Beyond Implementation: Sustaining AI-Driven Knowledge Documentation in Organisations

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Abstract

As organisations become increasingly dependent on digital workflows, the risk of knowledge loss grows amid rapid staff turnover and shifting work practices. While AI is positioned as a solution to these challenges, sustaining the adoption of AI-driven documentation systems remains problematic, often undermined by low engagement, inadequate training, and fragmented practices. This paper examines how organisations can embed AI-enabled knowledge documentation into everyday work to preserve institutional memory and strengthen resilience. Drawing on a mixed-methods study within a global technology company, including surveys (n=75) and four multi-level focus groups (n=23), the research develops a cyclical adoption framework that integrates software selection, system integration, motivation, and training. Findings highlight the socio-technical dynamics of adoption, where sustained use depends as much on organisational culture and workforce engagement as on system capability. The paper advances understanding of how intelligent digital technologies reshape work practices and enable more resilient forms of organisational learning.

Keywords: AI-Enablement, Knowledge Management, Systems Adoption, Organisational Resilience, Employee Engagement.

1.0 Introduction

Artificial Intelligence (AI) has been increasingly positioned as a mechanism to mitigate knowledge erosion by automating capture, augmenting discoverability, and adapting knowledge to an organisation's evolving needs (Dwivedi et al., 2021). In principle, AI-enabled documentation systems can transform knowledge practices from static repositories into dynamic organisational assets. However, in practice, the uptake of such systems is frequently compromised, as human–system integration falters due to usability challenges, misalignment with workplace routines, and insufficient motivation to document work consistently (Li et al., 2024). This tension reflects a broader concern within information systems scholarship. Seminal models such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and

Use of Technology (UTAUT) (Venkatesh et al., 2003) have clarified factors that drive initial system uptake, but they often under-specify the sustained engagement required to embed systems into organisational life. Conversely, socio-technical systems theory emphasises that enduring performance depends on the joint optimisation of social and technical dimensions (Bostrom & Heinen, 1977; Mumford, 2006). Yet gaps remain in explaining how sustained, cyclical adoption can be enabled in AI-enabled documentation contexts, where continual use, adaptation, and reinforcement are necessary for documentation practices to endure. Beyond the organisational sphere, knowledge documentation also carries broader societal resonance. Digital transformations are reshaping work practices, labour relations, and institutional memory, with implications for organisational resilience in volatile socio-technical ecosystems (Faraj et al., 2018). Documentation practices not only shape the efficiency of internal workflows, but also condition how organisations respond to external shocks, manage staff transitions, and preserve expertise for future generations. As AI systems increasingly mediate these practices, important questions arise about how to balance automation with human agency, how to embed learning and motivation into technology use, and how to ensure that digital systems strengthen rather than weaken the resilience of knowledge work.

This study addresses these issues by investigating the cyclical adoption of AI-driven documentation systems within a global technology firm. Conceptually, we adopt an organisational memory lens to examine how AI-enabled documentation becomes sustainable in everyday practice, framing organisational memory as the desired outcome of documentation and theorising sustained engagement as a cyclical process shaped by the alignment of configuration, motivation, and enablement (see figure 1).

Figure 1. **The cyclical model of Knowledge Documentation adoption, through system design, training, and motivation as driving factors (Source: Authors, 2025).**

Methodologically, we explore this phenomenon through a mixed-method case study, combining survey evidence on employee perceptions and usage patterns (n = 75) with four multi-level focus groups that surface the organisational conditions and lived experiences that shape documentation behaviour. The paper contributes a cyclical adoption framework that explains how AI capability translates into durable organisational memory over time, alongside practical guidance for designing and governing AI-enabled documentation systems that employees continue to use beyond initial rollout.

In doing so, the study develops a cyclical adoption framework that interlinks software selection, value communication, training, motivation, and feedback mechanisms into a repeatable socio-technical model. The contribution of this paper is twofold. Conceptually, it extends existing models of IS adoption by reframing documentation as a dynamic process of organisational learning rather than a binary acceptance decision, allowing deeper theorisation of how motivation, communication, and cultural alignment shape long-term engagement with intelligent systems. Practically, the framework provides organisations with actionable guidance to preserve institutional memory, embed AI documentation systems sustainably, and build resilience against knowledge loss. We therefore pose the following research questions: (1) How should AI-enabled documentation be configured to fit organisational workflows and enable sustainable knowledge capture and reuse? (2) What motivational mechanisms encourage employees to contribute to AI-enabled documentation consistently over time? (3) How can enablement mechanisms, particularly training and value communication, be designed to embed AI documentation into everyday work and sustain engagement?

2.0 Literature Review

2.1 Knowledge Documentation and Organisational Memory

The concept of organisational memory has long been recognised as central to sustaining organisational effectiveness. Walsh & Ungson (1991) define organisational memory as the stored information from an organisation's history that can be brought to bear on present decisions. Such memory is not confined to databases or documents but spans multiple retention facilities, including individuals, organisational culture, transformation processes, and physical artefacts. As Argote (2012) argues, organisational memory embodies both explicit and tacit knowledge, meaning that it is embedded in routines, norms, and practices as much as in formal repositories. The durability of memory and its accessibility, therefore, become decisive factors in determining whether organisations can maintain continuity and adapt to environmental change. From the perspective of the knowledge-based view (KBV) of the firm, knowledge is regarded as the most strategically significant resource for competitive advantage, because it is difficult to imitate and often context-specific (Grant, 1996). Documentation and knowledge management practices are therefore not merely administrative processes, but mechanisms that shape organisational learning, innovation, and resilience. By retaining and mobilising accumulated knowledge, organisations can draw on lessons from prior experience to coordinate complex tasks and respond more effectively to environmental volatility (Nonaka, 1998).

