AI-Powered Teams: How the Usage of Generative AI Tools Enhances Knowledge Transfer and Knowledge Application in Knowledge-Intensive Teams

Research Paper

Olivia Bruhin[1], Luc Bumann[2], Philipp Ebel[1]

[1] University of St.Gallen, Institute on Information Systems and Digital Business, St.Gallen, Switzerland
{olivia.bruhin,philipp.ebel}@unisg.ch
[2] University of St.Gallen, St.Gallen, Switzerland
{luc.bumann}@student.unisg.ch

Abstract. Generative Artificial Intelligence (GenAI) tools, including ChatGPT and GitHub Copilot, are revolutionizing software development by enhancing knowledge sharing and application. This study investigates the role of GenAI tools in software development teams, focusing on its impact on knowledge management processes and team performance. Through an empirical study with 80 software developers, we examine how GenAI usage influences the key knowledge management processes—knowledge transfer and application—and its subsequent effect on team performance. Our findings indicate that GenAI tools significantly enhance team dynamics, fostering efficient knowledge exchange and boosting productivity. In our study, we highlight the importance of integrating GenAI thoughtfully to maximize collaborative benefits, emphasizing its role as a catalyst for innovation and efficiency in knowledge-intensive environments.

Keywords: Human-AI Collaboration, AI in Knowledge Work, Collaboration

1 Introduction

The rapid advancement and widespread accessibility of Generative AI (GenAI) tools, such as ChatGPT and GitHub Copilot, are reshaping productivity, creativity (Dell'Acqua et al., 2023), strategic decision-making (Mariani & Dwivedi, 2024), and the broader work system (Bruhin, 2024), with particularly profound effects on knowledge-intensive work. GenAI refers to advanced technological systems capable of performing cognitive tasks traditionally attributed to humans, including learning, problem-solving, and creative thinking (Raisch & Krakowski, 2021). These capabilities are especially transformative in knowledge-intensive fields like software development, where efficient knowledge sharing, rapid problem-solving, and continuous innovation are critical to success (Robertson et al., 2024).

The emergence of GenAI tools has introduced significant productivity gains—GitHub Copilot alone has shown a 55.8% improvement in code completion rates (Peng et al., 2023). In this study, we distinguish between *team productivity*, referring to the efficiency and volume of task output (Ancona & Caldwell, 1992; Hackman, 1987), and *team performance*, which encompasses not only output but also collaboration quality, learning, and innovation capacity (Kozlowski & Ilgen, 2006; Salas et al., 2005). While productivity gains are increasingly evident, GenAI's broader impact on KM processes and team performance remains poorly understood. Understanding these implications is crucial because KM, the structured acquisition, sharing, and application of knowledge, is the cornerstone of organizational effectiveness, competitive advantage, and sustained innovation (Alavi et al., 2024; Tiwana, 2000). As organizations increasingly adopt GenAI technologies, there is a risk that if these impacts area not adequately explored, businesses may face unintended consequences such as the erosion of unique human expertise, reduced knowledge retention, or impaired decision-making capabilities (Fügener et al., 2021).

Insights from this research are essential for multiple stakeholders: organizational leaders, knowledge managers, software development teams, and policymakers. Organizational leaders and managers need to understand how integrating GenAI affects team performance and innovation to effectively guide their adoption strategies and manage change. For software development teams, clarifying GenAI's role in knowledge transfer and application can empower workers at varying skill levels, improving collaboration and productivity. Furthermore, policymakers can utilize these insights to formulate guidelines around the responsible and effective use of GenAI, minimizing potential disruptions to organizational knowledge structures and employee roles.

Traditional AI systems have historically been limited in their scope due to their complexity, reliance on pattern recognition, and technical barriers preventing widespread use among non-experts (Kaplan & Haenlein, 2010; Sundberg & Holmström, 2023). GenAI tools, however, particularly tools like ChatGPT, overcome these limitations by providing intuitive, user-friendly interfaces accessible to individuals with minimal technical knowledge. This shift democratizes advanced knowledge tools, facilitating greater accessibility, creativity, and innovation in knowledge-intensive work environments (Casheekar et al., 2024; Sedkaoui & Benaichouba, 2024). Recent studies underscore that GenAI not only automates repetitive tasks but significantly enhances human creativity and supports less-experienced workers by bridging skill gaps (Brynjolfsson et al., 2023; Ritala et al., 2023). Nevertheless, as organizations increasingly embed GenAI into their operations, critical questions remain unanswered about how these technologies shape core knowledge processes such as knowledge transfer, retention, and application within teams.

