The Impacts of Artificial Intelligence throughout the Software Development Life-cycle on Sustainability: A Mixed-method Study

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Abstract

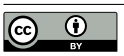
Artificial Intelligence (AI) is increasingly embedded in the software development life cycle (SDLC), reshaping the design, implementation, and maintenance of software. However, the impacts of sustainability remain insufficiently explored. This study investigates how AI affects sustainability across SDLC phases by integrating insights from academic research and industrial practice. We applied a mixed-method approach combining a systematic review of 64 peer-reviewed studies with 27 semi-structured interviews conducted across 12 countries. The analysis covers five dimensions of sustainability: environmental, economic, social, individual, and technical, highlighting both positive "handprints" and negative "footprints." The results indicated that AI is most widely adopted during implementation and testing, with limited use in the requirements, design, and deployment phases. AI improves productivity, code quality, and testing efficiency. However, major challenges persist, such as unmonitored energy consumption, vendor dependency, bias, skill degradation, and AI-related defects. Based on these findings, we propose actionable recommendations for integrating sustainability checkpoints, such as energy and cost monitoring, model size optimization, human oversight, and AI-aware quality reviews, into AI-assisted workflows. These measures aim to shift from incidental efficiency to intentional sustainability throughout the SDLC.

CCS Concepts

• **Computing methodologies** → **Artificial intelligence**; • **Software and its engineering** → **Software development process management**; • **Social and professional topics**; • **General and reference** → *Empirical studies*;

Keywords

Artificial intelligence, Software development lifecycle, Software sustainability, AI in SDLC, Footprint, Handprint



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1 Introduction

The growing importance of software systems as essential drivers of economic growth and innovation has positioned the Software Development Lifecycle (SDLC) as the core framework [32] [51]. In this environment, Artificial Intelligence (AI), including machine learning based and Generative AI techniques (e.g., Chat-GPT [1], GitHub Copilot [2]), is profoundly transforming software engineering by automating processes and introducing novel concepts throughout all phases of the SDLC [46, 51]. However, these advancements introduce Major sustainability challenges that extend beyond technical performance. In this study, we consider Sustainability in software engineering as broadly framed across five dimensions: environmental, economic, social, individual, and technical. [14]. AI will impact all these dimensions. AI's environmental foot- print includes energy consumption and carbon emissions from model training and inference [14]. Economic sustainability concerns high infrastructure costs and Return On Investment (ROI) [32]. Social aspects involve inclusivity and bias mitigation [40], while individual well-being addresses maintainability and managing technical debt in AI-augmented systems [3]. Few studies have systematically explored AI's broader sustainability impacts across the entire SDLC. This study addresses this gap by mapping how AI is integrated across SDLC phases and by comparing academic perspectives with real-world industrial practices to identify sustainability opportunities and risks.

2 Background & Related Work

2.1 AI Integration in the Software Development LifeCycle (SDLC)

The Software Development Life Cycle encompasses all phases of software creation and maintenance. It is defined by standards such

[1] https://chatgpt.com
[2] https://copilot.microsoft.com/

as ISO/IEC 12207 [3], which lays out the processes and tasks required for software development and upkeep. Key phases typically include requirement analysis, design, implementation (coding), testing, deployment, and maintenance [9].

Artificial intelligence approaches are increasingly used in SDLC phases to automate or support processes. AI-powered tools, for example, can help with requirements engineering tasks such as requirements gathering, analysis [41, 52, 57], and code completion throughout implementation [36], as well as automating testing [8] and debugging. AI has been found to increase developer productivity, improve code quality, and accelerate development cycles. Automated code creation, intelligent debugging and bug prediction, predictive software maintenance, and data-driven decision-making during the development process are key areas of impact. Recent empirical studies have explored how pre-trained models on platforms like Hugging Face assist with software engineering tasks, including code generation, testing, and documentation [23]. Moreover, AI "co-pilot" systems, such as Microsoft's Copilot [4], ChatGPT's Codex [5], and Amazon Q Developer [6], can eliminate manual effort and errors, hence speeding up the development process.

2.2 Sustainability in Software Engineering & SDLC

Sustainability has become a fundamental topic in software engineering because systems have a greater impact on the environment, economy, and society. It is commonly described as addressing current needs without affecting the ability of future generations to meet their own [30]. According to the Karlskrona Manifesto for Sustainability Design, sustainability is generally viewed across five dimensions: *environmental, social, economic, individual*, and *technological* [11].