Documentation, however, is a complex activity. Ackerman & Halverson (2004) demonstrate that organisational memory should not be understood as a static artefact but rather as an evolving process and function, constructed through everyday practices. Systems must align with the lived experiences of work. When documentation is perceived as an additional burden, or when its benefits are invisible to contributors, participation diminishes, leaving repositories incomplete or out of date. The socio-technical nature of organisational memory therefore demands that technical infrastructures are complemented by incentives, are culturally aligned, and obtain managerial support. The challenges have become more acute in digitally transformed and distributed workplaces. Employee mobility, hybrid work arrangements, and the decline of face-to-face mentoring weaken informal knowledge-sharing channels (Hislop et al., 2018). Simultaneously, the proliferation of collaboration platforms creates multiple sites for documentation, leading to fragmentation, redundancy, and information overload (Eppler & Mengis, 2004). These conditions complicate the ability of organisations to establish coherent knowledge practices that are sustainable and effective.

2.2 Beyond Initial Adoption: Toward Cyclical Engagement

The adoption of information systems has long been explained through models that focus on individual perceptions and behavioural intentions. The Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) are the most widely cited frameworks, highlighting perceived usefulness, ease of use, and facilitating conditions as determinants of adoption. Bhattacherjee's (2001) Expectation-Confirmation Model (ECM) extends this logic by emphasising satisfaction and confirmation of expectations as drivers of continuance. These models have been invaluable for predicting early adoption and offering parsimony in empirical testing. However, their scope is limited in contexts where systems require sustained and repeated engagement, such as knowledge documentation. They tend to treat adoption as a threshold decision, i.e. whether a user chooses to accept or reject a technology, rather than as an evolving process of engagement, disengagement, and re-engagement (Bagozzi, 2007).

Insights from the post-adoption literature help clarify why this distinction matters. Jasperson et al., (2005) argue that once technologies are introduced, the critical question becomes not whether they are adopted but *how they are used and sustained*. Post-adoptive behaviours (including exploration, routinisation, adaptation, and avoidance) demonstrate that technology use evolves and is often unpredictable. These dynamics are highly relevant in settings such as documentation, where contributions may wax and wane depending on workload, managerial emphasis, or the perceived value of repositories. Similarly, Kim & Malhotra (2005) highlight that continuance is not reducible to satisfaction but emerges from a mixture of intention, habit, and contextual enablers. This perspective shifts attention from one-off acceptance to the mechanisms through which engagement becomes embedded or erodes over time.

DeSanctis & Poole's (1994) Adaptive Structuration Theory demonstrates how technologies are appropriated differently depending on organisational context, interpretive flexibility, and user agency. Technology features do not determine outcomes; rather, users engage with them selectively, often in ways not envisioned by designers. In the case of knowledge documentation systems, contributors may choose to bypass formal templates, rely on shortcuts, or repurpose features for communication rather than storage. Such practices directly influence whether repositories become comprehensive and sustainable, or whether they fragment into partial, underutilised archives. Appropriation thus highlights how systems are continually reshaped in practice, complicating assumptions that adoption is linear or uniform. Resistance and ambivalence are equally important in understanding adoption as a social process. Lapointe & Rivard (2005) state users may actively resist or passively disengage from technologies that clash with professional identities, redistribute power, or impose unwanted work practices. Documentation systems exemplify this tension; although organisations may view documentation as essential, employees often perceive it as peripheral to their core tasks. In the context of AI-driven systems, recent evidence indicates that significant resistance stems not from poor functionality but from misalignment with organisational norms and power dynamics. Madanchian & Taherdoost (2025) found that employees resist AI when it is perceived as imposing on their autonomy or reshaping work in ways they find epistemically alien or culturally misaligned. This underscores that disengagement may be subtle and organisationally embedded, rather than rooted merely in system usability.

Contemporary IS research also stresses the role of resilience and adaptation in post-adoption contexts. Lyytinen et al. (2016) argue that digital resilience depends on an organisation's ability to adaptively reconfigure socio-technical practices as technologies evolve. Similarly, Dwivedi et al. (2021) emphasise that AI adoption cannot be explained solely through intention models, as it involves trust, explainability, ethics, and sustained cultural alignment. These studies underscore that while foundational models illuminate early acceptance, continuing engagement with intelligent systems requires a more dynamic lens.

2.3 Socio-Technical Perspectives

The discussion of appropriation, resistance, and post-adoptive dynamics points toward a broader conclusion; adoption cannot be explained through individual attitudes alone but must be situated within the social and organisational contexts in which technologies are embedded. This is the core claim of socio-technical perspectives, which view information systems as the joint product of technical artefacts and social arrangements. Early socio-technical systems theory, originating from studies of industrial work in the mid-twentieth century, demonstrated that sustainable performance requires the co-optimisation of technological design and human organisation (Bostrom & Heinen, 1977). In the IS field, this perspective has been carried forward by design scholars such as Mumford (2006), who argue that participatory approaches and cultural alignment are critical to system success. These contributions established the principle that technical adequacy is necessary but insufficient without corresponding attention to organisational and human factors.

Contemporary IS research extends this logic in response to the complexities of digital transformation. Orlikowski & Iacono (2001) state that technologies cannot be treated as neutral inputs, instead examined as ensembles of material and social elements whose meaning and impact emerge in practice. Orlikowski's (2000) practice lens makes this argument concrete by showing that technologies are enacted through recurrent organisational routines, and that their significance changes as practices evolve. Barrett et al. (2012) further advance this socio-material view, with technologies becoming inseparable from the organisational contexts in which they are embedded. Such perspectives move beyond seeing adoption as a discrete event, highlighting instead the ongoing negotiation between technologies, people, and practices.

These arguments have taken on new urgency with the advent of AI and algorithmic systems. Faraj et al. (2018) suggests that algorithms can act as organising devices that redistribute responsibilities and reshape expertise, particularly because their opacity limits the ability of workers to fully understand or challenge them. This opacity does not simply reduce transparency; it restructures how employees interpret their roles and responsibilities, introducing new dependencies on technological outputs. Van Den Broek et al. (2021) explored how the introduction of AI into hiring processes reconfigured the relationship between human experts and technological systems. Rather than replacing expertise, AI shifted how expertise was enacted, requiring recruiters to engage in new forms of sensemaking and validation of machine-generated recommendations. Similarly, Lebovitz et al. (2022) revealed how professionals in healthcare systems negotiate whether, and how, to engage with AI, often balancing its affordances against perceived risks to autonomy, judgment, and accountability. These studies illustrate that AI systems not only support existing practices but also alter the social and organisational contexts in which expertise is performed.

