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GenAI and Software Engineering: Strategies for Shaping the Core of Tomorrow's Software Engineering Practice

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GenAI and Software Engineering: Strategies for Shaping the Core of Tomorrow's Software Engineering Practice

Completed Research Paper

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Abstract

The rapid integration of Generative Artificial Intelligence (GenAI) into Software Engineering (SE) transforms how software is designed, developed, and maintained, introducing significant managerial challenges. This study examines these emerging challenges and proposes strategic actions for managing SE in the future. We provide an overview of the current GenAI development within SE and analyze its implications across three critical pillars: People, Process, and Technology. Our findings indicate that GenAI introduces a dynamic complexity to these elements, demanding a combined managerial approach. We propose six strategic actions essential for shaping the future of SE practice. This study aims to help practitioners make strategic decisions regarding GenAI implementation and offers researchers insights into past findings and opportunities for further investigation.

Keywords: AI-driven Software Development, IT Management, GenAI Implementation

Introduction

With over 100 million users within just two months, the Generative Artificial Intelligence (GenAI) tool ChatGPT (OpenAI, 2024) is one of the fastest-adopted consumer software applications globally (Milmo, 2023). Similarly, since its launch in March 2022, GitHub Copilot (GitHub Copilot, 2024) – a GenAI-based code completion tool co-developed by GitHub and OpenAI - has been adopted by a million software engineers and 20,000 organizations (Woodward, 2022). Expected to contribute up to \$7 trillion to the global economy (Goldman Sachs, 2023), GitHub Copilot and similar GenAI tools are revolutionizing the Software Engineering (SE) process. These tools go beyond automating routine tasks by generating code snippets, offering real-time suggestions, and enabling developers to focus on more complex problem-

solving activities, thereby significantly enhancing code quality and developer productivity (Brynjolfsson et al., 2023).

This rapid development equally influences research and practice, as both continuously explore and investigate the capabilities and limitations of the technology to develop innovative solutions for upcoming challenges and problems (Teubner et al., 2023). While GenAI is not a fundamentally new technology, its enhanced refinement has elevated its functionality and expanded its use. Traditional Artificial Intelligence (AI) applications primarily focused on data analysis, e.g., for pattern recognition (Santos & Qin, 2019), automation of routine tasks (Jha et al., 2019), recommendation systems for decision support (Nica et al., 2022), and image and speech recognition for presence verification (Siddiqui et al., 2020). However, GenAI extends these capabilities, especially in content generation, based on unlimited training data and numerous parameters (Ray, 2023). The ability to generate high-quality content and its universal applicability across various scenarios has intensified the general interest in GenAI. GenAI tools also introduced a new level of usability and accessibility, leveraging AI-generated content to a broader range of professionals, requiring less technical competence to integrate it into their existing work environment (Nguyen-Duc et al., 2023).

In SE research and practice, the application of AI is well-established (Kotti et al., 2023; Martínez-Fernández et al., 2022; Barenkamp et al., 2020; Bull & Kharrufa, 2024). However, the use of GenAI is a new topic (Nguyen-Duc et al., 2023). Even though the promise of GenAI and its capabilities has been acknowledged for some time, GenAI was not prominent in SE research until 2020 (Jovanovic & Campbell, 2022). The aspects of conversational engagement with AI systems (Atefi & Alipour, 2019), the generative capabilities (Huang, 2023; Muller et al., 2022), the widespread adoption (Ebert & Louridas, 2023), and the improved accessibility (Stonier et al., 2023) represent innovative advances in this technology.

While GenAI's potential to improve efficiency is widely acknowledged (e.g., Imai, 2022; Moradi Dakhel et al., 2023), concerns about the quality of the generated outcome (Shollo et al., 2022; Feuerriegel et al., 2024) and the potential skills gap (Brynjolfsson et al., 2023) remain, challenging the effective use of GenAI tools. Also, increased user-driven enthusiasm to use GenAI tools can raise overly optimistic expectations (Russo, 2024). Finally, the integration of GenAI into SE workflows poses interpretive challenges and may disrupt established practices (Sun et al. 2023). It is therefore necessary to examine how GenAI fits within or alters existing SE processes to fully realize its benefits.

This study provides an overview of GenAI's current role in SE, highlighting practical use cases. Based on 15 strategic discussions with IT-Executives, IT-Managers, and Software Engineers, we identify six managerial challenges that are aligned with the three critical pillars of SE: People, Process, and Technology. We propose six strategic actions to address these challenges and guide the effective integration of GenAI in SE. With our study, we aim to help practitioners make decisions about the use of GenAI in the software development lifecycle (SDLC) and provide researchers with an overview of existing research and starting points for further studies exploring GenAI-driven SE.

This paper is structured as follows: In Section 2, we present the relevance of GenAI for SE and showcase GenAI-driven use cases. In Section 3, we describe the applied method. In Section 4, we present the identified challenges in GenAI-driven SE and provide six strategic actions for managing GenAI in SE in the future. Finally, in Section 4, we conclude the study by addressing limitations and suggesting future research directions.

Foundations of GenAI and its Application in SE

GenAI represents an evolution of the modern AI landscape, aiming to develop algorithms capable of generating new data that closely mimics the real-world data on which they are trained (Ray, 2023). For this purpose, Large Language Models (LLMs) such as GPT (OpenAI, 2024) and Gemini (Google, 2024) are used, which try to understand and generate human language (Anil et al., 2023; OpenAI, 2024). Generally, GenAI is used to generate complex text data that is both content-coherent and structurally correct. The underlying capability of LLMs derives from their architecture and training methods (Vaswani et al., 2017). These models identify patterns, clusters, or anomalies in data to gain insights and establish probability distributions for generating new data. Based on these distributions, the probability of one word or phrase

following another is estimated. A random factor is introduced to ensure that the same input leads to varied outputs, not just identical results (Reiss, 2023).

