating role of governance are the elements most likely to transfer, and they should transfer most readily to organisations that share four properties: a statutory regulatory mandate that imposes data-custodianship and accountability obligations; an existing centralised KM function with identifiable repositories; a mix of structured and unstructured knowledge assets; and public-sector procurement, data-sovereignty and records retention. constraints that limit the use of public cloud-hosted models. Where these properties are absent — in a commercial organisation without custodianship obligations or an agency without an established KM function — the cluster weightings and, in particular, the primacy of the Data and Process clusters should not be assumed.

The elements least likely to transfer are the empirical particulars: the frequency distribution across the DOI attributes, the specific LEIQ™ factor scores, and the composition of the four strategic thrusts, all of which reflect this organisation's maturity, workforce and regulatory position at the time of study. Another agency applying the framework should expect to re-run the diagnostic — the DOI-framed interviews and the LEIQ™-scored SWOT — and to derive its own weightings, using the framework as the instrument rather than the results as the finding.

G. Limitations

Five limitations bound the findings. First, the design is a single-organisation case study with purposive sampling, so the findings characterise this organisation and extend to others only analytically, subject to the conditions in Section V-F. Second, the expert-review panel comprised three specialists. This meets the stated minimum for content-validity assessment [31] but sits at its lower limit; the reported I-CVI and S-CVI values should be regarded as indicative until confirmatory validation is performed with a larger panel. Third, the thematic analysis rests on consensus coding by two researchers rather than on an inter-rater reliability coefficient, for the reasons set out in Section III-F; readers who require such a coefficient should treat the coding consistency as procedurally established but numerically unverified. Fourth, the frequency counts reported in Fig. 5 index prominence in the corpus and should not be read as measures of effect size or of participant agreement. Fifth, the study assesses feasibility and content validity, not outcomes: no claim is made that adopting the framework improves KM performance, since that would require longitudinal evaluation against operational indicators.

TABLE VII. CONSOLIDATED TOWS STRATEGY MATRIX

TOWS	Strengths (S)	Weaknesses (W)
Opportunities (O)	SO: leverage AI for enhanced decision-making; AI-driven KM; AI-powered regulatory tools; AI innovation hubs; data-driven policymaking; process optimisation; AI-enhanced public services; AI-driven collaboration.	WO: comprehensive AI training; structured adoption plan; enhance IT infrastructure; AI-specific roles and teams; clear AI governance; improve data quality and management; foster a culture of innovation; develop in-house AI capabilities.
Threats (T)	ST: leadership support against resistance; IT capability for data security; knowledge to counter misinformation; human-centric approach; good governance for regulatory compliance; resource allocation for currency; large datasets for reliable decisions; knowledge sharing for interdepartmental collaboration.	WT: comprehensive training programme; robust data security; clear governance and ethical guidelines; change-management strategy; cross-departmental collaboration; in-house AI solutions to reduce vendor lock-in; data-quality management system; AI innovation task force.

TABLE VIII. BOUNDARY CONDITIONS FOR TRANSFER OF THE KMAI FRAMEWORK TO OTHER SETTINGS

Element of the study	Transferability	Condition required for transfer
Five-cluster framework structure (People, Process, Technology, Content and data, and Culture)	High — construct coverage is domain-general and expert-validated	Organisation performs knowledge-intensive work with identifiable repositories; no regulatory mandate required
Governance and ethics as a moderator of adoption	Moderate to high — proposed as a theoretical extension for confirmatory testing	Organisation is subject to data-custodianship, privacy or accountability obligations that constrain tool selection
Multi-method design (DOI interviews + LEIQ™ SWOT + TOWS + CVI)	High — the method is the reusable contribution	Access to internal informants across management levels and to external subject-matter experts
Relative weighting of clusters (primacy of Data and Process)	Low — case-specific	Must be re-derived from a local diagnostic; not to be assumed
DOI attribute frequencies and LEIQ™ factor scores	Not transferable — reflect this Organisation's maturity and workforce	Re-run the diagnostic instrument locally
Four strategic thrusts and the implementation sequence	Low to moderate — structure may guide, content may not	Comparable statutory mandate, existing centralised KM function, and public-sector procurement and data-sovereignty constraints

VI. RECOMMENDATION

This section converts the validated framework of Section IV-E and the strategic analysis of Section V into an implementable programme. It does not restate the framework's components or the TOWS strategies; it specifies who acts, in what order, and against what indicators, and it states what must be validated before the programme is extended beyond the organisation.