Work on algorithmic management underscores the socio-technical reorganisation of authority and control. Kellogg et al. (2020) highlight how algorithmic systems that allocate and evaluate work create new regimes of visibility and accountability, often constraining autonomy while simultaneously offering efficiencies. In documentation contexts, similar tensions are likely: AI may automate classification, summarisation, or retrieval, but it may also introduce new structures of oversight and performance measurement. Employees may therefore perceive documentation not only as knowledge sharing but as a form of monitored compliance, with implications for motivation and trust.

2.4 Artificial Intelligence in Knowledge Management and Documentation

The socio-technical challenges outlined earlier become salient in the domain of knowledge management (KM) and documentation. If AI can reconfigure expertise, authority, and organisational practice, then KM systems represent a crucial arena where these tensions are played out. Documentation systems are not neutral repositories of information but socio-technical infrastructures that mediate what is remembered, how knowledge is classified, and whose voices are privileged. With the rise of AI, these infrastructures do not merely become more efficient; they are transformed, amplifying longstanding debates about trust, motivation, and organisational alignment (Ackerman & Halverson, 2004; Jarrahi, 2018). One major area of transformation is knowledge capture. Traditional KM initiatives often struggled with participation, as employees were reluctant to codify tacit or experiential insights. AI now promises to alleviate these burdens by automatically extracting entities, detecting relationships, and generating metadata from unstructured sources such as emails, chats, and documents. Recent studies highlight how AI can act as a partner in KM, converting unstructured data into structured artefacts that enrich organisational memory (Jarrahi et al., 2023; Pai et al., 2022). Taherdoost & Madanchian (2023) emphasised that automation lowers participation costs and broadens the range of knowledge captured, addressing one of the most persistent bottlenecks in documentation. Yet, as socio-technical perspectives remind us, automation does not guarantee meaningful engagement; without attention to motivation and context, contributions may remain superficial, and tacit knowledge risks being lost.

AI can also reshape knowledge retrieval and recommendation. Traditional repositories frequently create information overload, with employees overwhelmed by redundant or poorly indexed materials. AI offers personalised, context-aware retrieval through recommendation systems and conversational agents, which adapt to user intent and generate summaries of relevant materials (Choudhury & Harrigan, 2014; Mikalef et al., 2021). Jarrahi (2018) argued that such systems augment human cognition by reducing search burdens and supporting decision-making. However, algorithmic opacity raises concerns: retrieval is not a neutral process but one shaped by embedded assumptions and data biases (Glikson & Woolley, 2020). This introduces risks that certain forms of knowledge are systematically privileged while others remain invisible, echoing socio-technical critiques about the politics of information systems.

A third area of transformation involves knowledge creation and temporality. Generative AI tools can produce draft documents, meeting summaries, and procedural guidelines in real time, effectively collapsing the distance between knowledge creation and consumption (Dwivedi et al., 2021). While this promises responsiveness and efficiency, it risks producing knowledge that is plentiful but shallow, lacking the contextual richness on which organisational learning depends. Nonaka & Von Krogh (2009) stress that tacit knowledge remains essential to organisational memory, while von Krogh (2018) warns that digitalisation may exacerbate tensions between codification and tacitness. Alavi & Leidner (2001) underscore how knowledge reuse depends not only on documentation but on its relational context. These research studies caution that AI-generated documentation may accelerate capture but inadvertently erode depth.

2.5 Research Gap and Conceptual Foundation

Across adoption, socio-technical, and knowledge-management literatures, prevailing models explain initial uptake and, to a lesser extent, continuance, but they do not account well for the dynamic, recurrent patterns through which systems are engaged over time. Classic models emphasise initial acceptance (Davis, 1989; Venkatesh et al., 2003) or satisfaction-driven persistence (Bhattacherjee, 2001; Kim & Malhotra, 2005), whereas post-adoptive work shows use cycling through exploration, modification, avoidance, and abandonment (Jasperson et al., 2005). Contemporary accounts similarly characterise digital work as episodic and fluid rather than linear (Sarker et al., 2019). This limitation is acute for knowledge-documentation systems, which depend on repeated, discretionary contributions, with an emphasis of technical adequacy and antecedents of initial participation (Hislop et al., 2018; Kankanhalli et al., 2005). There is a lack of theory on how contributions wax and wane as pressures, trust, and priorities shift. The rise of AI heightens this theoretical need. Intelligent systems can reconfigure work and redistribute expertise, often introducing new regimes of visibility and control (Faraj et al., 2018; Kellogg et al., 2020). Within KM, AI can automate capture, classification, and retrieval, promising efficiency while raising concerns about legitimacy, explainability, and motivation (Jarrahi et al., 2023; Lebovitz et al., 2022). This calls for a new understanding of how engagement with AI unfolds over time, employees toggling between trust and scepticism, and between compliance and resistance, and designing for sustained engagement in digitally transforming contexts where contributions are intermittent and discretionary (Majchrzak et al., 2016; Shrestha et al., 2019). While organisational memory, documentation, and technology use are often examined separately, this study integrates them to explain how AI-enabled documentation becomes sustainable in practice. We treat organisational memory as the intended outcome, reflected in knowledge that is retained, retrievable, and reusable beyond individual contributors. AI-enabled documentation is the central practice through which this memory can be built, but only where engagement is sustained rather than treated as a one-time adoption decision. We therefore conceptualise use as a cyclical post-adoption process, shaped by the alignment of three mechanisms: configuration (the socio-technical setup that embeds documentation into workflows and enables retrieval), motivation (the drivers that encourage repeated contribution), and enablement (organisational supports such as training, communication, and reinforcement that stabilise participation). Where these elements align, documentation practices persist and accumulate into reusable artefacts, allowing AI capability to translate into durable organisational memory; where they misalign, engagement attenuates and knowledge erosion persists. Against this backdrop, this research study examines how engagement with AI-enabled documentation systems evolves as a cyclical process of adoption, disengagement, and re-engagement within an organisational context. To keep the inquiry rigorous and faithful to the case, the following is explored:

Research Question 1 - How should AI-enabled documentation be configured to fit organisational workflows and enable sustainable knowledge capture and reuse?

