Integration of AI-generated Information Into Organizational Knowledge Through Coherent HRM - and KMM Processes

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Abstract: This position paper argues that the integration of AI-generated information has the potential to disrupt existing human agencies in organizational routines. This disruption of agency is a result of displacement of judgement particularly when routine automation reduces human agency to higher dependencies on these AI outputs leading to lower sense-making. Reinforcement of agency requires conscious moves between different epistemic modes translated into Human Resource Management (HRM) and Knowledge Management (KMM) frameworks and processes. Such a robust epistemological framework epistemological framework relies on orchestrating coherence between high-level exploratory knowledge and low-level pragmatic knowledge that enables justifying, validating by human agents.

Keywords: Knowledge uncertainty, Human in the loop, Transfer learning

1. Introduction

In an era where artificial intelligence generates vast amounts of information for organisational decision-making, a critical challenge emerges: how can AI-generated information be meaningfully integrated into existing organisational routines and knowledge systems without undermining human judgment or creating epistemic misalignment? This position paper argues that human-in-the-loop mechanisms, grounded in modal consciousness and epistemic functional testing, offer a promising pathway to address this challenge.

We propose the development of integrated HRM–KMM (Human Resource Management – Knowledge Management and Mobilisation) protocols that embed epistemic functional testing as a reciprocal validation process. These protocols systematically compare AI-generated pragmatic outputs against human-mediated epistemic frameworks, drawing on different knowledge modalities: epistemic (what is knowable), doxastic (what is believed), deontic (what is obligatory), and alethic (what is possible or necessary). By enabling continuous iteration and adaptation of knowledge representations in SMEs, such protocols help align pragmatic routines with the theoretical possibilities and limitations of AI tools.

Modal logic and Kripke-frame semantics are used here metaphorically as a lens for mapping “possible worlds” of employee data scenarios against real-world organisational constraints. This approach allows organisations to adopt a proactive stance toward AI in HRM, striking a deliberate balance between technological automation and human judgment. The result is the transformation of epistemic uncertainty into more sustainable knowledge ecosystems.

Building on Wiersma (2026), who highlights the role of human reflective capacity and reinforcement learning in reducing epistemic uncertainty, this paper extends that framework to AI-augmented HRM and KMM contexts. While AI excels at automating closed-loop routine tasks, it remains insufficiently reliable for highly contextual, dynamic, and value-laden HRM decisions (e.g., performance evaluation, talent development, or ethical trade-offs). Such situations require nuanced human epistemic stances and the creation of new semantic codes within everyday routines. Tailored human-in-the-loop approaches are therefore essential to ensure situational accuracy and preserve human agency.

The paper introduces epistemic functional testing as a reinforcement mechanism that reflects AI-derived pragmatic outputs against human-mediated theoretical frameworks. This process supports continuous adaptation of SME knowledge representations through reinforcement and transfer learning, reframing epistemic uncertainty not merely as an opportunity but as a navigable organisational constraint. In doing so, it transforms knowledge inertia into situational certainty modelling, enabling SMEs to incorporate AI responsibly while safeguarding human judgment.

This position paper thus advances a balanced, human-centred approach to AI integration in HRM and knowledge management. It aligns with Wiersma’s emphasis on structured innovation spaces while offering both theoretical depth and practical guidance for building sustainable knowledge ecosystems amid rapid technological change.

The central research question guiding this paper is: How can AI-generated information be effectively and efficiently integrated into existing organisational knowledge and routines using humans in the loop to realise coherent HRM and KMM processes?

The remainder of the paper is organised as follows: After this introduction Section 2 presents key definitions, followed by Section 3 which provides an overview of the relevant literature. Section 4 outlines the methodology, and Section 5 discusses the findings. Consequently a quadrant based typology is presented in Section 6. Finally, Section 7 concludes this paper by answering the research question.