From an *environmental* perspective, software development contributes to energy consumption and carbon emissions [34, 37] through activities such as data center operations, resource-intensive computation, and hardware production [33]. For example, the ICT sector is estimated to contribute about 1.4% to 3.9% of global greenhouse gas emissions [21]. However, it also possesses the potential to reduce emissions in other sectors by up to 15% by enabling technologies [18], which is seven times greater than its impact. The *social* and *individual* dimensions of sustainability emphasize well-being, inclusivity, and long-term engagement of users and developers [38]. This includes fostering inclusive access, minimizing cognitive overload, and supporting positive work environments for development teams. *Economic sustainability* relates to cost efficiency and long-term value creation, recognizing that sustainable software can reduce operational expenses, extend product lifespans, and improve return on investment [28]. *Technical sustainability* focuses on maintainability, adaptability, and resilience of systems, ensuring they can evolve without excessive rework or degradation in quality [28].

Earlier work identified persistent challenges in integrating sustainability into the SDLC [35]. More recent research, including the introduction of the Green AI paradigm, highlights that sustainability considerations remain unevenly addressed in AI-intensive software development despite increased awareness [27]. According to Betz et al. [12], tools and methods to support sustainability-aware decisions in software engineering practice are lacking. Furthermore, explicit sustainability standards, insufficient industry knowledge, and the absence of defined measures for sustainability evaluation have contributed [38].

2.2.1 Footprint & Handprint. While sustainability has typically focused on eliminating harm, recent research has introduced the complementary concepts of *footprint* and *handprint* to reflect the negative and positive impacts, respectively. A *footprint* measures the negative impacts of software operations, including carbon emissions, water consumption, and resource depletion, throughout its lifecycle [44]. A *handprint* indicates the beneficial contributions of software or organizations toward environmental or social progress [5, 24]. Guillaume et al. [24] define the handprint as a constructive metric that "encourages actions with positive impacts," complementing the footprint's emphasis on harm mitigation. Kühnen et al. [29] link handprints to the UN Sustainable Development Goals (SDGs) [7], underlining the importance of organizations not only reducing negative impacts but also actively contributing to societal good.

Applying these concepts to the SDLC allows for a dual-lens assessment: minimizing the software footprint (e.g., through energy-efficient architectures and sustainable deployment strategies) while maximizing its handprint (e.g., by developing software that supports sustainability goals in other domains). For example, AI-based optimization tools may increase energy consumption during model training, but provide long-term benefits by decreasing operational inefficiencies.

3 Methodology

This study used a mixed-methods qualitative approach, combining a systematic literature review (SLR) [13] using semi-structured interviews with practitioners. The objective was to investigate how Artificial Intelligence (AI) is integrated into the Software Development Life Cycle (SDLC) and to examine the resulting sustainability implications. Both the SLR and the interviews were designed to address the same research questions throughout the SDLC phases and sustainability dimensions. The SLR captured the state of the art from academic research, while the interviews provided the state of practice from the industry. Integrating both sources offered a balanced understanding of AI adoption patterns, sustainability perceptions, and practical challenges across SDLC phases.

3.1 Research Questions

This study is guided by one main research question and two subquestions. These questions explore the integration of Artificial Intelligence (AI) into the Software Development Life Cycle (SDLC) and examine how this integration influences software sustainability. The aim is to bridge academic and industrial perspectives by analyzing both the theoretical understanding of sustainability in research and its practical application within organizations.

[3] https://www.iso.org/standard/63712.html
[4] https://copilot.microsoft.com/
[5] https://chatgpt.com/codex
[6] https://aws.amazon.com/q/developer/
[7] https://unric.org/en/united-nations-sustainable-development-goals/

- **RQ1:** How does current research conceptualize sustainability within the integration of Artificial Intelligence (AI) into the Software Development Life Cycle (SDLC)?
- **SRQ1:** What are the current use cases of Artificial Intelligence (AI) across the different phases of the Software Development Life Cycle (SDLC), and what benefits (handprints) and challenges (footprints) do they present?
- **SRQ2:** How is sustainability addressed in existing frameworks and industry strategies for AI integration, and what improvements or recommendations could enhance their effectiveness?

