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An AI-Assisted Knowledge Management System Prototype for Fisheries Extension Officers: A Usability Evaluation

Dani Saepuloh[1], Irman Hermadi[2], Yani Nurhadryani[3]

[1]Computer Science, Postgraduate Program, IPB University, Bogor, Indonesia

[2,3]Computer Science, School of Data Science, Mathematics, and Informatics, IPB University, Bogor, Indonesia

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Corresponding Author:
Author Name*:
Dani Saepuloh
Email*:
d4n1.saepuloh@gmail.com

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Abstract. Fisheries extension officers accumulate tacit knowledge that is rarely documented and at risk of loss as senior officers retire, while existing systems lack structured capture and motivation mechanisms. This study develops and evaluates a Knowledge Management System (KMS) prototype integrating AI-guided narrative acquisition, knowledge mapping, and gamification to support tacit-knowledge externalization. Using PHP, MySQL, and Google Gemini 1.5 Flash, spoken field narratives are structured via the STAR framework under human review, visualized through a weighted expertise graph, and reinforced through a Self-Determination-Theory-based motivational mechanism. Ten fisheries extension officers (five senior, five junior) evaluated the prototype through scenario-based testing, the System Usability Scale, and interviews. Functional black-box testing confirmed that all six core scenarios (authentication, voice-based STAR extraction, moderation, knowledge mapping, gamification, and messaging) executed correctly (6/6, 100% pass rate), and the prototype achieved a mean SUS score of 83.5 (excellent), with qualitative findings indicating reduced perceived documentation burden and increased motivation, alongside dialect-recognition and internet-dependency limitations. This integrated prototype architecture demonstrates preliminary perceived effectiveness rather than validated organizational impact, given the small sample and short-term evaluation.

Keywords: AI-Assisted Knowledge Management System (KMS); Knowledge Mapping; Large Language Model (LLM); STAR Framework; Tacit Knowledge Externalization

1. INTRODUCTION

Knowledge management has become a decisive factor in the competitiveness and resilience of organizations operating in primary and resource-based sectors such as agriculture and fisheries, where field practitioners accumulate rich, context-dependent expertise through years of direct engagement with local communities and ecosystems. Recent quantitative evidence indicates that sharing this tacit dimension of knowledge embedded in intuition, judgment, and hands-on skill contributes more strongly to organizational creativity than the sharing of explicit, codified knowledge alone [1]. Yet international studies in the primary sector show that externalizing tacit expertise from field practitioners remains difficult, constrained chiefly by limited digital literacy, uneven technology adoption, and organizational cultures not yet fully conducive to open knowledge sharing [2]. These barriers position tacit-knowledge management not merely as a technical challenge but as a structural precondition for sustaining institutional memory in knowledge-intensive extension services worldwide.

For clarity, four constructs central to this study are defined as follows. Tacit knowledge refers to knowledge rooted in an individual's personal experience, intuition, and hands-on skill, which is difficult to codify or transfer through formal documentation alone [3],[4]; in the fisheries extension context, this includes field-acquired judgment such as diagnosing aquaculture disease from subtle visual cues or mediating community conflict using locally attuned communication strategies. Externalization denotes the process of converting such tacit knowledge into explicit, articulable form the second mode of Nonaka and Takeuchi's SECI model of organizational knowledge creation [5] and constitutes the central cognitive bottleneck this study addresses. Knowledge sharing culture refers to the organizational norms and practices that either encourage or inhibit voluntary knowledge exchange among employees [1]; in BPPSDMKP, this culture currently manifests informally through unstructured channels rather than institutionalized mechanisms. Knowledge mapping refers to the process and resulting artifact typically a graph or network visualization that identifies who holds specific expertise within an organization and how that expertise is distributed, thereby reducing the search cost of locating relevant knowledge holders [6]. These four constructs jointly frame the problem this study addresses: tacit knowledge exists but is neither externalized, culturally incentivized to be shared, nor made navigable once captured.

In Indonesia, the national development agenda toward a resilient blue economy and food security places fisheries extension officers at the frontline of translating government policy and technological innovation into practice across thousands of coastal communities [3]. Their mandate, formally defined under Ministerial Regulation No. 18 of 2022 on the Fisheries Extension Officer Functional Position, extends beyond information dissemination to the enhancement of knowledge, skills, and attitudes among fisheries stakeholders [4] a definition that inherently places knowledge transfer at the core of the profession. Fulfilling this mandate, however, depends on a documentation ecosystem capable of capturing the practical, experience-based knowledge that generic manuals and standard procedures cannot adequately convey. The prototype developed in this study is scoped specifically to the operational context of BPPSDMKP; it is not designed, tested, or claimed to generalize to fisheries extension services administered by other Ministry units or provincial governments, although Section 5 discusses this broader integration as future work.

Within the Agency for Extension and Human Resources Development of Marine and Fisheries (BPPSDMKP) under the Ministry of Marine Affairs and Fisheries, this dependency has become an acute organizational risk. As of the first semester of 2025, BPPSDMKP employed 4,026 fisheries extension officers, of whom 638 officers (15.8%) were above the age of 50 [7] [5], a figure drawn from an official, digitally certified workforce update issued by the Center for Marine and Fisheries Extension and corroborated by the agency's publicly disseminated distribution summary for the same reporting period a demographic segment that concentrates decades of field-based expertise while simultaneously approaching retirement. The resulting threat of irreversible knowledge loss directly undermines the achievement of BPPSDMKP's strategic target of a competent marine and fisheries workforce and risks lowering the agency's electronic government performance index [8]. Compounding this risk, the tacit expertise that extension officers rely on ranging from diplomatic mediation of community conflict to intuitive diagnosis of aquaculture disease and locally adapted modification of fishing gear is rarely documented in any structured form [9], and instead circulates informally through fragmented channels such as WhatsApp groups, where it is easily lost and difficult to retrieve [10]. No dedicated digital infrastructure currently exists within the Ministry to capture, structure, and disseminate this class of knowledge systematically.