2. Definitions

This paper employs the following key definitions and constructs:

Human Resource Management (HRM) HRM refers to the management decisions and practices related to policies that shape the employment relationship and are aimed at achieving organisational goals (Boselie et al., 2021). In this study, HRM practices are conceptualised as organisational routines that are inherently dynamic. Following Feldman and Pentland (2003), routines possess both an *ostensive* aspect (the idealised script or template that describes the routine) and a *performative* aspect (the actual enactment of the routine by human actors in real time and context).

Modal consciousness refers to the deliberate awareness of multiple possible epistemic states (or "possible worlds") when making choices in organisational routines, situations, or contexts. It emerges through reflective capabilities and enables the integration of new knowledge by linking experience-based choices to logical schemas. Drawing on Wiersma (2026), modal consciousness operates at both individual and organisational levels: it supports assimilation at the individual level and integration at the organisational level through knowledge absorption. This form of consciousness equips agents and organisations with advanced epistemic capabilities to manage uncertainty, experiment with new approaches, and justify knowledge claims in innovative activities.

Knowledge Absorption Capacity Knowledge absorption capacity is the organisation's ability to identify, assimilate, transform, and exploit new external information or knowledge.

Epistemic functionality is defined here as the mutually enabling and sustaining relationship between knowledge and its practical function. In this reciprocal dynamic, knowledge evolves in response to contextual functional needs, and improvements in functionality depend on increasingly context-sensitive knowledge (Schyfter, 2020).

3. Literature

Organisational routines are dynamic systems characterised by a fundamental tension between their ostensive aspect the idealised pattern or script and their performative aspect — the actual enactment by human actors in real time (Feldman & Pentland, 2003). This tension creates opportunities for variation, learning, and innovation, but it can also generate inefficiency, conflict, and modal rigidity when not actively managed through reflection, facilitation, and HRM-supported moderation. Environmental dynamics further shape these routines, resulting in a dualistic ontology in which routines are both stable and changeable.

In this context, human agents play a critical role as intermediaries in the transfer, assimilation, and integration of external knowledge. However, their effectiveness is often constrained by structural limitations. Actors frequently draw on the same social and informational networks that create structural holes, thereby restricting broader knowledge flows (Burt, 2004; Kalish & Robbins, 2008; Soda, 2009). Additionally, the capacity of key individuals to span institutional or organisational boundaries can be undermined by ambiguous role definitions and unclear responsibilities (Jacoby, 2001; Hislop, 2005).

Recent literature highlights the importance of dynamic human capabilities to prevent epistemic misalignment in rapidly changing environments (Aas & Breunig, 2024). In particular, Wiersma (2026) emphasises the central role of modal consciousness in enabling reflective learning and overcoming semantic and epistemic barriers. Modal consciousness allows human agents to navigate multiple knowledge modalities when interacting with AI-generated outputs — for instance, interpreting predictive tools through a doxastic lens (what is believed), assessing epistemic uncertainty in model training, exploring alethic possibilities (what is possible or necessary), or evaluating deontic obligations (what is required).

As artificial intelligence becomes increasingly embedded in organisational routines, epistemic uncertainty — stemming from incomplete identification, validation, and contextualisation of AI-generated knowledge — represents a major challenge to effective knowledge integration. This uncertainty is particularly salient in SME contexts, where resources for validation and boundary spanning are often limited. The integration of generative AI therefore calls for new HRM practices that support human agents in their evolving roles as moderators and reflective practitioners, ensuring that pragmatic routine performance remains aligned with higher-level epistemic frameworks.

3.1 Human Agents and Agency

Epistemic uncertainty differs fundamentally from aleatory (non-epistemic) uncertainty. Aleatory uncertainty arises from inherent randomness or variability in processes and outcomes and cannot be reduced through additional knowledge (Martin-Löf, 1996; Hüllemeier & Waegeman, 2021; Moss, 2018). In contrast, epistemic uncertainty stems from limitations in knowledge representation, incomplete information, or multiple possible interpretations (Angelelli, 2021). It originates from several sources: the inherent complexity of phenomena and processes, gaps or inaccuracies in data collection, and high environmental variability — such as rapid shifts in markets or regional dynamics — which together hinder organisations' ability to accurately assess and absorb knowledge.