A. Strategic Thrusts, Ownership and Indicators

The programme is organised around four strategic thrusts — People, Process, Technology and Data — that aggregate the five framework clusters into units for which accountability can be assigned (Fig. 11). Culture is treated as a cross-cutting condition realised through the People and Process thrusts rather than as a separate accountability unit, because the FGD evidence located cultural resistance in specific people and process practices rather than in a free-standing cultural deficit. Table IX assigns each thrust an owner, a set of first-order actions and the indicators against which progress is to be measured.

Two design rules govern the thrusts. First, no thrust proceeds ahead of the data thrust: the interview and FGD evidence are consistent that output accuracy, and therefore user trust, is a function of data classification and quality, so data functions as the gating thrust. Second, each thrust must carry at least one indicator that is observable to users rather than only to the programme, because observability was one of the two mechanisms by which uncertainty was reduced in the interviews; progress that is invisible to staff will not convert into adoption.

B. Phased Implementation Plan

Implementation should be incremental, and the sequence should follow the priority ordering derived in Section V-C: defensive and enabling work first, opportunistic gains continuously.

Short term (0–12 months). Establish data-governance and ethics guidelines and an acceptable-use policy for Gen AI; complete a data-classification exercise across the divisions holding the principal repositories; appoint AI champions in each targeted division and constitute the AI innovation task force; and run controlled pilots confined to divisions with mature data repositories, each with a defined success measure and human validation of outputs. The purpose of this phase is to make experimentation safe, not to scale it.

Medium term (1–3 years). Scale the successful pilots to the divisions that share their data conditions; institutionalise AI-specific roles and the training programme; harden infrastructure and security to support organisation-wide use; and establish quality-assurance and continuous-improvement loops with periodic review of outputs against operational indicators.

Long-term (3–5 years). Build in-house capability and invest in a customised model appropriate to the organisation's data-sovereignty constraints; integrate the KMAI framework with enterprise strategy so that AI-enabled KM is a core organisational capability rather than an isolated initiative; and extend measurement from process indicators to decision-quality and operational-efficiency outcomes.

The pace implied by this sequence is deliberate. Industry analysis distinguishes an AI-accelerated posture, in which AI is integrated into core operations and decision-making to drive productivity, creativity and engagement, from an AI-steady posture characterised by operational integration, scalability, governance, improved return on investment and continuous improvement [45]. Given the evidence of positive perceptions across all five attributes but immature data governance, the Organisation should pursue the accelerated posture only as the governance conditions established in the short-term phase are met; until then, a steady posture with controlled pilots is the appropriate setting.

C. Conditions for Reuse by Other Agencies

Public-sector agencies with comparable regulatory mandates and data-custodianship obligations may reuse the framework and the diagnostic method but should do so as adopters of an instrument rather than as recipients of a result. Three requirements follow from Section V-F and Table VIII. The framework structure and the diagnostic method may be adopted directly. The cluster weightings, the sequencing of thrusts and the content of the strategies must be re-derived locally by re-running the DOI-framed interviews and the LEIQ™-scored SWOT within the adopting organisation. And the moderating role of governance should be treated as a hypothesis to be checked against local conditions rather than as an established property, since it has been tested in one setting only.

D. Priorities for Future Validation

Four validation steps would convert the present propositions into confirmed findings, and they are stated in the order in which they should be undertaken. First, repeat the content-validity assessment with a panel of at least six and preferably eight to ten experts drawn from more than one agency, reporting modified kappa alongside I-CVI so that agreement is adjusted for chance. Second, replicate the qualitative phases in at least two further public-sector organisations with comparable mandates to test whether the cluster structure and the primacy of the data cluster hold outside this case; a replication designed within a coding-reliability paradigm should pre-specify a codebook and report kappa or alpha. Third, operationalise the framework as a measurement instrument and test the moderating role of data governance and ethics quantitatively across agencies. Fourth, evaluate outcomes longitudinally in selected divisions, measuring the effect of framework-guided adoption on decision quality and operational efficiency, since feasibility and content validity do not by themselves demonstrate benefit.

