The Future of Software Engineering in an AI-Driven World

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While the introduction of high-level programming languages has played a major role in allowing developers to write concise and ex-

pressive code, a paradigm shift occurred in the early 2000s with the

widespread use of APIs (Application Programming Interfaces)

and libraries. Before that, programmers had to write extensive

amounts of code to perform even basic tasks. The shift towards us-

ing APIs and libraries had a profound impact on the efficiency and

capabilities of software development [28, 63]. Programming can

now be informally summarised as chaining the inputs and outputs

The intuitive, informative, and concise nature of variable and

API names is bringing our programs closer to resembling **human language**. Additionally, the ongoing evolution of higher-level pro-

gramming languages unmistakably demonstrates a trend towards making language constructs more closely aligned with human

speech [15]. Can this trend continue and eventually programming

will reach the pinnacle of abstraction: natural language? This is very

unlikely. Human speech lacks the basic criteria of programming languages (e.g., lack of ambiguity). However, this does not mean

that software engineers could not write programs specifying their

intent in natural languages. Developers have been using Stack-

Overflow.com (SO), to search for solutions of programming tasks

using natural language as queries. Indeed, SO and similar O&A

websites for developers [48] have become crucial tools to boost

pecially following the global launch of GPT3.5 and GPT4.0 by

OpenAI, have brought another revolution of programming, rapidly overshadowing platforms like SO [10]. While program synthesis

from natural language queries has been a subject of research for

many years [18], the performance of recent LLMs has shown results

that were unthinkable just a few years ago [6, 11, 19]. Now, develop-

ers no longer need to search on SO for code snippets; instead, they

can directly ask GPT (or other LLMs), and even have conversational

interactions to better understand and improve the generated code.

Recently, SO removed statistics on its daily visit counts and offi-

cially addressed concerns about declining website traffic in a blog

post¹. The post acknowledges the decline in visits and attributes the

trend to the release of GPT-4. We are witnessing a paradigm shift

in software development where software engineers use LLMs or

other AI systems to boost their productivity [12, 40]. We can confi-

dently say that LLMs, alongside high-level programming languages,

libraries, and developer Q&A websites, have become essential tools

LLMs are here to stay. Indeed, their capabilities and performance

in source code generation are set to improve in the future. This is

due to the increasing availability of open-source code for training

The recent rise of Large Language Models (LLMs) [62], es-

developer productivity [35, 35, 39, 42, 46, 47, 51].

of API calls, allowing an even higher level of abstraction.

ABSTRACT

A paradigm shift is underway in Software Engineering, with AI systems such as LLMs gaining increasing importance for improving software development productivity. This trend is anticipated to persist. In the next five years, we will likely see an increasing symbiotic partnership between human developers and AI. The Software Engineering research community cannot afford to overlook this trend; we must address the key research challenges posed by the integration of AI into the software development process. In this paper, we present our vision of the future of software development in an AI-driven world and explore the key challenges that our research community should address to realize this vision.

CCS CONCEPTS

 Software and its engineering → Software testing and debugging; Designing software; Software design engineering.

KEYWORDS

Software Engineering, Artificial Intelligence, Machine Learning, Large Language Models, APIs, Libraries, Software Testing, Requirements Engineering

ACM Reference Format:

1 INTRODUCTION

In the dawn of computing (1940s), programmers wrote machine code, consisting of binary instructions to directly program computer's hardware. It was quickly understood that programming **needed a higher level of abstraction from the hardware** [4]. This allowed programmers to write code that is more readable, understandable, and portable across different hardware. From assembly language (a more human-readable representation of machine code) to scripting languages (e.g., Python and JavaScript), the past 70 years of programming languages and practices have witnessed a continuous pursuit of a higher level of abstraction [15]. This is to increase the developers' efficiency and at the same time cope with the demand of increasingly complex software systems.

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¹https://stackoverflow.blog/2023/08/08/insights-into-stack-overflows-traffic/

for modern software development [12].

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Figure 1: Logical architecture of the envisioned future symbiosis of Software Engineers and AI

purposes, alongside the ongoing efforts of the AI community to enhance LLM performance. As such, over the next five years, we anticipate that software engineers will continue to use LLMs (or similar AI systems) in code development.

