The GenAI Who Knew Too Little – Revisiting Transactive Memory Systems in Human GenAI Collaboration

Research Paper

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Abstract. Generative artificial intelligence (GenAI) is rapidly transforming knowledge work, creating new collaborative dynamics that challenge traditional human-human interaction patterns. This study investigates how Transactive Memory Systems (TMS) manifest in human-GenAI collaboration. Through qualitative interpretive interviews with 14 knowledge workers and thematic analysis, we identified distinct TMS manifestations across its three main dimensions: (1) regarding specialization, expertise recognition exhibited asymmetry. Humans developed awareness of GenAI capabilities while GenAI demonstrated only temporary recognition of human expertise; (2) in terms of credibility, humans formed ambivalent trust relationships with GenAI, simultaneously attributing expertise to the latter while implementing additional verification processes; and (3) concerning coordination, where humans primarily directed more passive GenAI systems lacking initiative, resulting in hierarchical interaction patterns and unidirectional information flow. Our findings reveal that TMS manifests differently in human-GenAI compared to human-human collaboration, necessitating theoretical adaptations including trust markers, acknowledging GenAI's absent metamemory, and identifying its temporary memory.

Keywords: Generative AI, Transactive Memory Systems, Human-AI Collaboration, Knowledge Work

1 Introduction

Generative AI (GenAI) has rapidly evolved from a basic tool into sophisticated collaborative agents (Lu et al., 2024). Organizational adoption rose from 33% in 2023 to 71% by late 2024, with individual work-related use increasing from 8% to 20%, and 50% of users combining personal and professional applications (McKinsey, 2025). Moreover, 35% of 300 surveyed senior executives reported widespread use of AI agents (PwC, 2025) that are capable of collaborating in the context of complex knowledge work. GenAI now assists across diverse knowledge tasks, including text generation, programming, information retrieval, and ideation (Ozkaya, 2023; Huynh, 2024; Ruta et al., 2025). These emerging human-AI collaborations, distinct from traditional human-to-human interactions (Torkamaan et al., 2024; Söllner et al., 2025), raise theoretical challenges: GenAI alters interaction and information processing compared to human teams reliant on social dynamics (Ozkaya, 2023; Lewis, 2003; Lewis & Herndon, 2011).

Transactive Memory Systems (TMS) theory captures these underlying socio-cognitive processes and structures: Originally conceptualized by Wegner et al. (1985, p. 256) as "a combination of individual minds and the communication among them", TMS explains how humans collaborate based on a shared awareness of 'who knows what' within teams. This structure manifests through three behavioral dimensions: *specialization* (recognition of other's expertise), *credibility* (trust in others' expertise), and *coordination* (effective task division) (Lewis & Herndon, 2011). TMS theory has proven helpful in explaining human-human collaboration (e.g., Alahmari et al., 2022; Hopf et al., 2024) and has been leveraged in Information Systems (IS) research in various contexts, such as virtual teams (Chen et al., 2020), distributed IT projects (He et al., 2022), and management (Donate et al., 2023).

As GenAI increasingly integrates into knowledge work, it challenges TMS theory which was developed and utilized to explain collaboration solely among humans (Qu et al., 2023; Restrepo-Tamayo et al., 2024). A critical tension emerges because while TMS theory relies on socio-cognitive processes built through human social interaction, GenAI functions through algorithmic patterns without these social mechanisms. This creates a theoretical gap where purely social frameworks cannot adequately describe what has become a socio-technical relationship. Therefore, empirical examination of human-GenAI collaborations in practice is essential to determine which aspects of TMS persist, transform, or disappear in these novel work arrangements. Hence, our study addresses the following research questions:

(RQ1) *How do the dimensions of TMS manifest in human-GenAI collaboration?*

(RQ2) *How can a nuanced perspective on TMS account for new socio-technical relationships emerging in human-GenAI collaboration?*

To investigate our research questions, we conducted qualitative interpretive interviews with 14 knowledge workers who regularly engage GenAI for knowledge tasks. A thematic analysis (Braun & Clarke, 2006) revealed distinct TMS manifestations in human-GenAI collaboration across the three key TMS dimensions: (1) humans recognized GenAI's capabilities, but GenAI only temporarily recognized human expertise; (2) humans exhibited ambivalent trust, simultaneously attributing expertise to GenAI while also seeing the need to verify its results (3) humans led interactions with passive GenAI, resulting in unidirectional information flow and engagement.