Several prior studies have attempted to address related knowledge management challenges in Indonesian public and agricultural institutions, yet each leaves specific gaps relevant to the present context. Hermadi et al. developed and evaluated a participatory knowledge management prototype for oil-palm smallholders using the System Usability Scale and Cognitive Task Analysis, improving usability from 71.6 to 80.6 through iterative refinement; the study, however, relied on conventional textual input and did not incorporate structured narrative acquisition or graph-based expertise visualization [11]. Nurhadryani et al. designed a front-end module for a digital village knowledge management system aimed at accelerating innovation adoption among rural communities, but the work concentrated on one-way information dissemination rather than interactive, two-way knowledge capture [12]. In the public-sector governance domain, Syazwina and Ikhwan, along with Mahgfiroh et al., demonstrated that web-based knowledge management systems can preserve institutional memory and strengthen staff understanding in government agencies, yet both implementations remained passive document repositories without mechanisms for actively locating expertise or sustaining user participation [13], [14]. Sugiarti et al. examined the agribusiness supply chain for aglaonema farmers and identified weak communication and limited innovation as persistent adoption barriers, reinforcing the relevance of sociocultural constraints in primary-sector knowledge management but stopping short of proposing a motivational solution [15]. Finally, Pelealu found that knowledge sharing significantly affects employee performance and loyalty, providing empirical justification for prioritizing knowledge-sharing behavior, yet without addressing how such behavior can be deliberately engineered into a system's design [16]. Collectively, these studies confirm the value of knowledge management systems in Indonesian public and agricultural contexts, but none combines AI-guided narrative acquisition, graph-based expertise visualization, and a theory-driven motivational mechanism within a single, integrated architecture.

At the international level, the rapid maturation of large language models has renewed interest in AI-assisted knowledge management. O'Leary characterizes generative AI and prompt libraries as a “rebirth” of enterprise knowledge management, arguing that LLMs increasingly function as an active layer for organizing and retrieving organizational knowledge rather than a passive repository [17]. He and Burger-Helmchen similarly trace how AI reshapes the social dynamics of knowledge management, cautioning that AI should augment rather than substitute the interpersonal processes through which tacit

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knowledge is conventionally shared [18]. Closer to the present study's methodological approach, Zuin et al. propose an LLM-based agent that iteratively reconstructs organizational tacit knowledge through simulated conversational interaction, reporting high recall in retrieving distributed knowledge without requiring direct access to a single domain expert [19]. While these studies establish that LLMs can meaningfully support tacit-knowledge externalization and retrieval at the enterprise level, they are validated in generic corporate or simulated settings and do not address field-based, low-digital-literacy extension work, nor do they combine narrative structuring with expertise visualization and sustained-motivation mechanisms within one deployed prototype.

Taken together, the domestic and international literature reveal a consistent, two-part gap directly connected to the three contributions this study proposes. First, existing Indonesian knowledge management systems address only isolated dimensions of the knowledge management cycle passive storage [11], [12], one-way dissemination [10], or usability-focused capture without structured narrative acquisition [9] motivating this study's first contribution: a structured, AI-guided narrative acquisition mechanism. Second, while recent international work demonstrates that LLMs can support tacit-knowledge retrieval and organizational knowledge dynamics [27]–[29], none integrates this capability with graph-based expertise navigation and a theory-driven, sustained-motivation mechanism suited to a field-based, variable digital literacy workforce motivating this study's second and third contributions: knowledge mapping for expertise navigation and Self Determination Theory grounded gamification for sustained participation. No prior system, domestic or international, has been designed and evaluated specifically for fisheries extension work, where officers face acute time constraints, variable digital literacy, and geographically dispersed, informal knowledge-sharing habits.

Figure 1 (research flow, Section 2.1) is preceded conceptually by the following theoretical framework linking constructs to system components in a sequential chain. The framework begins with the Externalization mode of Nonaka and Takeuchi's SECI model [15] as the theoretical starting point, representing the conversion of tacit field knowledge into explicit form. This conversion is operationalized through a STAR Narrative structure, which decomposes a field experience into Situation, Task, Action, and Result components to reduce the cognitive burden of unguided free-text documentation. A Large Language

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Model (LLM), paired with speech-to-text input, assists officers in structuring spoken narratives into this STAR format under human review before publication. Structured narratives then populate a Knowledge Mapping module, which visualizes expertise as a weighted graph to make fragmented knowledge navigable. To sustain long-term participation, a Gamification mechanism grounded in Self-Determination Theory's three psychological needs of competence, autonomy, and relatedness [20] incentivizes continued contribution. Together, sustained contribution is theorized to strengthen organizational Knowledge Sharing, which is evaluated in this study through Perceived Usability (via the System Usability Scale) and qualitative perception data, rather than through longitudinal behavioral or organizational-performance outcomes, which lie beyond the scope of this evaluation.

To close this gap, this study proposes a Knowledge Management System that integrates three complementary pillars within a single architecture, following the conceptual framework above. First, an AI-assisted guided narrative mechanism operationalizes organizational storytelling [10] through the Situation-Task-Action-Result (STAR) framework, combined with speech-to-text and large language model processing, to minimize the cognitive burden of tacit-knowledge externalization identified as the central bottleneck of the Externalization mode in the SECI model [15]. Second, a weighted-graph Knowledge Mapping module transforms narrative entries into a dynamic expertise locator, resolving the fragmentation that conventional repositories leave unaddressed. Third, a gamification mechanism points, badges, and leaderboards is deliberately designed around the three psychological needs of Self-Determination Theory (competence, autonomy, and relatedness) [16] to support sustained participation, rather than being applied ad hoc as in prior implementations. While each of these elements has individually been explored in prior knowledge management research, their holistic integration narrative-based externalization, graph-based expertise mapping, and theory-driven gamification within one deployed system has not previously been demonstrated within the specific operational context of fisheries extension services; this study does not claim this combination to be novel in an absolute or global sense.

Accordingly, this study aims to (1) design and develop a functional KMS prototype that integrates STAR-based guided narrative acquisition with knowledge mapping for the externalization and visualization of tacit knowledge; (2) implement a gamification

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mechanism intended to strengthen the intrinsic motivation and active participation of extension officers in knowledge sharing; and (3) evaluate the usability and perceived effectiveness of the resulting prototype through mixed-methods testing involving end users.

2. METHODS

2.1. Research Design

This study adopts a concurrent mixed-methods design, in which quantitative usability data and qualitative perception data are collected and analyzed in parallel to cross-validate the evaluation of the resulting prototype. The overall research procedure problem identification, literature review, requirements gathering, system modeling, prototype development, and testing and evaluation is illustrated in Figure 1. The prototype development itself follows the Knowledge Management System Life Cycle (KMSLC) [17], selected for its comprehensive coverage from infrastructure assessment through implementation, adapted in this study to accommodate the integration of three intervention pillars: guided-narrative acquisition, knowledge mapping, and gamification (Figure 2).