Research Question 2 - What motivational mechanisms encourage employees to contribute to AI-enabled documentation consistently over time?

Research Question 3 – How can enablement mechanisms, particularly training and value communication, be designed to embed AI documentation into everyday work and sustain engagement?

This research addresses these questions through the lens of a single organisation, using transparent selection logic and designable interventions that others may adapt by similarity of context. Conceptually, it advances a cyclical-adoptive lens for AI-enabled documentation, which addresses re-engagement and adaptation over time. Methodologically, it offers a case-based approach, a tentative framework suitable for analytic (rather than statistical) generalisation and subsequent evaluation through replication and extension.

3.0 Methodology

3.1 Research Design and Stance

An interpretivist, problem-driven single-case design was adopted to explain how a large, knowledge-intensive technology organisation selects and prepares to embed an AI-enabled documentation solution. Looking at how employees can be motivated and equipped for sustained, discretionary contribution. A case-based strategy preserved socio-technical interdependencies (practices, governance, incentives, and platform capabilities) and aimed for analytic, not statistical, generalisation to mechanisms and design principles, consistent with guidance on theory building from cases, interpretive validity, and case-study rigour (Eisenhardt, 1989; Klein & Myers, 1999; Yin, 2009).

3.2 Case Setting, Unit of Analysis, and Research Questions

The study was situated in a large, knowledge-intensive multinational technology firm that was consolidating fragmented documentation practices into a single, AI-assisted approach. The organisation is well known for its direct-to-customer approach and strong position in both consumer and enterprise markets. It helps companies to modernise their technology by offering integrated solutions, flexible consumption models and supports for the technology lifecycle. The inquiry-based problem for the organisation was framed as the need to "*create a framework to allow artificial intelligence to facilitate knowledge transfer*," with specific concerns about limited AI involvement in documentation, loss of tacit knowledge, inconsistent motivation to contribute, and the absence of a shared policy or process convention. To make the inquiry tractable, the scope was delimited to four tightly coupled domains: i) platform selection, ii) implementation preparation, iii) user adoption, and iv) cyclical adoption evaluation, so that design choices could be derived from concrete organisational constraints rather than abstract desiderata.

The unit of analysis was the socio-technical system of knowledge documentation. Focusing on the interplay of people and their practices, governance arrangements, and candidate platforms rather than any single application. Because the focal practices centre on capture, articulation, and integration of knowledge, the researchers treated learning-as-internalisation as adjacent (addressed through training design) rather than as the primary object of analysis; an AI-augmented SECI lens was used heuristically to ensure portfolio fit across socialisation, externalisation, and combination capabilities when assessing options (Nonaka et al., 2000).

The research design was classified as a "convergent mixed design" according to Creswell (2021). Quantitative and qualitative data were simultaneously collected to complement one another. The former provided valuable numerical information determining desirable system features, preferred methods of learning, motivation and value communication. The latter enabled a holistic understanding of various aspects of a system's use, including the perceived value of knowledge documentation, the best incentives from both employees' and managers' perspectives, effective methods for learning new technologies, personal experiences with existing systems, and the manager's viewpoint on KPIs for adoption evaluation. The Quantitative and Qualitative data collection methods complemented each other, the first expressing what and the second expressing why.

3.3 Quantitative Strand: Survey and Multi-Criteria Evaluation

An organisation-wide pulse survey was administered to a population of 100 IT employees and yielded 75 complete responses, which satisfied an a priori threshold equivalent to approximately 90% confidence level with a 5% margin of error. The online survey combined multiple-choice and 1–5 Likert scale questions. Items covered: Documentation burdens, priorities for general platform features, priorities for AI capabilities, preferred value-communication channels and messages, preferred learning modalities, and motivational levers. Construct scaffolding drew on the IS-success and task-technology-fit traditions, system, information, and service quality; task coverage; and perceived usefulness or benefits, and was extended with practice-proximal questions tailored to AI-assisted documentation (DeLone & McLean, 2003; Goodhue & Thompson, 1995; Hinkin, 1998; MacKenzie et al., 2011). Cognitive pretesting was used to refine wording and response processes before fielding. Survey items asked participants questions on – problems they experienced with knowledge documentation, features necessary for effective knowledge documentation systems, reasons for using such a system, methods to learn new systems, what would demonstrate the value of knowledge systems, and motivational factors for use, etc.

The quantitative data then informed a transparent multi-criteria decision analysis with simple additive weighting to operationalise Research Question 1, as a platform-agnostic comparison. Criteria were organised in three sets: i) General features (including interface quality, role-based access control, version control, integrations, encryption, flexible editing, and analytics), ii) AI capabilities (including chat or assistive functions, semantic or contextual search, machine-learning support for text, audio, and video, automated taxonomy, and knowledge-graph support), and iii) Employee-proposed additions (including restricted AI access for sensitive data, AI-assisted versioning, and AI translation). For the fourteen baseline criteria, each platform received a score equal to the survey mean for that criterion. Where a platform offered machine-learning support only for text, a documented coefficient of 0.5 was applied to that item. Integration scores were scaled by the number of in-use tools supported, with six tools in scope. Each employee-added feature contributed three points, reflecting its central tendency on the 1–5 scale. Scores were normalised to a common range and then aggregated to produce a rank order. To guard against construct overlap, the researchers examined adjacent criteria to avoid double-counting. Weight deliberations and any departures from default settings were recorded in a decision log. One-way sensitivity checks were run on high-leverage criteria to test robustness. The resulting selection rubric (see Appendix A), comprising criteria, weights, normalisation rules, and the decision log, forms the quantitative artefact for Research Question 1 and was designed to be recalibrated by other organisations.