Our study builds upon foundational KM frameworks, particularly the Socialization, Externalization, Combination, and Internalization (SECI) model introduced by Nonaka and Takeuchi (1995) and further extended by Nonaka and Konno (1998). Despite their widespread acceptance, these models have not been extensively analyzed in the context of emerging technologies like GenAI. By examining how GenAI influences knowledge transfer and application within software development teams, our study contributes a novel theoretical perspective by adapting and extending these established models to account for AI-driven interactions and digital knowledge contexts.

RQ1: What is the impact of GenAI tools in software development on knowledge transfer and knowledge application?

RQ2: What is the impact of GenAI tools in software development on team performance?

Addressing these questions will provide crucial insights into how GenAI integrates into team environments, revealing implications that may fundamentally redefine collaborative knowledge management and enhance organizational effectiveness in an increasingly AI-driven workplace.

2 Related Literature and Hypothesis Development

2.1 SECI Model and its Relevance for Knowledge Management in Software Development

With the emergence of a knowledge-based view of the firm, effective management of explicit and tacit knowledge has become crucial for innovation, competitive advantage, and resource optimization (Alavi & Leidner, 2001). In knowledge-intensive industries, particularly software development, managing both forms of knowledge is key to maintaining innovation, optimizing resources, and enhancing productivity. KM practices support software teams in handling complex information flows, promoting continuous learning, and fostering collaboration. Effective KM processes can improve both individual performance and collective productivity by ensuring that knowledge is readily accessible and consistently applied across projects (Khalil & Khalil, 2020).

The SECI model developed by Nonaka and Takeuchi (1995) describes how organizational knowledge is created and converted through four continuous KM processes: Socialization (sharing tacit knowledge directly), Externalization (articulating tacit knowledge explicitly), Combination (integrating explicit knowledge), and Internalization (converting explicit knowledge into tacit understanding). Agile software development inherently supports these processes. Socialization occurs naturally in collaborative environments such as pair programming, Externalization and Combination occur when teams document and integrate explicit knowledge in shared repositories, and Internalization occurs through continuous application and reflection during iterative development cycles (Ouriques et al., 2018). Building on this understanding of how GenAI influences KM processes, we next explore how these changes potentially impact overall team performance.

2.2 Transformation of Knowledge Management Processes through GenAI

The rise of GenAI tools in KM has introduced transformative changes to KM practices across sectors, including software development (Ulfsnes et al., 2024). These tools, powered by advanced models like GPT-4, act as cognitive extensions, allowing users instant access to vast, diverse explicit knowledge bases, thereby assisting with tasks ranging from code generation to troubleshooting (Alavi et al., 2024; Jarrahi et al., 2023). GenAI tools support software developers by providing rapid access to information and solutions, enhancing problem-solving capabilities and enabling quicker and more precise knowledge Externalization and Combination. By synthesizing and suggesting contextually relevant knowledge, these tools also bridge gaps in tacit knowledge, offering nuanced insights that can optimize decision-making and support knowledge-intensive activities, facilitating smoother Internalization.

In software development, tools like GitHub Copilot reshape team interactions and dynamics, particularly by automating code suggestions (Combination) and reducing barriers in knowledge transfer (Socialization and Externalization), thus improving efficiency in knowledge-intensive activities (Peng et al., 2023). This transformative influence of GenAI on knowledge processes implies a potential extension of the SECI model, suggesting that GenAI tools act as facilitators or catalysts of knowledge transformation processes. Nevertheless, GenAI also raises important considerations regarding human-AI interaction and cognitive reliance. The risk of over-reliance on AI-generated content may negatively impact team effectiveness, particularly if team members prioritize AI outputs over collaborative problem-solving (Socialization) or miss opportunities for collective learning (Internalization) (McWilliams & Randolph, 2024). These shifts underscore the need to balance GenAI-enhanced productivity with interpersonal dynamics and human judgment (McWilliams & Randolph, 2024).

