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Agentic AI for Knowledge Management in the Agriculture Community

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Abstract

The integration of Artificial Intelligence (AI) into Knowledge Management Systems (KMS) offers new opportunities to address persistent challenges in agriculture, particularly in crop disease identification and treatment. A novel conceptual model of an Agentic AI-empowered KMS tailored for the agricultural community of farmers and farming experts is proposed. Unlike conventional decision-support systems, the model introduces agency through AI components capable of autonomously acquiring, retrieving, storing, and applying knowledge while engaging in continuous feedback with human experts. Multimodal interfaces, i.e., chatbots for natural language queries and image recognition for both text and visual diagnoses, enable farmers to contribute real-time field data. Knowledge graphs and Large Language Models (LLMs) mediate the transformation of inputs into validated, context-aware treatment and pesticide recommendations. The model is grounded in Activity Theory, providing a socio-technical lens to align user requirements, community participation, and role distribution with KM processes. The originality of this approach lies in combining agentic AI capabilities with collaborative knowledge exchange, creating a self-improving agricultural knowledge ecosystem. Anticipated contributions include enhanced decision-making, improved crop yields, and sustainable farming practices, establishing a foundation for future empirical validation and system implementation.

1. Introduction

Agriculture remains the essential sector to ensure global food security, economic stability, and sustainable development. As the demand for food continues to rise, the agriculture sector faces increasing pressure to enhance the productivity of agricultural management [1]. One of the critical challenges in modern agriculture is the reliance on pesticides [2]. While pesticides are effective in reducing crop losses caused by pests and plant diseases, their overuse and mismanagement have raised significant risks to crop quality and threaten biodiversity [3].

Traditionally, the agricultural agency has implemented manual practices in knowledge transfer, where the agency team scheduled periodic meetings with the farmers to guide them on pest and plant disease control. In doing so, the booklets are distributed to the farmers for their reference, consisting of illustrations of common plant diseases along with recommendations of suitable pesticides for treatment. However, this approach still presents challenges. Farmers often struggle to make informed decisions, which can negatively affect the results, time management, and ultimately the overall performance of the sector [4]. Clearly, the meetings and booklets are insufficient in ensuring proper knowledge transfer to the farmers, as they somehow lack in knowledge exchange between the farmers and the agency. A full understanding of the on-the-field situation remains necessary to make the right real-time decision.

The essence of the problem is the knowledge gap between farmers and the community of experts, particularly in crop disease management [5]. For instance, the agricultural agency has implemented a web-based system to share information on plant diseases, treatments, and pesticide prescriptions [6]. However, decision-making at the farm level is often inadequate and lacks sufficient support systems. This proves that although information has been shared in the agricultural community system, the static nature of explicit knowledge is not fully conveyed or tacitly understood. Hence, a customized Knowledge Management System (KMS) for agricultural decision-making on pesticides can serve as an effective solution to address these issues [7].

The emergence of Agentic AI, i.e., AI systems with autonomy, proactivity, reasoning, and interactivity, offers opportunities to reimagine KMS as a dynamic ecosystem rather than static archives [8]. Unlike conventional AI tools, agentic systems act as partners in knowledge work, interpreting human input, generating new insights, and facilitating collaboration between human experts. Focusing on facilitating farmers with reliable knowledge of treating plant diseases for better decision-making on pesticides, this paper introduces a conceptual model for Agentic AI in KMS, drawing upon four interrelated dimensions of knowledge processes: acquisition, exchange, storage, and retrieval. The model integrates Natural Language Processing (NLP), Machine Learning (ML), Large Language Models (LLMs), and Knowledge Graphs to enable adaptive and context-sensitive knowledge flows.

2. Related Works

This section covers the relevant reviews found in the literature regarding knowledge management systems, artificial intelligence (AI), and agentic AI. The research gaps are presented to conclude this section.

2.1 Knowledge Management Systems (KMS)

Research on Knowledge Management Systems has evolved across three generations [9]. The first generation focused on codification, with databases, document management, and file storage. The second emphasized personalization through communities of practice and expert networks [10]. The third, influenced by AI, integrates advanced analytics, semantic technologies, and adaptive systems [11]. Despite these advances, many KMS remain limited in their ability to contextualize or reason about knowledge.

