PERCEPTIONS AND CHALLENGES OF AI-DRIVEN CODE REVIEWS: A QUALITATIVE EXPLORATION OF DEVELOPER EXPERIENCES

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Perceptions and Challenges of AI-Driven Code Reviews: A Qualitative Exploration of Developer Experiences

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Abstract

AI-driven code review tools represent transformative advances in software development, improving efficiency, productivity, and accuracy in code reviews. Despite these potential benefits, concerns about trust, reliability, and contextual comprehension persist, limiting their widespread adoption. This qualitative study explores software developers' perceptions and challenges associated with AI-driven code review tools. Through semi-structured and thematic analysis involving software developers, technical leads, and architects, the study identifies central themes, including trust in AI-generated recommendations, impacts on developer productivity, ethical considerations, and contextual awareness. While participants acknowledge the efficiency gains and educational value provided by AI tools, skepticism remains regarding the tools' ability to interpret complex business logic and domain-specific scenarios. Participants advocate for enhancements in AI-driven tools, highlighting the need for improved contextual awareness, transparency, ethical integration, and seamless workflow integration. This research adds valuable empirical insights to ongoing discussions in software engineering literature, emphasizing AI-driven code reviews as complementary tools that augment human expertise in software development processes.

Keywords: AI-driven code review, trust in AI, developer perceptions, developer experiences.

Introduction

AI-driven code review tools have emerged as promising innovations designed to improve the efficiency and effectiveness of software development processes. According to Vijayvergiya et al. (2024), modern code review is a collaborative practice where peers review code contributions before they are integrated into the version control system, ensuring compliance with established best practices. Manual code reviews effectively identify defects, enforce coding standards, and facilitate knowledge sharing among developers (Tufano et al., 2021; Rasheed et al., 2024). However, with increasing software complexity and larger projects, maintaining thorough and frequent manual reviews becomes increasingly challenging. To address this challenge, AI-driven tools have been developed to automate various aspects of code review, such as detecting code smells, recommending refactoring, and predicting potential errors based on historical data (Almeida et al., 2024; Gerede & Mazan, 2018).

Despite their potential, adoption of these AI-driven code review tools remains slow. Developers express skepticism concerning the reliability, contextual accuracy, and ethical considerations associated with AI-generated feedback (Bird et al., 2023; Ernst & Bavota, 2022). A recurring concern is whether AI can effectively comprehend and handle the nuances of business logic and project-specific contexts, which are critical to meaningful code assessments beyond superficial issues like syntax errors (Bird et al., 2023). Addressing these perceptions and challenges is essential to enhancing trust and integration of AI-driven tools into development workflows.

This qualitative study investigates software developers' perceptions and challenges associated with AI-driven code review tools. Through semi-structured interviews and thematic analysis, this research explores

developers' experiences to identify key factors influencing their trust, acceptance, and integration of AI technologies in established development workflows. This investigation provides valuable insights into the strengths, limitations, and potential roles of AI-driven code review tools, emphasizing their capacity as complementary aids rather than replacements for human reviewers. This study contributes to enhance the future development, adoption, and effective use of AI in software engineering contexts by addressing the following research question:

RQ1: What are the perceptions and challenges experienced by developers when using AI-driven code review tools?

Review of the Literature

Modern Code Review

Modern Code Review (MCR) plays a crucial role in maintaining and enhancing the security and quality of software. The OWASP Code Review Guide (OWASP Foundation, Inc., 2017) provides a comprehensive framework for secure code reviews, emphasizing their integration into the software development life cycle (SDLC) to identify and mitigate vulnerabilities early, thus enhancing application security. The guide advocates for code reviews to promote a culture of security awareness and responsibility among development teams, facilitating knowledge sharing and skill development within organizations, leading to more secure software products. Furthermore, Khleel and Nehéz (2020) explore the role of code reviews, contrasting formal inspections with modern code reviews (MCR). While formal inspections are thorough, their cost and rigidity make them less suitable for agile environments. In contrast, supported by tools, MCR offers a flexible, collaborative approach that improves review efficiency and software quality. The study underscores optimizing code review processes by considering technical and non-technical factors to enhance collaboration and learning.