At the individual level, routine performance can foster routine proneness highly automatic, low-reflective behaviours that rely heavily on tacit knowledge and closed pragmatic loops (Ersche et al., 2017). These deeply embedded routines are often invisible to traditional HRM practices and offer limited potential for developing dynamic capabilities (Wiersma, 2026). When AI is introduced into such routines, the risk of epistemic misalignment increases because human agency may be displaced by automated outputs without sufficient reflective oversight.

To address this challenge, reinforcement learning (RL) and transfer learning provide promising mechanisms for adaptive knowledge refinement. Reinforcement learning enables agents to learn optimal behaviours through trial-and-error interactions with their environment, gradually reducing uncertainty by rewarding actions that better align knowledge representations with real-world outcomes (Sutton & Barto, 2018). Transfer learning complements this process by allowing pre-trained models from one context to accelerate learning in another, although it introduces its own epistemic challenges when source knowledge is unreliable (Gimelfarb, 2023).

When applied to continuous AI-driven knowledge representations and combined with human feedback loops, these approaches support the creation of situational certainty modelling adaptive, context-sensitive frameworks that dynamically predict and validate knowledge under varying conditions. This extension builds on Wiersma's (2026) human-centric perspective by incorporating AI-augmented co-creation while preserving human reflective capacity and agency.

3.2 Epistemic Uncertainty in Knowledge Transfer

Epistemic uncertainty represents a central challenge in knowledge transfer, especially in multi-agent organisational settings. In contrast to aleatoric uncertainty — which stems from inherent randomness or variability in data — epistemic uncertainty arises from gaps in knowledge representation, incomplete information, or conflicting interpretations (Kudukkil Manchingal et al., 2025).

Wiersma (2026) highlights how pragmatic routines (closed-loop, efficiency-focused practices) frequently clash with theoretical insights, generating semantic noise and trust barriers that hinder effective knowledge integration. For example, differing interpretations of "efficiency" between frontline actors and strategic levels can delay the adoption of new practices in SMEs, as organisations prioritise quick fixes over deeper validation.

Recent literature offers promising avenues for addressing this uncertainty through more structured and AI-supported approaches. Angelelli (2021) proposes a dynamical model of uncertainty in knowledge representation, in which agents actively mediate transfer by comparing and synthesising multiple epistemic states. This formal structure complements Wiersma's emphasis on reflective learning in innovation spaces by providing clearer mechanisms for validation.

Complementing these perspectives, Kudukkil Manchingal et al. (2025) advocate "epistemic artificial intelligence," in which AI systems learn from ignorance by quantifying what is currently unknowable and adapting accordingly. In reinforcement learning (RL) contexts, this approach manifests as epistemic-aware agents that explicitly measure model confidence — for instance through Bayesian methods (Gimelfarb, 2023) — thereby reducing the risk of over-reliance on incomplete or uncertain knowledge.

Collectively, these contributions suggest that epistemic uncertainty in organisational routines can be reframed as a "flux of new possibilities" (Gallagher, 2023). By developing continuous, evolving knowledge representations — such as AI models updated through real-time data streams and human feedback — organisations can move from knowledge inertia toward greater adaptability. This perspective directly extends Wiersma's (2026) call for iterative experimentation and reflective capacity in innovation spaces.

3.3 Reinforcement Learning for Uncertainty Reduction via Transfer

Reinforcement learning (RL) offers a powerful mechanism for reducing epistemic uncertainty by reinforcing behaviours and knowledge representations that better align with real-world outcomes. When combined with transfer learning, RL becomes particularly effective: transfer learning enables the reuse of knowledge acquired from source tasks to accelerate learning and reduce uncertainty in target tasks (Gimelfarb, 2023). In decision-making under epistemic risk, transfer models allow organisations to leverage prior experience while adapting to new contexts.