KMS have long been understood as socio-technical systems that integrate technology, organizational structures, and cultural practices to facilitate knowledge creation, storage, retrieval, and sharing [12]. Early generations of KMS emphasized codification through databases and document repositories, later evolving toward personalization approaches such as communities of practice and collaborative platforms [10]. Recent work highlights the need for a more holistic KMS that aligns digital platforms, governance, and organizational routines with strategic outcomes [13], [14]. With digital transformation accelerating, new research emphasizes the integration of KMS with enterprise-wide data fabrics and analytics tools, particularly in healthcare, small and medium-sized enterprises (SMEs), and international business contexts, where knowledge quality and governance mechanisms strongly determine performance outcomes [15].

The latest wave of research increasingly investigates AI-enabled KMS. Generative AI (GenAI) and NLP are seen as augmenting core KM functions by accelerating codification (summarization, extraction), improving retrieval (semantic and conversational search), and even facilitating knowledge creation through synthesis and ideation [16]. At the same time, these capabilities introduce risks related to bias, explainability, and provenance, highlighting the need for socio-technical governance frameworks [17]. Complementary studies emphasize the role of knowledge graphs (KGs) in structuring organizational knowledge, enabling entity-relation reasoning, and grounding retrieval-augmented generation (RAG) approaches that enhance the accuracy and transparency of

LLM-based outputs [18]. These hybrid models—blending structured KGs with adaptive LLMs—represent a promising frontier for the evolution of KMS.

Empirical evidence suggests that AI-integrated KMS can foster innovation, reduce knowledge discovery cycles, and optimize problem-solving efficiency when supported by high-quality data, privacy safeguards, and organizational change management. Recent reviews in knowledge management journals affirm that GenAI challenges traditional frameworks such as Nonaka's SECI model, prompting theoretical reframing of how knowledge is created and disseminated in human–AI ecosystems [19]. Practitioners and researchers alike caution that nondeterminism and hallucinations in generative systems demand careful oversight, private deployments, and transparent validation processes, particularly for accuracy-critical tasks [20]. Taken together, the literature points to the convergence of human expertise, organizational practices, and hybrid AI architectures, shaping the next generation of socio-technical KMS.

2.2 Artificial Intelligence (AI) in Knowledge Management

Artificial intelligence (AI) has long been applied in KMS, from expert systems in the 1980s to current AI-driven analytics [21]. Recent advances in NLP and LLMs, such as GPT-4, PaLM, LLaMA, enable human-like interpretation and synthesis of unstructured texts. Knowledge Graphs offer a structured representation of relationships across entities, supporting inference and semantic search [18]. Yet, these systems are often applied in isolation, lacking integration into agentic frameworks.

Artificial intelligence has rapidly evolved from being an adjunct to core knowledge-management tasks (search, classification) to becoming a central capability that reshapes how organizations capture, curate, and apply knowledge. Recent systematic reviews and thematic studies highlight that AI techniques, especially NLP, machine learning, and GenAI, have support for accelerated codification (automatic extraction and summarization), semantic indexing, and conversational access to institutional knowledge, thereby improving discoverability and reuse [22]. At the same time, the literature stresses that AI's benefits depend on organizational investments in data curation and domain adaptation (e.g., fine-tuning LLMs), since out-of-the-box models often underperform on domain-specific knowledge without proper grounding and quality control [23].

A major technical theme in recent work is hybrid architectures that combine large language models with structured knowledge representations (knowledge graphs, ontologies) and retrieval pipelines to improve factuality, traceability, and task effectiveness. Retrieval-Augmented Generation (RAG) variants, entity linking/NER pipelines, and KG-backed grounding have been proposed and evaluated across industrial and scientific settings to reduce hallucinations and to enable explainable, evidence-anchored responses from generative models [24]. Empirical prototypes in manufacturing, healthcare, and enterprise documentation report meaningful gains in operator support and knowledge transfer when LLM outputs are constrained and augmented by authoritative KGs and indexed corpora [24]. These studies emphasized the technical trade-offs, i.e., complexity and maintenance overhead of KGs versus the generative flexibility of LLMs, and they advocate modular RAG+KG pipelines as a practical compromise.