3.4 Qualitative Strand: Focus Groups and Whiteboards.

To surface mechanisms and contextual constraints, four focus groups were convened with a total of 23 participants taking part across the four sessions. Each focus group lasted for 60 minutes, and these sessions were held both in-person and online, depending on participants availability and preference. Participation was stratified by tenure bands (fewer than five years; five to ten; more than ten years' experience). Each session was recorded and transcribed and was accompanied by a Microsoft Whiteboard that captured structured canvases for employees and executives. These materials elicited feature needs, integration points, governance concerns, motivational drivers, learning preferences, and value-communication routines. A managerial interview provided additional context on governance and adoption practices. The qualitative corpus was therefore comprised of eight primary sources: four transcripts and four whiteboards, plus one interview. The focus groups and whiteboard sessions focused on four themes: Platform selection, Motivation and Contribution, Learning and Training preferences, and the Assessment of Engagement.

Analysis followed reflexive thematic analysis utilising Nvivo software. Descriptive coding across the corpus produced 590 initial codes, which were reviewed, deduplicated, and clustered into 9 themes through iterative consolidation, memoing, constant comparison, and team challenge sessions. The themes informed two design artefacts central to Research Questions 2 and 3. The first was a motivation rule catalogue that records, for each barrier identified in the data, the mechanism it engaged (autonomy, competence, or relatedness), the workflow preconditions required for the technique to operate, the anticipated trade-offs (including cognitive-load or compliance risks) and the minimal instrumentation needed to assess uptake later. The second was a learning blueprint that specified modular, task-embedded micro-learning with progressive difficulty and immediate practice opportunities at the point of work. Preferred channels (such as collaboration tools, the intranet, and newsletters), content types (such as task-specific videos with transcripts and searchable FAQs), and message frames (linking a clear promise to concrete proof and an explicit call-to-action) were consolidated into templates that could be adapted to role and task.

4.0 Findings

4.1 Technological Fit

Technological fit was operationalised through a survey-weighted comparison rubric that aggregated three empirically derived families of criteria. The first family captured baseline usability and governance: user interface quality, role-based access control (RBAC), data encryption, version control, a flexible page editor, and integrations with the existing toolchain, reflecting the frictions repeatedly reported by employees around findability, access, and structuring. Within this set, the highest-weighted items in the survey were the usability of the interface and the breadth of integrations, followed closely by encryption, RBAC, and version control. The second group addressed the cost of retrieval and curation by assessing AI capabilities such as semantic/contextual search, automated taxonomy or generation, knowledge-graph leverage, multimodal ML (text, audio, video), and conversational assistance; semantic/contextual search and automated taxonomy attracted the greatest weight among AI items. The third, translated requests voiced in workshops into explicit criteria: restricted AI access for sensitive data, AI-assisted version control, AI translation, and peer feedback/collaboration, so that governance concerns and day-to-day work practices were represented directly within the scoring logic rather than treated as narrative context.

The review of online options comprised sixteen AI-enabled products relevant to knowledge documentation. The shortlist was illustrative rather than exhaustive and was compiled by inclusion rules (documentation relevance and AI capability) rather than a time-bounded systematic scan. Scoring followed simple additive weighting with transparent conventions. For the fourteen baseline criteria, a platform received the survey-mean importance when the capability was present; where ML support was limited to text, the ML item was halved (0.5) by design; integration points were scaled by the number of in-use tools supported (six were in scope). Employee-proposed controls, which were not part of the original list, contributed fixed points when available. Features marked "*n/a*" were treated as zero in this application on the rationale that these are requirements rather than optional enhancements; it was noted that an alternative treatment (excluding non-applicable items) would tend to favour specialised tools and would require a different requirement profile to be justified. The complete scoring sheet was preserved to allow third-party recalculation.

Interpreted through this rubric, the fit in the focal organisation entailed combining robust usability and governance baselines with tight integrations and deploying AI specifically to lower the effort of finding and curating information, while also meeting the employee-requested controls. Tools that are strong on analytics but lack documentation essentials (e.g., version control or a flexible editor) forfeit heavily weighted points even when their AI functionality was sophisticated. Applying the rubric to the sixteen AI-platform shortlist yielded ranked outcomes (see Table 1. below). ClickUp, Guru and Notion rank highly on this review, with accumulated points across all three family features. Shelf and Elium indicate that a single employee-proposed capability or broader integration coverage can shift ordering at the margin. Several AI-centric tools trailed because they registered "*n/a*" against documentation essentials and did not satisfy the employee-proposed controls.

AI-Product Review	Ranking
ClickUp	64.98
Guru	59.68
Notion	53.96
Shelf	52.18
Elium	52.04
Moveworks	48.85
Document360	48.19
Catalog	47.49
Happeo	47.43
Squirro	44.48
Confluence	44.21
ClickHelp	42.38
Starmind	40.36
DeepHow	37.95
Scribe	36.64
Paligo	28.56

Table 1. Ranking of the AI-Enabled Products for use in Knowledge Documentation.

As a portfolio check, mapping candidates to the study's AI-augmented SECI view placed the leading options primarily in Externalisation (authoring/sharing) while also strengthening Combination (integration/search), which aligned with employees' twin problems of capture and findability; tools optimised solely for analytics or tacit capture did not align with the expressed needs. Two transparency notes delimited the claim.

First, while the matrix implemented four employee-proposed criteria as fixed-point additions, an earlier method note referenced three; this research retained the matrix implementation and flagged the discrepancy for harmonisation. Second, no formal sensitivity analysis was reported; accordingly, the ranking was weight-sensitive and therefore case-bound. Its transferable value lies in the explicit rubric, which can enable other organisations to re-weight criteria to their own priorities and re-score. Finally, the analysis was reproducible and neutral. The anonymised scoring sheet and rubric are preserved for independent recalculation, and no vendor relationships or sponsorships influenced inclusion, weighting, or interpretation.