Figure 1. Research Flow Diagram

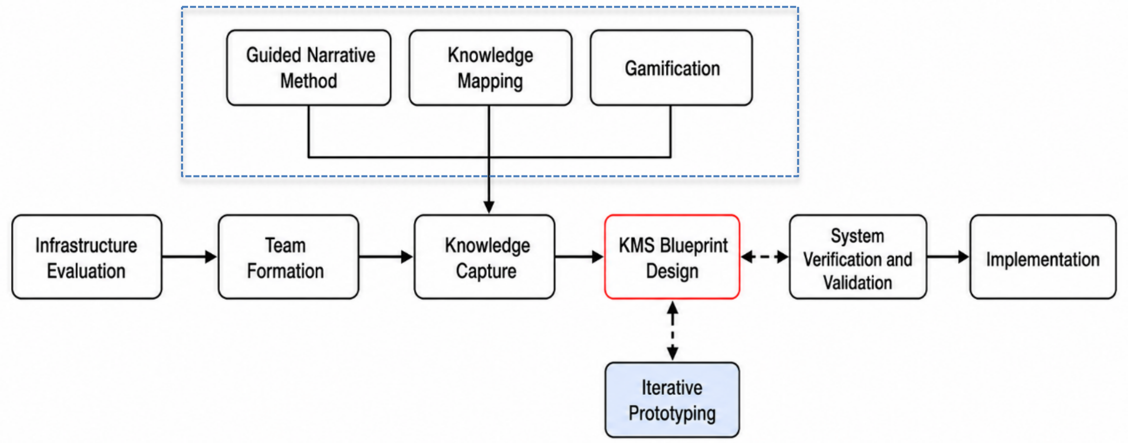

Figure 2. Adapted KMSLC model integrating three intervention pillars

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2.2. Infrastructure Assessment and Team Formation

The KMSLC begins with an infrastructure assessment to determine organizational readiness. This step confirmed that the Ministry's existing Wide Area Network, cloud-based data center, and mobile connectivity at the field level were adequate to support a web-based system with AI-driven voice processing, while also revealing that no existing information system was dedicated to managing structured, narrative-based intellectual assets. A multidisciplinary development team was subsequently formed, comprising a project champion, a knowledge manager, subject-matter experts (senior extension officers), a knowledge engineer, a system developer, and a quality assurance role, to ensure that both technical validity and domain relevance were maintained throughout development.

2.3. Requirement Analysis and Knowledge Acquisition

User requirements were gathered through in-depth qualitative interviews with prospective users, focusing on how officers currently narrate field experience, which categories of knowledge they consider most critical to share, and what factors motivate or inhibit digital knowledge sharing. This stage was designed to elicit user requirements rather than tacit knowledge itself, and its output directly informed the system blueprint, including the decision to operationalize storytelling as a Guided Narrative Method structured around the Situation-Task-Action-Result (STAR) framework, in which the practitioner not the interviewer owns the narrative while a logical scaffold ensures completeness. The exact number of participants involved in this requirement-gathering stage, and a formal interview protocol distinct from the semi-structured guide used in the subsequent evaluation stage, were not systematically documented at the time and are therefore not reported quantitatively; this is acknowledged as a reporting limitation in Section 4, and future iterations of this work will document requirement-gathering procedures with the same rigor applied to the evaluation stage reported in Section 2.5.

2.4. System Design and Development

The blueprint was translated into an N-tier architecture separating the presentation, application logic, and data layers, with a front-controller pattern centralizing session authentication and request routing. Three modules were implemented to realize the three research pillars:

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1) Guided-narrative acquisition module.

A Web Speech API captures spoken field narratives in real time and transmits the resulting raw text, via a REST/HTTPS/JSON interface, to the Gemini 1.5 Flash large language model, which is prompted to act as an information extractor that classifies the narrative into the four STAR components. The extracted structure is returned to the user interface for review rather than committed directly to the database, implementing a human-in-the-loop mechanism in which the extension officer, as domain expert, validates or corrects the AI output before publication. This human validation step is the sole reliability safeguard adopted in this study; no systematic, quantitative evaluation of extraction accuracy (e.g., correction-rate analysis, inter-rater comparison against expert-coded STAR fields) was conducted. This is acknowledged as a limitation of the present prototype-stage evaluation, and quantifying AI extraction reliability is identified as a priority direction for future work (Section 4).

2) Knowledge Mapping module

Validated narratives are tagged for key entities and represented as a weighted graph, rendered client-side using the JavaScript vis-network library, with extension officers and knowledge categories as nodes and contribution frequency encoded as edge thickness. This module functions as a dynamic expertise locator that allows users to identify who is knowledgeable about a given topic without manual profile curation.

3) Gamification module

An event-driven rule engine allocates 50 points for each published narrative and 5 points for each discussion comment, with all point transactions implemented as atomic database operations to prevent exploitation. A badge validator object evaluates point thresholds in real time and updates user predicates accordingly (e.g., from "New Contributor" to "Field Expert"). Points, badges, and leaderboard rankings are surfaced through a user dashboard, operationalizing the three psychological needs of Self-Determination Theory competence through badge recognition, autonomy through free choice of narrative content, and relatedness through leaderboard visibility and discussion features.

Prototyping followed an iterative cycle of build–test–refine until functional stability was reached, using PHP, MySQL, and Bootstrap 5 on a standard development workstation.

2.5. Evaluation Method

Prototype verification and validation followed a two-stage procedure. First, black-box testing was conducted to verify functional correctness of authentication, voice-based STAR extraction, knowledge mapping, and gamification logic against expected outputs, without inspecting internal code structure. Second, end-user evaluation employed purposive sampling [21] to recruit ten fisheries extension officers, divided into two role-based groups: five senior officers (more than 20 years of experience), evaluated as knowledge producers, and five junior officers (fewer than 5 years of experience), evaluated as knowledge consumers. Beyond this experience-based grouping, detailed demographic characteristics of participants (age distribution, gender balance, regional origin, digital-literacy level, and prior exposure to digital knowledge management tools) were not systematically recorded, which limits the extent to which the sample's representativeness can be assessed; this is acknowledged as a limitation in Section 4. This sample size is consistent with usability-testing conventions indicating that a large share of usability problems can be identified with a small number of participants [22], with additional participants beyond ten yielding diminishing informational returns [23]. Each participant completed a role-specific scenario senior officers externalizing a challenging field experience via the STAR voice interface, junior officers locating a solution via the Knowledge Map after which they completed the System Usability Scale (SUS) questionnaire [24] and a semi-structured interview addressing the perceived effectiveness of the STAR interface, the clarity of the Knowledge Map, and the influence of gamification on motivation [25]. The evaluation setting (e.g., field office versus training environment) was not formally documented and is likewise noted as a reporting limitation.