Alongside technical advances, a strong and growing body of literature and practitioner guidance highlights governance, operationalization, and the emergence of "agentic" AI as key considerations for AI-enabled KMS. Not only are agentic AI autonomous, goal-directed, and could orchestrate multi-step tasks, but they also promise proactive knowledge discovery and workflow automation. Nevertheless, agentic AI also introduces new risks around accountability, data security, and emergent behavior. This has led to recent reviews demanding layered governance, which includes data quality processes, provenance, and provenance-linking of LLM outputs through KGs and RAG, human-in-the-loop validation, and role redesign to integrate AI agents as "non-human resources" with oversight and lifecycle management [22]. In short, the current literature converges on a view of next-generation KMS as hybrid socio-technical ecosystems—technically anchored by LLM with KG integrations and operationally governed by robust oversight, validation, and change management.

2.3 Agentic AI

Agentic AI is characterized by autonomy, goal-oriented behaviour, adaptability, and the capacity to interact with humans in natural ways [25]. Unlike task-specific AI, agentic systems exhibit initiative in negotiating goals and mediating between human contributors. Recent work in multi-agent systems [26] highlights their role in distributed decision-making, but integration into KMS remains underdeveloped.

Agentic AI has emerged as a distinct research and practice area that emphasizes autonomous, goal-directed systems capable of planning, reasoning, and acting with limited human supervision. Early technical demonstrations of the most notable generative agents focused on augmenting large language models with memory, planning, and reflection modules, producing agents that exhibit sustained, believable, multi-step behaviour in simulated social environments [25]. Conceptual and review pieces since 2024 have begun to differentiate ordinary task-oriented "AI agents" from truly agentic systems that combine autonomy, long-term state, and the ability to set or pursue goals across time, laying groundwork for taxonomies and formal definitions

[27], [28]. These foundational studies establish agentic AI not merely as a capability bundle between NLP and automation but as an architectural and behavioural paradigm that requires new evaluation metrics for persistence, adaptability, and emergent interaction.

On the systems and architecture side, the literature has converged on hybrid patterns that combine LLM-based reasoning with subsystem modules for memory, planning, perception, and grounding to external data sources. Practical blueprints formulated by industry and academia have described modular pipelines where observation, memory encoding, deliberation/planning, action, and reflection form a recurring loop [25]. Retrieval-augmented and KG-grounded components are often recommended to reduce factual errors and to provide traceability for decisions made by agents [25]. Research also highlights multi-agent orchestration as a scalable design for complex workflows – ensembles of specialized agents in which task automators, domain orchestrators, and collaborators, coordinated by an orchestration layer, can accomplish composite goals while enabling separation of concerns, auditability, and role-specific governance [27]. These architectural patterns are now being prototyped in both research sandboxes and enterprise pilots, showing promise but also exposing engineering and maintenance trade-offs such as complexity, data hygiene, and lifecycle management.

Finally, a rapidly growing body of practitioner and governance literature addresses sociotechnical, ethical, and organizational implications of deploying agentic systems. Leading consultancies and business journals argue that agentic AI will reshape work by acting as persistent "digital labour," prompting role redesign, new oversight roles (e.g., agent owners, chief AI officers), and layered governance frameworks that set autonomy levels, decision boundaries, provenance requirements, and monitoring/audit mechanisms [29]. Simultaneously, cautionary analyses call attention to emergent risks of hallucinations amplified by autonomous action, prompt or data-injection vulnerabilities, and accountability gaps when agents make consequential choices, recommending human-in-the-loop validation, rigorous testing, and provenance-linking to authoritative knowledge sources [29]. [30]. In sum, the Agentic AI literature is coalescing around three intertwined priorities: robust architectural patterns for agency, empirical evaluation of agent behaviour and value, and governance models that make autonomy safe, auditable, and aligned with organizational goals.

3. Methodology

The methodological approach for this study followed a structured, design-oriented research process aimed at developing a conceptual model of Agentic AI in the context of a knowledge management system (KMS). The process was conducted in three main stages: requirements gathering, analysis, and conceptual model design, with Activity Theory (AT) serving as the analytical framework for mapping user needs to socio-technical system design. In addition, the methodology was explicitly aligned with the core knowledge management processes of knowledge acquisition, retrieval, storage, exchange, and application, ensuring that the conceptual model directly addressed by KM practices.