In line with the SECI model (Nonaka & Takeuchi, 1995), we conceptually position knowledge transfer as primarily linked to the externalization and combination phases of knowledge creation, where tacit knowledge is articulated and then synthesized into explicit, shareable forms across team members. In contrast, knowledge application aligns closely with internalization, as it involves embedding shared or explicit knowledge into team members' work routines, decisions, and problem-solving strategies. While the SECI model provides a holistic view of knowledge creation, our study focuses on these two critical sub-processes—transfer and application—as they are most directly observable and measurable in software development settings, especially in relation to GenAI tool usage.

Based on this conceptual positioning, we examine how GenAI tools influence these two KM processes within software development teams. By supporting externalization and combination, GenAI may enhance the sharing and structuring of knowledge, while its role in internalization could foster the effective application of that knowledge in practice. These theoretical linkages form the foundation for the following hypotheses:

H1.1: The use of GenAI tools positively influences knowledge application in software development teams.

H1.2: The use of GenAI tools positively influences knowledge transfer in software development teams.

2.3 Transformation of Knowledge Management Processes through GenAI

The effectiveness of software development teams heavily depends on team performance, encompassing not only individual productivity but also effective collaboration, problem-solving, and innovation at the collective level. Historically, research has predominantly concentrated on individual productivity improvements resulting from the usage of GenAI tools rather than examining their impact on collective team performance (Ulfsnes et al., 2024, p. 222). For example, studies such as those conducted by Peng et al. (2024) demonstrate that developers using GitHub Copilot can achieve more than a 50% increase in task productivity, particularly in code completion tasks. However, this substantial boost in individual efficiency does not necessarily translate uniformly across the broader software development lifecycle, such as during complex software modeling or design tasks, where AI support has shown mixed results (Cámara et al., 2023). Thus, understanding whether GenAI tools genuinely enhance overall team productivity in diverse tasks remains an open research question.

Additionally, the introduction of GenAI into software development teams significantly affects team dynamics and knowledge-sharing interactions. Empirical studies by Ulfsnes et al. (2024) highlight notable changes in communication patterns, coordination behaviors, and collaborative interactions following the integration of GenAI tools. These changes potentially influence team cohesion, a critical factor in the Socialization and Internalization dimensions of the SECI model. For instance, over-reliance on GenAI-generated outputs may inadvertently reduce direct interpersonal communication, decreasing opportunities for tacit knowledge sharing and collective experiential learning (Ulfsnes et al., 2024). Thus, based on the literature reviewed, we propose the following hypothesis:

H2.1: Knowledge Application positively influences team performance in software development.

H2.2: Knowledge Transfer positively influences team performance in software development.

H2.3: The use of GenAI tools positively influences team performance in software development.

Building on the previous argumentation and our hypotheses, we propose the following conceptual framework (Figure 1)

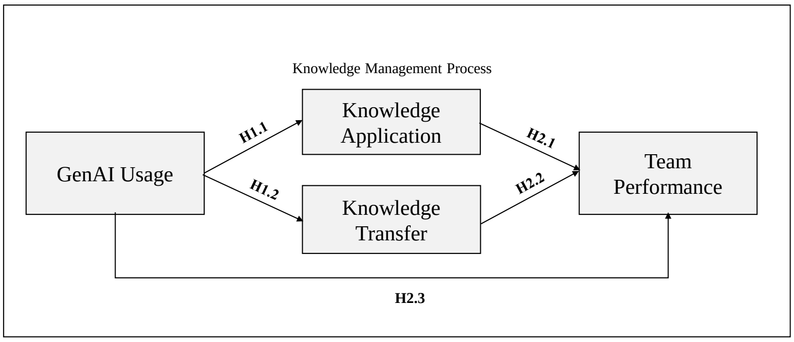

Figure 1. Conceptual framework.

