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Beyond Code: The Impact of Generative AI on Work Systems in Software Engineering

Short Paper

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Abstract

The development of Generative Artificial Intelligence (GenAI) in Software Engineering (SE) is driving significant transformations in work systems, impacting work practices, information management, and development processes. This study applies Work System Theory to explore how GenAI not only enhances individual tasks but also redefines entire workflows and collaboration models within SE environments. Through a case study involving expert interviews at a telecommunications and software company, the research uncovers both substantial benefits and emerging challenges associated with GenAI integration. The findings contribute to a structured framework that offers guidance for effectively implementing GenAI to enhance productivity and foster innovation in SE. These insights are essential for practitioners managing the rapidly evolving SE landscape, ensuring the successful and sustainable adoption of GenAI within work systems.

Keywords: Generative AI, Software Engineering, Work Systems, Digital Transformation

Introduction

In the dynamic field of Software Engineering (SE), the integration of Generative Artificial Intelligence (GenAI) marks a significant shift in work systems. The challenges of adopting GenAI go beyond the technical domain, encompassing workforce adaptation, data management policies, and redefined development practices. This research aims to investigate the impact of GenAI on various components of the SE work system and provides guidance for future introduction of GenAI in SE.

In November 2022, OpenAI, supported by Microsoft, released ChatGPT[1], a groundbreaking GenAI chatbot. Utilizing advanced large language models (LLMs), ChatGPT quickly gained popularity, reaching 100 million users within two months (Hu, 2023). Currently, LLMs like OpenAI's ChatGPT and GitHub's Copilot[2] are at the center of attention, signaling a substantial shift in technological capabilities. These advancements are expected to contribute up to $7 trillion to the global economy and potentially elevate productivity growth by 1.5% over the next decade (Goldman Sachs, 2023). The ability of this technology to create human-like content marks a transformative change at the intersection of social and technical systems, with far-reaching implications for the global economy. Businesses are on the threshold of widespread adoption, with those who embrace the technology able to secure a competitive advantage (Zao-Sanders & Ramos, 2023).

Recent research has further explored the broader implications of AI on work systems. Cazzaniga et al. (2024) discuss how AI is expected to profoundly change the global economy, particularly in labor markets, where it both complements and threatens various job roles. Similarly, Perino (2024) highlights the

[1] https://openai.com/chatgpt

[2] https://github.com/features/copilot

transformative impact of AI and automation on workplaces, emphasizing the potential for enhanced productivity alongside significant workforce transitions.

The integration of GenAI across industries has been the subject of extensive research, particularly in areas such as Education (e.g., Chiu, 2023; Luo, 2024), Research (e.g., Al-Zahrani, 2023; Atkinson, 2023), Creative Work (e.g., Bauer et al., 2024; Tsao & Nogues, 2024), and Health Care (e.g., Yim et al., 2024). In the context of SE, several studies have started to explore the transformative potential of GenAI. For instance, Ozkaya (2023) highlights the efficiency gains achievable through the automation of routine tasks, allowing developers to focus more on complex and conceptual challenges. Similarly, Nguyen-Duc et al. (2023) discuss the impact of GenAI on specific processes such as code creation and test case refinement, noting its potential to enhance operational efficiency and effectiveness. Research has also focused on different stages in the SE process, such as requirements engineering (e.g., Marques et al., 2024; Naik et al., 2024), and the role of autonomous agents in SE (Suri et al., 2023). However, Fontes et al. (2023) and Choudhuri et al. (2024) raise significant concerns regarding the nature and quality of AI-generated solutions compared to those produced by human engineers.

However, while these studies contribute valuable insights, the specific impact of GenAI on work systems in SE – particularly how it reshapes work processes, roles, and collaboration within organizations - remains underexplored. Given the rapidly expanding body of literature on GenAI and its applications, this work seeks to fill a critical gap by providing a deeper analysis of how GenAI not only alters individual tasks but fundamentally transforms SE work systems on a structural level.