Table 1 *User requirements for the agentic AI KMS*

Stakeholder	Functional Needs
Farmers	• Easy-to-use interface to report symptoms of crop diseases in text and/or images • Quick and accurate recommendations on treatment and pesticide usage • Reliable identification of plant diseases from field-level data • Specific treatment and pesticide suggestions that are relevant to the crops and region • Digital tools that can interpret natural language queries, recognize plant disease symptoms from images, and recommend treatments • Recommendations aligned with agricultural best practices and safe pesticide usage guidelines • Access to an agricultural knowledge community for learning and peer exchange • Timely, accurate, and actionable recommendations for crop disease management
Experts	• Interface to validate, update, and refine the knowledge stored in the system • Evidence-based support on agricultural practices • Storage and retrieval mechanisms for refining and updating agricultural knowledge • Collaborative interaction tools to share findings, validate data, and advise farmers • Collection of real-time field data on symptoms, crop conditions, treatment, and choice of pesticides from field data • System to enhance agricultural knowledge repositories with validated inputs

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3.1 User Requirements Gathering

The first stage involved collecting user requirements from stakeholders in the agricultural community, i.e., the farmers and agricultural experts who are mainly from the agricultural agency. This included exploratory interviews, observation, and literature-informed elicitation. The requirements were categorized into functional needs and non-functional needs, in which the functional needs that are relevant to the system design are summarized in Table 1.

Table 2 *Activity system of the agentic AI KMS*

AT Element	What	Requirements by Element
Subject	Who performs the activity	• Farmers are the primary subjects who initiative the interaction with the KMS • The Community of Experts acts as secondary subjects who refine and validate knowledge, providing datasets for data training
Object	The goal or problem space	• The diagnosis and treatment of crop diseases • Transformed into an actionable outcome of precise recommendations for disease treatment and pesticide application
Tools	Mediating artefacts used to perform an activity	• Chatbot interface: facilitates natural language interaction • Image capture: enables visual input of diseased crops • NLP: for text interpretation, processing farmers' queries • Image recognition: for plant disease identification on captured images, classifies visual symptoms • ML: for disease determination, supporting decision-making • Knowledge Graphs: map disease-to-treatment and treatment-to-pesticide pathways • LLMs: as knowledge bases, enriching reasoning and generating adaptive responses • File storage: preserves training data for continual learning
Rules	Norms and constraints shaping activity	• Agricultural best practices: adherence to evidence-based farming recommendations • Ethical AI use: ensuring transparency, fairness, and avoiding harmful advice • Community validation protocols: expert checks to ensure data reliability • KM rules: structured storage, retrieval, acquisition, and updating of knowledge
Community	Social context	• Farmers form the user community • Agricultural experts constitute the validating and knowledge-enriching community • The agricultural agency governs the use of KMS and activities in the system
Division of Labour	Structure of tasks and responsibilities	• Farmers: provide field-level observations and apply recommendations • Agentic AI modules: process inputs, retrieve mappings, and generate recommendations autonomously • Experts: validate system outputs, update mappings, and contribute tacit and explicit knowledge • KMS interface: enables coordination between farmers and experts
Outcome	Result of the activity	• Improved agricultural decision-making: farmers receive reliable, AI-assisted recommendations • Increased crop productivity and sustainability: through timely, accurate treatments • Enhanced collective knowledge: system continuously evolves as more inputs and validations enrich the knowledge base

3.2 Analysis through Activity Theory

The requirements were analysed using Activity Theory (AT) [31], [32]. AT has been used as an analysis tool by various researchers to facilitate the understanding of the system design and needs, especially in developing AI-based systems [33], [34], [35]. AT conceptualizes human activity as a system comprising subjects, objects, tools, community, rules, and division of labour. Each of these elements was systematically mapped to both user requirements and the KM processes, as shown in Table 2.