This research contributes to theory by extending TMS from a purely socio-cognitive to a socio-technical framework, introducing three key theoretical adaptations: human metamemory augmentation with trust markers, recognition of GenAI's absent persistent metamemory, and identification of conversation-bound temporary memory structures. Practically, our findings reveal critical gaps in current human-GenAI collaboration including the need for persistent expertise recognition mechanisms, verification processes for ambivalent trust relationships, and solutions to GenAI's passive coordination approach, thereby outlining key research directions for future system design and providing foundational insights for understanding why current human-GenAI collaborations operate sub-optimally.

2 Background

2.1 Human-(Gen)AI Collaboration

Collaboration can be defined as “working together on an intellectual endeavour” (Malone & Crowston, 1994, p. 4), and more specifically, as “an evolving process whereby two or more social entities actively and reciprocally engage in joint activities aimed at achieving at least one shared goal” (Bedwell et al., 2012, p. 130). Within the context of knowledge work, it is further understood as goal-oriented interaction between entities (Mattesich & Monsey, 1992), such as individuals or organizations, that involves coordinating actions and sharing knowledge to jointly complete tasks (de Vreede et al., 2016; Patel et al., 2012; Xue et al., 2010).

Within IS research, collaboration has traditionally been examined with a focus on IS as an enabler of collaboration between humans (Ahuja et al., 2020). In this role, IS function as mediators, supporting, structuring, or even making collaboration between humans possible in the first place (Schuetz & Venkatesh, 2020). With the rise of increasingly capable GenAI systems, this dynamic is shifting. Rather than serving merely as passive tools, these systems actively contribute to the collaboration process by generating new creative content (Chen et al., 2021; Reisenbichler et al., 2022), ideas (Memmert & Tavanapour, 2023; Chang & Li, 2025), or solutions (Picard et al., 2024; Urban et al. 2024) in tandem with humans.

Generative AI engages humans in an emergent co-creation process, where its outputs shape and are shaped by the user’s input, leading to a dynamic interplay between human and machine (Feuerriegel et al., 2024), in which their complementary strengths are combined through a tandem of human direction and AI-driven generation (Dellermann et al., 2019). Jarvenpaa et al. (2024) further characterizes this socio-technical entanglement as co-evolutionary and dialogic. In such a setting, the human typically defines the task’s direction and context, while GenAI contributes content, offers suggestions, or presents new perspectives that the human evaluates, critiques, and builds upon (Mirkovski et al., 2024). This iterative loop enables continuous refinement of results, with AI-generated content prompting humans to reconsider prior understanding, reframe problems, or explore previously unconsidered directions (Tarafdar et al., 2023).

The success of human-AI collaboration often hinges on factors such as domain expertise, self-efficacy, and trust. For instance, AI acceptance is shaped by users’ expertise (Jussupow et al., 2021) and confidence in their abilities (Jussupow et al., 2022). Interestingly, while disagreement with AI can appear problematic, it may also provoke reflective thinking and deepen understanding (Abdel-Karim et al., 2023). However, the integration of AI into decision-making processes may reduce human effort and suppress unique knowledge contributions (Fügener et al., 2021), raising concerns about long-term skill development.

Another factor at play is the “irony of automation”, where users must exert more effort to manage systems designed to assist them (Rowe et al., 2024). This ties closely to the dynamics of trust and control. While some users avoid AI recommendations due to algorithm aversion (Dietvorst et al., 2018), others prefer them, especially when retaining final decision authority (Logg et al., 2019).