Recently, GenAI systems such as OpenAI’s ChatGPT or Microsoft’s Copilot (Microsoft, 2024) have become available to the public through both free and paid services. GenAI systems have revolutionized the way individuals communicate with LLMs (Chiu, 2023; Moorhouse et al., 2023) without the complexity of using advanced programming languages (Gattupalli & Maloy, 2023; Jacobs & Fisher, 2023). At the heart of this interaction lies *prompt literacy*, a skill bridging natural human language to unlock the capabilities of GenAI and guide its outputs. The commands formulated by using everyday language are called *prompts* (Gattupalli & Maloy, 2023).

GenAI can be used in various application scenarios, e.g., in data reconstruction or data imputation. However, a prominent feature of GenAI is the generation of realistic new data, which makes it a potential tool in areas such as computer graphics, design, and natural language synthesis (Hutson & Plate, 2023; Yun, 2022). GenAI’s advanced capabilities raise ethical questions and challenges that hinder their real-world application (Ray, 2023). Technical limitations at the model level can result in incorrect outputs due to probabilistic algorithms, leading to errors and misinformation (Spitale et al., 2023). This issue, known as hallucination in LLMs, generates plausible but nonsensical content (Ji et al., 2023). Also, the reliability of GenAI models relies heavily on training data quality, with correctness checks hindered by the black-box nature of AI systems (Rai, 2020). While correctness checks may inhibit certain outputs, trust in outputs remains essential, especially in closed-source systems (Rai, 2020). Furthermore, GenAI can pose risks of copyright infringement and privacy issues by producing content resembling copyrighted works (Smits & Borghuis, 2022). This issue is particularly important as prompts in GenAI models are routed via cloud-based or international servers and may contain personal, sensitive, or company-specific data. Finally, environmental concerns arise from the high electricity consumption of LLMs, contributing to a negative carbon footprint (Schwartz et al., 2020). Efforts to mitigate these challenges include developing more carbon-friendly AI algorithms and optimizing hardware (Schwartz et al., 2020).

In sum, existing research on GenAI has a strong focus on technical and societal concerns, such as the occurrence of errors, the potential for misinformation and hallucination, possible privacy infringements, or environmental concerns. However, the specific organizational challenges encountered when integrating GenAI into particular business functions, such as SE, are often overlooked. It is therefore necessary to examine how GenAI technologies are deployed within specific corporate structures and workflows. By focusing on the managerial challenges of implementing GenAI in SE, we aim to contribute valuable insights into optimizing GenAI integration in a way that addresses the organizational dynamics essential for successful application in specialized areas.

Using GenAI to Advance the Software Development Lifecycle

Over the last years, GenAI tools like OpenAI’s ChatGPT, GitHub’s Copilot or Amazon’s Q Developer (Amazon, 2024), have become increasingly present in SE practice, supporting various managerial and technical project activities (Nguyen-Duc et al., 2023). GenAI is democratizing AI technology by making it accessible to a broader audience, extending beyond traditional data science and SE professionals to include users with various levels of expertise through user-friendly programming tools and cloud services (Teubner et al. 2023).

The integration of GenAI tools in the SDLC presents a transformative approach to optimizing project duration and costs (Barenkamp et al., 2020; Fontes et al., 2023; Song & Minku, 2023). GenAI has the potential to enhance engineers’ efficiency by automating repetitive tasks and reducing cognitive load (Ozkaya, 2023). By allowing engineers to focus on more complex and challenging tasks, these tools contribute to two key objectives in SE: increasing productivity (Dell’Acqua et al., 2023; Li et al., 2024) and enhancing code quality (Bouschery et al., 2023). To date, code generation and test case refinement represent areas with the most significant impact for operational efficiency and effectiveness (Nguyen-Duc et al., 2023).

Recent studies have highlighted various strategies for integrating AI into SE, empathizing the need for strategic alignment with organizational goals, adaption to existing processes, and the importance of upskilling engineers to effectively collaborate with AI tools (Brynjolfsson et al., 2023; Iansiti & Lakhani, 2020). Research also suggests that integrating AI into SE should involve iterative, phased implementations to allow for learning and adaption (Wilson & Daugherty, 2018). Additionally, an emerging focus is ensuring that AI-driven processes align with human-centered design principles to mitigate risks and enhance user satisfaction (Raisch & Krakowski, 2021; Feuerriegel et al., 2020). These strategies underscore the importance of a thoughtful, well-planned approach to AI integration, ensuring that the benefits of AI are fully realized while mitigating potential risks, such as skill gaps and resistance to change.

To advance the understanding of GenAI's impact on the SE, we provide an overview of its integration in the SDLC following the Unified Software Development Process (Jacobson et al., 1999). Table 1 shows the described GenAI use cases in the SDLC.

Step in SDLC	GenAI-Use Cases	References
Planning and Requirement Analysis	<ul style="list-style-type: none"> Assist business analysts and product managers by automatically generating software documentation and draft requirements Improve application prototypes 	Barenkamp et al., (2020), Calegario et al. (2023), Pothukuchi et al., (2023)
Software Design	<ul style="list-style-type: none"> Assist developers by automatically transforming SRS into architectural diagrams 	Calegario et al. (2023)
Implementation	<ul style="list-style-type: none"> Assist developers in generating code using prototypes derived from human language Assist developers in finding code snippets affected by changes 	Barenkamp et al. (2020)
Testing and Deployment	<ul style="list-style-type: none"> Assist developers in test case generation, optimization, prioritization, and selection Assist developers in test data and test oracle definition 	Amalfitano et al. (2023), Fontes et al. (2023)
Maintenance	<ul style="list-style-type: none"> Assist developers in modernizing legacy code and redundant code Advance automation and prioritization of maintenance tasks through chatbots and monitoring systems 	Barenkamp et al., (2020), Calegario et al. (2023)
Table 1. Software Development Lifecycle according to Jacobson et al. (1999)		