This approach extends naturally to Wiersma's (2026) framework of innovation spaces and routine dynamics. RL agents operating in multi-agent systems can learn directly from pragmatic feedback generated by SME routines, feeding insights back into higher-level theoretical models. The resulting reinforcement loops reward actions that progressively reduce epistemic uncertainty, creating iterative cycles of knowledge refinement and alignment.

Recent literature supports the integration of RL and transfer learning for managing epistemic uncertainty in dynamic environments. For example, the "curiosity in hindsight" approach (Clark et al., 2025) introduces intrinsic rewards that encourage exploration of unpredictable outcomes in stochastic settings — directly relevant to handling epistemic uncertainty in evolving organisational routines. Similarly, instance-based generalization techniques (Bertran et al., 2020) help bound value gaps between training and test environments, enabling more robust transfer across situational variations.

Complementing these methods, neuro-symbolic AI approaches (Acharya et al., 2025) enhance robustness through ensemble methods and Bayesian uncertainty quantification, narrowing epistemic gaps during knowledge transfer. These mechanisms align closely with Wiersma's emphasis on reflective capacity: RL reward functions can function as "logical principles" that reinforce knowledge renewal, gradually transforming epistemic constraints into actionable possibilities.

3.4 Continuous Knowledge Representations and Epistemic Functional Testing

Continuous knowledge representations — evolving AI models that adapt through ongoing data integration and feedback — form the foundation for reducing epistemic uncertainty in organisational routines. While Wiersma (2026) emphasises iterative refinement of knowledge within innovation spaces, extending this logic to AI environments suggests that knowledge should not be treated as static but as dynamically updated representations. Angelelli (2021) supports this view by proposing dynamical models of uncertainty in knowledge representation, in which agents combine multiple epistemic states. Such approaches are particularly suited to neural networks and other continuous models that evolve through transfer learning.

Gallagher (2023) further argues that knowledge representations must handle constant flux by incorporating metaknowledge, moving beyond closed-loop systems toward more open, adaptive structures. For SMEs, this translates into AI models functioning as "certainty engines" — systems that continuously generate and update situational knowledge, which must then be validated against actual routine performance to maintain alignment between pragmatic action and theoretical possibilities.

3.5 Testing Through Functionality in Routines

Epistemic functional testing provides the mechanism for evaluating these continuous representations within organisational routines. Drawing on Wiersma (2026), who illustrates how theoretical models are iteratively tested against pragmatic routine performance, the proposed test assesses whether AI-generated knowledge effectively informs action and supports adaptation. In AI-augmented contexts, this occurs through reinforcement learning feedback loops, where models are rewarded for compatibility with real-world routines.

Recent contributions reinforce this approach. Amayreh (2025) proposes an interactive AI theory for knowledge production, in which epistemic validation serves as a critical human-in-the-loop layer for testing AI representations in practical settings. Similarly, Agustian et al. (2025) highlight the role of epistemic practices and reflective capacity in addressing wicked problems, showing how models can be refined through situated testing to reduce uncertainty. Together, these elements create a virtuous cycle: AI models transfer knowledge into routines, receive reinforcement based on performance outcomes, and continuously adapt their representations — thereby extending Wiersma's human-centric co-creation into AI-augmented HRM and KMM processes.

3.6 Situational Certainty Modelling

Situational certainty modelling emerges as the outcome of effective epistemic functional testing. It refers to adaptive, context-specific frameworks that provide probabilistic confidence in knowledge under varying conditions. This concept aligns with Wiersma's (2026) emphasis on contingency and flexibility within innovation spaces, where rigid routines are challenged and reformed.

3.7 The Model of Modal Consciousness and Organisational Routines

Building on Wiersma (2026), who conceptualises modal consciousness as the reflective and intentional movement of human agents between different epistemic modes — epistemic (what is knowable), doxastic (what is believed), deontic (what is obligatory), and alethic (what is possible or necessary) — this paper extends the model to AI-augmented organisational contexts.