Badampudi et al. (2023) also provide a comprehensive survey of MCR practices, proposing a research agenda to align academic research with industry practices, thereby enhancing the effectiveness and efficiency of MCR processes. The authors emphasize that MCR practices are essential for improving code quality, reducing post-delivery defects, and facilitating knowledge sharing among developers. Furthermore, Doğan and Tüzün (2022) identify prevalent code review smells in open-source software (OSS) projects, which impact software quality and development efficiency. Addressing these issues can reduce technical debt and improve code review practices, software quality, and collaboration. Finally, Afzali et al. (2023) highlight vulnerabilities in modern web-based code review systems due to inadequate integrity mechanisms, stressing the importance of code reviews in ensuring software quality and security.

Ethical Considerations

While the above research demonstrates substantial advancements in modern code review practices, ethical considerations continue to represent significant challenges that require further investigation. Trust, reliability, and contextual accuracy in AI-driven development environments (AIDEs) is crucial for their effective and ethical integration into software development. Ernst and Bavota (2022) discuss the emergence of AIDEs and their transformative potential in software engineering, exemplified by tools like GitHub Copilot, which use large language models such as Codex to automate routine coding tasks and enhance developer productivity through real-time code suggestions. Complementing this discussion, Bird et al. (2023) underscore the necessity of trust in AI-generated code and ethical considerations to adopt these tools

effectively. Their research calls for future studies to enhance the reliability, contextual accuracy, and ethical implications of AI-powered programming tools, ensuring they complement developers' workflows and contribute positively to the software development process. Developers must balance the benefits of AI suggestions with potential risks, such as reduced code comprehension and increased security vulnerabilities. The integration of AI in software development underscores the need for new skills, particularly in code review and validation, and understanding the dynamics between developers and AI tools is essential for optimizing their use in real-world settings.

Integrating Artificial Intelligence (AI)

Recent research has highlighted the transformative potential of machine learning and AI in enhancing the efficiency and effectiveness of code review processes. Gerede and Mazan (2018) investigate the potential of predicting whether a source code change proposal will require revisions during a review. Using machine learning, the researchers achieved a 94.59% accuracy rate in predicting the necessity of revisions, with Random Forest algorithms emerging as the most effective method. This study highlights the potential of predictive models to streamline the code review process, reduce iteration counts, and improve developer satisfaction by providing actionable ideas before reviews begin.

Building on these advancements, Pejic et al. (2023) explore enhancing pull request recommendation systems, particularly in large-scale repositories with extensive developer involvement. The findings highlight the importance of optimizing reviewer recommendations to manage large-scale repositories effectively, thus supporting better management of reviewer workloads and improving review process efficiency. Future research should explore additional basic filters and refine the technique for broader applicability, providing a robust foundation for optimizing reviewer recommendation systems in complex environments (Pejic et al., 2023). Additionally, Turzo et al. (2023) present a novel approach to enhancing code review (CR) analytics through the automated classification of CR comments. The authors developed a deep neural network (DNN)-based model that leverages code context, comment text, and code metrics to classify CR comments into five high-level categories. This model can prioritize high-priority feedback, improving the efficiency and effectiveness of CR tasks. In a related context, Yin et al. (2023) address the challenges posed by the increasing volume and complexity of the code review process by proposing an automated code review model that enhances learning through the combination of program structure and code sequence. Based on the pre-trained CodeBERT architecture, the model employs a program dependency graph serialization (PDG2Seq) algorithm to convert the program dependency graph into a unique graph code sequence, retaining both program structure and semantic information. The findings highlight the importance of preserving structural and semantic code information in analysis models and contribute to advancing automated tools for managing complex software development processes (Yin et al., 2023).