Quantitative SUS responses were scored using the standard formula (odd-item scores minus one; five minus even-item scores; sum multiplied by 2.5) and interpreted against the conventional acceptability benchmark of 68. Qualitative interview transcripts were analyzed using six-phase thematic analysis [26] familiarization, initial coding, theme searching, theme reviewing, theme definition, and reporting with resulting themes mapped against the SECI model (cognitive barriers to externalization) and Self

Determination Theory (motivational needs). Coding was conducted by the research team without a formal multi-coder inter-rater reliability procedure or participant member checking; this single coder approach is acknowledged as a methodological limitation that may affect the trustworthiness of the thematic interpretation, and future work will adopt dual-coder verification and member-checking to strengthen qualitative rigor.

2.6. Ethical Considerations

Participants took part in an internal service-improvement evaluation activity coordinated through their extension work unit. Formal documentation of individual informed consent, data anonymization procedures, and institutional ethics committee review was not maintained for this study; this absence of formal ethical documentation is acknowledged as a limitation, and future deployment-stage studies involving this prototype will incorporate a documented informed consent process and institutional ethics review consistent with standard human subjects research practice.

3. RESULTS AND DISCUSSION

3.1. System Architecture and Blueprint

The prototype was implemented as a web-based, N-tier application separating presentation, application logic, and data layers, with a front-controller pattern centralizing authentication and request routing. Table 1 summarizes the technical components mapped against their function within the SECI knowledge conversion model.

Table 1. Technical components of the KMS blueprint mapped to SECI functions

Component	Technology/Method	SECI Function
Interface	Bootstrap 5, Web Speech API	Tacit knowledge capture
Logic engine	PHP native (router pattern)	Data-flow governance
AI processor	Google Gemini 1.5 Flash (LLM)	Externalization (tacit to explicit)
Data visualization	vis-network (graph theory)	Combination and socialization (navigation)
Motivation engine	SDT-based gamification	Sharing-culture sustainability

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Component	Technology/Method	SECI Function
Database	MySQL (relational schema)	Intellectual-asset storage

Two actors were defined in the system's use-case model (Figure 3): the Extension Officer (knowledge worker), authorized to externalize knowledge (manual or voice input), navigate the expertise map, access the e-library, and participate in discussion forums; and the Administrator, authorized to moderate content, manage users and categories, and audit gamification points. The activity diagram of the narrative externalization workflow confirmed an asynchronous exchange between the client interface, the Gemini AI engine, and the database, incorporating a human-in-the-loop review step before any knowledge entry is committed. The sequence diagram of the gamification engine confirmed that point allocation (50 points per published narrative, 5 points per comment) and badge threshold evaluation execute as atomic, real-time transactions following each successful database write.

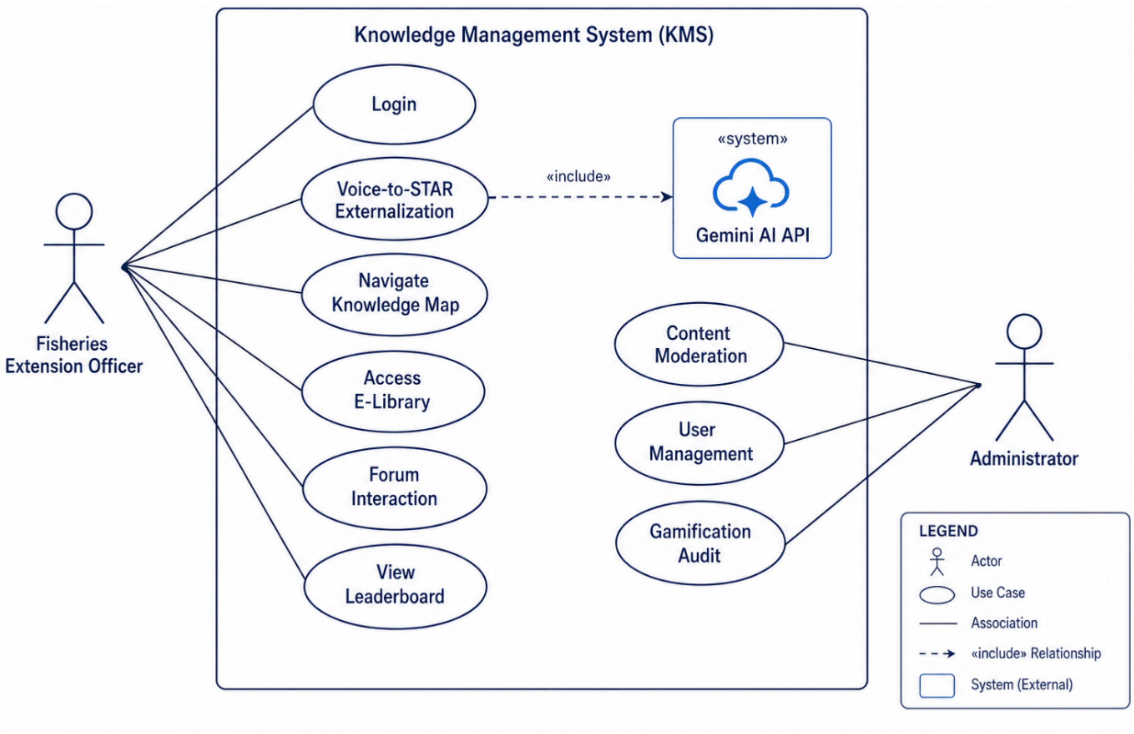

Figure 3. Use case diagram

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3.2. Guided-Narrative Acquisition Module (STAR + Voice AI)

The interface (Figure 4) offers users a choice between manual STAR entry and voice-based narration. In the voice mode, the Web Speech API captures spoken narrative, and the Gemini 1.5 Flash model parses the resulting raw text into the four STAR components (Situation, Task, Action, Result) returned as structured JSON. The extracted fields populate an editable review form, allowing the extension officer to correct any element before publication.