Our research community must acknowledge and address the opportunities and challenges that arise from the use of AI in software development. Concerns persist regarding the quality of AIgenerated code [30], with notable issues regarding security and privacy [58]. Yet, there are numerous opportunities presented by the versatile capabilities of LLMs, especially when fine-tuned for specific tasks, code bases or company practices. Indeed, LLMs have proven highly effective in various software engineering tasks beyond code generation, including documentation generation [16, 33], testing [43, 59], and program repair [26, 55]. Our research community stands at the forefront of this revolution, we need to tempestively address the challenges of the **symbiotic partnership between human developers and AI**.

In this paper, we present our vision of the potential future of an AI-driven software engineering, alongside the key research challenges and opportunities associated with the increasing integration of AI into the software development process.

2 AI-DRIVEN SOFTWARE DEVELOPMENT

Figure 1 overviews our envisioned **AI-driven software development framework**. While certain aspects of this framework may appear overly optimistic about the capabilities of future AI systems, it presents an interesting thought process for understanding the potential symbiotic synergy between AI and software developers. Moreover, it sheds light on the research challenges that our community must address to realize this vision someday. Indeed, such a vision is not completely unrealistic. We know that current AI systems can accomplish most of the specified tasks, albeit with limited quality [16, 20, 26, 33, 43, 55, 59].

The framework touches all main phases of the **Software Development Life Cycle**: Requirement Engineering, Software Design, Implementation, Testing, and Maintenance. Note that we are not assuming a waterfall model, the cycles may overlap, especially in agile development methodologies where development cycles are shorter and more flexible.

The Actors in our framework are software engineers (e.g., developers, architects, and tester) and a generic AI system (e.g., an LLM). It is important to mention that we believe we are still very far from completely replacing software engineers with prompt engineers. Capable software engineers (with prompt engineering training) will remain indispensable for understanding, reviewing, improving, combining, validating, and maintaining the source code generated by AI. In the short and medium term future, AI is merely a tool to enhance developers' productivity. While it can automate certain tasks, we assume the presence of humans in the loop.

With our proposed framework, engineers can either directly create or update the artifacts (i.e., requirements, design, production and test code) or instruct the AI (e.g., through prompt engineering) on how to do that. We envision a **bi-directional communication** between humans and AI, where humans can ask questions or provide instructions, and the AI can notify engineers of any detected issues or opportunities for improvement. Software engineers will communicate with AI through **conversational interactions** facilitated by the conversational capabilities of LLMs. This interface empowers engineers to seek clarifications and explanations about the artifacts as well as the AI system's output.

Another important clarification is that, for simplicity, Figure 1 represents a single AI system. Clearly, the AI system would not be the same for every task. It is reasonable to assume that a dedicated AI system, fine-tuned for the specific task, will be in place.

AI System: The primary research challenge in integrating AI into the software development process will be orchestrating the various AI subsystems that focus on specific development tasks and seamlessly integrating them using a single human-AI interface.

In particular, the AI subsystems must effectively communicate with each other and with various software analysis tools responsible for gathering information on the software artifacts in development. As the number of available AI systems continues to grow, to prevent information overload, humans will interact with a single **unified interface**. Similar to mediator bots [41], an **orchestrator of AIs** can efficiently manage all interactions with the AI subsystems behind the scenes. We envision that the AI's orchestrator will constantly monitor changes in the artifacts (after every update from engineers) and invoke the dedicated AI subsystem to check for consistency and integrity of the artifacts.

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2.1 Requirements Engineering

Requirement Engineering: The main research challenge will be to enable AI agents that can understand user needs.

Understanding stakeholder needs is a complex activity due to, for example, ambiguities in natural language, stakeholders not always knowing what they truly need, and changing needs. Yet, AI, and LLMs in particular, can still assist in requirements engineering activities. They are capable of analyzing, organizing, and summarizing large amounts of data. Thus, they can play a crucial role in the preliminary phase of requirements elicitation. Stakeholders can provide any form of documentation, and LLMs can summarise large documents or translate them into formal requirement specifications. Additionally, Chatbots powered by LLMs can also aid in the elicitation of requirements by engaging in conversations with stakeholders. They can generate questions and suggestions to help stakeholders articulate their needs more clearly. Moreover, they can propose relevant examples or scenarios to facilitate discussions and clarify ambiguities. For example, AI agents could produce mock ups of interfaces or rapid prototypes to confirm understanding of user needs. Stakeholders often describe their envisioned solutions to a problem, rather than the problem itself. The AI systems will need to ensure stakeholders proposed solutions do not limit the possibilities of innovative designs.