3 Methodology

3.1 Survey Design

For this study, we used a structured online survey for data collection from September to December 2024. This survey targeted software developers working in various industries, aiming to understand how GenAI tools influence KM processes—specifically knowledge transfer and knowledge application—and their subsequent effect on team performance. The survey was based on validated scales and adapted to measure the specific impact of GenAI tools on KM processes and team performance (Choi et al., 2010; Ko et al., 2005; Lewis, 2003).

Participants were asked to rate their experience with GenAI tools such as GitHub Copilot and ChatGPT on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree), measuring the perceived benefits of these tools on their work, as well as their integration into team workflows. Questions related to KM processes were adapted from existing literature and are displayed in Table 1.

3.2 Sample and Data Collection

The sample consists of 80 software developers, recruited through Prolific, a professional survey platform that enabled us to target individuals with relevant expertise in software development and GenAI tool usage. To ensure that only experienced software developers were included, participants were pre-screened based on their profession and AI tool usage frequency (minimum 2–6 times per week). This criterion was essential to capture insights from participants who actively use GenAI tools in their work environments and have practical experience with the technologies in question.

3.3 Variables and Measures

This study examines how GenAI tools influence knowledge transfer, knowledge application, and team performance in software development teams. The core constructs analyzed are GenAI tool usage, knowledge transfer, knowledge application, and team performance. To ensure validity and reliability, measurement scales were adapted from established literature and adjusted to fit the study's context. Participants rated their experiences using a 7-point Likert scale (1 = "strongly disagree" to 7 = "strongly agree").

Knowledge transfer measures were adapted from previously validated scales by Ko et al. (2005) and Choi et al. (2010), capturing the extent to which team members effectively share knowledge within software development teams. The original scales were slightly modified to clearly reflect the interactions among team members during cooperation on software projects. Knowledge transfer was assessed through four items measuring the degree to which team interactions increased understanding, expertise, work capability, and knowledge application readiness for future tasks.

Knowledge application, referring to the effective use of acquired knowledge to address new problems, was similarly adapted from Ko et al. (2005) and Choi et al. (2010). The construct was operationalized with three items, assessing the extent to which team members apply experiential knowledge and explicitly use it for solving new problems within software development contexts.

Team performance was operationalized as a multidimensional construct, incorporating both effectiveness and efficiency criteria in line with established measures from Hsu et al. (2012) and Lin et al. (2012). Team performance encompasses goal achievement, adherence to quality standards, timely completion, and resource efficiency. The scale includes seven items, each evaluating aspects such as the extent to which teams successfully completed projects, maintained high-quality outputs, adhered to schedules and budgets, and accomplished defined project goals.

To measure the level of GenAI tool usage and its perceived impact on productivity, ease of use, effectiveness, and quality of work, we adapted eight items from Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), supplemented by Russo (2024). While the items reflect multiple UTAUT dimensions—such as performance expectancy, effort expectancy, and perceived control—they were modeled as a single latent construct capturing the overall perceived effectiveness and integration of GenAI tools in software development workflows. This approach aligns with recent studies in emerging technology contexts (e.g., Noy & Zhang, 2023) and was chosen to maintain parsimony given the sample size and exploratory nature of the study. Given that this study specifically addresses software development teams utilizing GenAI, item wording was contextualized accordingly, clearly referencing "GenAI tools" in relation to software project activities and workflows.

The constructs and measurement items are provided in detail in Table 1.

Table 1. Overview of Measurement Constructs and Items

Constructs	Items	References
Knowledge Transfer (KT)	Please assess to which degree the following statements are true. (1) “During project cooperation, interactions among team members increased our understanding of this project”. (2) “During project cooperation, interactions among team members increased our knowledge and expertise”. (3) “During project cooperation, interactions among team members increased our ability to work.” (4) “During project cooperation, interactions among team members facilitated knowledge application in future tasks.”	Ko et al. (2005), Choi et al. (2010)
Knowledge Application (KA)	Please assess… (1) “Our team members apply knowledge learned from experiences.” (2) “Our team members use knowledge to solve new problems.” (3) “Our team members apply knowledge to solve new problems.”	Ko et al. (2005), Choi et al. (2010)