Furthermore, Zydroń and Protasiewicz (2023) explore the automation of code review processes to improve efficiency and accuracy in large-scale software development projects. They highlight the challenge of manually assigning reviewers to pull requests and propose automated techniques utilizing machine learning, heuristic-based algorithms, and social network analysis to recommend suitable reviewers. The results indicate that the proposed automated review system can significantly enhance efficiency and accuracy in code review processes. Integrating natural language processing (NLP) and machine learning techniques, such as pre-trained models such as ChatGPT4, enhances review annotation and accuracy. These findings suggest that automated review systems can increase transparency and accountability, positively impacting project outcomes (Zydroń & Protasiewicz, 2023).

In a comprehensive study, Almeida et al. (2024) explore the application of Artificial Intelligence (AI) in code review processes to enhance the quality and efficiency of software development. Their research demonstrated significant improvements in review efficiency and effectiveness. AICodeReview, a tool developed by the authors, reduced review time, detected more code smells, and facilitated more effective refactoring compared to manual reviews. These findings support the continued development and integration of AI-driven tools in software development workflows, emphasizing the importance of combining automated tools with human expertise for optimal outcomes in code reviews. Integrating AI-based techniques in code review processes offers significant potential for improving overall software quality and development efficiency (Almeida et al., 2024).

Finally, Baumgartner et al. (2024) present an AI-driven pipeline designed to address data clumps in software repositories. Data clumps, or variables frequently appearing together, indicate poor code structure and pose maintenance challenges. The study shows that by integrating LLMs like ChatGPT, the pipeline provides semantic insights that improve refactoring accuracy, address maintenance challenges associated with data clumps, and reduce technical debt. The automated refactoring process enhances overall code quality and maintainability. The study concludes that combining AI-driven techniques with human expertise results in more effective refactoring processes, highlighting the potential of AI in transforming software maintenance practices (Baumgartner et al., 2024).

Human Oversight

The evolving landscape of code review processes highlights the interaction between automated tools and human oversight. Whether through peer reviews in distributed environments, automated task integration, or the use of advanced AI models, the emphasis remains on enhancing efficiency and effectiveness while maintaining the critical role of human expertise. Dos Santos and Nunes (2018) investigate the effectiveness of peer code review in distributed software development (DSD) using objective data from code repositories and subjective data from developer surveys. The study emphasizes the importance of considering technical and non-technical factors in DSD. While automated tools enhance the review process, they cannot replace the need for active human participation. The balance between review thoroughness and efficiency is critical, especially in DSD contexts. By combining empirical data and subjective insights, the study provides a comprehensive understanding of code review effectiveness, highlighting the nuanced requirements of peer code reviews in distributed environments (Dos Santos & Nunes, 2018). In a related study, Baumgartner et al. (2024) demonstrate how the automated refactoring process enhances overall code quality and maintainability. Their findings underscore that combining AI-driven techniques with human expertise results in more effective refactoring processes, highlighting AI's potential to transform software maintenance practices (Baumgartner et al., 2024).

The literature illustrates significant advances in software quality facilitated by Modern Code Review (MCR) and AI-driven tools. According to Keary (2017), integrating structured security-focused code review practices into the software development life cycle (SDLC) enables early vulnerability detection, enhances software security, and fosters collaborative knowledge sharing among development teams. Khleel and Nehéz (2020) highlight MCR's adaptability for agile environments compared to traditional inspections. AI tools like AICodeReview and GitHub Copilot further enhance review efficiency and developer learning but raise ethical concerns around transparency and trust (Ernst & Bavota, 2022; Bird et al., 2023). Human oversight remains critical, particularly in complex and distributed contexts (Dos Santos & Nunes, 2018;

Baumgartner et al., 2024). While AI-driven code reviews have transformative potential, their success depends on ethical integration and a balanced partnership with human expertise.