This AT-guided analysis ensured that the design accounted not only for technological affordances but also for the integration of KM processes into the sociotechnical system. Table 3 summarizes the AT elements above as they are mapped to the KM processes and relevant elements in the proposed agentic AI for KMS.

Table 3 *Mapping of activity theory elements, KM processes, and KMS design features*

AT Element	Mapped KM Process	Relevant Element in Agentic AI for KMS
Subject (actors)	Knowledge Acquisition – Farmers provide experiential knowledge (text, images), Experts contribute tacit/explicit knowledge	Farmers (end-users), Experts (validators, contributors)
Object (goal/problem)	Knowledge Application – The object of activity is achieved when knowledge is applied to solve farmers' problems in the field	Identifying plant diseases and recommending suitable treatment and pesticides
Tools / Artefacts (mediating technologies)	Knowledge Acquisition (capturing input via tools), Knowledge Retrieval (AI-driven search/mapping), Knowledge Storage (databases, LLMs), and Knowledge Application (recommending solutions)	Chatbot, Image Capture, NLP, Image Recognition, ML, Knowledge Graphs, LLMs, File Storage
Rules (norms, constraints)	Knowledge Storage & Retrieval – Ensures structured, validated, and ethical use of knowledge; governs how knowledge is stored, shared, and reused	Agricultural best practices, AI ethics, expert validation protocols, and KM procedures
Community (social actors)	Knowledge Exchange – Collaboration between farmers and experts enriches and validates the knowledge system	Farmers, Experts, Researchers, AI developers
Division of Labor (role distribution)	Knowledge Acquisition (farmers input data), Knowledge Retrieval (AI interprets & recommends), Knowledge Storage (experts refine/update databases), Knowledge Exchange (interactions among actors)	Farmers provide field inputs; AI processes and analyses; Experts validate and refine; KMS coordinates interactions
Outcome (final result)	Knowledge Application & Exchange – Knowledge is not only applied by farmers but also circulated back into the system for refinement and reuse	Reliable, actionable treatment recommendations; evolving knowledge base; improved agricultural practices

Fig. 1 illustrates the Activity Theory (AT) analysis, in which the KM processes are mapped to the relevant AT elements as stated in Table 3.