Team Productivity (TP)	Please assess… (1) “Our team accomplished project efficiency.” (2) “The quality of work our team produced was high.” (3) “Our team successfully completed the project to meet it goals.” (4) “Our team completed the work as quickly as possible without compromising quality.” (5) “Our team met the scope of the project.” (6) “Our team adhered well to schedules.” (7) “Our team adhered well to budgets.”	Hsu et al. (2012), Lin et al. (2012)
GenAI usage (AI)	Please assess... (1) “Using GenAI tools in my job enables me to accomplish tasks more quickly.” (2) “Using GenAI tools improves my job performance.” (3) “Using GenAI tools in my job increases my productivity.” (4) “Using GenAI tools enhances my effectiveness on the job.” (5) “I find GenAI tools useful in my job.” (6) “I find GenAI tools easy to use.” (7) “Using GenAI tools improves the quality of work I do.” (8) “Using GenAI tools gives me greater control over my work.”	Venkatesh et al. (2003), Russo (2024)

4 Data Analysis and Results

Of the initial pool of 81 respondents, all met the pre-screening criteria and completed the survey. Following Osborne (2013), we removed outliers whose completion time exceeded three times the standard deviation, leaving a final sample of 80 valid responses. The respondents came from a diverse range of company sizes and industries, reflecting the broad application of GenAI tools in software development. Most participants worked in medium to large organizations, distributed across various functions including development, operations, and quality assurance. The sample demographics included 72.5% male and 27.5% female participants, with the majority (78.75%) between ages 22 and 34. Participants had varying levels of professional experience, from under 1 year (10%) to over 5 years (26.25%). Most respondents worked in teams of 6 to 9 members, typical for software development, and were employed by companies with over 500 employees (33.75%).

The data was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM), suited for testing complex relationships between multiple constructs, particularly in exploratory studies (Hair et al., 2021). PLS-SEM allows simultaneous assessment of the relationships between Gen AI usage, KM processes, and team performance, offering robust insights into the moderating effects of GenAI tools. We conducted reliability and validity checks for all constructs, including Cronbach’s alpha, composite reliability, and average variance extracted (AVE), following guidelines by Hair et al. (2021). Relationships were tested by estimating path coefficients and assessing statistical significance using bootstrapping with 5,000 resamples. Control variables such as gender, work experience, firm size, and team size were included to account for confounding effects. As reliability and validity metrics, we used indicators including Cronbach's Alpha, Composite Reliability (rhoC), AVE, and Construct Reliability (rhoA). Values for each construct ranged from 0.779 to 0.908, all exceeding the 0.7 threshold, indicating strong internal consistency and convergent validity for Knowledge Transfer, Knowledge Application, Team Performance, and GenAI Usage. Thus, no further action regarding measurement validity is needed.

To analyse discriminant validity, the heterotrait-monotrait ratio (HTMT) was applied (Hair et al., 2021, p. 79). Resulting values were 0.849 (KA-KA), 0.445 (TP-KA), 0.729 (AI-KA), 0.498 (TP-KT), 0.612 (AI-KT), and 0.436 (AI-AI). Only KT and KA (0.849) approached the threshold value of 0.90. As none exceeded this threshold, discriminant validity is established.

To ensure path coefficient estimations were not biased by high construct correlations, variance inflation factor (VIF) values were calculated for each predictor. All values (TP-KT: 2.006; TP-KA: 1.919; TP-AI: 1.269) were within the acceptable range, so no collinearity issues are apparent.

Significance was assessed using bootstrapping standard errors to calculate t-values of path coefficients or confidence intervals. "A path coefficient is significant at the 5% level if zero does not fall into the 95% confidence interval" (Hair et al., 2021, p. 117). Bootstrapping avoids assumptions about distribution and supports confidence in small sample sizes, as in this study. Based on academic literature, the bootstrapping method with 5,000 samples was used to evaluate the significance and relevance of structural model relationships (Y. Wang et al., 2018). According to Hair et al. (2021, p. 126), values should exceed 1.960 to be significant.

Table 2 shows the resulting path coefficients. The following direct paths were significant at a 95% confidence level: KA-TP (0.428), AI–KT (0.441), AI–KA (0.398), and AI–TP (0.182). These results suggest that compared to knowledge transfer, knowledge application has a stronger positive effect on team performance, confirming Choi et al. (2010). AI usage shows a positive significant effect on both KM processes.