Wiersma's work shows that modal consciousness enables individuals and organisations to intervene effectively in routines by bridging pragmatic action with higher-level theoretical understanding. This paper argues that while AI is a powerful driver for automating routine tasks, it currently lacks the contextual adaptability and nuanced judgment required in dynamic HRM environments. In such settings, modal consciousness serves as an essential advanced epistemic layer for sensemaking.

Sensemaking, as defined by Weick (1988), involves ongoing processes of interpreting ambiguous or chaotic situations to create plausible meaning and guide action. When routines lose stability, the absence of deliberate sensemaking can turn them into traps that limit adaptability (Weick, 1988; Weick et al., 2005). Modal consciousness addresses this limitation by enabling deliberate, reflective shifts between epistemic modes. These shifts move beyond purely intuitive or pragmatic sensemaking and are actively orchestrated and supported through coherent HRM and KMM frameworks.

A key function of modal consciousness is to facilitate transfer arenas — spaces in which pragmatic routines are systematically validated against theoretical models, leading to hybrid adaptations rather than wholesale replacement (Wiersma, 2026). In the context of AI integration, such arenas become particularly important. Current AI practices for fully autonomous operation in highly situational and value-laden HRM contexts remain limited and underdeveloped (Sizikova, 2019; Rajaram & Tinguely, 2024; Vandaele, 2026). Modal consciousness, supported by epistemic functional testing, offers a structured human-in-the-loop mechanism to bridge this gap and preserve human agency.

4. Methodology

First, a systematic literature review of routine dynamics and epistemic uncertainty in hybrid human-AI systems is synthesized with modal logic and Kripke-frame semantics to formalize modal consciousness as the meta-cognitive capacity to navigate between epistemic modes. Second, a micro-level decomposition of routines, identifying smallest embedded (atomic) routines as the foundational, closed pragmatic units that underpin higher-order dynamic capabilities. This decomposition is achieved through iterative epistemic mapping and reflective-loop analysis (Epistemic Framing Theory – EFT), whereby high-level theoretical/exploratory loops are systematically tested against and integrated with low-level pragmatic/routine-based loops. Third, the framework is validated through conceptual case illustrations and action-research episodes in SME innovation spaces, in which human agents function as critical moderators who perform deliberate modal-shift acts to resolve ostensive-performative tensions and achieve epistemic alignment. HRM practices are positioned as constitutive mechanisms for selecting, training, and rewarding these moderators, thereby operationalizing the dynamic exchange between AI-generated knowledge and embedded routines. The overall methodology is abductive and iterative, moving from theoretical abstraction to situated application, and explicitly treats epistemic uncertainty not as a barrier to be eliminated but as a generative condition to be managed through conscious, principled reflection. This approach yields both a theoretical model and actionable HRM guidelines for knowledge integration in highly dynamic contexts.

5. Findings

This paper demonstrates that Wiersma's (2026) empirical work on innovation spaces can be meaningfully extended by integrating reinforcement learning and transfer learning mechanisms. By developing continuous AI-generated knowledge representations and subjecting them to epistemic functional testing within organizational routines, epistemic uncertainty can be systematically reduced, ultimately giving rise to situational certainty modelling that are better adapted to dynamic and context-specific realities. The findings underscore the importance of seven interrelated process elements that together enable conscious and effective AI integration in knowledge transfer practices. These elements are: (1) human agency, (2) semantic noise, (3) specific operational environment, (4) reflective capacity, (5) transfer loops, (6) critical moderator, and (7) the design of learning environments. When thoughtfully combined, these components form a robust framework for bridging pragmatic routines and theoretical models in multi-agent systems.