Therefore, this study is guided by the following research question: *How does the introduction of generative artificial intelligence tools influence the work system in software engineering?*

Steven Alter's work system theory (WST) provides the conceptual framework for this investigation, enabling a structured exploration of the processes within work systems and the changes imposed by GenAI. Through a case study involving 10 in-depth expert interviews with a telecommunications and software company, I gained insights into how GenAI is reshaping SE work systems. The findings indicate that GenAI integration includes both challenges and opportunities, necessitating a deeper understanding of these dynamics to effectively navigate the future of SE practices.

This paper presents an overview of GenAI as a supporting tool in SE, introduces WST as the theoretical framework, presents initial research findings, and outlines the implications and next steps for this study.

Conceptual Background

GenAI Assistance for Software Engineering

The concept of a "programming apprentice" from the 1980s, which initially involved symbolic AI and design patterns to assist in programming, has evolved significantly with the rise of machine learning (ML), in SE activities (Yang et al., 2022). A key development was integration of GenAI through LLMs, as seen with GitHub Copilot[3], which initially launched for free and is now available as a subscription-based service within various IDEs (Zhao et al., 2023).

The integration of GenAI in SE practice has proven to be fundamental in enhancing productivity and efficiency. Studies have shown that GenAI can significantly boost productivity (Dell'Acqua et al., 2023; Sadowski & Zimmermann, 2019; Li et al., 2024), facilitate improved team collaboration (Ziegler et al., 2022; Meyer et al., 2014), and enhance code quality (Bouschery et al., 2023).

These advances not only facilitate more intuitive interaction between developers and their tools, but also highlight the need for deeper integration with IDEs and improved traceability mechanisms to better understand the foundations of the code suggestions generated. Despite the potential of GenAI in SE, challenges remain such as the need for continuous refinement (Nguyen-Duc et al., 2023), the non-deterministic nature of GenAI outputs (Ouyang et al., 2023; Liu et al., 2023; Sun et al., 2023), and issues like data sensitivity or AI hallucination (Liu et al., 2023; Sun et al., 2023; Alkaissi & McFarlane, 2023). Initial studies indicate that the promise of GenAI-driven automation in SE could be on the horizon (Carleton et al., 2022), if these challenges will be addressed in the future.

[3] https://github.com/features/copilot

Work System Theory and Effects of Disruptive Technology

The concept of work systems, being extensively utilized within sociotechnical studies, emphasizes significant developments in understanding and analyzing IT-reliant systems in organizations. WST, introduced by Alter (2013), builds upon decades of sociotechnical research (Trist, 1981; Bostrom & Heinen, 1977; Mumford, 2006). Alter's articulation of the term "work system" has refined and expanded its use, particularly emphasizing its relevance as a central concept for analyzing systems that rely heavily on information technology (Alter, 1999, 2003, 2008). See Figure 1 for a visualization of the WST.

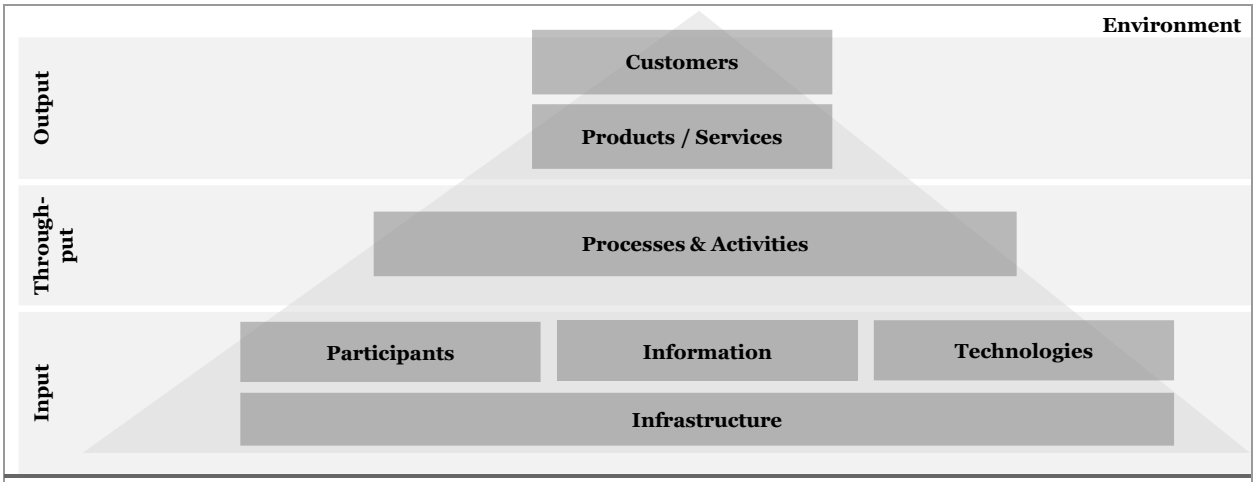

Figure 1. Work System Theory (according to Alter, 2013)