In the *Planning and Requirements Analysis* stage, GenAI tools can automate the generation of software documentation and requirements drafts, supporting Business Analysts and Product Managers (Barenkamp et al., 2020; Calegario et al., 2023). These tools can also help Software Engineers enhance application prototypes and user stories by facilitating solution discovery (Pothukuchi et al., 2023). During *Software Design*, GenAI can automate the Software Requirement Specification (SRS) into detailed architectural diagrams, improving visualization and efficiency (Kneuper, 2018; Calegario et al., 2023). In the *Implementation* stage, GenAI assists developers by generating code from human language and real-world problems, as well as identifying code snippets affected by changes (Barenkamp et al., 2020). The use of GenAI is shifting towards creating and explaining working code, highlighting the need for engineers to focus on well-defined problems when integrating GenAI tools (Valový & Buchalceva, 2023). During the *Testing and Deployment* phase, GenAI revolutionizes traditional software testing by enhancing the efficiency of test case generation, prioritization, and data definition. This leads to streamlined processes and significant cost reductions (Amalfitano et al., 2023; Fontes et al., 2023). During *Maintenance*, GenAI supports software adaption to new requirements and standards, modernizes legacy codes, and automates maintenance tasks through AI-driven tools, ensuring system reliability (Barenkamp et al., 2020; Calegario et al., 2023). Overall, GenAI acts as both a tool and a collaborative partner throughout the SDLC, streamlining processes, enhancing decision-making, and improving software project outcomes (Ahmad et al., 2023).

Method

Research Approach and Expert Selection

This study employs an exploratory qualitative research approach to explore the managerial challenges caused by the integration of GenAI in SE and propose strategic actions for managing SE in the future. We gathered data through in-depth interviews with 15 SE experts from different companies with at least 2000 employees with their company headquarters in either Germany or Switzerland, operating mainly in Central Europe.

Three main factors underpinned our selection of the interviewed experts. First, the experts we chose already have proven experience in working with GenAI tools in SE. For example, Interviewee 1 (I1) has already implemented GitHub Copilot in the SE department of the Telecommunication company and is currently in the test phase. I2, a IT-Project Manager in a Manufacturing company, also uses GitHub Copilot and Amazon Code Whisperer in the test phase and has already implemented Microsoft Copilot. Second, the experts represent different roles in SE. We chose the roles of IT-Executives, IT-Managers, and Software Engineers to get a holistic view of the changes in the context of GenAI-driven SE. Third, we have built up good contacts with the experts interviewed over the last few years through collaboration on consulting and research projects. According to Sjödin et al. (2022), positive contacts to industry experts can enable researchers to collect more in-depth descriptions of their work and corresponding challenges – in our case their attempts to integrate GenAI into SE.

Data Collection

We adopted a qualitative research approach, using expert interviews as our primary source of information, following Bogner et al. (2009). Expert interviews are a valuable method for obtaining detailed insights from professionals on a specific topic, helping to understand complex issues and explore potential solutions (Meuser & Nagel, 2009).

Inter-viewee Code	Position of Interviewed Expert	Industry	Company Abbreviation	Duration (in min)
I1	Head of Data & AI	Telecommunication	TeleComp	73
I2	IT Project Manager	Manufacturing	ManuComp1	61
I3	Head of Digital Products	Insurance	InsurComp1	43
I4	Global Director IT Solution Development	Manufacturing	ManuComp1	62
I5	Application Analyst	Manufacturing	ManuComp2	45
I6	Digital Project Manager	Manufacturing	ManuComp2	58
I7	Senior Application Analyst	Manufacturing	ManuComp3	46
I8	IT Project Manager	Manufacturing	ManuComp3	45
I9	Chief Information Officer	Construction	ConstComp	41
I10	Head of IT Sales & Marketing Applications	Manufacturing	ManuComp4	54
I11	Chief Information Officer	Insurance	InsurComp1	43
I12	Head of IT Operations	Financial Institution	FinanComp	53
I13	Head of IT Services	Insurance	InsurComp2	45
I14	IT-Innovation Manager	Automotive Technology	AutoComp	46
I15	Senior IT Manager	Software Development	DevComp	56

Table 2. Overview of Interview Participants.

We conducted 15 expert interviews online via Microsoft Teams¹ from November 2023 to February 2024. These interviews were held in German and were recorded and transcribed using Microsoft Teams' live transcription feature. The transcripts were carefully reviewed, and any spelling mistakes were corrected. Subsequently, the interviews were translated into English, ensuring their intended meaning was accurately preserved. All experts in our sample have a minimum of 6 years of experience in their current role and possess first-hand experience with the integration of GenAI in SE teams. All participating companies employ their own internal development team and engage in SE to develop software products for their own use. This study encompassed a diverse range of industries and companies. This variety of organizational settings helps us understand the impact of the industry's nature and dynamic settings in the integration of GenAI tools in their SE processes.

To comply with data protection agreements with our interview experts, we anonymized the interviews in this study. However, to be able to identify the sources of the interviews, we have disclosed the positions of the interviewed experts and the industry their company is operating in Table 2. To ensure clarity in the flow of this paper, we used abbreviations for the companies (see under 'Company Abbreviations' in Table 2). Additionally, we have documented the duration of our conversations with the experts, indicating that we spoke with all of them for at least 40 minutes. This detail is intended to demonstrate that we conducted in-depth discussions, ensuring a comprehensive understanding of their insights.