AI will also check for inconsistencies, conflicts, and missing requirements. Figure 1 illustrates the interaction solely between the Software Engineer and the AI. However, the AI could also engage in conversations with stakeholders (e.g., clients, product owners) to elicit, analyse, specify, and validate requirements. Nonetheless, humans will remain in the loop. Software Engineers should oversee these conversations, refine and validate the requirements, and intervene if issues arise.

We will also need define a new **prompt-friendly requirement language** that can enhance collaboration between humans and AI systems in transitioning from requirement engineering tasks to development tasks. We call this language "prompt-friendly" in the sense that it should be easily understood by LLMs so that they could generate the associated source code. For example, the language might need to unambiguously separate functional and non-functional requirements to help the LLM generate code. More research on fine-tuning and prompt engineering is needed to understand what are good prompts to specify requirements and at the same time to generate the corresponding source code.

2.2 Software Design

Starting from the requirements, AI will work alongside the software engineer to automatically propose initial design suggestions. These suggestions can serve as starting points for further refinement and validation by the engineers. LLMs should be fine-tuned with best practices, design patterns, and knowledge from previous similar projects. We believe that human input will be needed for this step.

In particular, the AI should explain to developers the specific trade-offs that alternative design solutions entail, aiding them in decision-making. Explainable AI is an important an active research

topic in the AI community [57]. More research is needed to leverage explainability techniques in the context of software design.

Software Design: An important research challenge will be to understand how software engineers can effectively integrate AI into their design workflows, communicate with them, and interpret their suggestions. In particular, AI must provide explanations for their design suggestions to increase trust and facilitate human understanding.

2.3 Software Development and Testing

We envision that software development and testing will be intertwined, as automated testing should be conducted to verify the correctness of the components generated by AI, as well as their seamless integration into the code base. Given a set of unimplemented requirements, AI will automatically generate and test the production code, after which humans and AI will collaborate to improve and verify it.

Software Development: The key research challenge will be to understand how effective prompt engineering can guide code generation, particularly when aiming for seamless integration into the code base while matching the design and technologies. Indeed, requirements might be too high level, and it remains a challenge how to decompose high-level requirements into low-level implementation details.

An important opportunity arises from the potential sharing of low-level implementations generated by AI within the **opensource community**. Low-level implementations could be generated as stateless, and immutable APIs. The advantage is that these APIs undergo human and automated verification and testing. This enables other software project to reuse them rather than attempting to re-generate them from scratch. By accessing existing databases of AI-generated APIs, AI systems can explore alternatives before resorting to generating code from scratch. This concept parallels the notion of "APIzation" recently explored for Stack Overflow code snippets [51, 52].

Testing will play a crucial role, as we need to ensure the correctness of the LLM-generated code and its integration with the codebase. Test cases can, of course, be created by developers, but they can also be generated automatically. The latter type of test cases will be crucial for verifying AI-generated code. While LLMs can generate test cases, we envision that automated test generators (e.g., RANDOOP [37], EVOSUITE [14], and PYNGUIN [32]) will work in combination with LLMs to improve the quality and fault detection effectiveness of the generated tests. We are already witnessing the first attempt of this combination, yielding promising results [29]. While LLMs can be somewhat effective in generating test cases [43, 59], current LLMs do not guarantee compilable or runnable test cases [59]. Therefore, an integration with traditional test generators that compile and run test cases is necessary. Additionally, the feedback from compiling and running test cases is known to be extremely useful in improving LLM-generated tests [43, 59], or automatically generate test cases in general (e.g.,

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feedback-directed approach [38]). More research is needed to better exploit the synergy and complementarity of LLMs and traditional test case generators [29].

Software Testing: The key research challenge will be to automatically generate test cases with effective oracles to verify AI-generated code.

Indeed, generating **effective oracles** that correctly distinguish between correct and incorrect executions is crucial. We cannot expect humans to write oracles for (many) AI-generated test cases; we need automatically generated oracles. Unit test generators (e.g., RANDOOP [37] and EVOSUITE [14]) generate (regression) oracles based on the implemented behavior, not the intended one. They capture the implemented behavior of the program with assertions that predicate on the values returned by method calls and fail if a future version leads to behavioral differences. Thus, they are only useful in a regression testing scenario, and their effectiveness is usually evaluated in such a scenario [23, 45]. Regarding AI-generated code, the regression scenario is not useful as we want to expose faults the current version of AI-generated code.