WST posits that systems in organizations should primarily be viewed as work systems, incorporating technologies as components rather than standalone systems, unless the focus is on fully automated systems. This approach aligns with the sociotechnical perspective that considers both the social and technical aspects of organizational systems. The WST provides a robust framework for understanding the intricate relationships and dynamics within IT-reliant systems, offering valuable perspectives for both academic research and practical application in the field of information systems. By focusing on the integration of technology within the broader context of organizational work systems, WST encourages a holistic view of system design and management that is crucial for the successful deployment and operation of technology-driven systems. (Alter, 2013)

Disruptive technologies, as defined by Christensen (1997), fundamentally alter work systems by introducing innovations that challenge established practices. While initially underperforming and appealing to niche markets, these technologies eventually transform industries (Barrett & Walsham, 1999). Ubiquitous computing, a prime example, merges physical and electronic spaces, enabling new forms of work and collaboration. This integration fosters continuous connectivity, real-time data monitoring, and the rise of smart environments, which redefine how organizations operate and create value. As these technologies evolve, they drive significant changes in knowledge acquisition, task automation, and workplace dynamics, ultimately reshaping organizational structures and processes (Cascio et al., 2016).

Research Approach

Data Collection

To investigate the impact of GenAI on SE work systems, I conducted a case study with a telecommunication and software company referred to as TeleComp. TeleComp, headquartered in Switzerland, operates with a significant IT workforce comprising 523 experts distributed across Switzerland, the Netherlands and Lithuania. Within its SE core, TeleComp employs self-managing and self-organizing teams that operate

under the Scaled Agile Framework (SAFe)[4]. This organizational structure provides an ideal context for examining how GenAI integration influences the work system in SE.

The questionnaire development process began with a thorough literature review to identify key themes and potential areas of influence that GenAI could have on the SE work system. Drawing from this foundation, the questionnaire was structured to explore these themes in depth, addressing both technical and organizational dimensions of GenAI integration. Insights from the multi-layered model of organizational structure proposed by Plekhanov et al. (2023), which distinguishes between internal and external layers of influence within a firm, informed the questionnaire's design, capturing perspectives from different organizational layers and roles. The groups were defined as follows: *Group A*, the Core (Firm-Internal), consists of individuals who are directly affected by GenAI, with daily interactions involving GenAI tools and technologies. *Group B*, the Periphery (Firm-Internal), includes individuals who are not yet directly influenced by GenAI but are expected to engage with it soon, particularly through collaborative projects or cross-functional initiatives. *Group C*, the Environmental (Firm-External), encompasses external influences that may impact GenAI's adoption and use within the company, including factors such as public media, technological advancements, and communications from external stakeholders like vendors or partners.

Data Analysis

I conducted semi-structured interviews with key stakeholders from each of the identified groups within TeleComp's IT core. The interviews were designed to obtain in-depth responses regarding the integration of GenAI into their working systems, the challenges encountered and the potential areas for further attention (see Table 1 for more information about the interview participants).

Code	SAFe Role of the Interviewee	Duration of the interview (in min)
I1	Epic Owner	42
I2	Epic Owner	35
I3	Enterprise Architect	34
I4	Solution Architect	35
I5	Product Owner	46
I6	Business Owner	61
I7	Tribe Chief	43
I8	Team Coach	37
I9	Agile Coach	34
I10	IT-Manager	53

Table 1. Overview of Interview Experts.

Preliminary Findings

The data analysis provides a foundational understanding of the multifaceted impacts of GenAI on TeleComp's SE work systems. The integration of GenAI is driving changes at various organizational levels, each with its own set of challenges and opportunities.