Data Analysis

To analyze our data, we followed a thematic analysis as suggested by Braun & Clarke (2006). In the first step of our analysis, we performed an in-depth examination of our interview transcripts. Two researchers carefully read every interview transcript several times, highlighting phrases, passages, and quotes that added knowledge to our overarching research goal (Langley, 1999; Locke & Golden-Biddle, 1997). We used the AI-based software Atlas.ti² for the collaborative coding process. Individual discrepancies in coding were resolved through discussions with the broader research team, as recommended by Forman & Damschroder (2007), to ensure stability, validity, and reproducibility of our research results. We applied an open coding approach of the common topics mentioned by our experts, as suggested by Merriam and Grenier (2019) and Saldaña (2013), related to their endeavor to integrate GenAI in their SE core. Throughout the analysis, we observed a variability in the stages of development among companies adopting GenAI. While some organizations have progressed further, having already deployed applications and empowered multiple teams to use them (e.g., Telecom, ManuComp1, and InsurComp), others are just starting their journey into integrating GenAI into SE (e.g., ManuComp2). Our sample thus captures a diversity of approaches, enabling us to make general statements about the challenges and required actions in integrating GenAI in SE.

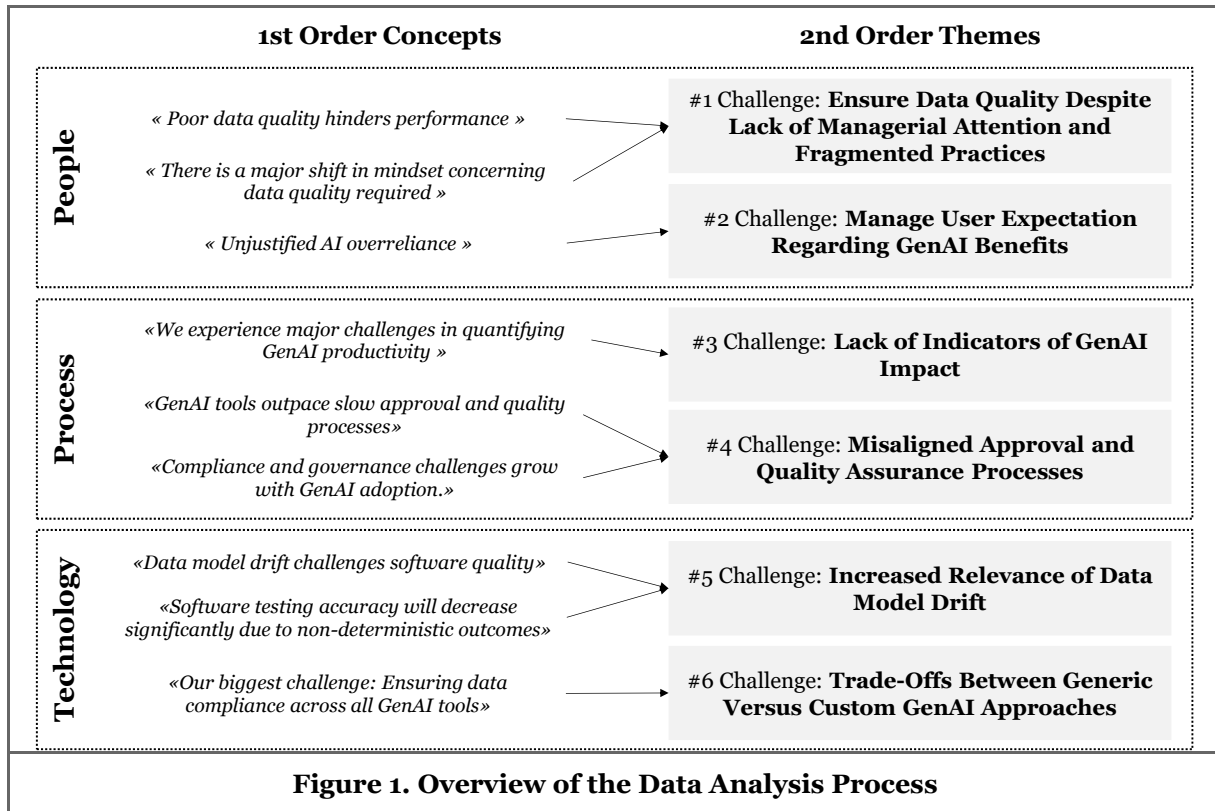
In the second step of the analysis, we examined the elements identified in Step 1 to detect recurring patterns and common issues among them. By analyzing the data, we identified key challenges that organizations face when integrating GenAI into their SE practices. These challenges emerged from the practical difficulties and inconsistencies highlighted in the interviews, such as the misalignment between GenAI's rapid evolution and existing approval processes. This step allowed us to pinpoint specific areas where the integration of GenAI presents significant hurdles, setting the stage for developing targeted strategies.

After identifying the key challenges in Step 2, we developed specific streams that represent focused areas of action needed to address the issues. Through a combination of insights from the literature and interview data, the structure led to the three critical pillars in SE: People, Process, and Technology. The three elements, as suggested by Khodabandeh & Palazzi (1994) and Koch (2009), are essential in every SE project and thus help us to structure the identified challenges and strategic actions. This framework emphasizes

¹ <https://www.microsoft.com/microsoft-teams/>

² <https://atlasti.com/>

the interconnectedness of human factors, systematic processes, and technological tools, making it a comprehensive approach to analyzing complex systems (Khodabandeh & Palazzi, 1994).



After choosing the framing of our data, we subsequently discussed its suitability within the broader research team, consisting of four researchers, and ensured collective consensus. See Figure 1 for an overview of the results of steps 1-3. Finally, in the fourth step of the analysis, we further derived strategic actions based on insights gained through the analysis from our expert interviews (see Figure 2).