Perception and attribution biases also shape collaboration outcomes. Celiktutan et al. (2024) show that individuals judge GenAI-supported work differently based on whether they or someone else initiated the collaboration. This self-other asymmetry can undermine trust in team settings, especially when people assume others use AI merely to offload work rather than for co-creation. On the other hand, working with GenAI may reduce impression management behaviors and foster more open communication (Gnewuch et al., 2023), potentially enhancing transparency and knowledge sharing within teams. However, organizational reliance on GenAI for knowledge management may reduce human-to-human exchange and inhibit the preservation of tacit knowledge (Alavi et al., 2024). Dennis et al. (2023) found no algorithm aversion in teams, with AI often perceived as objective and conflict-resolving. Yet, AI performance and team size modulate perceptions: smaller teams benefit more from AI, while larger teams may suffer from diminished unique contributions (Fügener et al., 2021). Trust in AI team members increases when their performance is high (Hopf et al., 2024), reinforcing the idea that trust and role clarity are essential.

In summary, GenAI collaborates with humans through an iterative, dialogic process in which both parties shape the outcome. Humans typically guide direction and context, while GenAI offers content and suggestions that prompt reflection and refinement. This co-evolutionary interplay relies on the dimensions of TMS, making it a valuable lens for understanding human-GenAI collaboration.

2.2 Transactive Memory Systems

TMS were originally conceptualized as systems that combine individual cognition with interpersonal communication (Wegner et al., 1985) in a knowledge sharing and application context. They describe the socio-cognitive structures and mechanisms (Aissa et al., 2022) by which dyads and larger groups cooperatively learn, store, and access knowledge on a group-level (Wegner, 1987; Hollingshead, 2001). In TMS, each group member doesn't need to recall relevant information alone while accomplishing a task. Instead, individuals in a group have unique knowledge and draw on each other as necessary. Wegner et al. (1985) and Wegner (1987) thus conceptualized TMS as individuals' interconnected memories that collectively hold knowledge, supported by specific cognitive processes for accessing and utilizing that information.

In TMS, personal memory describes an individual's cognitive system that stores and organizes information. It encompasses knowledge (facts, experiences, skills) and organizational labels for categorization of this knowledge and access. Memory function relies on three processes: encoding (initial processing), storage (retention), and retrieval (access) (Wegner et al. 1985; Wegner 1987). Personal memory also includes metamemory structures that track what one knows and doesn't know. Metamemory additionally extends cognition to external storage systems (like books or notes) by recording information labels and locations rather than the information itself, enabling retrieval from these external repositories (Wegner et al. 1985; Wegner 1987).

TMS further extend these cognitive principles to the group level, creating a distributed network (Wegner, 1995). Like individuals using metamemory to track archival knowledge locations, groups utilize their individuals' metamemories to track and utilize expertise across group members. Personal memories function as interconnected components within a larger system rather than in isolation. Each member's unique knowledge becomes a specialized entity in the group's collective coordination architecture. Individual metamemory processes expand to track others' expertise domains, creating what Wegner (1995, p.326) called a directory of "who knows what".

Transactive processes are mechanisms through which group members coordinate knowledge creation, storage, and retrieval from each other for effective task application in cooperative settings. These include encoding (learning expertise distribution), storage (maintaining awareness of who knows what), and retrieval (accessing information through appropriate team members).

These structures manifest in three behavioral dimensions: *specialization* (recognition of other's expertise), *credibility* (trust in others' expertise), and *coordination* (effective task division) (Lewis & Herndon, 2011). These have been shown to enhance group performance, creativity, and adaptation across various collaborative contexts. For instance, Kanawattanachai & Yoo (2007) found task-oriented communication fosters specialization and credibility, which facilitates coordination. Over time, coordination becomes a key factor in enhancing group performance, while communication frequency loses direct impact. Aissa et al. (2022) found that TMS behaviors associated with specialization and coordination directly impact group creativity. Regarding the role of information technology, Sparrow et al. (2011) found individuals use search engines as external memory aids in a TMS manner, remembering where information can be retrieved rather than the information itself. Choi et al. (2010) found knowledge management solutions positively impact TMS development by supporting meta-knowledge.