Furthermore, Turzo (2023) proposes improving modern code reviews (MCR) effectiveness by automating tasks, such as reviewer selection and bug identification, to reduce time and resources spent. Integrating these models with static analysis tools can identify and suggest potential solutions for code defects that might otherwise be missed. This approach aims to streamline code reviews, making them more efficient while relying on human oversight to ensure the quality of the automated tools. Furthermore, Kotsiantis et al. (2024) explore AI-assisted programming, focusing on utilizing code embeddings and transformers to enhance software development tasks. These technologies reduce manual coding efforts and minimize errors, making software development more efficient. Kotsiantis et al.(2024) highlights the importance of addressing the limitations and challenges of current AI technologies. It emphasizes the need for collaboration between AI researchers and software developers to advance AI-assisted programming, suggesting that these tools will be widely adopted in integrated development environments (IDEs), playing a crucial role in the evolution of software development.

Methodology

This study focuses on qualitative research design to investigate the perceptions and challenges experienced by software developers using AI-driven code review tools. Specifically, thematic analysis was selected due to their ability to capture complex, nuanced perceptions and experiences that quantitative methods may overlook (Creswell, 2013).

Instrument

The instrument consisted of a semi-structured interview guide with open-ended questions organized into six sections. Section one focused on background and experience, section two explored perceptions, section three addressed challenges, section four gathered suggestions for improvement, section five examined future and ethical considerations, and section six included closing questions. This approach enabled in-depth research and proved effective in detailing the experiences of participants and understanding the context in which these experiences occurred (Guest et al., 2006).

Sampling

Semi-structured interviews were conducted with 10 participants, including software developers, team leads, and software architects who used AI-driven code review tools for at least six months. The sample size is based on data saturation, which occurs when no new themes or insights emerge from additional data collection (Guest et al., 2006). This approach ensures rich and meaningful data collection while preserving research efficiency.

Data Collection

The data was analyzed using thematic analysis, a method for identifying, analyzing, and reporting patterns in qualitative data (Creswell, 2013). The interviews were transcribed and the initial codes were generated systematically throughout the dataset, reviewed and categorized into themes. The themes were then refined and validated to reflect the essence of the data in relation to the research questions. A thematic map was also created to illustrate the relationship between themes (Creswell, 2013).

Results

In regard to the research question, this study conducted a qualitative analysis of interview data from 10 participants, including software developers, team leads, and software architects. The analysis performed using Quirkos, a qualitative data analysis software, allowed for systematic coding, organization, and visualization of insights, ensuring a comprehensive examination of developers' perceptions and challenges with AI-driven code review tools. The results revealed six key themes: efficiency, learning, trust, challenges, collaboration, and future expectations, providing a comprehensive understanding of how these tools affect software development workflows.