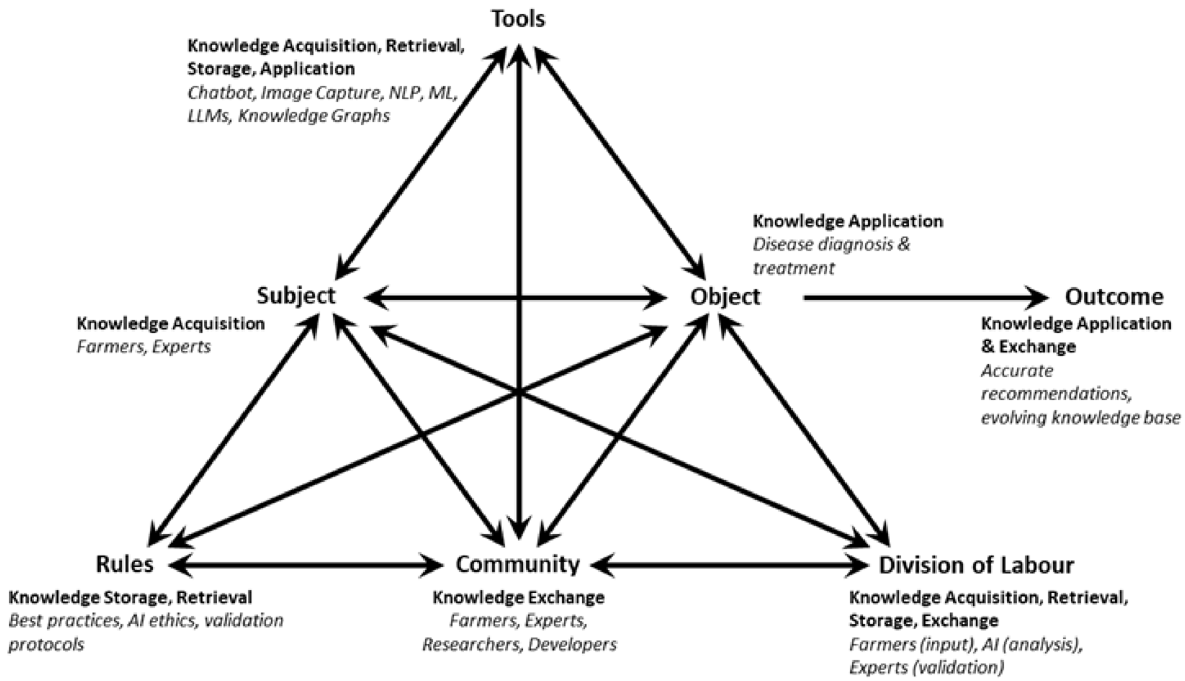

Fig. 1 *Activity theory framework mapped to knowledge management processes of the case study*

3.3 Conceptual Model Design

The final stage involved designing the conceptual model of agentic AI-enabled KMS, based on the AT analysis and KM process mapping as shown in Table 3 and Fig. 1. The design integrated requirements into a structured model where agentic AI supports the full KM cycle for the studied case of agricultural community, i.e., from facilitating knowledge acquisition, to enabling knowledge storage and retrieval, to promoting knowledge exchange that involved farmers and community of experts, and finally enhancing knowledge application. The model was iteratively refined through internal reviews, ensuring alignment with both Activity Theory and KM processes.

4. Agentic AI in KMS

The proposed conceptual model integrates Agentic AI into a Knowledge Management System (KMS) to support farmers in identifying and treating plant diseases through intelligent knowledge acquisition, retrieval, storage, and exchange. Knowledge application refers to the whole KMS in which knowledge is applied to meet the objective of disease diagnosis and treatment for the crops. Fig. 2 shows this illustration, which integrates human actors, intelligent interfaces, and AI-driven processes across the four dimensions of knowledge management.