3.2 Systematic Literature Review

The systematic literature review (SLR) followed the guidelines established by Brereton et al. [13] and the snowballing protocol proposed by Wohlin [53]. The primary objective was to identify peer-reviewed studies that addressed sustainability within Artificial Intelligence (AI)-integrated Software Development Life Cycle (SDLC) frameworks.

The searches were conducted between **June and July 2025** across four major digital libraries: *IEEE Xplore*[8], *ACM Digital Library*[9], *Scopus*[10], and *ScienceDirect*[11]. The unified search string used across all databases was as follows:

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("Artificial Intelligence" OR "AI") AND ("Software Development" OR "SDLC") AND ("Sustainability")
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In total, **278 papers** were retrieved (IEEE, 73; ACM, 71; Scopus, 49; ScienceDirect, 85). Duplicate, non-English, and inaccessible papers were removed before the screening process. The screening process was independently performed by **Researchers 1 and 5** following the inclusion and exclusion criteria defined in Table 1. The review included studies from 2015 onward, reflecting the adoption of modern machine learning techniques in software engineering, with sustainability relevance as an inclusion criterion to align with the study's goals.

Table 1: Inclusion and Exclusion Criteria

Category	Criteria
Inclusion	Peer-reviewed journals or conference papers (2020–2025); addressed AI use in any SDLC phase. discusses sustainability (environmental, economic, social, technical, or individual). report the empirical or conceptual results.
Exclusion	Non–peer-reviewed; Not focused on AI or SDLC. No information on AI benefits, opportunities, or any use cases related to SDLC

After screening, **32 studies** met the inclusion criteria. Subsequently, one round of *backward snowballing* was conducted, which identified an additional **32 relevant studies**, resulting in a total of **64 primary studies** included in this review. Figure 1 illustrates the overall review process encompassing the database search, screening, inclusion, and data analysis phases. Data extraction and thematic synthesis were conducted collaboratively by **Researchers 1, 2, and 3** to ensure reliability and consistency throughout the analysis.

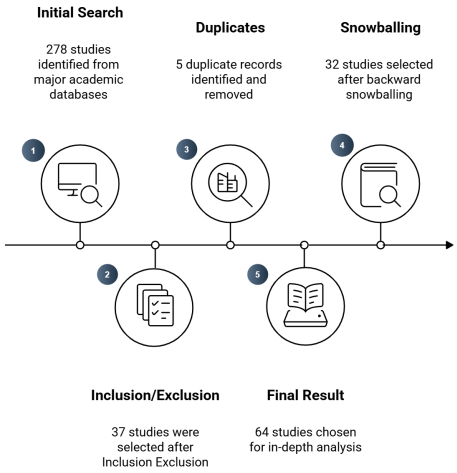

Figure 1: Literature Review Process

3.3 Practitioner Interviews

Semi-structured interviews were conducted with ten questions across three main themes: (1) AI use cases in practice, (2) impacts of AI, and (3) recommendations for sustainable integration. Data were collected between **August and September 2025** through virtual Microsoft Team sessions. The consent of participants was obtained regarding recording, information use, and their identities, and organization details were anonymized to ensure confidentiality. Participants were selected through a combination of purposive and snowball sampling, to ensure representation across industries and roles. Each interview involved two researchers: one moderating and one taking notes. A total of 27 practitioners from 12 countries participated, with Finland representing the largest share at (37%). Table 2 summarizes the distribution of organizations by country and industry domain. Participants included principal architects and software engineers with 1 to 20 years of experience. All participants were involved in at least one SDLC phase, and all organizations applied AI in at least one phase. One organization reported using an internally developed large language model for software development tasks.