He et al. (2022) investigated how TMS address dispersions in functional expertise on individual creativity in information technology project teams. Their study revealed that TMS and geographical dispersion interactively moderate individual-level idea generation and implementation processes in multidisciplinary teams, but in qualitatively different ways. Bienefeld et al. (2023) found that access to AI knowledge leads to increased sharing of suggestions and information between team members. McWilliams & Randolph (2024) found that TMS positively affects trust in AI systems, leading to increased knowledge sharing. Hopf et al. (2024) further highlight that AI systems fulfil sufficient requirements to pose as an entity within a TMS, lifting the previous assumption that only human collaboration can be examined in the TMS context.

In summary, research has identified behavioral dimensions and underlying structures regarding TMS, what fosters their development, and effects on human collaborative work. Studies have demonstrated how technology supports TMS and even established that AI can be incorporated into the TMS discourse. However, literature has not yet shown how TMS processes and structures manifest in practice, nor whether differences between human-only and human-GenAI collaboration warrant necessary changes to theory surrounding TMS in the context of human-AI collaboration.

3 Research Design

To investigate TMS as a socio-technical relationship in human-GenAI collaboration, we adopted a qualitative, interpretive research approach that supports contextual understanding and meaning-making (Walsham, 2006; Myers, 1997). Following Klein and Myers' (1999) principles for interpretive field research, we conducted semi-structured interviews to gather rich, practice-oriented insights.

Participants were selected using purposive, criterion-based sampling (Eisenhardt, 1989; Palinkas et al., 2015). Inclusion criteria required that participants use GenAI systems at least twice per week for cognitively demanding knowledge work. This requirement was clearly communicated in recruitment invitations, and participants were screened for eligibility prior to interviews. Three individuals were excluded during this stage for not meeting the criteria. Recruitment was primarily conducted via text-based outreach through the researchers' personal and professional networks, with strict adherence to the inclusion criteria to ensure analytic relevance. Table 1 provides a comprehensive overview of the sample

Data collection and analysis proceeded iteratively. An initial wave of ten interviews was conducted based on the guideline that core themes emerge after approximately six interviews (Guest et al., 2006). Following preliminary analysis, further interviews were conducted until theoretical saturation was reached, when no new themes or insights emerged (Charmaz, 2014; Mikhaeil & Robey, 2024). In total, 14 interviews were conducted, representing the final sample. All interviews were conducted via video call by the same researcher and ranged from 19 to 89 minutes (average: 29 minutes).

We analyzed the data using Braun and Clarke's (2006) thematic analysis framework, involving familiarization with transcripts, inductive coding, and the development of broader themes through progressive refinement.

Table 1. Participants

ID	Gender	Age	Education	Knowledge Domain
P01	M	28	Master's degree	Business informatics
P02	M	22	Secondary School Certificate	Computer science
P03	M	29	Master's degree	Business psychology
P04	M	22	Secondary School Certificate	IT-Administration
P05	F	25	Bachelor's degree	Social Research
P06	M	30	Bachelor's degree	Teaching
P07	M	30	Master's degree	Management Consulting
P08	M	30	Bachelor's degree	Teaching
P09	F	30	Master's degree	Psychology
P10	M	32	Master's degree	Architecture
P11	M	29	Secondary School Certificate	Healthcare
P12	F	32	Bachelor's degree	Healthcare
P13	M	26	Master's degree	Computer Science
P14	M	28	Master's degree	Computer Science

4 Results

GenAI was integrated in a wide range of knowledge tasks, including text editing, programming, knowledge gathering, and personal assistance. Among the most common tasks was text processing: "*So I always write down bullet points of the information […] then, after this process is complete, I first sort the points again […] and then I copy and paste that directly into ChatGPT […] then I copy and paste the [results] into the reports, and then I check again whether I like the phrasing, because sometimes they are a bit clunky and mistakes still happen. I then correct those*" (P09). Participants also integrated GenAI into programming: "*I got an error, then I also ask for feedback and correction of my code, saw the answer, follow-up questions, then understood the code, tried to replicate and implement the code myself, got an error and then questioned further to find the solution to the problem*" (P07). GenAI has also largely replaced traditional search engines for information gathering: "*I've shifted to asking AIs more, because it's simply closer to communicating with a person. You can throw follow-up questions at it when you want more specific answers*" (P04). Executing our research design resulted in the identification of the four major themes shown in Table 2.

