American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN: 2320-0936
Volume-14, Issue-9, pp-07-13
www.ajer.org
Research Paper Open Access

Transforming Software Development: A Comparative Study of Traditional and AI-Integrated SDLC Approaches

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Abstract
The Software Development Life Cycle (SDLC) is a structured process that includes the need to collect, design, implement, test, deploy, and maintain. Traditional SDLC functioning, such as waterfalls and agile, are primarily manual, which lead to inefficiencies, inaccuracy, and scalability challenges. It examines the integration of Artificial Intelligence (AI) in SDLC to address these limitations by automating paper functions and increasing decision-making processes. In particular, AI-operated techniques such as natural language processing (NLP) and future analytics are examined, including analysis, design, testing, and maintenance of requirements for their ability to customize the major stages of SDLC. Out of comparative investigation of traditional and AI-operated approaches, this research assesses output, efficiency, and their influence on quality in software development. Three research questions lead the investigation, focusing on the adaptation of SDLC stages, the advantages, and disadvantages of creativity, problem-solving, and adaptation of person roles in decision-making. Conclusions, emphasizing the constant importance of human inspection and expertise, highlight the transformational ability of AI to improve software development practices.

Keywords—*AI, optimization, software development lifecycle, artificial intelligence, techniques, comparative analysis.*

Date of Submission: 26-08-2025 Date of acceptance: 04-09-2025

I. INTRODUCTION

The systematic phases of software delivery, such as requirements collection, system analysis, design creation, coding, testing, deployment, and continuing maintenance, are described by the Software Development Life Cycle (SDLC). Because they are mostly manual, SDLC procedures like waterfall and agile are sluggish and imprecise. These mistakes lead to gaps in scalability and slow productivity [1][2]. This issue can be effectively resolved by artificial intelligence (AI), which enhances decision-making and automates tasks. Predictive analytics, for example, might automate testing and maintenance, while natural language processing (NLP) could be used for requirements analysis[3]. Even with the growing literature on AI in product improvement, existing research lacks a comprehensive comparison between traditional and AI-enhanced approaches across all SDLC stages. In addition, the influence of AI on person roles, especially in terms of creativity and ethical decision-making, stays underexplored

Thecontributions of this paper:
This paper addresses these gaps through the following key contributions:
1. A systematic evaluation of AI-driven and traditional SDLC approaches, assessing their effectiveness in productivity, efficiency, and software quality.
2. An investigation into how AI reshapes developer roles, focusing on creativity augmentation, problem-solving, and ethical implications in automated decision-making.
To guide our analysis, we explore three research questions:

1. How do traditional methods and AI-powered techniques compare in terms of optimizing the Software Development Lifecycle (SDLC) phases—such as requirements gathering, design, implementation, testing, and maintenance?

2. When compared to traditional methods, what are the primary advantages and disadvantages of AI-driven approaches in terms of production, effectiveness, and quality?
3.How do AI-powered technologies affect the human role in the SDLC, namely in terms of creativity, problem-solving, and decision-making?

II. LITERATURE REVIEW

The Software Development Life Cycle (SDLC) has long been the foundation of software engineering, offering a constructed framework for providing high-standard products. Traditional methodologies, such as the waterfall model and agile methods, have been widely adopted but are often attacked for their manual procedures, inefficiencies, and scalability challenges [4][5]. These restrictions have stimulated interest in utilizing emerging technologies, especially Artificial Intelligence (AI), to enhance SDLC processes.

Traditional SDLC Methodologies

The waterfall model, one of the oldest SDLC frameworks, confirms a linear, sequential method to product development [4]. While it offers lucidity and construction, its rigidity often causes difficulties in obliging inconstant demands. Agile methods, instituted in reply to these limitations, prioritize flexibility, repeated development, and cooperation with clients [5]. Nonetheless, even agile practices depend heavily on manual effort, which can result in inefficiencies and person mistakes, mainly on large-scale ventures [6].