All interview sessions were recorded, transcribed, and thematically analyzed by two researchers following Braun and Clarke's six-phase framework [12]. An inductive coding method was used in an Excel sheet to uncover patterns pertaining to AI adoption and sustainability within the software development lifecycle (SDLC). The coding methodology was repetitive and benefited from conversations, producing aligned themes concerning the roles of AI, its merits, obstacles, and implications for sustainability. These findings were compared with a literature review to highlight the similarities and differences between academic and industrial viewpoints on the sustainable integration of AI in the SDLC. This study provides a

[8]https://ieeexplore.ieee.org/
[9]https://dl.acm.org/
[10]https://www.scopus.com/
[11]https://www.sciencedirect.com/
[12]https://www.vappingo.com/word-blog/braun-clarkes-six-phase-framework/

Table 2: Distribution of Participating Organizations

R.ID	Country	Domain	R.ID	Country	Domain
R1	UK	Financial Services	R15	Japan	Software Development
R2	Finland	Cloud Services	R16	Finland	Research and Development
R3	Singapore	Banking	R17	Finland	Research and Development
R4	Finland	Industrial	R18	Canada	Gaming
R5	Bangladesh	Software Development	R19	Dubai	Software Development
R6	Sweden	Telecommunications	R20	Sweden	Software Development
R7	Finland	Aviation	R21	Sri Lanka	Software Development
R8	Finland	Research and Development	R22	Estonia	Software Development
R9	USA	IT Services & Consulting	R23	Sweden	Research and Development
R10	Singapore	Software Development	R24	Finland	Software Development
R11	Finland	Software Development	R25	New Zealand	Banking
R12	Finland	Energy	R26	Finland	Software Development
R13	Pakistan	Software Development	R27	Canada	Ecommerce
R14	Australia	Software Development			

Note: R.ID = Respondent ID (interview participant).

replication package [13] for transparency, including the SLR protocol, search strings, criteria for inclusion/exclusion, data extraction tools, and coding schema for interview analysis, along with an Excel coding sheet and privacy-preserved interview results.

4 Results

The results combine findings from a systematic literature review and practitioner interviews to provide an integrated understanding of sustainability in AI-integrated SDLCs. The comparison highlights how academic research (state-of-the-art) and industrial practice (state-of-the-art) align or diverge across the SDLC phases and sustainability dimensions.

4.1 AI Use Cases Across Software Development Phases (SRQ1)

The findings combine evidence from the systematic literature review (SLR) and practitioner interviews. Together, they reveal how Artificial Intelligence (AI) is being applied across different phases of the Software Development Lifecycle (SDLC). Both sources show a growing integration of AI, but with varying levels of maturity and focus across phases. This section establishes a baseline for the adoption of AI across the SDLC phases. This baseline was later used to analyze sustainability handprints and footprints. The analysis identified that most AI adoption concentrates on implementation and testing, while the requirements and deployment phases remain less explored in both research and practice [22, 46, 48].

4.1.1 State of the Art. Table 3 shows AI use cases reported in the literature across SDLC phases. Most studies propose AI techniques for implementation and testing tasks, such as code generation, defect prediction, and automated test generation [31, 46]. Design-related research focuses on model-driven approaches and pattern identification, whereas requirements engineering and deployment receive comparatively limited attention [22, 48]. Implementation and testing dominate in terms of the depth and maturity of AI integration rather than the number of publications per phase. Across the reviewed studies, AI adoption is primarily motivated by efficiency, automation, and software quality improvement, with sustainability considerations often implicit rather than explicitly addressed [48, 55]. Therefore, the table serves as a reference point for examining sustainability impacts in the subsequent sections.

4.1.2 State of the Practice. Table 4 summarizes the interviews conducted with practitioners. All 27 participants applied AI in at least one phase of the SDLC, primarily during implementation and testing. The main applications include code generation, refactoring, debugging, and automating tests. Some teams also utilize AI for clarifying requirements and prototyping designs through integrated development environment (IDE) assistants and conversational tools.

The emphasis is on speed, quality, and cost rather than sustainability indicators. Participants observed indirect benefits such as reduced rework, quicker testing, and improved resource utilization. A few large companies operate internal LLMs for domain-specific coding and documentation. Challenges continue to exist, including issues with accuracy, security, and integration into existing pipelines. The impacts on sustainability are largely unquantified, in contrast to academic research that assesses lifecycle effects[39, 46]. This discrepancy drives the analysis presented in Sections 4.2 and 4.3.