4.2 Workflow

A wide range of challenges were identified across the organisation's existing knowledge documentation systems and workflows. These ranged from broken features to poor usability. These challenges impacted users' willingness to use systems and influenced long-term adoption. For instance, search functions within the current platforms were imprecise, as explained by Participant 2 "*you have a got a lot of different articles returned that are not specific enough for your questions* (FG1)." Likewise, there were comments made about on-going role-based access issues, "*access has been revoked because of an update*" (FG1, P3). Similarly, another major issue was fragmentation. As one participant in FG4 stated, "*There are too many platforms, would be great to have a common platform* (P2)." A participant from FG3 commented, "*Various instances of the same tools exist and do not connect well together… difficult to leverage information across different orgs* (P5)." These observations point to poor cross-organisational integration. Additionally, concerns were raised about knowledge loss during transitions. For example, Participant 3, FG1 noted, "*There's a lot of movement to another team or manager, and the knowledge is not kept up to date or shared*." In such cases, documentation often becomes obsolete or inaccessible over time, especially if there's no follow-up responsibility to update content. While historical insights may exist, without clear structure or system enforcement, their value is lost. Survey data revealed that participants were more interested in finding information from systems rather than creating this data, with 86% focused on the search and retrieval of information from AI knowledge documentation systems. Knowledge users are savvy about security with 82% seeing it as an essential requirement for using any AI tools in their work processes. To make AI an integral part of workflow processes the participants wanted a good user experience, with current experiences coming at 69%

satisfaction rates. A new AI documentation system would need to offer users everything they want with different response levels.

4.3 Motivational Techniques for Sustained Contribution

This section examines motivational techniques for sustained use of the new AI knowledge tool, addressing research question two. A "design lever" was used as a *controllable change to the platform or its operating routines* that intended to shift contribution behaviour (e.g., templates, prompts, feedback signals, message framing). The motivation to document stems primarily from prosocial values and recognition of these, moderated by practical frictions. The strongest motivational drivers were seeing one's work improve team outcomes (87%) and knowing others use what was shared (83%); feeling valued for contributions was also high (82%). By contrast, clarity about the tool's value sat mid-range (71%) and receiving feedback/recognition lagged (57%). The 30-point gap between top and bottom drivers reveals that users prioritise impact visibility over traditional recognition. This indicates that users want to know their work matters and is being used, but current feedback mechanisms may be insufficient to close this motivational loop. Focus-group (FG) narratives echoed this pattern, describing documentation as worthwhile when it solves a colleague's problem and prevents repeat queries: "*When your manager says thanks for uploading that, it helped the team, that sticks. It makes it worth it,*" (FG4, P1). Barriers map onto everyday effort and uncertainty. Participants pointed to time pressures, cumbersome processes, unclear quality standards, and fragmented or outdated materials as recurring deterrents, alongside low feedback visibility (not knowing if a page was seen or useful) and trust concerns about content quality and when to rely on AI assistance. A smaller but persistent theme was anxiety about being judged for imperfect drafts, which encouraged private notes or ephemeral chat over shared documentation: "*Time is probably a big one… after something is completed… it just falls through the cracks,*" (FG1, P3).

The first lever for change was identified as friction reduction at the point of work. Participants asked for workflow-embedded capture, one-click or templated contribution, and inline prompts/checklists that make the "*right way*" the "*easy way*". They emphasised willingness to contribute when documentation can be completed without context switching, with sensible defaults (titles, metadata, and a suggested taxonomy) and minimal formatting overhead: "*If it is straightforward to do, you will do it. But if it's a pain, you will do everything to avoid it*," (FG4, P2). This was similarly echoed by other participants: "*Make it fast and frictionless… I will do it if it takes two minutes, not twenty,*" (FG1, P3), with some suggesting resources would also help to improve overall use: "*A sample reference template would streamline the task; you'd be more inclined to do it as you have a baseline*," (FG4, P3).

A second lever centred on closing the feedback-visibility gap. Contributors asked for lightweight usage signals (e.g., views or reuse indicators), specific acknowledgements from beneficiaries, and clear routes for improvement (comments or peer suggestions visible to the author). Recognition was consistently described as most motivating when specific, proximal, and non-monetary: "*Even if you create a knowledge base, you can see the number of views… Often, no one's going to look at it, it might have 10 views,*" (FG3, P5).

A third lever involved proof-over-proclamation communication. When asked what convinces, respondents overwhelmingly preferred real examples of improved daily work (91%) and short demonstrations with quick wins (69%); KPI-linked messages (48%) and peer success stories (47%) sat in the middle, while generic leadership messages (16%) were least persuasive. Participants describe a coherent communication approach that pairs concrete, task-level microcontent with deliberate multi-channel delivery. As one put it, they want "*actual examples of what we are going to be doing… short clips saying, 'Here is how you do this,'*" (FG4, P2). Complementing this, another emphasised the need for multiple touchpoints: "*We send emails, post on SharePoint, use Teams, and run webinars/demos… multiple touchpoints increase engagement*," (FG2, P1). A fourth lever for change emphasised confidence through guided practice. Where confidence or ambiguity constrained participation, employees preferred guided templates, before/after exemplars, and peer-to-peer support over generic classes. Preferred learning modes were short and practical; step-by-step video walkthroughs (65%), peer-to-peer training (49%), and self-experimentation (48%), with content prioritising the efficient use of AI (81%), the user interface (80%), and the documentation process (60%). Participants also asked for role-specific hooks and visible knowledge champions to anchor practices locally: "*User champions become advocates. (They) help train others and make sure the tool is being used correctly,*" (FG2, P2). A final lever focused on aligning governance and AI controls with risk perceptions. Clear standards for "*what good looks like*," versioning conventions, defined review roles, and restricted AI access for sensitive content to reduce perceived risk and make contributions feel safe. Equally, AI-assisted version control, automated taxonomy, and reliable semantic search were all identified as sustaining motivation indirectly by keeping contributions findable and current, i.e., worth the effort to create: "*What does it mean for me and my job? Who ensures the quality… Can you trust the output?*" (FG 2 whiteboard).