Table 2. Themes and Example Codes

Themes	Example Codes
Recognized Expertise, but Questioned Credibility	Conditional trust; Factual unreliability concern; Mandatory verification behavior
Human Coordination facing GenAI's lack of Initiative	Human Initiator; AI passivity; Hierarchical workplace metaphor
Asymmetric and Volatile Expertise Recognition	Memory reset; Temporary session-bound learning; AI ignorance of user expertise
Unilateral Resource Integration	Copy-paste workflow; One-way documents

4.1 Recognized Expertise, but Questioned Credibility

Contrary to the TMS structure where credibility manifests through expertise recognition, participants revealed an ambivalent relationship with GenAI regarding trust. Participants simultaneously attributed expertise to GenAI for specific knowledge tasks while also doubting the results for tasks they had entrusted GenAI with.

Outputs based on content that had already been vetted by participants and passed to GenAI for further processing were generally seen as credible: "*I find improvements of texts that are already clear in terms of content or are asking for improvement in language, I find that's always really great*" (P08). This stands in contrast to tasks that incorporated unknown information provided by GenAI, where participants stated that outputs can't be trusted: "*Especially when it comes to scientific facts, [AI is] always wrong somewhere, and quotes anyway, so I […] critically questioned it*" (P08); "*And currently we have it such that I don't trust the output, well I don't trust it 100 percent in any case*" (P01); "*the AI is very reliable at spreading fake news. Yes, it always acts as if it knows everything, even when it doesn't*" (P02).

As a result, participants saw themselves forced to incorporate additional manual verification processes: "*AI also tends to sometimes make things up a bit, and this experience has shown that for me in the professional world, the direct one-to-one application of AI is simply not feasible, and there is still a certain amount of effort required for verificatio*n" (P10). When working with human collaborators, participants didn't feel the need to verify information due to an inherent trust, especially toward those in higher positions that were associated with greater expertise: "*humans are reliable, [I] would describe the qualitative difference or the confidence in the output as a bit better*" (P07); "*and with my supervisor I'm much more like, oh yes, okay, if he says it like that, then it must be that way, because he is much, much smarter than I am*" (P05).

4.2 Human Coordination facing GenAI's lack of Initiative

Whereas TMS describes a distributed system where members actively coordinate based on recognized expertise domains, participants revealed an asymmetric process for distributing labor with GenAI. While cognitive tasks were divided between human and GenAI, this division occurred through hierarchical assignment rather than drawing on each other's strengths through mutual exchange of ideas and expertise.

As one participant stated, "*with AI, I am the initiator*" (P01) while another reinforced this dynamic by explaining "*with AI it's always like this, the AI is very passive [...], actually only ever reacts to what I give it*" (P04). This relationship was frequently framed in explicitly hierarchical terms through workplace metaphors. Participants used descriptions like "*boss-employee [dynamic]*" (P01), "*assistant*" (P08), and "*service provider*" (P05), characterizing GenAI as a subordinate team member.

The hierarchical dynamic created a workflow where participants issued directives and AI executed without contributing desired direction: "*when it comes to AI, I still feel like [the AI] might know a bit more, but I'm still the one who decides [...], because in the end it's up to me what I accept from [the AI] or what not*" (P05). This contrasted with human collaboration, which was described as more balanced: "*A human is proactive, has more initiative and also approaches me*" (P04).