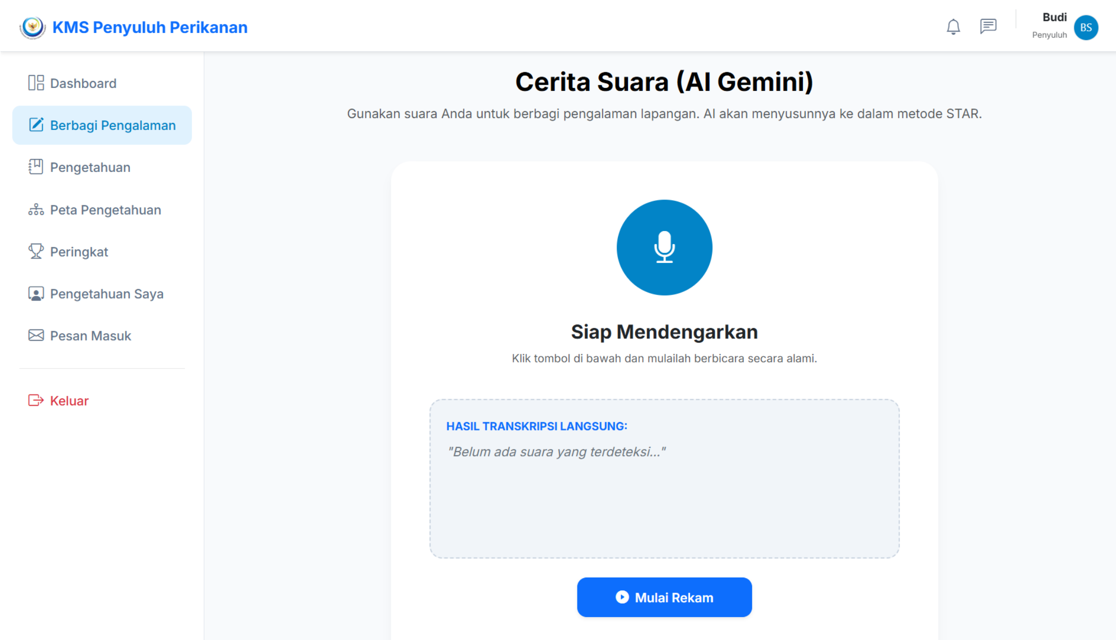

Figure 4. STAR entry and voice-based narration

To illustrate how AI extraction and human review jointly shape the published narrative, an anonymized, representative example from the evaluation is presented below. Speaker and location identifiers have been removed or generalized to protect participant privacy.

Raw spoken narrative (transcribed): *"So there was a farmer, his shrimp pond, the water suddenly turned cloudy and a lot of shrimp died in one night, he called me, I went to check the pond, I checked the dissolved oxygen and it was very low, so I told him to run the paddlewheel aerator immediately and reduce the feeding, after two days the pond recovered and he didn't lose the rest of the harvest."*

AI-generated STAR structure (Gemini 1.5 Flash, before human review): Situation: "A shrimp pond experienced sudden water turbidity and mass mortality overnight." Task:

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"Diagnose the cause and restore pond conditions before further losses occurred." Action: "Measured dissolved oxygen and found it critically low; advised the farmer to run the paddlewheel aerator and reduce feeding rate." Result: "The pond recovered within two days and the remaining harvest was saved."

Human-corrected STAR output (as published, after officer review): The Action field was edited to add the specific dissolved-oxygen threshold that triggered the aerator recommendation (below 3 mg/L), a numeric detail the officer considered essential for another practitioner to replicate the diagnosis; the AI-generated Situation, Task, and Result fields were accepted without change. This single case is illustrative rather than representative of correction frequency across all submissions, since a systematic correction-rate log was not implemented in this evaluation cycle (Section 3.1.8); instrumenting and reporting correction rates across all submissions is identified as a priority for subsequent evaluation (Section 3.2.4).

3.3. Knowledge Mapping Module

The Knowledge Map (Figure 5) renders extension officers and knowledge categories as nodes in a weighted graph, with edge thickness proportional to contribution frequency. The interface simultaneously lists the most active contributors per category, allowing users to identify subject-matter experts directly from the visualization without manual profile search.

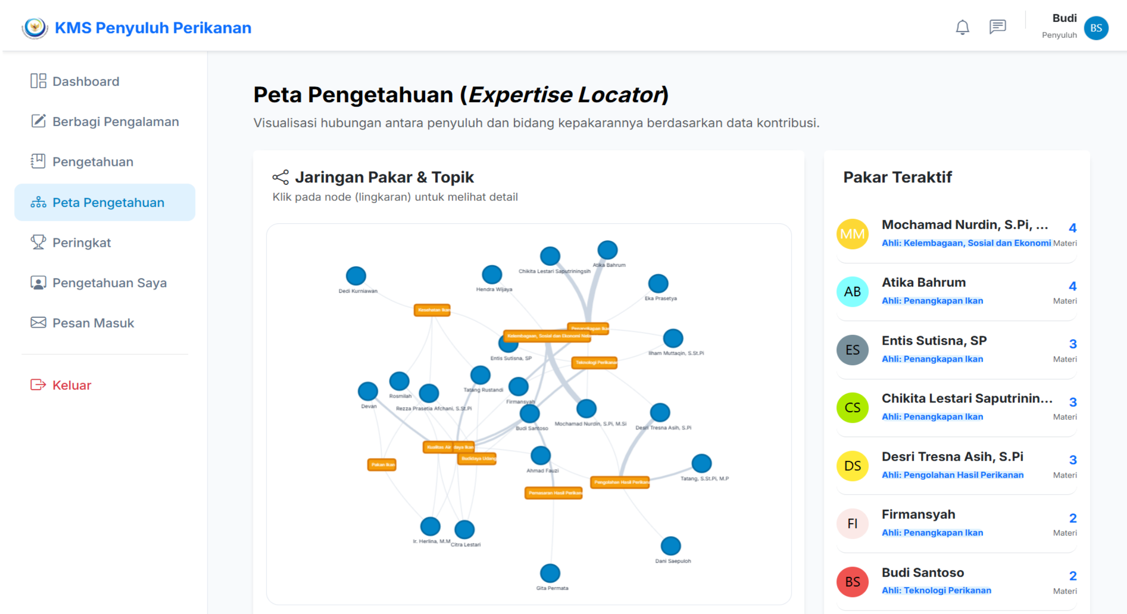

Figure 5. Knowledge Map visualizing extension officers and knowledge categories

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3.4. Gamification Module

The gamification dashboard (Figure 6) displays each user's cumulative points, current badge tier, and progress toward the next tier, alongside a leaderboard ranking all users by total points earned.