Table 2. Direct path coefficients and significance.

	Original Est.	**Bootstrap Mean**	**Bootstrap SD**	**T Stat.**	**2.5% CI**	**97.5% CI**
KT - TP	0.154	0.172	0.144	1.073	-0.117	0.490
KA - TP	0.428	0.416	0.152	2.814*	0.091	0.699
AI - KT	0.441	0.462	0.100	4.423*	0.265	0.653
AI - KA	0.398	0.411	0.109	3.638*	0.193	0.614
AI - TP	0.182	0.182	0.091	2.007*	0.007	0.363

Although the indirect path from AI through KT to TP was not significant, the direct relationship between GenAI usage and team performance remains significant. Thus, the results indicate a direct positive relationship between GenAI usage and team performance rather than an indirect effect mediated by knowledge transfer.

With the coefficient of determination, the explanatory power of the model's endogenous constructs (KA, KT, and TP) is evaluated. According to the results, the explanatory power of team performance can be described as moderate to strong. However, the explanatory power of the KM processes was relatively low (KT = 0.195, KA = 0.158), suggesting the model may not fully capture all relevant variables or impact paths affecting KM. Further exploration of additional explanatory variables or potential control factors is recommended to enhance model completeness and accuracy. Figure 2 shows the final model with the significant path coefficients.

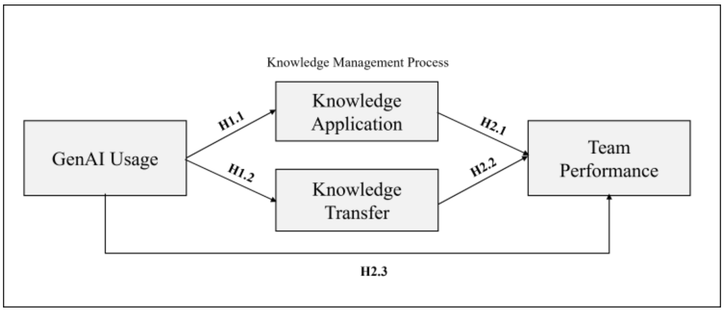

Figure 2. Final model with significant path coefficients.

5 Discussion

The integration of GenAI into TMS marks a new frontier in team collaboration, where AI not only automates tasks but also enhances cognitive processes such as knowledge specialization, credibility, and coordination (Zhang et al., 2023). This study contributes to AI-human collaboration literature by empirically demonstrating that GenAI tools can improve team dynamics and performance when effectively integrated into TMS frameworks.

Addressing RQ1, our findings support the hypothesis that GenAI usage positively influences both knowledge application and knowledge transfer within software development teams (H1.1, H1.2). Specifically, tools like GitHub Copilot and ChatGPT help team members apply explicit knowledge to solve problems (H1.1) and improve knowledge sharing (H1.2). However, while GenAI enhances transfer, it does not significantly improve performance unless the knowledge is effectively applied.

For RQ2, GenAI shows a direct positive impact on team performance (H2.3), primarily mediated by knowledge application (H2.1), not transfer (H2.2). This suggests that transferred knowledge must be actively and contextually applied to boost outcomes—underscoring application as the critical mechanism. Future studies should explore when knowledge transfer meaningfully improves performance.

Our findings highlight GenAI as a strong driver of knowledge application and a moderate one for knowledge transfer, but other factors likely influence these processes. Variables like team climate, leadership, and AI experience warrant attention in future research to refine models of AI-supported knowledge work.

Theoretically, this study extends KM literature by emphasizing practical knowledge application over simple dissemination and enriches human-AI collaboration research by showing GenAI's direct impact on team performance beyond traditional KM pathways.