Input Factor: Infrastructure

Integrating GenAI tools into existing environments raises complex questions regarding compatibility, scalability, and evolution of technology stacks. These issues are not merely technical but also involve organizational decision-making regarding the sustainment or renovation of current systems to harness the potential of GenAI effectively. As I4, Solution Architect at TeleComp, noted: "*The challenge lies in not just updating the old systems but in deciding whether it's worth the effort to modernize them or if we should start fresh to fully leverage what GenAI has to offer.*"

Input Factor: Participants

To analyze the Participants area, I differentiated between how employees are affected by using GenAI tools and divided them into the three groups A (internal, directly affected), B (internal, indirectly affected) and C (external, environment). For the directly affected group A, I additionally considered the crafting theory

[4] https://scaledagileframework.com

(according to Wrzesniewski & Dutton, 2001) to differentiate the impact of GenAI tools. I analyzed the categories of the job content (physical component), the meaning of tasks (cognitive component) and the relationships with others in the job environment (social component) of novices and experts.

For Group A, consisting of firm-internal and directly affected employees by GenAI tools, the results show both opportunities as well as barriers arising from the introduction of GenAI tools.

Regarding the *physical component*, the introduction of GenAI tools has provided software engineers with tangible and interactive experiences, bringing AI into their daily work environment as a lived reality rather than a distant concept. As interview partner I5 pointed out, *"With GenAI tools, we now have something tangible and experiential; this is why many traditional machine learning cases are resurfacing in our awareness. AI is becoming integrated into our everyday work lives."* However, alongside with these opportunities, significant concerns arise about the potential loss of expertise, especially among younger employees. Additionally, the notion that GenAI could become a competitor for engineer's jobs raises fears among affected employees. I4 additionally highlighted that if GenAI continues to improve, it could reduce the need for software developers, further intensifying anxieties about job displacement.

On a *cognitive level*, GenAI influences employees individually, altering their work fields, tasks, and processes. As expert I8 noted, *"People are influenced by technology on an individual level, and they change their work environment, tasks, and processes accordingly. Through their behavior, GenAI also adapts to their work."* This interaction is not one-sided; instead, it illustrates a co-evolution between technology and work processes, where GenAI adapts to how employees use it. However, this dynamic also seems to widen the performance gap between employees. High performers are likely to excel even more with the aid of these tools, while low performers may struggle, potentially leading to increased stress and a more pronounced disparity in performance levels.

On a *social level*, the integration of GenAI has streamlined communication within the organization. For example, rewriting internal emails and messages with the help of GenAI has reduced misunderstandings, resulting in more efficient workflows. However, there has also been a noticeable shift in how employees seek information. Where employees previously might have consulted a specialist within the team or organization for insights, many now turn to GenAI for quick inputs. I2 stated: *"Sometimes I also ask GenAI for some input to get an idea, where previously I might have gone to a specialist in the team or organization."* This shift may reduce collaboration and the sharing of expertise within the team, potentially affecting the overall knowledge exchange.

Group B, individuals who are not yet directly influenced by GenAI but are expected to engage with it soon, offered insights how these employees will react to the anticipated challenges and opportunities associated with GenAI soon. Regarding opportunities, the introduction of GenAI tools is perceived as making AI also more tangible for employees outside of traditional IT, gradually integrating into the everyday work lives of all employees. I5 noted: *"With the introduction of GenAI, AI has become something that we can interact with and experience firsthand, making it possible for us – even not as close to IT as others – to experiment with AI use cases."* However, challenges are also anticipated, particularly concerning the long-term impact of GenAI on work processes. While many employees are currently open to experimenting with GenAI due to its novelty, there is uncertainty about how it will continuously influence their workflows. Additionally, there is a lack of clarity on how to effectively use GenAI tools, especially when it comes to consuming and applying prompts from others in a meaningful way. This uncertainty raises concerns about whether employees will be able to adapt to the evolving demands of their roles as GenAI becomes more embedded in their work.