Challenges and Strategic Actions for Integrating GenAI in SE

In the following, we will describe each challenge with its resulting strategic action based on our discussions examining the implications of GenAI on SE. These findings are conceptualized along the three critical pillars in SE: People, Process, and Technology. For each dimension, we will first explain the underlying challenge, supported by the original quotes of our interview experts. Subsequently, we will propose recommendations as strategic actions for each challenge. These challenges and recommendations are derived from a thorough analysis of the interviews, offering a comprehensive approach to successfully managing GenAI-driven SE in the future.

#1 Challenge: Ensure Data Quality Despite Lack of Managerial Attention and Fragmented Development Practices

In SE, ensuring high-quality data has emerged as a critical challenge, particularly concerning user perceptions of data quality in software products. Our discussions with industry experts revealed that user perceptions of data quality are increasingly crucial as the outputs of GenAI systems are directly influenced by the data they are trained on, making high data quality a non-negotiable factor in the development of reliable software products. Several interviewees expressed concerns about the current state of data quality, indicating that it may not meet the standards necessary for effective utilization of GenAI in SE. I13 emphasized this shift, noting that *“The problem of data quality is not new with GenAI, but it is much more important now. Before, we primarily used data in AI and Machine Learning practices to analyze and*

improve processes. Now, we train generative models that are foundational to these technologies". This comment highlights the increased importance of data quality in the context of SE, as the outputs of GenAI are only as reliable as the data on which they are trained. Another interviewee, the Head of Data & AI at TeleComp (I1), expressed skepticism about the immediate viability of AI solutions due to perceived inadequacies in data quality, stating, *"What I see so far, maybe I'm too critical, but I don't see that tomorrow we will have GenAI that can solve individual business problems because I cannot see sufficient data quality"*.

These statements highlight two primary factors contributing to these for data quality perceptions. First, the lack of managerial attention to data quality is evident in corporate performance management practices, which often prioritize immediate success over data accuracy and maintainability. As I2 articulated, the focus on short-term performance metrics often overshadows the importance of long-term data quality. *"The lack of data quality has a lot to do with corporate performance management... employees are measured based on immediate success (e.g., number of features delivered) rather than the accuracy, completeness, or maintainability of the data they produce"*.

Second, fragmented development practices across departments intensify the issue. The Head of IT Operations of FinanComp (I12) highlighted the fragmented nature of data across development, teams, and various IT systems, leading to incompatible systems and data sets. This often arises from a lack of integration and collaboration between teams, resulting in disjointed software solutions. I12 stated: *"The reason for poor data quality is our siloed thinking in terms of use cases... Different departments adopt disparate systems without considering data integration"*. While this challenge is not new, the increased quality requirements for GenAI make it more prominent, ultimately impacting user perception of software reliability.

#1 Strategic Action: Introduce Data-As-An-Asset-Mindset

Several interviewees emphasized the challenge of ensuring data quality, which poses a significant obstacle to the effective integration and utilization of GenAI tools. Based on insights from our expert interviews, a nuanced approach is needed to address this. Users often express doubts about the feasibility and reliability of GenAI-driven software solutions, primarily due to concerns about the underlying data quality. To address this challenge, a strategic shift in mindset is needed, focusing on managerial attention and standardized practices across the SDLC. Industry experts suggest adopting a "Data-As-An-Asset"-mindset across the entire SDLC, empathizing that upper management should lead in recognizing data quality as a strategic asset and establishing structured practices that promote data maintainability and reliability. Implementing comprehensive guidelines across the SDLC is also crucial, as the IT-Project Manager at ManuComp1 (I2) elaborated, emphasizing the need for guidelines to incentivize consistency in data quality throughout the development process, addressing code review practices, automated testing, and continuous integration to enhance user confidence in software products.

#2 Challenge: Manage User Expectation Regarding GenAI Benefits

As initial research indicates, GenAI tools promise immense productivity and efficiency boosts (Dwivedi et al., 2023; Bouschery et al., 2023; Dell'Acqua et al., 2023; Li et al., 2024). Promoted for their simplicity, accessibility, and user-friendliness by both tool providers and the public (e.g., business platform LinkedIn), these characteristics set a certain level of expectation among users. The experiences many employees have with these tools in their personal lives further enhance the elevated expectations towards the performance of GenAI tools. The users' heightened expectations often directly translate to the workplace, where employees are eager to test the tools. I4 puts it as follows: *"People start the GenAI pilot with very different expectations. But we already see that most of the employees have already tried out a lot themselves, mostly outside the company, many in their private lives"*.

Due to the users' heightened expectations regarding the capabilities of GenAI tools, employees tend to view GenAI as a universal problem solver for their day-to-day problems. However, this perception often exceeds the actual capabilities of the current technology, which is challenging for IT-Managers. They face a dual challenge: On the one hand, they want to use the intrinsic motivation of employees in GenAI to drive technology and project implementation forward. On the other hand, they also know that some employees

may lack the necessary knowledge about the use and application of GenAI tools, and their high expectations often cannot be met. I9 summed up this problem the following way: *“Currently, I am fighting a lot against an expectation that comes from somewhere, but which is not yet really justified. At the moment, artificial intelligence is being trusted, especially by people who are working with the systems for the first time with this movement. Now, for every problem you see somewhere, the solution is an AI system or a language model. However, the solution to all problems or challenges can't just be to complete a subscription and then you have it solved”*. Employees, particularly Software Engineers, are eager to test and utilize new tools, as noted by I6, Digital Project Manager at ManuComp2: *“Developers are like children eager to play with new toys”*. This sentiment highlights the enthusiasm among employees, especially software engineers, for adopting GenAI tools, despite the challenges of aligning their expectations with the actual capabilities of the technology. As I4, I6 and I9 indicated and other interviewees verified, our findings show that IT-Managers struggle to coordinate the expectations of the companies' employees regarding GenAI. While employees were informed about new tools through the intranet and internal company communication in the past (as noted by I2), employees now start to advise themselves individually over business platforms such as LinkedIn because of their intrinsic motivation and technology affinity to understand more about the technology (concluded by I4). Consequently, employees often perceive GenAI to be an easy out-of-the-box solution for many of their pain points.