4.2 Handprints (positive impacts) and Footprints (negative impacts) (SRQ1)

Figure 2 illustrates the normalized distribution of AI-related sustainability handprints across different phases of the Software Development Life Cycle (SDLC). The handprints are most prominent during the implementation and testing phases, reflecting the widespread use of AI for tasks such as automation, productivity enhancements, and improvements in code quality and maintainability [46, 48]. Technical handprints (E5) peak during implementation and testing, which aligns with findings that highlight AI's role in enhancing readability and providing efficient automation in programming

[13] https://github.com/fazla/SLR-Interviews-AI-SDLC-Sustainability.git

Table 3: AI-Related Use Cases Across SDLC Phases Reported in Literature (State of the Art)

SDLC Phase (ID)	AI Use Cases Reported in Literature
S1	AI-based project management and effort estimation [22, 54, 55], requirement extraction and analysis from stakeholder documents [56], and improved requirement clarity using large language models [26].
S2	UML and architecture generation [22], model-driven design automation [14], pattern identification and optimization [48, 55], and GUI generation for user interface design [26].
S3	Code generation and completion [31, 43], automated code summarization and review, refactoring and defect prediction [31], and automated library migration by using deep learning [16].
S4	Automated test case generation and prioritization [46], assertion generation, bug localization and program repair [6], and anomaly detection via model-based testing [42].
S5	AI-driven DevOps and Continuous Integration/Continuous Delivery (CI/CD) pipeline optimization [22, 48], incident response and anomaly detection in cloud services [1, 19], defect and maintenance effort prediction [2, 55], technical debt reduction [4], and automated program repairs [25].

Legend: S1 Requirements, S2 Design, S3 Implementation, S4 Testing, S5 Deployment/Maintenance.

Table 4: AI Use Cases Across SDLC Phases (State of the Practice)

SDLC Phase (ID)	Observed AI Use Cases (R1–R27)
S1	• Brainstorming and idea generation (R17, R23) • Requirement extraction from documents and meetings (R1, R10) • Effort estimation and project planning (R1) • Identifying edge cases (R7)
S2	• UML and architecture generation (R22, R26, R5, R23, R14, R12) • Feature ideation and architecture design (R10, R11) • Process optimization and automation (R7)
S3	• Code generation, completion, and summarization (R3, R10, R22, R6, R17) • Automated review, triage, and refactoring (R3, R12, R22) • Library migration and optimization (R23)
S4	• Test generation, prioritization, and execution (R1–R27) • Assertions and repair automation (R14) • Test data creation (R7)
S5	• CI/CD pipeline automation and configuration (R6, R25, R27) • Root cause analysis (R7) • Anomaly detection and operational monitoring (Multiple)

Legend: S1 Requirements, S2 Design, S3 Implementation, S4 Testing, S5 Deployment/Maintenance. R = Interview Respondent ID (R1–R27).

and testing tasks [45, 56]. Economic handprints exhibit a similar pattern, supporting literature that emphasizes faster delivery and cost reductions achieved through AI-assisted development [14]. In contrast, the requirements and design phases show a limited presence of handprints. Individual handprints (E4), such as reduced developer stress and skill support, are noted only sporadically in the early phases, despite studies suggesting that AI has the potential to lower entry barriers and promote inclusive learning [19, 49, 55]. The deployment and maintenance phases exhibit moderate environmental and economic handprints related to operational efficiency [7, 14, 47]; however, technical handprints remain scarce, indicating a lack of focus on long-term maintainability after deployment. A detailed mapping of studies to the handprint categories and SDLC phases is available in the replication package.

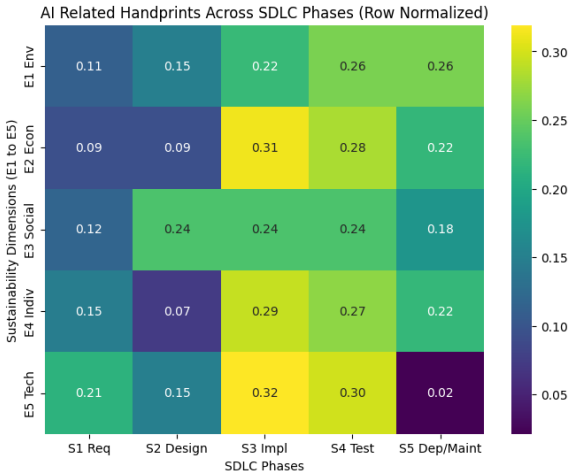

Figure 2: . Row-normalized distribution of AI related sustainability handprints across SDLC phases (State of the Art)