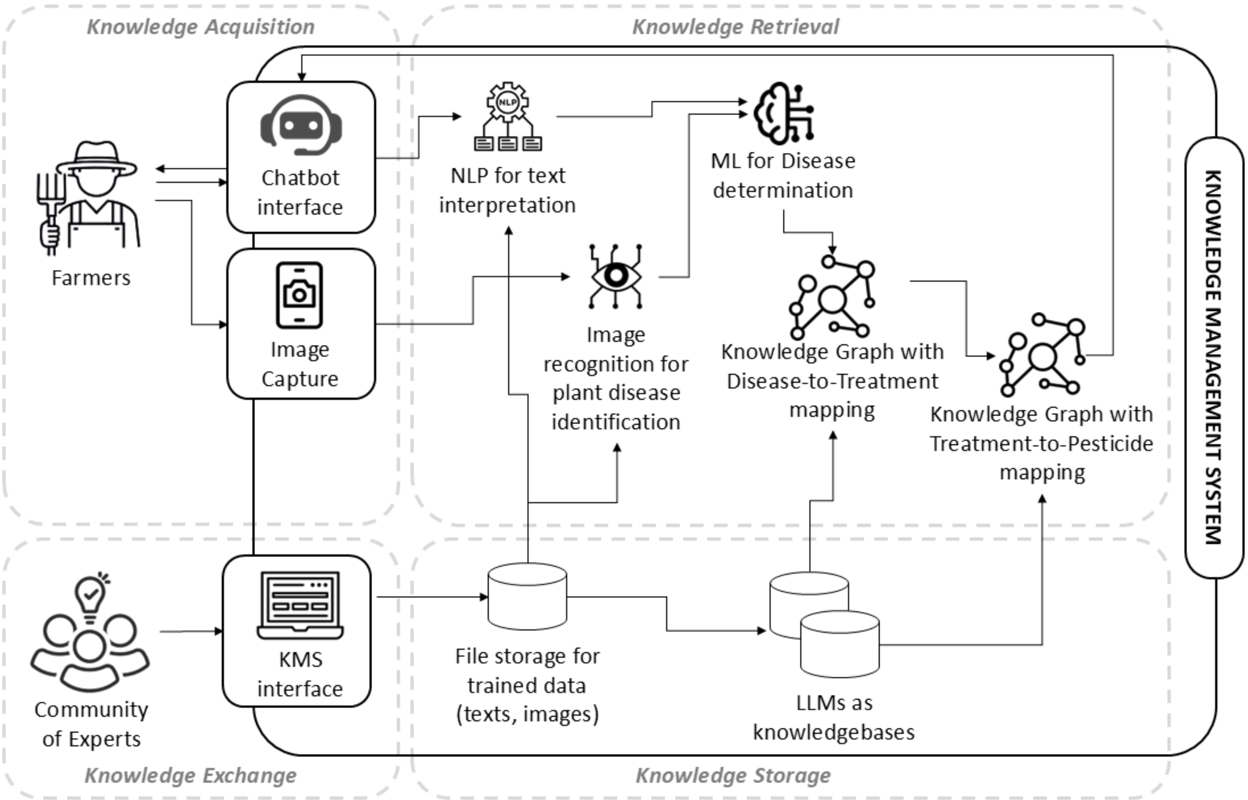

Fig. 2 *Agentic AI in KMS for the agricultural community*

Knowledge Acquisition: Fig. 2 shows how the farmers acquire knowledge through two main entry points of the KMS on the mobile device. Farmers input questions or descriptions of the crops' condition in natural language through the chatbot interface, and/or upload or capture an image of the diseased crops. These inputs feed into the AI modules, namely the natural language processing (NLP) that interprets textual queries, and the image recognition module that identifies crop diseases from images. At the end of the KM processes, the farmers will acquire the feedback, i.e., acquire knowledge, on the pesticide recommendation for the relevant identified diseases.

Knowledge Retrieval: Fig. 2 shows the processes that involve five AI modules: NLP, image recognition, machine learning (ML), and two knowledge graphs. Machine learning models determine the type of crop disease based on text or image inputs. This determination is based on the sample images produced from a set of trained data stored in the file storage. Knowledge graphs organize and map relationships across domains: disease-to-treatment mapping and treatment-to-pesticide mapping. Disease-to-treatment mapping connects identified diseases with appropriate treatment strategies, whereas treatment-to-pesticide mapping further links the treatments to specific pesticides available or recommended. This part of knowledge retrieval ensures accurate, evidence-based recommendations that are generated for farmers.

Knowledge Storage: As shown in Fig. 2, the KMS maintains both structured and unstructured data in the file storage. File storage keeps trained datasets that are derived from text and image data for model improvement. This storage is referred to by the AI modules for the knowledge retrieval process, as mentioned above. On the other hand, another element that exists and is being used and referred to from this storage is the large language models (LLMs). LLMs serve as dynamic knowledge bases, capable of generating context-aware recommendations and explanations. Stored knowledge continuously evolves as it is being updated with new data inputs, improving the system's accuracy and adaptability.

Knowledge Exchange: The basic idea of this KMS is to allow and facilitate knowledge exchange among the community members, which mainly consists of the farmers and the experts. The community of experts would include those from the agricultural agencies, as well as senior practitioners and pesticide experts. The KMS interface connects the farmers with the community of agricultural experts, enabling bi-directional knowledge exchange. Experts can validate, refine, and extend the knowledge stored in the system, ensuring both scientific accuracy and local contextual relevance, such as the type of crops, soil, and environmental factors. This collaborative feedback loop strengthens the credibility of recommendations delivered to farmers.

The overall agentic nature of the AI portrayed in Fig. 2 lies in its ability to autonomously interpret multimodal inputs (i.e., text and images), retrieve relevant disease-treatment-pesticide pathways, leverage LLM-based reasoning to refine outputs, facilitate expert validation and update the knowledge repository, and deliver actionable, personalized guidance back to the farmers in an accessible format.

This conceptual model transforms the agricultural KMS into a self-improving, community-driven, AI-powered ecosystem. The combination of the farmers' real-time field data, expert knowledge, and advanced AI-driven retrieval mechanisms ensures timely, precise, and contextually relevant crop disease management solutions, ultimately supporting sustainable agricultural practices and improving farmer productivity.