As a result, GenAI rarely challenged thinking or pushed conversations in new directions: "*I just get the output, but then there isn't a follow-up question or a different opinion coming back where you can discuss things further*" (P01). With humans, participants could "*hack out a plan*" (P07) together: "*You discuss and get from one topic to another, and inspire each other*" (P12).

4.3 Asymmetric and Volatile Expertise Recognition

Unlike traditional TMS, where collaborators maintain an awareness of each other's knowledge domains for efficient coordination, participants revealed that GenAI operated with no meaningful understanding of human collaborators' expertise or skills.

Participants reported they held awareness of the GenAI's capabilities, while GenAI lacked the awareness of participants' background and expertise: "*the AI usually doesn't have that much contextual knowledge about me, but I have more contextual knowledge about the AI. And with humans, it's more reciprocal*" (P03); "*I don't have the feeling* *that the system knows me or my behavior*" (P10). This imbalance manifested in GenAI's inability to calibrate responses to match participants expertise: "*I don't believe that AI says, yes okay, on this topic I don't need to give him as much context, because he already knows a lot about it*" (P01);

However, participants explained that AI was able to develop a temporary recognition of participants expertise within a temporary context. This understanding emerged through ongoing interaction: "*And when [AI] has been well fed with information in a chat, I have the feeling that the AI definitely has more contextual knowledge*" (P03). However, this recognition remained strictly confined to individual sessions. GenAI's ability to understand a participant's background, skills, and knowledge disappeared when starting a new interaction: "*As soon as I go to a different chat, it's lost again. Then I have to start from the beginning again. So it's always like a restart*" (P01).

Participants identified this limitation as a disadvantage compared to human collaboration, where recognition of expertise persists across interactions: "*And that's an ability that humans have. When I talk with colleagues or people who already know me, they know my attitudes toward things, they know what I work on, they basically know my knowledge base. And with them, you can start at a completely different level right away"* (P01). According to participants, this persistent memory enables humans to act proactively: "*AI is, as mentioned, very limited, simply in the sense that it's only in this specific context [...]. But with humans, it's more like they have their own agenda [...] if I'm the person with relevant expertise, they come to me on their own*" (P04).

4.4 Unilateral Resource Integration

While TMS emphasize external storage as an extension of group memory where documents function as shared cognitive artifacts accessible to all collaborators, participants described an asymmetric approach to document-mediated collaboration with GenAI, which differed from their traditional human-human collaborative practice.

With GenAI as a collaborative partner, sharing often only took place in one direction, rather than through truly collaborative documents which both parties use to actively store, share and process information. Knowledge tasks often included integrating external information through uploading files: "*upload those to [the AI] for example and tell it, let's summarize this briefly*" (P12); "*they are sent directly as PDF, bam, sent over*" (P02). Manual pasting of text was another strategy: "*so I always work in a way that I just send over code snippets, [...] and [the AI] then gives me a revised version back [...] my workflow [...] Copy, paste, send it*" (P02). One participant with a background in psychology described sharing clinical notes: "*so while I conduct these diagnostic conversations, I'm taking notes the whole time [...]. So I always write down bullet points, that is, the information that I have, so to speak, gathered from the conversation [...] and then I copy and paste that directly into [the AI]*" (P09).

This one-sided flow of information stands in contrast to human-human collaboration, where participants recognized the value of mutual engagement with shared documents. As one participant noted: "*If I load a document now, it's a bit one-sided in the sense that the AI explains something to me, but I can't really discuss it properly with it. But with humans, in my opinion, the ability to discuss the material again is better*" (P04).

5 Discussion

5.1 Reflection of TMS Manifestation and Human-GenAI Collaboration

Addressing RQ1 on how TMS manifest in human-GenAI collaboration, our analysis reveals both parallels and deviations across the three key TMS dimensions. Concerning *specialization*, we found that participants developed awareness of GenAI specializations, but GenAI failed to recognize human expertise domains. Regarding *credibility*, participants displayed an ambivalent trust relationship towards GenAI, simultaneously attributing expertise while also doubting its outputs. For *coordination*, human-GenAI collaboration was characterized by hierarchical rather than mutual dynamics, with humans directing and GenAI acting without initiative. Additionally, unlike human collaborators which jointly access and contribute to shared knowledge stores (Lewis & Herndon, 2011), GenAI engaged minimally with external information sources, creating a one-way knowledge flow from human to machine in respect to knowledge stores.