TABLE IX. STRATEGIC THRUSTS: OWNERSHIP, FIRST-ORDER ACTIONS AND INDICATORS

Thrust	Suggested owner	First-order actions	Progress indicators
Data (gating)	Information and data management division	Data classification across principal repositories; data architecture and taxonomy; quality-management system, and access and retention controls	Proportion of repositories classified; data-quality exception rate; time to retrieve a governed record; number of access incidents
Process	Strategy and planning, with KM division	Governance and ethics guidelines; acceptable-use policy; risk management; quality assurance and human validation of outputs; adoption plan	Policy in force; proportion of AI-assisted outputs subject to documented human validation; pilot success against pre-defined measures
People	Human capital, with divisional AI champions	Tiered training programme; AI champion network; AI-specific roles; change-management and communication plan	Training completion by management level; number of active champions; self-reported competence; staff-visible demonstrations delivered
Technology	Digital / ICT services	Secure and scalable infrastructure; integration with existing productivity tools; user-interface and UX work; evaluation of in-house model options	Availability and response time; number of integrated workflows; user-satisfaction score; reduction in use of unsanctioned public tools

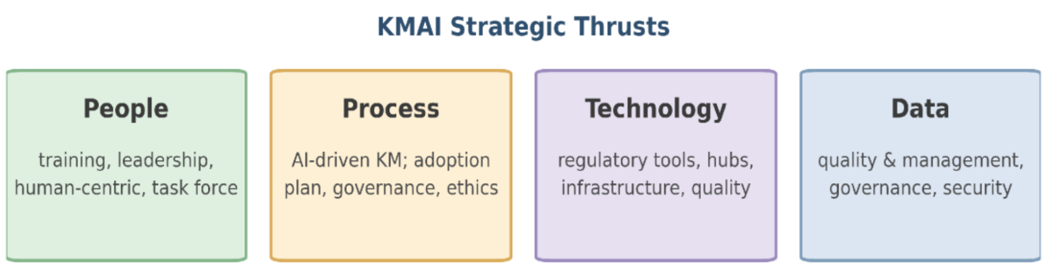

Fig. 11. KMAI strategic thrusts and strategies.

VII. CONCLUSIONS

This study set out to examine the issues and challenges that affect the adoption of Gen AI and LLMs to enhance the organisation's KM practices and to develop and validate a framework for that purpose. The potential organisational impact was evaluated using a SWOT framework targeting optimisation, efficiency, and accuracy, and the resulting factors were converted into strategies through TOWS analysis.

The evidence indicates that adoption is feasible in this setting. All five DOI attributes were perceived positively, and the barriers participants identified were organisational rather than technological: data classification, competence, role definition and governance. The study's principal theoretical contribution is the positioning of data governance and ethics as a condition on the relationship between the innovation attributes and adoption, rather than as one component among others. Its principal practical contribution is the KMAI framework, refined through expert evaluation and translated into four strategic thrusts and a phased implementation plan for the organisation.

These contributions are bounded by the design. The findings derive from one organisation, a purposive sample and a three-member expert panel and are therefore offered as analytically transferable propositions subject to the conditions set out in Section V-F, not as results generalisable to public-sector agencies at large. The framework's content validity is established but indicative, and its effect on KM outcomes is untested. Confirmatory validation with a larger expert panel, replication in comparable agencies, quantitative testing of the proposed moderation, and longitudinal measurement of decision quality and operational efficiency are the necessary next steps, and the organisation is well placed to undertake the first of them as it develops an integrated technology roadmap over the next three to five years.

Declaration on the Use of Generative AI

The authors declare the following pursuant to the journal's policy on the use of generative artificial intelligence. In the preparation of this manuscript, generative AI tools (large language model-based assistants) were used by the authors only for language editing, for improving readability and grammar, for assisting with the formatting of the manuscript to the journal template, and for assisting in the preparation of figures illustrating the study's frameworks and results. The generation, analysis, or interpretation of research data, the production of research findings, and the drafting of scientific claims were not assisted by generative AI. The authors performed all conceptual development, methodological design, data collection, thematic analysis, content-validity computation, and interpretation.

Generative AI and large language models are also the object of study in this research; their use as an object of investigation is described in the Methodology and Findings sections and is distinct from the authorial assistance disclosed here. The authors have used these tools in the writing of the article and take full responsibility for all content in the published article. Generative AI tools were not credited as authors and do not qualify for authorship.

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