#2 Strategic Action: Foster AI-Community of Practice

The second challenge related to people highlights the employees' affinity toward GenAI tools, leading to an organic, bottom-up approach in their adoption. Rather than perceiving this trend as a hindrance to IT security policy control, companies should embrace it to harness the full potential of these tools.

To make use of this employee-driven technology adaption, IT-Managers should establish a platform for employees to share ideas and experiences regarding both new and existing GenAI tools. I4 emphasizes: *“We bring everyone together in a community to help each other understand how the whole thing works. [...] Asking questions and working in this environment with emails or messages in Microsoft Teams is a completely different way of prompting. We are currently mainly learning about what is possible from Microsoft itself, but we would also like to discuss this within our own community”*. Confirming this opinion, I6 underscored the importance of community-building for mutual learning and problem-solving: *“We are building an internal community. We want to connect people that are interested in being involved in this test phase and want to go on the journey to learn from each other. Our goal is to become aware of challenges that can occur when you're working with GenAI and to collectively learn from the mistakes others already made”*. Based on insights from our experts, we propose establishing an AI community of practice to manage user expectations in the long term. This community should comprise interdisciplinary teams, including Software Engineers, Data Scientists, and other stakeholders, all working together to cultivate a GenAI-focused environment within the company.

The responsibilities of IT-Managers in establishing this community of practice are crucial. They include identifying community moderators among employees who show technical expertise and intrinsic interest in GenAI. Additionally, IT-Managers should motivate and incentivize employees to actively participate and share their experiences. The community should engage in regular knowledge-sharing sessions, ideally in person, but online if necessary, to enhance collaboration and knowledge exchange.

#3 Challenge: Lack of Indicators of GenAI Impact

On the process level, we have identified the challenge of determining key performance metrics for integrating GenAI tools. This challenge has significant implications for strategic decision-making, particularly in relation to licencing costs and personnel management. Many experts have empathized management's interest in quantifying productivity gains from GenAI tool usage, which is essential for evaluating the cost-effectiveness for software licenses.

However, as noted by IT-Project Manager (I2), quantifying these gains often relies on subjective self-assessment, complicating objective measurement. I2 stated: *“We can evaluate whether more story points are delivered, but we lack fact-based evaluations. Traditional metrics like lines of code written are becoming less meaningful, making it challenging to measure GenAI tool productivity and efficiency”*. This

raises fundamental questions for IT-Managers about establishing relevant metrics and determining which existing performance indicators should be adapted to measure successful GenAI integration. Measuring performance and efficiency improvements from GenAI tools significantly influences companies' strategic decisions in two critical areas.

First, contract negotiations with software providers play a crucial role. Companies must evaluate both their current usage and future potential when negotiating software contracts. Understanding the relationship between licensing costs and productivity gains is essential for making informed decisions. As I4 pointed out: *“The inability to measure gained productivity complicates comparisons with licensing costs. Without estimating potential benefits, ensuring costs don't exceed benefits becomes challenging”*. This insight underscores the importance of a clear assessment of GenAI's impact on operational efficiency, which enables companies to negotiate better terms and plan for potential future software license price increases.

Second, personnel management is a key area affected by the integration of GenAI tools. Companies are prompted to consider future personnel decisions based on anticipated productivity gains. While some experts expect cost savings, particularly in personnel expenses, the actual outcomes may vary. Although some organizations calculate productivity gains of up to 10%, challenges such as significant backlogs and requirements for security and compliance can hinder resource reductions in IT departments. As the IT-Project Manager at ManuComp1 (I2) explained, *“We anticipate productivity gains, but a large backlog of bugs remains unaddressed. Balancing downsizing expectations with anticipated productivity increases poses a dilemma”*. This statement highlights the complex balancing act that companies face as they integrate GenAI tools into their operations.

#3 Strategic Action: Develop GenAI Impact Assessment Rubric

Determining the productivity and efficiency improvements resulting from the use of GenAI tools presents a significant challenge at the process level, particularly regarding licensing costs and personnel considerations. Understanding the financial implications of licensing is crucial for making informed operational decisions and strategic planning. The measurement of productivity related to GenAI in SE is discussed controversially in the literature. While some authors suggest measuring productivity quantitatively (Barke et al., 2023; Imai, 2022; Sikand et al., 2024; Vaithilingam et al., 2022), others argue for a more nuanced qualitative approach (e.g., Forsgren et al., 2021). Given this, a blended approach that incorporates both qualitative and quantitative elements is widely regarded as best practice. I2 shared an illustrative example of their method for evaluating the impact of GenAI tools: *“The plan is to conduct a survey after about 3 months to see if they also feel the added value or not directly the developers themselves, and if not, we would take a closer look and possibly speak with GitHub again to understand why. We may also approach individuals who consciously do not use the tool to find out why they are not using it.”*

Based on insights from our expert interviews, we recommend developing an AI impact assessment to be integrated into each stage of the SDLC. This assessment will help evaluate and mitigate risks associated with GenAI tools, providing IT-Managers with guidance on navigating the changes these tools introduce on the work system (e.g., following the framework outlined by Alter, 2013). By applying a comprehensive impact assessment, managers can better understand how licensing costs affect technology, people, and activities as well as processes. For example, the assessment can help determine if high licensing fees justify the productivity gains or if alternative solutions should be considered.

#4 Challenge: Misaligned Approval and Quality Assurance Processes

The second challenge at process level can be divided into two characteristics. Existing approval and quality assurance processes encounter new, rapid developments due to the introduction of GenAI tools. Additionally, existing processes that ensure compliance and governance can no longer be used under the changed framework conditions.