These findings call for a critical reflection on the current state of GenAI as a collaborative partner. Overall, the observed manifestations align broadly with the idea of a joint intellectual endeavor (Malone & Crowston, 1994), particularly in the sense of pursuing shared goals through coordinated activity (Bedwell et al., 2012). However, the ideal of active, reciprocal engagement (Jarvenpaa et al., 2024) remains only partially realized. While the turn-based nature of GenAI interfaces structurally enables dialogic interaction (Feuerriegel et al., 2024), this interaction often proves functionally asymmetrical in practice. Across all three TMS dimensions reflecting collaboration, the human participants primarily drove the interaction, with GenAI responding reactively. In this dynamic, GenAI most frequently assumed the role of a task-oriented contributor, primarily acting as a content generator.

As such, GenAI did contribute toward the shared goal and played a role as a partner. However, its inability to perceive and adapt to its counterpart (coordination), to assign tasks (coordination), or to consistently provide fully trusted information (credibility) limits its capacity to truly excel in collaborative contexts, especially those in which human partners would ideally build upon GenAI outputs (Mirkovski et al., 2024).

5.2 A Nuanced Perspective on TMS in Human-GenAI Collaboration

Addressing RQ2 on how a nuanced view on TMS theory can cover for these collaborative relationship changes, our analysis suggests theoretical adaptations to memory structures within TMS that reflect the unique dynamics of human-GenAI knowledge collaborations, as depicted in Figure 1.

Expertise recognition in TMS functions as a mental directory for identifying knowledgeable collaborators. While TMS theory would predict rejection of unreliable sources, participants actually maintained GenAI as a knowledge partner despite trust concerns, simply adding verification steps. This suggests an evolution in TMS metamemory structure, where expertise recognition includes trust markers that trigger verification behaviors during collaboration, creating a spectrum-based rather than categorical approach to collaborative information processing with variably reliable partners.

Further, according to TMS, while humans maintain robust mental directories of collaborators' expertise, GenAI demonstrated fundamental limitations in this architecture. Based on GenAI's passive approach to collaboration, where it fails to initiate collaborative behaviors and utilize shared storage only when explicitly human-directed, we diagnose the absence of a persistent metamemory structure for GenAI compared to human counterparts within TMS. GenAI simultaneously maintains extensive knowledge but lacks the metamemory required to store domain-expertise associations about potential collaborators, preventing it from seeking information or initiating other forms of collaborative behaviors. We therefore suggest the existence of another memory type within the personal memory of GenAI: conversation-bound temporary memory. While GenAI lacks persistent metamemory for expertise recognition, it can temporarily store both knowledge and metamemory components within its current conversation context. This temporary memory allows GenAI to reference both task-related knowledge and expertise recognition information shared earlier in the same session, creating a limited simulation of metamemory function within the conversation boundary. However, these temporary memories remain isolated and volatile, disconnected from GenAI's core knowledge base and unable to persist across separate interactions. This further distinguishes GenAI's memory architecture from the human counterpart.