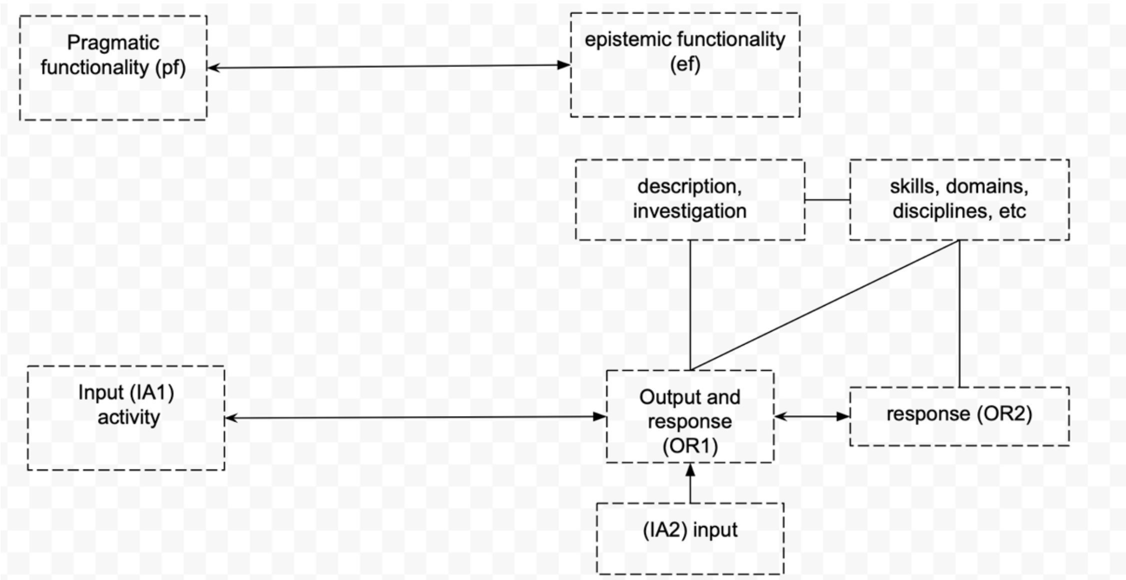

Figure 1: Pragmatic perspective as a foundation for epistemic functionality

Figure 1 illustrates how pragmatic knowledge (routine-level performance) serves as the foundational layer for higher-order epistemic functionality. The diagram shows how the introduction of new AI-generated information perturbs existing activities and outputs, generating compound functionalities and epistemic uncertainty. Epistemic functionality is conceptualised here as an enabling construct that describes the practical capacity of knowledge to inform action and decision-making under conditions of varying certainty.

In the model, input IA2 represents new information entering the system (for example, AI-generated outputs from emerging technologies). This new input influences ongoing activities and alters the original output-response cycle (OR1), leading to modified or additional outcomes (OR2, OR3, etc.). As a result, the original input IA1 becomes compound — it now carries relational, temporal, and situational dependencies with both the new information (IA2) and the resulting outputs. This compounding effect often produces a temporary loss of intentionality and requires organisations to develop denser epistemic representations (e.g., richer concepts, propositions, or judgments).

The framework highlights that effective acquisition (judgments) and assimilation (new beliefs) of knowledge in multi-agent environments demand modal consciousness — the deliberate awareness and switching between different epistemic modes (epistemic, doxastic, deontic, and alethic). By enabling dynamic integration and reflective judgment, modal consciousness helps reduce uncertainty arising from these compound functionalities. Ultimately, the diagram emphasises the need for knowledge engineering practices that explicitly address epistemic doubts and uncertainties through structured human-in-the-loop validation. The model shows how new AI-generated information (IA2) perturbs existing routine activities and outputs (OR1 → OR2/OR3), creating compound knowledge functionalities. Solid arrows represent information flow; dashed arrows indicate validation and reflective feedback loops. Epistemic functionality emerges when pragmatic outputs are tested against multiple epistemic modes via human moderation."

6. Quadrant-based Typology of SME Absorptive Capacity in UAS Collaborations Based on Modal Consciousness

Absorptive Capacity Based on Modal Consciousness and Epistemic Alignment

Modal consciousness refers to the human capacity for reflective awareness and deliberate navigation across different epistemic modes (e.g., epistemic, doxastic, deontic, and alethic). It enables agents to consciously shift between alternative ways of knowing — such as theoretical versus pragmatic perspectives or human-intuitive versus machine-generated knowledge — and to adapt effectively amid uncertainty (Wiersma, 2026). Agents with high modal consciousness can recognise "epistemic twins" (similar but distinct knowledge modes), modulate their epistemic stance, and facilitate the co-creation and absorption of new knowledge.