From a practical standpoint, these findings offer important implications for several key stakeholder groups. Organizational leaders can leverage GenAI tools to enhance productivity and innovation but should ensure that their integration supports—not replaces—human expertise and team cohesion. Knowledge managers should focus on fostering environments where GenAI complements knowledge processes, especially in knowledge application, while guarding against over-reliance that may undermine tacit knowledge exchange. Software development teams can benefit from tailored training and collaborative practices that maximize the value of GenAI without reducing opportunities for interpersonal learning. Finally, policymakers may consider developing guidelines that encourage responsible AI integration in high-knowledge sectors, balancing efficiency gains with long-term knowledge retention and workforce development. By revisiting these stakeholder perspectives in light of our findings, we close the loop on the study's broader relevance and highlight how GenAI's integration into team-based knowledge work can be steered in strategically meaningful ways across organizational and societal levels.

This study has limitations that open avenues for future research. First, the modest sample size (n = 80) limits generalizability, despite the use of bootstrapping for statistical rigor. Second, reliance on self-reported data may introduce response biases. Mixed-method approaches using observational or performance data could strengthen future analyses.

Also, while constructs were adapted from validated sources, some items may lack GenAI-specific anchoring. Future studies should better align construct wording with GenAI usage to enhance validity. Furthermore, the relatively low explanatory power of knowledge constructs suggests a need to refine the GenAI usage variable, potentially by separating usage behavior from performance expectations.

Our cross-sectional design also limits insights into how GenAI's influence evolves over time. Longitudinal studies are needed to examine dynamic changes in team behavior and tool integration. Finally, this research focuses on software teams; industry-specific studies in sectors like healthcare or finance are needed to understand how GenAI impacts knowledge work under varying conditions.

Furthermore, while the study focuses on the role of GenAI in shaping knowledge management and team performance, the constructs for knowledge transfer, knowledge application, and team productivity were adapted from validated sources but not explicitly anchored in GenAI-specific contexts. Although participants were pre-screened for frequent GenAI usage and the survey introduction framed questions in relation to GenAI use, the potential lack of explicit GenAI reference in some items could introduce ambiguity. Future research should ensure tighter coupling between construct wording and GenAI-specific activities to improve construct validity.

While our study found a significant relationship between GenAI usage and KM outcomes, the explanatory power of the knowledge management constructs (KT = 0.195, KA = 0.158) was relatively low. This may, in part, reflect limitations in how GenAI usage was operationalized. Although our construct showed strong reliability and validity, it aggregated multiple dimensions of GenAI experience into a single latent factor, which may have attenuated its explanatory precision. Future research should explore a more granular operationalization—distinguishing, for example, between performance expectancy and actual use behavior—to better capture the nuanced impact of GenAI on KM processes.

Finally, the study focuses on software development teams and does not explore how industry-specific factors might shape the effectiveness and challenges of GenAI adoption. Different industries have varying levels of reliance on tacit versus explicit knowledge, as well as different regulatory, security, and ethical considerations. Examining GenAI's role in other knowledge-intensive fields, such as healthcare or finance, could provide a broader understanding of its impact and help to identify industry-specific best practices and challenges.

6 Conclusion and Further Research

This study explores the role of GenAI tools in enhancing KM processes and team performance within software development teams. By examining the impact of GenAI on knowledge transfer and application, we found that these tools support faster, more efficient access to information, streamline complex workflows, and help boost team productivity. The findings suggest that GenAI tools, like ChatGPT and GitHub Copilot, act as cognitive extensions, assisting team members in retrieving and applying knowledge with greater ease. However, our results highlight the importance of thoughtful integration to prevent over-reliance on AI, which may inadvertently reduce the richness of interpersonal knowledge sharing and hinder the development of human expertise. While GenAI effectively facilitates explicit knowledge transfer, it has limitations in understanding and sharing tacit knowledge, crucial in collaborative problem-solving contexts. This study emphasizes that GenAI's benefits are maximized when complementing rather than replacing human expertise. Organizations should thus promote balanced usage, where AI supports routine tasks but preserves essential human-driven collaboration.

Future research is recommended to explore the long-term effects of GenAI usage on KM practices across diverse organizational contexts, especially in fields relying heavily on contextual and experiential knowledge. Additionally, research into the psychological and social dynamics of human-AI collaboration, such as trust in AI outputs and impacts on team cohesion, would provide deeper insights. Finally, longitudinal studies could offer a more comprehensive understanding of GenAI's influence on team performance and KM, guiding organizations aiming to fully harness GenAI's potential.

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