5. Findings and Discussion

The conceptual model developed in this study integrates Agentic AI capabilities with the fundamentals of knowledge management (KM) processes. The design was derived from the analysis made using the Activity Theory (AT) framework, which ensured that the model addresses not only technological affordances but also the social and organizational dimensions of knowledge work, although the roles of system developer and other administrative positions are excluded. The model thus positions Agentic AI as a socio-technical mediator, enabling adaptive, autonomous, and accountable support for organizational knowledge ecosystems.

The model emphasizes interactional dynamics of the agricultural community, instead of static components that make up the whole KMS. User activities are mediated by AI agents, following the protocols of KM processes of autonomously acquiring, retrieving, storing, and facilitating exchange. In retrieving knowledge, the ML module also refers to the sample data previously generated from trained data stored in the file storage to produce the output of the identified crop diseases. The data training part is not shown in the conceptual model in Fig. 2, as it happens at the back end of the KMS.

Supplementing the need for determining the right treatments and pesticides for affected crops, knowledge graphs are referred to. These knowledge graphs are also not static in nature, as they are dynamically updated based on the updated data in the file storage, through the LLMs that act as the knowledge base for the KMS. This highlights the dynamic criteria that agentic AI offers in enhancing the capacity and capabilities of the KMS.

The conceptual model contributes both theoretically and practically, as it bridges the three aspects to make the design significant, i.e., the AT, KM processes, and agentic AI. It offers a blueprint for designing and/or evaluating KMS that leverage agentic AI responsibly, making the KMS specifically relevant to the needs of the agricultural community. It is expandable to a wider range of users that constitute the agriculture ecosystem, such as pesticide suppliers, agricultural funders and investors, and governing bodies. It is also scalable, in terms of producing data visualization and analytics from the retrieved and updated data, as well as forecasts and predictions for future strategic planning and management, which will lead to economic growth and sustainable agriculture in the country.

6. Conclusion

This study has proposed a conceptual model of Agentic AI in Knowledge Management Systems (KMS), grounded in Activity Theory (AT), and aligned with the core KM processes of knowledge acquisition, storage, retrieval, and exchange. By integrating user requirements, socio-technical analysis, and agentic AI capabilities, the model positions autonomous AI agents as mediators of community knowledge work, enabling more adaptive, accountable, and collaborative knowledge ecosystems.

This conceptual model proves its usability in public sector and community-based knowledge initiatives, in which the agentic AI can enhance inclusivity and accessibility, ensuring that knowledge resources are discoverable and usable by diverse stakeholders, specifically the farmers. Knowledge is accessible from the palm of the farmers' hands, where they need it in real-time, on the field, as they act as the frontline, active participants in the agricultural ecosystem. The model is not domain-specific but rather adaptable to varied organizational contexts where knowledge is the central need in ensuring the efficiency of knowledge work and the effectiveness of producing quality products.

In conclusion, the proposed conceptual model contributes both theoretically and practically to the fields of knowledge management and artificial intelligence. Theoretically, it advances the conversation by bridging KM processes, AT, and agentic AI into a unified socio-technical framework. Practically, it offers organizations a blueprint for designing or evaluating next-generation KMS that are adaptive, trustworthy, and aligned with human and organizational goals.

Future research should move beyond conceptualization and toward empirical validation. This includes prototyping agentic AI-enabled KMS, testing them in different community domains, and evaluating their impact on knowledge productivity, collaboration, and decision quality. Further work should also explore the governance framework for agentic AI, addressing issues of accountability, explainability, and human oversight. Finally, interdisciplinary collaboration will be essential for the expansion of this study, such as insights from information systems, AI research, organizational studies, and ethics.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Declaration of AI Use in Manuscript Preparation

The authors used Grammarly to assist the grammar checking and language editing. All content generated was reviewed and verified by the authors, who take full responsibility for the final submission.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Shahrinaz Ismail, Nurul Izzatie Husna Fauzi;* ***data collection:*** *Shahrinaz Ismail, Nurul Izzatie Husna Fauzi;* ***analysis and interpretation of results:*** *Shahrinaz Ismail, Siti Haryani Shaikh Ali, Nurul Izzatie Husna Fauzi, Nor Azizah, Jacques Morcos;* ***draft manuscript preparation:*** *Shahrinaz Ismail, Nurul Izzatie Husna Fauzi. All authors reviewed the results and approved the final version of the manuscript.*

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