Figure 1. Word Cloud

Figure 2. Categories

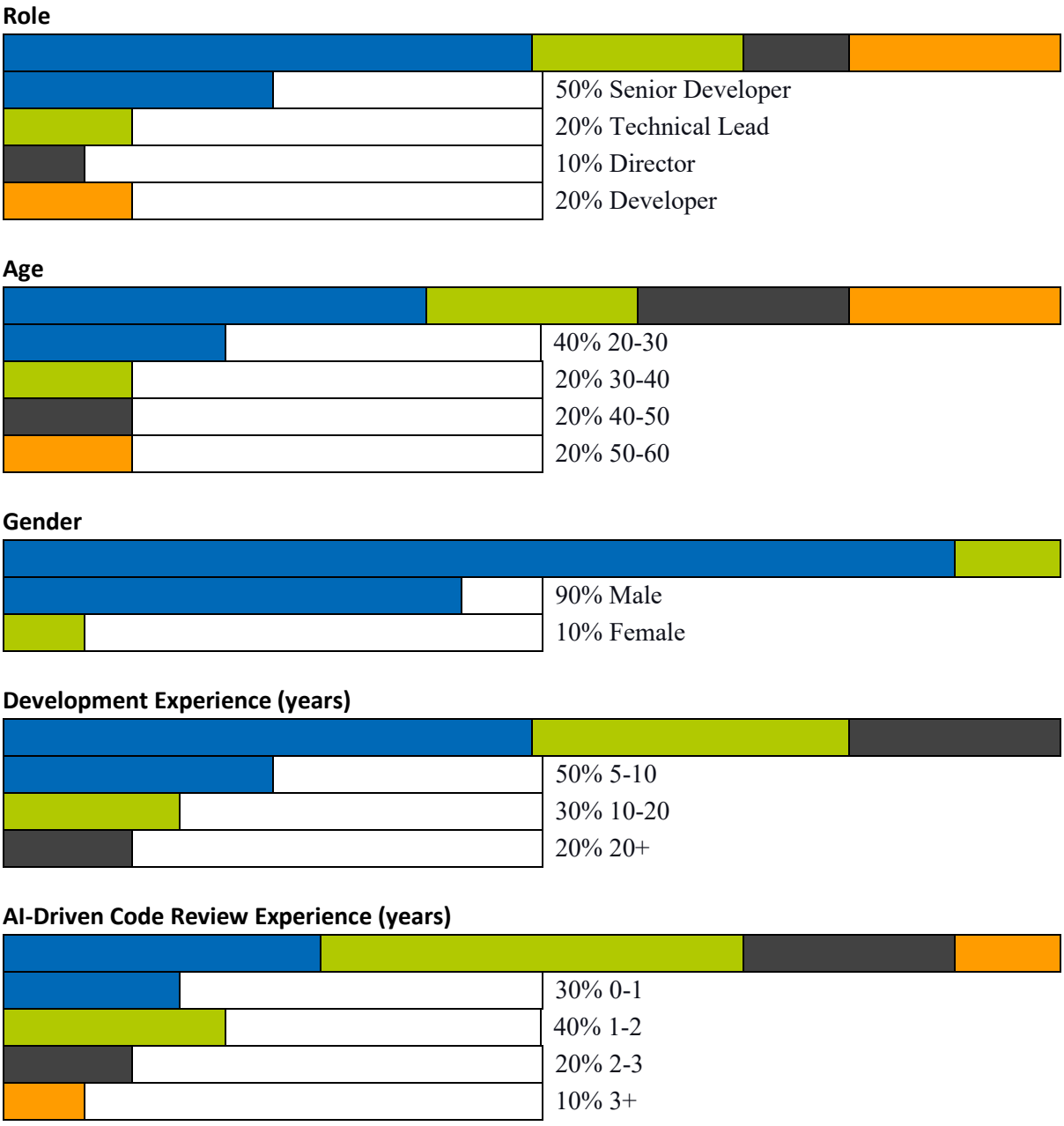

Table 1. Themes

Title	Parent	Total Codes
Learning and Knowledge	Impact on Developer Skills	2
Educational Tool	Impact on Developer Skills	7
Challenges	Trust	3
Hallucinations	Skepticism	4
Context Awareness	Trust	5
Code Consistency	Skepticism	6
Data Privacy Issues	Skepticism	3
Bias	Ethics and Security Concerns	1
Incorrect or Irrelevant Feedback	Skepticism	14
Impact on Developer Skills		4
Trust		22
AI vs. Traditional Code Reviews	Trust	6
Efficiency and Speed	Productivity	7
Potential to Evolve	Future Expectations and Improvements	15
Transparency	Skepticism	6
Ethics and Security Concerns		11
Human-AI Collaboration	Ethics and Security Concerns	14
Skepticism	Trust	13
Reliability in Code Review	Trust	14
Lack of Context Understanding	Skepticism	17
Future Expectations and Improvements		20
Productivity		19
Reduce Workload	Productivity	12
Integration in Workflows	Productivity	5
Total Codes	**230**	
Total Quirks	**24**	

Efficiency and Productivity

Participants highlighted that AI-driven tools reduced manual code review time and allowed focus on complex tasks, with many noting rapid feedback as a key benefit. The thoroughness of AI in detecting errors and suggesting improvements was a recurring theme, boosting productivity. Participants also noted that AI tools minimized human error, ensured consistency, and enabled faster development cycle iterations. Several participants emphasized that time saved with AI tools allowed them to allocate more effort to innovation, demonstrating the perceived value of these tools in improving workflow efficiency.