Epistemic alignment, in contrast, is the degree of coherence and compatibility achieved between different epistemic profiles, perspectives, or sources for example, the alignment between human beliefs/intuitions and AI-generated outputs (Clark et al., 2025).

Table 1 presents a quadrant-based typology that crosses levels of modal consciousness (high/low) with levels of epistemic alignment (high/low). The typology illustrates how these two dimensions influence SMEs' absorptive capacity their ability to recognise, assimilate, and apply new knowledge, particularly when collaborating with universities of applied sciences (UAS) or integrating AI technologies.

Table 1: Quadrant-Based Typology of SME Absorptive Capacity

Quadrant	Modal Consciousness	Epistemic Alignment	Key Organisational Characteristics	Typical Profile / Illustrative Cases
Optimal	High	High	Strong internal reflective practices; low organisational inertia; proactive boundary spanners (e.g., designated champions or receptive managers); dedicated low-risk experimentation environments	Younger or dynamically positioned firms, such as technology-oriented logistics or care-innovation SMEs with leadership open to questioning established heuristics
Reflective but Isolated	High	Low	Reflective capacity exists (e.g., introspective leadership), but structural barriers limit external knowledge bridging (closed networks, lack of boundary roles, or low interaction frequency)	Family-owned businesses with reflective leadership but limited external connectivity
Connected but Passive	Low	High	Good external connectivity and input flow, but weak internal reflective depth; routines remain largely tacit and unquestioned, with minimal deliberate sensemaking or routine revision	Larger SMEs that regularly receive external inputs but lack effective follow-up mechanisms for internal integration
Rigid	Low	Low	High organisational rigidity (e.g., entrenched "this is how we have always done it" culture); minimal reflective agency; few or no boundary-spanning functions; absence of protected experimentation space	Very small, traditional craft-oriented SMEs with strong tacit knowledge cultures and generational inertia

This typology highlights that high absorptive capacity in AI-integrated or UAS-collaborative settings requires both strong modal consciousness (internal reflective capability) and high epistemic alignment (effective integration of external inputs, including AI outputs). The framework can guide HRM practices in designing interventions that strengthen the weaker dimension in each quadrant.

7. Conclusion

This paper poses the following research question: How can AI-generated information be effectively and efficiently integrated into existing organizational knowledge and its routines using humans in the loop realizing coherent HRM and KMM processes?"

As an answer to this question, we propose four distinct HRM approaches.These approaches reflect increasing levels of HRM maturity and reflective capacity:

- **Permissiveness Strategy** (Grieser et al., 2023): Emphasises controlled experimentation within operational routines to ground new information and reduce uncertainty. This approach requires moderate to high HRM maturity.
- **Flexible Arrangements** (Wang et al., 2023): Focuses on designing transferable and adaptable routines that foster innovation-oriented behaviour. It demands significantly greater HRM involvement than traditional knowledge management practices.
- **Inverted Measurement Strategy** (Ersche et al., 2017): Shifts focus from performance metrics to personal development and reflective capacity regarding habitual routines at the individual level.
- **Dynamic Capabilities Arrangement** (Wiersma, 2026): Aims to align organisational routines with evolving environmental dynamics. This approach requires the highest level of HRM maturity to effectively manage complex and deeply embedded routines.

Together, these four approaches illustrate a progression from basic experimentation toward more mature, reflective, and adaptive HRM practices. By embedding modal consciousness and epistemic functional testing into HRM–KMM protocols, organisations — particularly SMEs — can harness the benefits of AI while safeguarding human agency and building sustainable knowledge ecosystems in an era of rapid technological change. These approaches need further empirical validation which further research.

Ethics Declaration: Ethical clearance was not required

AI Declaration: Ai was used enhancing the English quality of the paper.

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