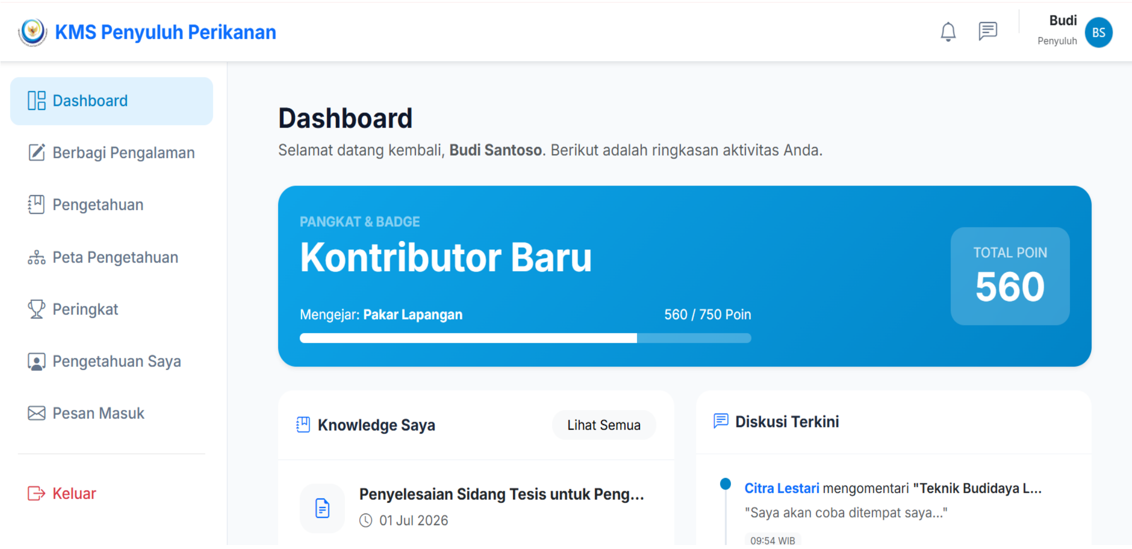

Figure 6. Gamification dashboard displaying points, badge tier, and leaderboard

3.5. Functional Testing (Black-Box Testing)

Black-box testing was performed by the research team (the developer and the knowledge manager acting jointly as internal testers) rather than by independent testers external to the development team; this is noted as a limitation of internal validity, and independent or third-party testing is recommended for subsequent evaluation cycles. Testing verified the functional integrity of six core scenarios prior to end-user evaluation. All six scenarios produced the expected output, for a 100% (6/6) pass rate (Table 2).

Table 2. Black-box testing results

Code	Feature	Test Scenario	Expected Result	Status
F01	Authentication	Login with registered credentials	Access to role-based dashboard	Success

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Code	Feature	Test Scenario	Expected Result	Status
F02	Voice AI	Record spoken field experience	Speech parsed automatically into STAR format	Success
F03	Moderation	Admin changes status from Draft to Published	Entry appears in e-library; user gains 50 points	Success
F04	Knowledge Map	Click a knowledge-category node	List of experts in that category displayed	Success
F05	Gamification	User submits a discussion comment	User gains 5 points; badge tier updates automatically	Success
F06	Inbox	Send a private message to an author	Real-time notification delivered	Success

3.6. Usability Evaluation (System Usability Scale)

Ten extension officers (five senior, five junior) completed the SUS questionnaire after their respective scenario tasks. The mean SUS score was 83.5 out of 100, well above the conventional acceptability benchmark of 68 and classified as "Excellent" on the adjective rating scale [23]. Individual scores are summarized in Table 3.

Table 3. Recapitulation of System Usability Scale scores

Respondent	Profile	SUS Score	Interpretation
R-01	Senior	80.0	Good
R-02	Senior	80.0	Good
R-03	Senior	82.5	Good
R-04	Senior	77.5	Good
R-05	Senior	82.5	Good
R-06	Junior	87.5	Excellent
R-07	Junior	90.0	Excellent
R-08	Junior	82.5	Good

Respondent	Profile	SUS Score	Interpretation
R-09	Junior	87.5	Excellent
R-10	Junior	85.0	Excellent
Mean		83.5	Excellent

Table 3b. Descriptive statistics of SUS scores

Group	n	Mean	Median	SD	Min	Max	Range
Overall	10	83.5	82.5	3.94	77.5	90.0	12.5
Senior officers	5	80.5	80.0	2.09	77.5	82.5	5.0
Junior officers	5	86.5	87.5	2.85	82.5	90.0	7.5

The narrow SUS range (12.5 points) and low standard deviation (SD = 3.94) across the full sample indicate consistent perceived usability rather than a small number of highly favorable outliers driving the mean. Descriptively, junior officers reported a higher average score (M = 86.5, Mdn = 87.5) than senior officers (M = 80.5, Mdn = 80.0); both group means nonetheless fall within the "Good" to "Excellent" range. Given the small per-group sample (n = 5), this comparison is reported descriptively only, and no inferential statistical test was conducted to assess the significance of this difference; the observed gap should not be generalized beyond this sample.

3.7. Qualitative Evaluation

Thematic analysis of the semi-structured interviews produced four themes, summarized in Table 4. Overall, both user groups expressed strongly positive reactions to the prototype, particularly regarding the voice-based externalization and expertise-mapping features, while identifying dialect-recognition accuracy and offline accessibility as priority areas for further development.

Table 4. Key themes from qualitative user evaluation

Theme	Summary
1. Reduced documentation burden	Senior participants reported that voice-based narration eliminated the reluctance to type field reports; junior

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Theme	Summary
	participants valued it for hands-busy field conditions (e.g., aboard boats).
2. Effective expertise navigation	Participants reported that the Knowledge Map allowed them to identify relevant experts directly, replacing informal, uncertain queries in group chat channels.
3. Motivational shift toward active contribution	Points, badges, and leaderboard visibility were reported to increase willingness to contribute, with participants describing a sense of institutional recognition.
4. AI and connectivity limitations	Participants noted reduced transcription accuracy for local dialect terms and intermittent recording caused by unstable internet connectivity in aquaculture field sites.