Learning and Knowledge Enhancement

Participants expressed that AI-driven code reviews reinforced coding principles and provided educational value through detailed explanations. This theme was prevalent, with many participants recognizing AI tools as ongoing learning aids that helped them adopt best practices. Additionally, participants highlighted that

AI tools exposed them to alternative coding methods and encouraged them to stay updated with evolving standards. The guidance provided by AI tools was seen as particularly valuable for junior developers, providing mentoring support and accelerating their learning curve.

Trust and Reliability

While many participants acknowledged AI's reliability in detecting errors, they also expressed skepticism regarding its ability to understand complex business logic and project-specific contexts. This skepticism was a shared concern among several developers, indicating a pattern of cautious reliance on AI feedback. Some participants noted that while AI tools were reliable for syntax and structural checks, the feedback often lacked awareness of broader project objectives, leading developers to selectively adopt AI recommendations. The importance of human oversight was repeatedly emphasized, with developers advocating for a balanced approach where AI serves as an assistant rather than a replacement.

Challenges and Limitations

A notable challenge identified by participants was the AI's struggle with business logic, leading to improper suggestions. Contradictory feedback from AI tools created additional workload, and concerns about training data quality and ethical implications were often raised, highlighting widespread concerns. Developers reported that AI tools sometimes generated false positives, requiring careful review and offsetting some time-saving benefits. Ethical concerns included data privacy, bias in AI training models, and potential over-reliance on automated systems, which participants believed could undermine critical thinking and collaborative code review practices.

Collaboration and Workflow Integration

Participants had mixed experiences with AI tools. While some valued quick feedback that reduced reliance on human reviewers, others felt AI hindered peer discussions. A recurring suggestion was improving AI's contextual awareness for better workflow integration. Participants also noted that AI tools could disrupt established review processes by introducing conflicting suggestions that required mediation. However, many acknowledged that AI tools streamlined repetitive tasks when integrated effectively, allowing human reviewers to focus on high-impact code assessments, thus enhancing team efficiency.

Future Expectations

Participants expected AI tools to continue as complementary aids to human reviewers, with hopes for improvements that would reduce manual intervention. Several participants highlighted continuous training and adaptation of AI tools as essential, underlining the need for development. Participants expressed optimism about the future of AI-driven code review tools, such as improved contextual understanding, adaptive learning from project-specific code bases, and enhanced security features. The need for customizable AI-driven code review tools tailored to specific project needs was also stressed, with participants hoping for more transparent and explainable AI operations to build trust and improve adoption.

Discussion

The results of this qualitative study contribute to the existing literature by highlighting both positive perceptions and ongoing challenges faced by developers when using AI-driven code review tools.

Consistent with prior research, the participants acknowledged multiple advantages associated with integrating AI-driven tools, including enhanced efficiency, productivity, and opportunities for skill enhancement (Almeida et al., 2024; Rasheed et al., 2024; Tufano et al., 2021). Participants reported that AI-driven tools effectively reduced their workload by quickly identifying errors, suggesting relevant refactoring options, and automating repetitive tasks. These observations align closely with Almeida et al. (2024), who found that AI tools significantly reduced the time required for code reviews while improving overall code quality. Similarly, Gerede and Mazan (2018) demonstrated that AI-based predictive models increased review efficiency and improved developer satisfaction by proactively identifying code issues requiring review.