One senior developer noted, *"Energy consumption, I don't think that is relevant to us"* (R6). Energy and carbon impacts were largely unknown to participants.One senior developer stated. *"Who is developing this AI tool,they should consider when they develop these AI tools on energy consumption"* (R3) implying the energy consumption responsibility is with the relevant tool created party. In the Software Development Life Cycle (SDLC), the technical sustainability footprints (E5) are primarily linked to issues such as security vulnerabilities, AI hallucinations, technical debt, and an increasing reliance on unstable AI tools. During the requirements (req) and design (design) phases, research indicates early risks associated with unclear assumptions, insecure specifications, and an overreliance on AI-generated artifacts [14, 46]. These risks exacerbate during the implementation (impl) phase, where technical debt and hidden defects arising from AI-assisted code generation have been

reported [1]. The testing (test) phase is the most frequently discussed, with numerous reports detailing issues such as hallucinated test cases, unreliable oracles, and security blind spots introduced by AI-based testing tools [50]. In the deployment and maintenance (maint) phases, technical footprints persist due to model drift, tool dependency, and long-term maintainability challenges, especially when AI components are treated as black boxes [2, 46]. A complete mapping of studies to technical footprint categories and SDLC phases can be found in the replication package

4.3 Framework/strategies from academia and practice(SRQ2)

Literature offers multiple AI-integrated SDLC frameworks which highlighting environmental efficiency (Trinh et al., 2024; Akgül et al., 2025) as shown in Table 5, while practitioners focus on governance and policy-based control (e.g., internal LLMs, AI guardrails) as shown in Table 6.

Table 5: Frameworks Reported in the Literature

Frameworks
GREEN-CODE, RL-based framework for energy-efficient code generation [27].
Lifecycle-oriented framework covering requirements, design, coding, testing, and maintenance [46].
Template-based reporting with AI ID-cards [15].
FL-based governance framework for open-source AI models [31].
McLuhan's Tetrad for socio-technical impact analysis [1].
Integrate sustainability considerations from the requirements phase [48].

Table 6: Strategies Reported by Practitioners

Strategies
Apply Human-in-the-Loop practices and conduct peer reviews of AI outputs (R9, R15, R25, R23).
Adopt AI gradually, beginning with repetitive tasks and verifying generated outputs (R27, R1).
Use AI for design support instead of direct code generation to minimize risks (R19).
Leverage multiple AI tools and switch providers when needed (R24, R18, R15, R8).
Use AI with clear intent and rationale to maintain oversight and accountability (R14).
Establish company-level policies and guardrails for responsible AI use (R26, R9, R1).
Develop internal LLMs to ensure data security and control (R26).
Conduct regular training and awareness programs for developers (R2, R6, R7).
Adopt privacy-compliant AI tools and APIs for development workflows (R17, R24).
Perform controlled experiments and pilot testing before full-scale deployment (R26).
Create internal roadmaps for efficient and sustainable LLM adoption (R12, R20, R26).

R.ID denotes respondent identifiers See Table 2.

Practitioners highlighted increased productivity as the main benefit: *"If I wanna release a feature in one week with the agent support, I could do it in maybe probably 3 days or 3 1/2 days"* (R21). Yet, most noted the lack of organizational processes for validation: *"We should have a clear policies, a well defined written documentation about AI or how to utilize AI"* (R27).

5 Discussion

5.1 Bridging the State of the Art and the State of the Practice

The analysis shows alignment between research and practice regarding the application of AI, although there are differences in maturity and intent. Academic work predominantly focuses on implementation (S3) and testing (S4), highlighting areas such as automation, optimization, and quality improvement through methods like automated code generation and test prioritization [19, 46, 48]. These approaches are primarily assessed in controlled environments rather than in real-world production settings. Practitioners also report significant use of AI in S3 and S4, mainly for tasks such as code generation, debugging, refactoring, and test automation. However, the adoption of AI in earlier phases, such as requirements (S1) and design (S2), remains limited and reliant on tools. Additionally, the use of AI in deployment and maintenance (S5) is hindered by concerns related to security, reliability, and compliance. While research positions AI as a means to enable long-term optimization and sustainability [48, 55], practitioners tend to use it primarily to enhance delivery speed, reduce costs, and decrease manual effort. This reinforces the notion that sustainability tends to be a secondary outcome of an efficiency-driven approach to adoption.