First, we identified the misalignment between fast developments facilitated by GenAI and existing approval and quality assurance processes in organizations. While GenAI tools are rapidly evolving and new iterations are often released at short intervals, the approval process for these tools remains cumbersome and time-consuming, involving numerous steps and compliance checks. This misalignment creates tension within an

organization, as articulated by I15, Senior IT-Manager at DevComp: *“The same approval processes are used for the approval of GenAI tools as for previous projects. But by the time we know whether we are allowed to use the tool or not, the issue is sometimes no longer relevant”*.

Second, we learned about the increased challenge of aligning existing compliance and governance processes due to the new requirements of GenAI use cases. As articulated in the quote from Head of Data & AI at TeleComp (I1): *“The issues of data privacy and governance isn’t new but today, companies aren’t necessarily required to address them. With GenAI, the demand for data governance has naturally been increased. As if this wasn’t enough, we also see that data privacy and compliance are now dependent on the user and use case and can’t be solved generally anymore”*. Due to these characteristics, there is a risk that existing approval and quality assurance processes are misaligned with the requirements for the rapid implementation of GenAI use cases. As a result, GenAI tools may become obsolete by the time they clear approval hurdles. Yet, maintaining software quality standards remains critical. This creates a dilemma for IT-Managers. This dilemma is intensified by the high expectations of users who expect GenAI tools to deliver immediate and cutting-edge benefits. These high expectations put IT-Managers under considerable pressure to meet business demands. Failure to do so has the potential to stress not only the implementation of technology but also the trust and relationships between IT and business departments.

#4 Strategic Action: Establish AI-Specific Governance Measures

In our strategic discussions, we recognized the challenge of integrating GenAI tools into established approval and quality assurance processes. Also, the current processes designed to guarantee compliance and governance are no longer effective under the new conditions. Both characteristics of this challenge pose a significant hurdle for companies in striving to leverage the technologies effectively, highlighting the urgent need for a viable solution.

In addressing this challenge, companies should develop and establish AI-specific governance measures, particularly in the planning and design phases of software products. The measures should ensure that the use of GenAI is ethical, complies with industry standards, and aligns with project objectives. This is especially important considering recent developments of regulations, such as the General Data Protection Regulation (GDPR)³ and the EU Artificial Intelligence Act (EU AI Act)⁴, that guide the implementation and usage of AI tools. InsurComp2 (I13) addressed this challenge by implementing a comprehensive approach that involved several key steps. First, they have established company-wide guidelines that serve as mandatory directives for the use of (Gen)AI applications across the organization. In addition, they developed an internal data governance framework, which acts as a standardized entry point for reviewing and approving data-driven initiatives, ensuring consistency and compliance throughout the process. To further support this framework, they introduced an AI intake form – a structured template designed to gather all necessary information related to AI projects. This form ensures each AI initiative is thoroughly evaluated for compliance with legal and ethical standards before proceeding. These three steps enable the company to ensure compliance of approval and quality processes with GenAI guidelines across the enterprise without complicating the approval processes while maintaining quality standards.

#5 Challenge: Increased Relevance of Data Model Drift

As GenAI technology advances, the challenge of data model drift becomes increasingly critical. Data model drift occurs when a model’s performance gets worse over time due to changes in real-world conditions that were not accounted for in the original training data. The time lag between when training data is collected and when the trained model is deployed used in real-world applications. This can lead to inconsistencies in the model’s ability to deliver predictive results. The use of multiple data sources and achieving deterministic responses from GenAI tools further complicate the production of consistent, predictive outcomes.

³ <https://gdpr.eu/>

⁴ <https://artificialintelligenceact.eu/>

According to I1, data model drift can substantially impact the technological foundations of software, particularly in how software quality is measured and maintained.

A critical area of focus is the *Testing* phase, where the reliability and functionality of GenAI applications are directly addressed. I15 noted, *“I believe there will be significant changes in how we conduct software testing, particularly because of the non-deterministic nature of results. We need to acknowledge that outcomes may only be approximately 70% accurate”*. In this context, “70% accuracy” represents the anticipated performance level of AI models during testing, meaning that the AI-generated outputs are expected to align with the desired outcomes approximately 70% of the time. This percentage underscores the inherent unpredictability of AI results, reflecting the challenges posed by the complexity of the tasks these models undertake and the variability in the data they process, which prevent them from consistently achieving perfect accuracy.

#5 Strategic Action: Establish Continuous Monitoring and Validation of GenAI Models

As GenAI continues to evolve, addressing the technological challenge of data model drift is essential. To mitigate this issue, continuous monitoring and validation of AI models must be established. By integrating advanced monitoring tools into the *Deployment* and *Maintenance* phases, organizations can effectively track the performance and evolution of GenAI models over time. This technological solution ensures that models remain accurate and reliable, adapting to changes in real-world conditions and data inputs. I7 explained their implementation as follows: *“We have integrated real-time monitoring tools within our deployment process, allowing us to continuously assess and recalibrate our AI models to align with dynamic data conditions and maintain reliability”*.

#6 Challenge: Trade-Offs Between Generic Versus Custom GenAI Approaches

In our analysis, we identified that different GenAI use cases significantly vary depending on the specific tool, approach, guideline, and industry context involved. Each scenario requires uniquely tailored models or data processing methods. As Senior IT-Manager from DevComp (I15) notes, *“Evaluating the trade-offs between generic versus custom GenAI approaches is crucial for successful implementation. Different tools are applicable for different scenarios which demand tailored data management strategies to avoid excessive costs across diverse tools. In the whole process, our biggest challenge is ensuring data compliance across all GenAI tools”*. The complexity increases with the need to determine the appropriate size for language models. While LLMs are widely available and commonly used, they often fail to meet the requirements of specialized tasks due to inadequate data quality or volume. This discrepancy demands the development of more specialized models. I15 emphasizes, *“We have to decide when to use an LLM and when a smaller or medium-sized model would be more appropriate. Operating these models continuously is challenging, and it's not practical to deploy LLMs universally”*.