However, despite these perceived benefits, the study findings underscore persistent skepticism among developers, particularly regarding AI's limitations in handling complex business logic and domain-specific contexts. Participants expressed doubts about the AI tools ability to interpret deeper layers of contextual information, echoing concerns documented by Bird et al. (2023), who noted developers' reluctance to fully trust AI-generated suggestions due to perceived inadequacies in understanding intricate project-specific details. Ernst and Bavota (2022) further emphasized the importance of trust and reliability in AI-driven development environments, advocating that human oversight remains essential, especially when handling complex or sensitive software tasks.

Moreover, ethical considerations emerged as a significant dimension shaping developer perceptions. Developers expressed concerns about data privacy, inherent biases in AI training datasets, and the risk of excessive reliance on automation, which could undermine the critical thinking and collaborative practices of developers. These ethical challenges mirror concerns discussed extensively in prior studies, including Baumgartner et al. (2024), who underscored the necessity of transparent and explainable AI recommendations to mitigate bias and promote accountability. The developers' apprehensions around ethical issues, particularly data privacy and bias, align with broader ethical discourses highlighted in recent literature (Bird et al., 2023; Ernst & Bavota, 2022).

This study also reveals practical implications for improving AI-driven code review tools. Participants called for improvements in the contextual awareness and accuracy of AI tools, advocating for increased customization capabilities, transparency in recommendation processes, and seamless workflow integration. These findings are consistent with recommendations from the OWASP Code Review Guide (Keary, 2017), which emphasizes the integration of security best practices and transparency into software development processes. Furthermore, these findings align with studies by Pejic et al. (2023) and Zydroń and Protasiewicz (2023), which advocate for more contextually aware and customizable AI tools capable of adapting dynamically to specific project environments to optimize reviewer effectiveness and enhance overall software quality.

Participants also expressed future expectations for AI-driven code review tools, highlighting the need for continuous improvement in adaptive learning capabilities, better contextual awareness, and more robust integration into existing development workflows. These expectations resonate with suggestions from Almeida et al. (2024) and Rasheed et al. (2024), who have recommended ongoing refinement of AI's capabilities through deeper contextual learning and integration into established human-driven processes.

In summary, while the benefits of AI-driven code review tools in software engineering practices are recognized, there are still significant concerns about contextual understanding, trustworthiness, and ethical considerations. The current study reinforces the need for AI tools to evolve towards greater transparency,

contextual sensitivity, and seamless integration into existing workflows, achieving a balanced partnership between automation and human expertise.

Conclusion

This qualitative research explored the perceptions and challenges of software developers using AI-driven code review tools. The literature review highlighted existing knowledge regarding AI's ability to improve code review efficiency, productivity, and skills while underscoring prevalent concerns regarding trust, contextual understanding, and ethical implications (Almeida et al., 2024; Bird et al., 2023; Ernst & Bavota, 2022; Tufano et al., 2021).

Semi-structured interviews were conducted with software developers, technical leads and solution architects using thematic analysis. The thematic analysis revealed six key themes: efficiency and productivity, learning and knowledge enhancement, trust and reliability, challenges and limitations, collaboration and workflow integration, and future expectations. Participants acknowledged that AI-driven tools reduce repetitive tasks, increased productivity, and improved continuous learning. However, skepticism persisted regarding the tools' limitations in contextual understanding, ethical concerns, and reliability, underscoring the continued necessity of human oversight.

The discussion aligned these findings with previous studies, highlighting persistent challenges related to trust, contextual understanding, and ethical considerations when integrating AI tools in software development (Bird et al., 2023; Ernst & Bavota, 2022). Consistent with research advocating for human oversight in AI-driven software engineering practices (Baumgartner et al., 2024), this study underscores the necessity of balanced human-AI collaboration rather than complete automation.

In summary, this research provides evidence supporting a hybrid model, emphasizing the complementary role of AI-driven code review tools and human expertise. Future research should address AI limitations, especially contextual understanding and ethical transparency, aligning technological advances with ethical standards in software engineering.

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