Metamorphic Testing (MT) [7] could be the key to address this challenge. MT alleviates the oracle problem by using relations among the expected outputs of related inputs as oracles [8]. Research shows that such relations, called Metamorphic Relations (MRs), exist in virtually any software system [44]. MT proves highly beneficial when integrated into automated test generation, as a single MR can be applied to all test automatically generated inputs that satisfy the input relation. However, MT's automation and effectiveness depend on the availability of MRs. The automated generation or discovery of MRs presents a challenging and largely understudied problem [1, 8, 9, 44]. Only recently has the research community begun addressing metamorphic relation generation from different angles [2, 3, 5, 56, 60, 61]. More research is needed on MR generation [2, 3, 56] and oracle/generation improvement [21, 22, 36, 49, 50] to facilitate effective testing of AI-generated code.

2.4 Software Maintenance

We envision an AI-powered maintenance phase that remains constantly active in the background. The AI monitors external information about the software product and its ecosystem to gather potential issues or opportunities for improvement.

Software Maintenance: The primary research challenge will be to enable AI to autonomously process and utilize a vast amount of external information effectively to identify potential issues or opportunities for improvement. The AI should achieve this while ensuring fairness in its decision-making process and adherance to strategic direction.

Indeed, issues or maintenance opportunities are often buried in a **large amount of sources**, such as bug reports, discussions on developer forums, and feedback from app stores [53, 54]. The AI must be capable of extracting relevant insights, identifying potential issues or opportunities for improvement, and proposing appropriate fixes or changes to the software artifacts. In particular, there are ethical considerations when new product improvements and feature requests can be gathered from the crowd. The AI system should not solely focus on the most popular feature requests and issues but also those that are less popular but might target minority and disability groups [13, 34]. Further, the AI cannot simply add every feature users suggest, some consideration with the product strategy must be considered [27].

Additionally, software exists within an ecosystem of external libraries. The libraries upon which the project depends may release new versions to fix vulnerability issues or bugs, thus it is important to upgrade the project dependencies. However, in certain situations upgrade a library might not be beneficial (e.g., if the software system does not utilise any of the methods that have been updated), the AI has to automatically recognise the important upgrades. In particular, most library developers follow the semantic versioning scheme, where major, minor, and patch releases are specified by the release number. While for minor and patch releases, the AI should attempt to automatically update them, for major release versions, the AI system should discern whether updating the library is necessary for the given software project. Major releases are not backward compatible, and a new library version might offer different functionalities, which could entail a non-trivial task for adapting the client to the new library version. More research effort is needed to help developers in making this choice while at the same time automatically detect and propose fixes for resolving any static [25] or behavioral [24] breaking changes. This future research can be informed by existing studies on automated program repair [17, 31].

3 CONCLUSIONS

This paper presented a **vision of a symbiosis partnership between AI and software developers** motivated and inspired by recent advances in AI. This paper also discussed some key research challenges that need to be addressed by the software engineering community. While this paper focuses on specific software engineering challenges, it is essential to acknowledge broader AI-related concerns such as security, safety, bias, and privacy. Although not covered here, these issues are crucial but fall more within the domain of the AI community, and hopefully will be addressed soon.

We cannot ignore the opportunities that lie ahead. Nor should we disregard the concerns associated with them. Specifically, we must exercise caution **against over-reliance on AI**. While the next generations of software engineers should be trained in prompt engineering and AI, this should not overshadow the necessity of core software engineering knowledge. Human judgment remains indispensable for critically assessing AI-generated artifacts. It is crucial to emphasize again that AI serves as a tool to enhance developers' productivity and cannot (in the near future) replace humans. Putting too much trust on the software artifacts generated by AI can have serious repercussions on the quality and safety of our software systems.

This paper serves also as a **call to arms for our community**. We need multi-disciplinary collaborations across our community to address the key challenges and achieve the envisioned symbiotic partnership between human developers and AI. While our vision is ambitious, we believe that a five-year time frame is reasonable for realizing it.

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