5.2 Sustainability Footprints Across the SDLC

The adoption of AI in the Software Development Life Cycle (SDLC) brings both sustainability risks and efficiency gains. Research indicates that this adoption results in high energy consumption, increased computing demands, and lifecycle inefficiencies, especially with large models [14, 27, 55]. While automation enhances implementation and testing processes, these advantages are often counterbalanced by significant infrastructure and energy costs [20, 48]. Despite calls for measuring environmental impacts, there is a lack of standardized sustainability metrics. In practice, sustainability is rarely quantified. Practitioners often report indirect benefits, such as faster testing and reduced rework; however, decisions are primarily influenced by performance and delivery speed rather than sustainability objectives. This trend perpetuates a disconnect between awareness of sustainability issues and actual action taken [39, 46]. Research predominantly focuses on improving technical efficiency [27, 43], while social and individual impacts—such as skill erosion and cognitive strain—receive insufficient attention in both research and practical applications [1, 17, 19].

5.3 Suggestions for Reducing AI Impacts

The adoption of AI in the Software Development Life Cycle (SDLC) is increasing, but sustainability considerations are often neglected. While the benefits of efficiency and automation are widely acknowledged [46, 48], the negative impacts, such as higher energy consumption, growing technical debt, and skill degradation, are seldom addressed in practice (R14, R21, R25). To shift from incidental to intentional sustainability, we propose four targeted recommendations.

(1) **Align Model Size with Task Complexity**
Teams should adopt model tiering strategies that match model size to task complexity, as smaller models can achieve comparable performance for routine tasks with lower energy cost [14, 26].

(2) **Treat Technical Debt and AI Hallucination as Sustainability Risks**
AI hallucinations and generated defects increase rework and resource use, requiring AI specific quality checks and traceability to prevent hidden technical debt.

(3) **Address Skill Degradation in AI Assisted Development** To mitigate skill erosion from overreliance on AI tools, organizations should promote responsible use through targeted training and clear usage guidelines [10, 39].

5.4 Broader Implications

Researchers should shift their focus from isolated model evaluations to comprehensive lifecycle sustainability assessments. This can be achieved using tools validated in continuous integration environments rather than relying on external dashboards [22, 48]. In industry, sustainability checks should be integrated into code reviews and continuous integration (CI) pipelines. This integration should be supported by straightforward metrics that assess AI efficiency and data usage, addressing existing measurement gaps. For policymakers, establishing clearer reporting requirements, such as those outlined in the Corporate Sustainability Reporting Directive (CSRD), can enhance transparency and accountability regarding AI-related emissions. Educators should incorporate sustainability into software engineering curricula, emphasizing ethics, measurement, and the real-world energy and cost implications of AI systems.

5.5 Threats to Validity

This study has several limitations. First, the interview sample is small and geographically concentrated, which may limit the generalizability of the findings across different regions and industries. Additionally, interpretations of AI sustainability can vary depending on organizational and technical contexts. To address this ambiguity, we provided a common definition of sustainability and analyzed the responses in relation to the participants' roles. Moreover, the interviews relied on self-reported practices, which introduces the potential for recall and desirability bias. This was mitigated by involving two researchers in the process and employing cross-checked coding. The literature review encompasses studies up to mid-2025 and uses a single search string with one round of backward snowballing, which may result in the omission of some relevant work. To strengthen the validity of the findings, we applied triangulation between the literature and practitioner data.

6 Conclusion and Future Work

This study examined the adoption of artificial intelligence (AI) in the Software Development Life Cycle (SDLC) through a systematic literature review and practitioner interviews. Findings reveal that AI usage is mainly focused on the implementation and testing phases, aiming for automation, speed, and quality, rather than sustainability. The requirements and deployment phases are less explored, with sustainability often seen as a secondary consideration. Future research should focus on operationalizing sustainability metrics for AI within SDLC and CI/CD pipelines, measuring energy consumption with automated energy estimation, cost monitoring dashboards, quality, and bias across all SDLC phases, particularly in real-world Continuous Integration (CI) environments. Field studies should assess sustainability impacts using operational data like CI logs. Moreover, it's essential to validate lightweight sustainability indicators for Integrated Development Environments (IDEs) and examine AI-specific quality gates. Finally, more emphasis should be placed on human and organizational factors, including skill evolution, trust in AI, and governance practices.

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