4.4 Training and Value Communication Design

To address research question three, the study examined how training and value-communications should be designed so employees can confidently and continuously use an AI-enabled documentation system. Survey evidence revealed a stable preference for short, practice-proximal formats: Step-by-step video walkthroughs (65%), peer-to-peer training (49%), and self-experimentation (48%). Content priorities were equally pragmatic and skills-forward focused: Efficient AI use (81%), the user interface (80%), and the documentation process (60%), with soft-skills support (45%) in communication, collaboration, and AI literacy viewed as a useful complement. Focus-group accounts further translated these preferences into concrete enablement routines. Participants described a sequence that would build confidence over time, beginning with reference materials, before the use of hands-on sessions, and subsequently followed by shadowing/coaching opportunities. Participants also emphasised the value of office hours as a lightweight support mechanism, especially when offered across time zones. They asked for searchable, reusable resources to be embedded where work happens, for example, short videos with transcripts, FAQs, guided checklists, and stressed the need for safe "*play-in*" environments to trial features without risk. The request for inclusive design recurred: Materials should be "*step-by-step*" and in "*simple language*," with accessible fonts, contrast, and image descriptions so that different learning styles are supported. As one participant put it, "*We usually start with white papers or procedure documents, then hands-on training. We do shadow sessions until the trainee is comfortable using the tool,*" (FG4, P3).

Value-communication follows the same practical logic. Respondents overwhelmingly prefer concrete examples of improved daily work (91%) and short demonstrations with quick wins (69%), well ahead of more abstract broadcast messages. Participants warned that tools can remain under the radar: "*Sometimes a new tool is not known a year later,*" unless awareness is managed deliberately. It was advocated for a coordinated multi-touch approach (team meetings, quarterly updates, and in-tool artefacts) so the same "*how-to*" is encountered in the channels people already monitor, framed around effort-reduction and just-in-time help for common tasks. Furthermore, enablement and governance were revealed to be tightly coupled. Clear standards for '*what good looks like*', agreed versioning conventions, and defined review roles reduce ambiguity and make training actionable. Controls such as restricted AI access for sensitive content, together with AI-assisted version control, automated taxonomy, and reliable semantic search, ensure that newly learned practices produce artefacts that are safe, findable, and current. Participants also pointed to tool integrations (linking work items and documentation) to anchor habits, and to light, improvement-oriented instrumentation (such as simple indicators of views, reuse, or beneficiary feedback, and team-level summaries for managers) while cautioning against heavy-handed tracking that could feel punitive.

5.0 Discussion

5.1 Overview of Findings

The study shows that sustained engagement with an AI-enabled documentation system is not produced by any single decision but by the alignment of workflow configuration, motivation, and enablement through training. Workflow configuration herein refers to the socio-technical design of the documentation capability, specifically, the way the platform is configured in and around work practices, including integration, structured templates, permissions and versioning rules, validation and governance arrangements, and retrieval features that determine what becomes findable and reusable. Motivation captures the psychological and social drivers that sustain contribution over time, such as perceived usefulness, reciprocity, recognition, reduced rework, and trust in how contributions will be used and protected. Training enablement refers to the organisational supports that make sustained contribution feasible and repeatable in everyday work, including user skills building, value communication, time allocation, managerial reinforcement, and local norms around documentation quality. Platform selection contributes only when it removes the frictions that employees face in authoring effort, versioning uncertainty, and findability, under clear governance. Where those baselines are weak, even sophisticated AI features fail to translate into everyday value because contributors still confront high effort at the point of work and low trust in the durability or safety of what they share. Crucially, these frictions are not merely usability problems; they determine whether documentation accumulates into organisational memory. When configuration supports durable capture and trustworthy reuse, knowledge moves from individual workarounds into shared, retrievable artefacts that persist beyond the contributor.

Once workflow configuration reduces frictions, whether engagement persists depends on how people experience the system in practice. Contribution becomes routine when capture is genuinely easier than existing workarounds, when employees can see that their pages are used and appreciated, and when learning materials mirror the tasks they already perform. Integration breadth functions here as a behavioural lever as much as a technical one. By situating contribution inside the tools where work already happens, it collapses the opportunity cost of documenting and gives prosocial motives a direct channel of expression.

These dynamics clarify the role (and limits) of AI. Its value materialises chiefly by lowering retrieval and curation cost and by keeping artefacts findable and current; without visibility loops and agreed standards, the same capabilities introduce opacity that suppresses willingness to share. They also explain common failure modes: strong tools underperform when impact is invisible and risk ambiguous; broad training underdelivers when it is not embedded in the flow of work; and managerial exhortation changes little without tangible demonstrations and immediate, friction-reducing affordances. Finally, engagement is episodic rather than linear. Organisational memory forms when these cycles produce repeated contribution and reuse so that knowledge survives staff movement and becomes reliably findable and actionable for others over time. Employees cycle through trial, active use, symbolic compliance, disengagement, and re-engagement; the levers that matter is those that ease re-entry and make benefits legible quickly. Read together, the findings characterise sustained documentation as an emergent property of fit that reduces real frictions, motivational routines that make value visible, and enablement that is concrete, local, and continuous.

5.2 Implications for Theory

The findings advance organisational memory theory in AI-enabled contexts by specifying the socio-technical conditions under which documentation outputs become stable, retrievable, and reusable organisational assets rather than transient work artefacts. Recent theory on managing with AI emphasises a shift from task-level views to organisational arrangements and collective agency. The findings to the research questions 1-3 identify a shift in practices, by showing that fit derives from governance baselines, integration breadth, and retrieval-oriented AI, and that motivational and enablement routines convert that fit into dependable contribution (Baskerville et al., 2020; Hillebrand et al., 2025). The evidence also extends work on human-AI collaboration and algorithmic management; employees sustain engagement when the system makes contribution easier than workarounds and when effects are visible to authors and beneficiaries. Under opacity, by contrast, professionals disengage despite capability, consistent with studies of how workers cope with AI's inscrutability in judgement-intensive settings and how algorithmic systems reshape control and expertise (Kellogg et al., 2020; Lebovitz et al., 2022; Vaast & Pinsonneault, 2021).

Finally, the case speaks to understanding explainability and knowledge transfer in AI-augmented work. Where feature-based explanations and machine-induced reflection are available, users' information processing and confidence improve, aligning with the observation that visibility, standards, and example-led learning stabilise contribution and reuse. Conversely, where such affordances are absent, AI can increase uncertainty and suppress sharing. These dynamics connect contemporary explainable AI and reflective research with updated mechanisms of knowledge transfer, positioning AI not as a substitute for organisational memory but as an amplifier when socio-technical conditions are in place (Abdel-Karim et al., 2023; Argote et al., 2022).