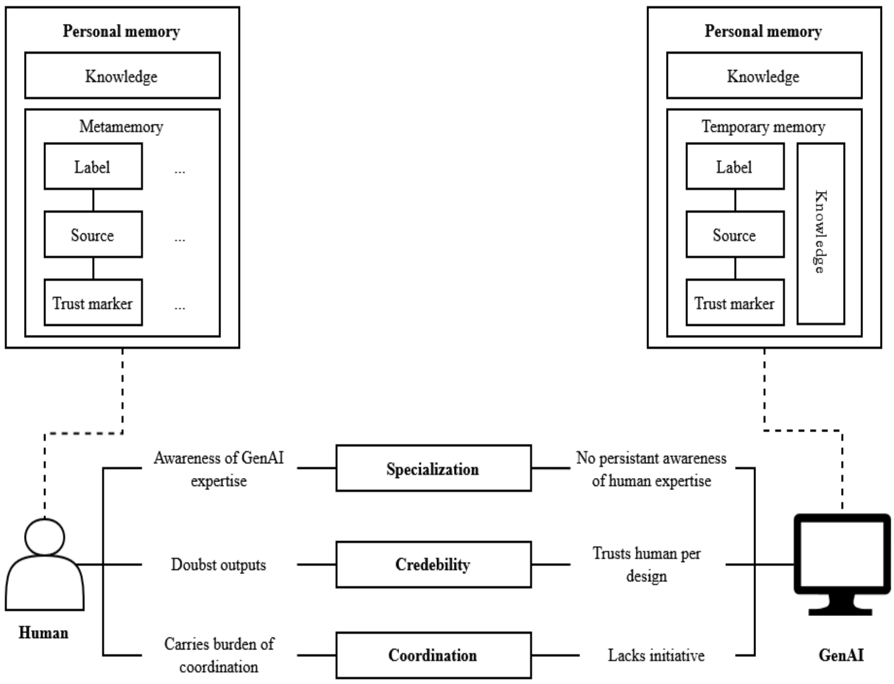

Figure 1. TMS manifestation and adapted memory structure in human-GenAI collaboration

5.3 Implication for theory and practice

Theory must transform TMS from a purely sociological construct into a comprehensive socio-technical framework by systematically revisiting each memory type and transactive process, while being open to discover completely new ones. This theoretical evolution requires mapping traditional socio-cognitive TMS components to appropriate socio-technical equivalents that account for GenAI's distinct technical architecture compared to the social nature of humans. Such reconceptualization will not only advance TMS theory but also provide crucial guidance for designing GenAI systems that better align with human collaborative cognition patterns. Our paper contributes to this discourse by starting to analyze the underlying TMS structures in human-GenAI contexts and provides first directions regarding the required mapping process.

Our findings also urge practitioners to reassess TMS to adapt structures for effective human-GenAI collaboration. Current collaborations operate sub-optimally due to socio-technical dynamics that traditional TMS fail to capture. IS professionals should design suitable mechanisms for persistent expertise recognition, offer appropriate verification mechanisms, and develop features countering GenAI's passive nature, by providing a metamemory structure for GenAI. Interfaces supporting bidirectional knowledge exchange and coordination mechanisms that complement GenAI's strengths could significantly improve collaborative outcomes, bridging theory and practice in human-GenAI knowledge partnerships.

6 Conclusion

This research investigated TMS in human-GenAI collaboration through qualitative interviews with knowledge workers, revealing disruptions to traditional TMS theory due to trust issues, hierarchical control maintenance, limitations in GenAI's proactive behavior, and absent awareness of human expertise, all impeding optimal collaboration. Our paper thus proposes adaptations to traditional TMS theory: augmentation of human metamemory with trust markers, acknowledgment of GenAI's absent metamemory, and identification of GenAI's temporary memory, aiding future GenAI system design.

The study's limitations include its sample size of 14 participants, which may not capture the full spectrum of human-GenAI collaborative experiences. Additionally, to adequately examine TMS structures, we selected participants familiar with GenAI who engage with it regularly for knowledge tasks to gain initial insights, though it's possible that novices could reveal additional facets in first contact scenarios. The self-reported nature of the data also relies on participants' subjective perceptions, which may not fully capture the objective reality of these collaborative interactions.

Future research should further examine the memory structures and transactive process to aid the TMS transition from a purely socio-cognitive to a socio-technical perspective. Studies should start to implement mechanisms for our identified memory adaptions in TMS and examine the impacts, before then investigating human-GenAI TMS in longitude studies with GenAI veterans as well as novices.

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