3.8. Evaluation Scope and Unmeasured Metrics

This evaluation was scoped to functional correctness (Section 3.1.5), perceived usability (Section 3.1.6), and qualitative user perception (Section 3.1.7). Metrics requiring dedicated instrumentation including quantitative AI-extraction accuracy (e.g., expert-rated correctness of STAR fields), the frequency and extent of user edits to AI-generated output prior to publication, task completion time, and error counts during scenario execution were not collected in this evaluation cycle and are therefore not reported. This is acknowledged as a scope limitation rather than a null finding, and Section 3.2.4 identifies these metrics as priorities for subsequent evaluation.

3.2 Discussion

3.2.1. KMS Model Design: Addressing Research Question 1

The first research question asked how a Knowledge Management System could be designed to facilitate structured externalization of tacit knowledge and organize the results through Knowledge Mapping. The results reported in Sections 3.1.2 and 3.1.3 confirm that the integration of Voice AI with the STAR framework directly addresses this question. Within the SECI model of knowledge creation, the Externalization mode converting tacit knowledge into explicit, shareable form is consistently identified as the most cognitively demanding and failure-prone phase [15]. The present architecture suggests that a large language model can function as a cognitive support tool: by assisting with grammatical structuring and classification under human review, the AI may reduce the burden of written composition, allowing practitioners to focus more directly on the substance of their technical expertise. This interpretation is based on participants' self-reported experience (Section 3.1.7, Theme 1) rather than a validated cognitive-workload measurement instrument, and should be read as an indicative rather than confirmed effect future work applying a standardized workload scale such as NASA-TLX would allow this claim to be tested more rigorously. This mechanism is consistent with the theoretical premise that organizational storytelling preserves the "contextual glue" that is typically lost when tacit knowledge is codified through conventional forms [10].

The Knowledge Mapping module further resolves a problem noted in the literature review namely, that field knowledge in extension contexts tends to fragment across informal, unstructured channels [9], [10]. By rendering contributor–category relationships as a weighted graph, the system transforms what would otherwise remain scattered narrative entries into a navigable expertise network, consistent with prior claims that visual knowledge mapping can reduce hierarchical and geographic barriers to expertise discovery [6]. This interpretation is drawn from participants' qualitative reports of ease in locating experts (Section 3.1.7, Theme 2); no quantitative measure of search time or retrieval accuracy was collected in this evaluation cycle (Section 3.1.8), and this is noted as a direction for future, more rigorous evaluation of the module's effectiveness. Compared with earlier Indonesian public-sector KMS implementations that remained limited to passive repositories [11], [12], the present system extends this line of work by coupling structured acquisition with expertise visualization within a single architecture.

3.2.2. Gamification Effectiveness: Addressing Research Question 2

The second research question concerned whether a gamification mechanism could strengthen intrinsic motivation and a sharing culture. The qualitative theme of motivational shift (Section 3.1.7, Theme 3) supports this outcome and is interpretable through Self Determination Theory [16]. Senior officers' expressed sense of institutional recognition upon receiving an expertise badge reflects fulfillment of the need for competence, while junior officers' reports of increased willingness to contribute together with leaderboard visibility and forum interaction reflect fulfillment of the need for relatedness, particularly relevant for officers stationed in geographically isolated postings. These findings should be interpreted as evidence of immediate, self-reported perceived motivation captured at a single post-interaction time point, not as evidence of

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sustained behavioral change over weeks or months; this study's short-term, scenario-based design does not support claims about long-term knowledge-sharing behavior, and longitudinal evaluation is required before such claims can be made. This distinguishes the present system from prior implementations that either omitted motivational mechanisms entirely [9]–[12] or examined knowledge-sharing outcomes without engineering a deliberate behavioral intervention [14].

At the same time, points-badges-leaderboard mechanisms carry recognized risks that this evaluation was not designed to detect. Leaderboard visibility can generate competitive pressure that discourages officers who are less active or less digitally confident, potentially reinforcing rather than reducing participation inequality between senior and junior officers. A points-based incentive structure may also encourage low-effort or low-quality narrative submissions optimized for point accumulation rather than knowledge value, particularly if moderation capacity is limited. Because the evaluation period was short and scenario-based, these risks were not observed in the current sample, but their absence in this evaluation should not be read as evidence that they do not occur under sustained field deployment; monitoring submission quality and participation equity is identified as a necessary component of any longer-term rollout (Section 3.2.4).

3.2.3. Effectiveness and Usability Evaluation: Addressing Research Question 3

The third research question addressed the usability and perceived effectiveness of the resulting prototype. This study evaluated perceived usability and short-term user perception; it did not evaluate, and does not claim to demonstrate, organizational-level effectiveness such as institutional knowledge retention, long-term adoption, or measurable improvement in extension service delivery these remain open questions for future longitudinal research. The mean SUS score of 83.5, falling within the "Excellent" category [27], with a low standard deviation of 3.94 across participants (Table 3b), provides consistent quantitative support for perceived usability specifically. Descriptively, junior officers reported somewhat higher SUS scores (M = 86.5) than senior officers (M = 80.5); given the small per-group sample, this pattern is offered as an observation for future confirmation rather than a validated group difference. Notably, this outcome runs counter to a common assumption in usability research that AI-based systems tend to score poorly among older user demographics due to technology anxiety; the voice-based

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interface may have functioned as a mechanism lowering the digital-literacy barrier for senior participants, consistent with their qualitative reports (Section 3.1.7, Theme 1), though this interpretation likewise remains indicative rather than confirmed.

Benchmarked against comparable prior work, the present score exceeds the 80.6 usability score achieved by a participatory KMS prototype for oil-palm smallholders following iterative refinement [9], and substantially exceeds the standard industry acceptability baseline of 68 [28] (Table 5). This comparison suggests that a conversational, voice-first interaction design may offer usability advantages over structured textual input for field-based, non-technical users, though the two systems differ in domain and evaluation context and this comparison is offered as contextual benchmarking rather than a controlled comparison.