5.3 Implications for Practice

Three practical lessons emerge for organisations seeking to convert AI-enabled documentation into durable organisational memory. First, platform selection benefits from a transparent, decision-analytic routine rather than ad hoc comparisons. By making Multi-Criteria Decision Analysis (MCDA) explicit this ensured underlying value judgements were transparent and therefore governable. Recent guidance in operations research specifies how to surface criteria dependencies, document weights, and structure elicitation to reduce arbitrariness. Complementing this with a light-touch sensitivity analysis on weights or scoring conventions strengthens credibility, especially when recommendations are case-bound and stakeholders may reasonably question whether a different emphasis would alter the ranking (Cinelli et al., 2020).

Second, AI features should be deployed with user cognition (and trust calibration) in mind. Field and laboratory evidence shows that feature-level explanations can change how non-experts process information and when override model suggestions. However, effects are task- and audience-specific, and poorly tuned explanations can entrench confirmation bias. In practice this argues for graded, context-appropriate explanation layers tied to the task at hand (e.g., retrieval versus classification) and to user expertise, together with simple uncertainty cues that help employees gauge when to trust the system and when to seek human corroboration (Bauer et al., 2023; Brasse et al., 2023; Larasati et al., 2023). Because explanation and control are governance issues as much as user experience, organisations should embed them in a broader AI-governance arrangement that allocates responsibilities, documents risk controls, and links technical affordances (e.g., access scoping, audit logs, data lineage) to policy commitments around privacy, fairness, and accountability (Mäntymäki, Minkkinen, Birkstedt, & Wessel, 2022; Stahl, Brooks, Hatzakis, Santiago, & Wright, 2023).

Third, enablement needs to be designed for the "flow of work." Evidence indicates that short, well-designed videos and micro-interventions outperform longer formats for procedural and just-in-time knowledge, particularly when paired with opportunities for practice and spaced repetition. In hybrid settings, multi-channel outreach (brief clips embedded in the tool, short live demos, and Q&A follow-ups) sustains attention and reduces time-to-competency. The implication is to prioritise concise, task-proximal artefacts over generic training, and to stage rollouts so that new capabilities arrive with immediately usable exemplars and searchable "how-to" snippets (Fyfield et al., 2022; Tønnessen et al., 2021). Finally, motivation mechanisms should emphasise visibility and appreciation while avoiding over-reliance on gamified rewards. Recent studies show that badges and similar tokens can increase contribution in some contexts but are inconsistent across populations and tasks. Combining light-weight recognition with clear task value and friction-free authoring remains a safer default for knowledge documentation (Balci et al., 2022; Cavusoglu et al., 2021; Ma et al., 2022).

5.4 Limitations

This study was case bound. The shortlist of tools is deemed illustrative rather than exhaustive, and although the scoring rules and weights are transparent, the ranking is sensitive to those weights and to the treatment of non-applicable capabilities. No formal sensitivity analysis was reported; robustness to alternative weightings or to "drop-one-family" tests remains to be demonstrated (Belton & Stewart, 2012; Triantaphyllou, 2000). The survey evidence is descriptive and situated in a single IT-intensive organisation, and behaviour was not observed longitudinally post-deployment; consequently, the study does not claim long-run effects or statistical generalisability. Likewise, the focus group sessions were time-bound snapshots of individuals lived experienced, designed only to extrapolate details on the why questions. Qualitative data does not intend to be generalisable, but instead to provide depth of understanding. These findings can be applied to similar contexts through reasoned interpretation rather than statistical generalisation, supported by the transparent documentation of the tools and methods used (Eisenhardt, 1989; Yin, 2009).

5.5 Conclusions

This study contributes by showing that turning AI-enabled documentation into durable organisational memory is not a one-off adoption event, but a cyclical socio-technical process in which configuration (how the platform/workflows are set up), motivation (why employees contribute), and enablement (the organisational supports that sustain contribution, such as training) must align to create sustained documentation practices that become retrievable, trusted, and reusable knowledge assets. Practically, it translates that insight into actionable guidance on what organisations should configure, reinforce, and support to make AI documentation sustainable rather than episodic. Considered at the level of the research questions, these findings outline that in terms of RQ1, platform fit in organisations is achieved when governance and usability baselines are combined with strong workflow integrations and retrieval-oriented AI knowledge systems. RQ2 meanwhile shows that sustained contribution is most effectively supported by motivation techniques that make effort visible, reduce capture friction, and reinforce prosocial impact through feedback and recognition. RQ3 meanwhile demonstrates that enablement is strengthened through short, practice-proximal training and value communication embedded in everyday tools, allowing confidence to build through repeated use. Configurations that reduce the dominant frictions of capture, findability, and governance perform best. Routines that make contribution easy, visible, and appreciated sustain participation; and supports for skill building that are short, role-aware, and embedded in everyday tools equips staff to act. The value of AI in this domain is realised not by maximising capability breadth but by lowering everyday effort under credible governance. The paper’s contribution is a transparent selection instrument and a set of mechanism-linked enablement routines that others can recalibrate to their own settings, together with a clear statement of the boundary conditions under which the findings should be interpreted.

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Appendix A.

General Features	Software - Name	Software - Name
User-Friendly UI		
RBAC		
Multilingual Support (Interface and Content)		
Tools Integration		
Version Control		
Data Encryption		
Flexible Page Editor		
Analysis and Statistics		
AI Features		
AI-Powered Chatbots		
ML for Text/Audio/Video Processing		
Semantic/Contextual Search Engine		
Knowledge Graphs Leveraging		
AI-Automated Taxonomy Generation		
LLM Multisource Knowledge Retrieval		
Employee Proposed Features		
Peer Feedback and Collaboration		
AI-Powered Translation		
AI-Version Control		
Restricted AI-Access to Sensitive Data		
Sum		

Table 2. Rubric for Software Comparison.