Group C entails external influences that may impact the adoption and use of GenAI within the company, including public media, technological advancements, and communications from external stakeholders such as vendors or partners. These external factors provide a broader context for understanding the role of GenAI within the organization. One of the key external concerns involves ethical considerations, particularly the question of whether humans should be replaced by machines. This debate has been ongoing even before the arrival of LLMs, but the rapid advancement of AI has intensified these concerns. There is a growing fear that what was once considered a support system for human workers might soon replace them in certain roles, raising significant ethical and practical questions about the future of work. As I9 remarked, *"We used to talk about AI as a tool to support human work, but now we're facing the reality that it might replace us sooner than we thought."*

Input Factor: Information

Information, the lifeblood of any GenAI system, faces significant challenges, particularly in terms of data, quality. There is an intensified demand for high-quality data, which is crucial for the successful implementation and operation of GenAI tools. Ensuring the integrity, relevance, and accuracy of data inputs is imperative, as they form the foundation upon which GenAI systems learn, evolve, and produce outputs.

A major issue is data drift, which presents several technical challenges. As data evolves over time, software testing processes must adapt, recognizing that results may not always be deterministic. As I3 pointed out, *"I believe there will be a significant change in how we test software, especially considering that outcomes may not always be deterministic. We need to account for the fact that the result is only 70% correct, and we must continuously measure whether there is drift in one direction or another because the business case depends on this 70% accuracy. For example, identifying 70% of text in an insurance claim to determine if it's covered or not."* The quality and quantity of data are now more important than ever to ensure a solid foundation for AI. However, there is a risk associated with relying on AI-generated code, particularly when data quality is insufficient. As I5 noted, *"There is a significant danger in relying directly on AI-generated code due to often insufficient data quality."* Additionally, the black-box nature of GenAI can complicate coding documentation, making it more difficult to understand and verify. Furthermore, the issue of code bias cannot be ignored. As I1 explained, *"Code has biases, which can lead you in a certain direction. The code that is produced is not always the most secure; it has its vulnerabilities, which leads to increased security efforts."* This statement highlights the importance of addressing biases in code to prevent vulnerabilities and ensure the security and reliability of the systems developed using GenAI tools.

Input Factor: Technology

Regarding Technology, high licensing costs and financial operations (FinOps) have emerged as a significant concern. The economic implications of adopting GenAI tools—characterized by substantial initial investment and ongoing operational costs—pose a significant challenge for organizations. These financial demands must be carefully balanced against the expected value generated from the use of GenAI tools. In this context, FinOps plays a crucial role in managing and optimizing the costs associated with these technologies, ensuring that the financial health of the organization remains aligned with its technological ambitions. I4 highlighted the technical challenges associated with this transformation, stating, "*Yes, we employ a lot of technicians to tackle these significant technical challenges. We are not just doing a simple lift and shift; we are fundamentally transforming our technology. We are rebuilding half of our applications so they can function properly on AWS (Amazon Web Services). This is undoubtedly a massive challenge."* This underscores the complexity and scale of the technological overhaul required to integrate GenAI effectively. Another key concern is governance, particularly around data management and privacy, which extends beyond just technology and finance. As expert I7 pointed out, *"The second major requirement is the entire governance surrounding this, especially regarding data. This isn't just about technology and finances, but about the entire data protection issue that everyone is concerned with."* This statement emphasizes the importance of robust governance frameworks to address not only the technical and financial aspects but also the critical issues of data security and privacy in the adoption of GenAI technologies.

Throughput Factor: Processes and Activities

GenAI tools are significantly transforming Processes and Activities carried out in SE. Each phase of the software development lifecycle—from creation to monitoring—is impacted by these advancements. GenAI tools have the potential to alter workflows drastically, necessitate the adoption of new methodologies, and demand fresh perspectives on software quality and delivery. As I6 pointed out, "*LLMs work incredibly well with code; I have almost no doubt that it works there. However, it will still require an additional quality review process for a long time. It will require more control processes. But overall, it will still be more efficient. However, the efficiency will not be linear."* This highlights the dual impact of GenAI tools: while they can enhance efficiency, they also introduce the need for additional quality review processes to ensure that the AI-generated code meets the required standards. The non-linear improvement in efficiency reflects the complexity and learning curve associated with integrating AI into existing workflows. Furthermore, while the core activities in agile frameworks may not change fundamentally, the roles within teams might shift. I8 observed, *"GenAI will have only a small influence on the work processes themselves; we will continue to do what we do. I am quite sure of that. We are fully agile, and we will not change that*

structure. However, we are already seeing that it will likely require fewer developers and, instead, more business analysts, because in the future, fewer developers will be needed to develop something, and more will be needed to understand what we are doing." This underscores a potential reduction in the need for traditional developers, offset by a growing demand for business analysts who can bridge the gap between technical capabilities and business needs.