Table 5. Comparison of usability scores across knowledge management systems

System / Study	End-User Context	Evaluation Method	SUS Score	Acceptance Category
Present KMS	Fisheries extension officers (Voice AI, graph mapping, gamification)	SUS + in-depth interview	83.5	Excellent
KMS Sawit Mobile [9]	Oil-palm smallholders (manual textual input)	SUS + Cognitive Task Analysis	80.6	Excellent
Global SUS baseline [26]	Global software industry standard	SUS (standard)	68.0	Acceptable

Nonetheless, this study transparently acknowledges the operational limitations surfaced in Theme 4 (Section 3.1.7) and Section 3.1.8. Reduced transcription accuracy for local dialect terminology indicates that the generative language model would benefit from domain-specific fine-tuning, while the system's dependence on cloud-based API connectivity exposes an environmental constraint in network-limited coastal and aquaculture areas. The absence of a quantitative AI-extraction accuracy measure (Section 3.1.8) further means that the reliability of STAR-field structuring, beyond the human-in-the-loop review step, has not been independently verified. These limitations do not undermine the usability findings but delineate clear boundaries for the system's current operational readiness and evidentiary strength.

3.2.4. Research Implications, Practical Implications, Threats to Validity, and Future Work

This study contributes preliminary empirical evidence that the SECI Externalization bottleneck may be mitigated through LLM-assisted narrative structuring under human review, and that gamification aligned with Self Determination Theory can be operationalized as a concrete engine within a knowledge management architecture. These implications are offered as preliminary given the prototype-stage, short-term evaluation design.

For BPPSDMKP and the Ministry of Marine Affairs and Fisheries, the prototype offers a candidate model for supporting the capture of tacit expertise from a workforce facing retirement-driven attrition, while providing junior officers a structured channel for peer learning. Realizing this potential at scale would require the additional validation and safeguards discussed below.

Because the system processes spoken field narratives that may reference community members' names, household or business locations, unresolved community disputes, or other sensitive operational information, its deployment beyond prototype evaluation raises governance considerations distinct from conventional document-based KMS, consistent with broader calls for structured responsible-AI governance frameworks in organizational AI deployment [29]. These include: (1) data-handling protocols for personally identifiable or locally sensitive information disclosed in narratives; (2) hallucination risk inherent to LLM-based extraction, where the model may generate plausible but inaccurate STAR content that a reviewing officer could overlook; (3) potential bias in whose narratives are captured, extracted accurately, and surfaced prominently in the Knowledge Map, particularly given the reported dialect-recognition limitation (Theme 4); and (4) the responsible-AI principle that the system is designed to support, not substitute, expert human judgment the human-in-the-loop review step (Section 2.4) is a necessary but not sufficient safeguard, as reviewing officers may not always detect subtle extraction errors. A formal data-governance and moderation policy covering consent for narrative content, retention rules for sensitive entries, and periodic auditing of AI-extraction quality is recommended as a prerequisite for any deployment beyond controlled prototype evaluation.

The evaluation involved ten participants selected through purposive sampling, a sample size appropriate for prototype usability validation but not intended for statistical generalization [18]–[20]. The evaluation period captured immediate post-interaction perceptions and did not assess sustained, long-term usage behavior, submission quality over time, or organizational-level impact, consistent with the study's defined scope. The absence of a multi-coder qualitative validation procedure and of documented demographic and requirement-gathering details (Section 2) further limits the interpretive strength of the qualitative findings.

In addition to the previously noted absence of dialect fine-tuning and reliance on stable connectivity, this evaluation did not include a validated workload measure (e.g., NASA-TLX), a quantitative measure of AI-extraction accuracy or user correction rate, task-based performance metrics, or monitoring of potential negative gamification effects (competitive pressure, low-quality submissions). These constrain the strength of causal claims that can be drawn from the present evaluation and are identified as priorities below.

Subsequent development and evaluation should prioritize: (1) fine-tuning the language model on a national fisheries glossary to improve local-term extraction accuracy, with systematic accuracy and correction-rate measurement; (2) administering a validated workload instrument (e.g., NASA-TLX) alongside SUS to substantiate documentation-burden claims; (3) task-based usability metrics (completion rate, time-on-task, error count) in a larger evaluation sample; (4) monitoring submission quality and participation equity under sustained gamification use; (5) developing a formal data-governance and moderation policy addressing the privacy and responsible-AI considerations above; (6) offline-capable mobile access; and (7) longitudinal, larger-scale deployment to assess organizational-level knowledge-sharing impact beyond the usability-level evidence reported here.

4. CONCLUSION

This study designed, implemented, and evaluated a Knowledge Management System prototype to support the capture and preservation of tacit expertise from fisheries extension officers in anticipation of workforce attrition. The prototype integrates three complementary components: AI-assisted guided-narrative acquisition based on the STAR framework, graph-based Knowledge Mapping as a dynamic expertise locator, and Self-Determination Theory-grounded gamification. Evaluation with ten fisheries extension officers using role-specific, scenario-based testing produced a mean System Usability Scale score of 83.5 (SD = 3.94), indicating excellent perceived usability, while qualitative findings suggested that the voice-based interface reduced perceived documentation effort, the expertise map facilitated identification of relevant knowledge holders, and the gamification mechanism enhanced short-term motivation to contribute. These findings indicate that a large language model can serve as a cognitive support mechanism for structuring field-based knowledge under continued human review, rather than as a substitute for expert judgment or autonomous knowledge validation. However, the study provides evidence only of prototype-level usability and short-term user perceptions and does not establish sustained knowledge-sharing behavior, long-term gamification engagement, knowledge reuse, organizational knowledge retention, or measurable improvements in extension-service performance. The findings are further limited by the small purposive sample, short evaluation period, lack of systematically documented participant demographics and formal requirement-gathering participant counts, absence of quantitative measures of AI extraction accuracy, user correction rates, task-completion performance, and validated workload assessment, as well as reliance on single-coder qualitative analysis without inter-rater verification or member checking. Potential adverse effects of gamification, including competitive pressure and point-driven low-quality contributions, also remain unassessed. Accordingly, the prototype should continue to employ human moderation and expert validation of AI-structured narratives until its reliability and longer-term organizational effects are demonstrated. Future research should prioritize quantitative assessment of AI extraction accuracy and correction rates, task-based usability and workload evaluation with larger samples, longitudinal assessment of both positive and negative gamification effects, adaptation of language models to local dialects, development of offline-capable mobile access for low-connectivity environments, establishment of formal data-governance and

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responsible-AI policies, and larger-scale longitudinal deployment, potentially integrated with official Ministry of Marine Affairs and Fisheries information systems, to determine whether the system can produce sustainable organizational-level improvements in knowledge sharing, retention, and reuse.

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