Therefore, IT-Managers must balance the performance needed against the computational resources and costs associated with deploying different GenAI models. To effectively navigate this complex landscape, IT-Managers must evaluate the trade-offs between generic solutions and customized approaches, considering the specific needs and resources available for each use case.

#6 Strategic Action: Develop GenAI Use Case Evaluation Framework

According to our interview experts, developing a GenAI Use Case Evaluation Framework has emerged as a viable solution to solve the challenge of evaluating trade-offs between generic and custom GenAI approaches. Two experts described their approach in detail. IT-Innovation Manager von AutoComp (I14) highlighted the benefits of their implementation, stating, *“We have introduced an AI use case framework for GenAI tools. In our framework, we have the option of tailoring each tool to specific project requirements. This maximizes performance and also allows us to move relatively quickly”*.

I6, Digital Project Manager at ManuComp emphasized the importance of assessing the business value (*“we specifically evaluate the factors ‘potential for automation’ and ‘alignment with strategic goals’”*) and ease of implementation (*“we look at ‘technical complexity’ and ‘data availability’ when we assess it”*) in their GenAI use case assessment. Several interviewees confirmed that this framework should focus on software design and testing phases to evaluate the appropriateness of GenAI tools for specific projects, ensuring

alignment with strategic objectives and operational efficiency. Interview experts who have not yet implemented a GenAI use case assessment confirmed that such a framework could assist them in selecting suitable GenAI use cases, tools, and models. When asked in which process step it should be utilized, they mentioned that this framework should be concentrated on the *Software Design* and *Testing* phases. By doing so, it would enable the evaluation of the appropriateness of GenAI tools for specific projects, thereby ensuring alignment with strategic objectives and operational efficiency.

	Challenges	Strategic Actions
People	Ensure Data Quality Despite Lack of Managerial Attention and Fragmented Practices	Introduce Data-As-An-Asset Mindset
	Manage User Expectation Regarding GenAI Benefits	Foster AI-Community of Practice
Process	Lack of Indicators of GenAI Impact	Develop GenAI Impact Assessment Rubric
	Misaligned Approval and Quality Assurance Processes	Establish AI-Specific Governance Measures
Technology	Increased Relevance of Data Model Drift	Establish Continuous Monitoring and Validation of GenAI Models
	Trade-Offs Between Generic Versus Custom GenAI Approaches	Develop GenAI Use Case Evaluation Framework
Figure 2. Summary of Challenges and Strategic Actions for Addressing the Key Challenges of Managing GenAI-driven Software Engineering		

Discussion

In this study, we have examined the current challenges within SE that arise from the integration of GenAI, aiming to enhance its adoption and usage in SE practices. Through 15 strategic discussions with IT-Executives, IT-Managers, and Software Engineers, we identified how GenAI impacts the three core pillars of SE: People Process, and Technology. We offer actionable recommendations to address these challenges, supporting practitioners in the effective adoption of GenAI tools by identifying potential pitfalls and providing preventive measures and solutions.

As we have pointed out in the course of the conceptual background, existing research on GenAI has addressed technical and societal issues, such as error rates, misinformation risks, privacy breaches, and environmental impacts. However, the organizational challenges specific to integrating GenAI into distinct business functions, especially in SE, has not been in the focus of previous research. In this paper we attempted to contribute to filling this gap by investigating the deployment of GenAI within the structured environments of corporate SE workflows. Emphasizing the managerial hurdles in GenAI implementation, this research delivers critical insights into optimizing GenAI integration. In particular, the study uses the three critical pillars of SE – People, Process, and Technology – to systematically assess these challenges and derive actionable strategies for handling them. Thereby, this work contributes to ongoing scholarly debate about research efforts on contextualizing AI deployment within specific business operations (Dwivedi et al., 2021; Rai, 2020).

Among the various stakeholders in SE, Software Engineers are likely to experience the greatest impact from GenAI initiatives. This is because the new culture and mindset introduced by GenAI might conflict with existing organizational cultures and individual work practices. As key domain experts, developers also play a crucial role in evaluating the feasibility, implementation, and adoption of GenAI advancements. IT-Managers, on the other hand, need to expand their responsibilities to include change-management

practices, particularly in the initial stages of GenAI integration. They are tasked with counter-checking developers' assessments and ensuring that GenAI initiatives align with organizational goals (e.g. business value). IT-Executives are mainly responsible for the governance, monitoring, and evaluation of these initiatives. They must also balance the GenAI project portfolio to prevent disruptions to day-to-day operations. Policymakers are required to reassess the performance metrics of a GenAI-infused workforce and ensure compliance with current data and AI regulations.

Limitations and Future Research

This paper is not without limitations. Due to its exploratory character, the generalization of our results would benefit from further evaluations and validation by an increased sample size. Furthermore, with software development becoming a strategic resource across all industries, a more heterogeneous sample would further strengthen our validity. Lastly, we call for longitudinal case studies to study the proposed roadmap, potentially leading to a maturity model as a means for an analysis framework. Further studies should broaden the data set and categorize the challenges within the phases of the SDLC. Special attention should also be given to the specific changes impacting individual roles within SE, including IT-Executives, IT-Managers, and Software Engineers. Additionally, it is crucial to examine the broader effects of GenAI on the entire work system, beyond the directly involved groups (e.g. Team Leaders, Scrum Masters, Product Owners, HR Managers, User Testing Groups, and Business Personnel). There should be a particular focus on how the roles, the collaboration between them, the performed activities, and underlying processes, as well as the resulting products and services change through the integration of GenAI into the SDLC.

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