Output Factor: Products and Services

The integration of GenAI into SE opens new avenues for innovation, enabling the development of novel products and services that were previously unattainable. GenAI's capabilities allow organizations to explore and create innovative solutions, significantly enhancing their product and service offerings. As I5 highlighted, *"Due to the possibilities offered by GenAI, we can now also develop internal products aimed at quality improvement. For instance, within just a few months, we developed an internal GenAI tool with minimal support from an external consultancy—a process that would have normally taken us a year."* This quote underscores the transformative potential of GenAI in accelerating the development cycle, allowing companies to innovate more rapidly and efficiently. The ability to create such tools internally not only boosts the speed of innovation but also improves the overall quality of the products and services offered.

Output Factor: Customers

The integration of GenAI into SE is reshaping customer expectations and enhancing user experiences. As customers become more aware of the capabilities of GenAI, their demands for more advanced and responsive software solutions continue to rise. One expert noted, "*We are already seeing that [user's] expectations are constantly increasing. Because people are constantly being shown the possibilities that can be implemented with GenAI through the media and providers, we as a provider company are also under pressure."* This quote highlights the growing pressure on companies to meet the elevated expectations of customers who are increasingly informed about what GenAI can achieve. As a result, organizations must continuously innovate and enhance their offerings to stay competitive in the market. In addition to rising expectations, GenAI also offers significant potential for improving user experiences. Another expert shared, *"We have already implemented GenAI in various B2C applications: chatbots for ticket avoidance (customer support, chatting with insurance policies, etc.). We aim to improve the customer experience on several levels: on the one hand, through better quality advice, but also through shorter waiting times."* This reflects how GenAI is being used to create more intelligent and responsive software solutions, leading to more satisfying interactions for customers. By leveraging GenAI, companies can deliver faster, more accurate support and services, thereby enhancing the overall user experience.

Conclusion and Discussion

This study presents initial findings from a case study examining the impact of GenAI on the SE work system at TeleComp, providing insights into how GenAI is transforming work systems, by highlighting both opportunities and challenges across various groups. The preliminary findings suggest that while the integration of GenAI tools has the potential to enhance productivity and streamline certain aspects of software development, it also introduces new complexities that must be carefully managed. Group A, directly interacting with GenAI, reported significant changes in their daily workflows, requiring adjustments in task coordination and execution. In contrast, individuals in the periphery group (Group B) expressed concerns about future changes and the need for upskilling to effectively collaborate with AI-driven systems. External influences (Group C) emphasized the importance of staying informed about industry trends and maintaining flexibility in adapting to new developments. This study builds upon existing research on GenAI's impact on various industries, including SE (e.g., Ozkaya, 2023; Nguyen-Duc et al., 2023; Fontes et al., 2023), and contributes to the ongoing discourse by addressing the underexplored area of GenAI's impact on work systems in SE (e.g., Cazzaniga, 2024; Perino, 2024; Marques et al., 2024; Naik et al., 2024; Suri et al., 2023; Choudhuri et al., 2024). While previous work has highlighted GenAI's potential to boost efficiency and productivity, this research provides a deeper analysis of how GenAI not only alters individual tasks but also fundamentally transforms SE work systems on a structural level.

Next Steps and Implications

The next phase of this research will delve deeper into the preliminary findings, aiming to develop a comprehensive model explaining the observed changes in work systems. This model will consider both the

benefits and challenges associated with GenAI integration, providing actionable insights for organizations navigating the transition to AI-augmented work environments. Further analysis of interview data, supplemented by quantitative metrics, will ensure a robust understanding of GenAI's impact on SE work systems, guiding future research and practice.

This research offers researchers a framework for studying GenAI's impact on SE work systems, guiding future research and curriculum development. For practitioners, it provides actionable insights to integrate GenAI effectively, enhancing productivity and innovation while navigating challenges. The study supports informed decision-making in technology adoption, workforce training, and process reengineering, helping organizations transition smoothly to AI-driven environments.

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