AI in Software Development

AI has appeared as a transformative strength in product engineering, providing solutions to automate repeated missions, refine decision-making, and increase general efficiency [7]. Natural Language Processing (NLP) has been used for demand gathering, allowing automated taking out and analysis of stakeholder requirements [8]. Likewise, machine learning algorithms have been utilized to forecast faults and enhancing testing procedures, decreasing the time and effort needed for quality assurance [9]. AI-driven tools have also been used in code generation and debugging, especially speeding the implementation stage[10].

Comparative Studies on AI-Driven and Traditional Approaches

Many studies have investigated the comparative success of traditional and AI-based SDLC approaches. For example, research by Amershi et al. (2019)emphasizes the potential of AI to automate repeated tasks, developing productivity and decreasing human effort. Nevertheless, the research also alerts against over-dependence on AI, highlighting the requirement for human oversight to address complex and unclear issues[7]. In like manner, Tantithamthavorn et al. (2019) illustrate that AI-driven testing tools can increase test coverage and detection of defects, but may face problems with usability and edge cases that require human intuition[9].

Human Role in AI-Driven SDLC

The role of human developers has been significantly impacted by the integration of AI into the software development lifecycle. While AI can increase human abilities by automating normal missions and offering data-driven perceptions, it also boosts concerns about the possible corrosion of creativity and problem-solving skills [11]. Research indicates that AI can enhance person decision-making by providing predictive analytics and pattern recognition, but ethical and emotional considerations remain a field where human judgment is indispensable [12].

3.Comparison Between Traditional Methods and AI-Driven Approaches in regards to Software Development Lifecycle (SDLC)

To compare traditional methods and AI-driven techniques across the SDLC phases, certain research questions were identified as stated in Section 1. This study attempted to address these research questions by outlining the following aspects: Role of traditional methods and AI-powered techniques compared in terms of optimizing the Software Development Lifecycle (SDLC) phases, the advantages, and disadvantages of using traditional methods and AI-driven techniques, and the effect of AI-driven techniques on the human role in the SDLC, namely in terms of creativity, problem-solving, and decision-making.

1. Traditional methods and AI-powered techniques compared in terms of optimizing the Software Development Lifecycle (SDLC) phases:

The software development lifecycle consists of five distinct stages: requirements collection, design, implementation, testing, and maintenance. This section will compare the optimization of these phases using traditional methods and AI-powered approaches as shown in Table 1. Recent research quantifies AI's transformative potential—for instance, Zhang et al. (2024) observed 40% faster development cycles with AI integration but noted a 15% increase in technical debt for AI-generated code, underscoring the need for balanced adoption. Similarly, Garcia and Lee (2025) propose an *"autonomous SDLC"* framework, where AI automates 80% of routine tasks while reserving human oversight for ethical alignment and creative problem-solving[13][14].

1. Requirements Gathering Phase
Traditional Methods:
- Process: The requirements are extracted using stakeholder interviews, workshops, and manual documentation[15][16].
- Strengths: Humans are unique in their ability to understand subtle requirements, context, and edge cases that may not be explicitly stated[16].
- Limitations: Time- exhaustion, susceptibility to human error, and inability to often scale for large projects [15].

AI-Driven Techniques:
- Process: AI-powered tools, such as natural language processing (NLP), examine communication logs, emails, and documents to automatically excerpt and prioritize demands[20][21].
- Strengths: Faster, more efficient, and scalable. AI can handle large amounts of data and identify patterns that humans might miss[20].
- Limitations: May struggle with vague or ill-defined requirements. Over-reliance on AI can lead to misinterpretation of stakeholder needs[21].Such as GPT-4 reduced requirements gathering time by 60% but struggled with ambiguous stakeholder inputs, requiring human validation.[22]

2. Design Phase
Traditional Methods:
- Process: Designers deliberate and generate system architectures and user interfaces manually, often depending on background and intuition[20][21].
- Strengths: Human creativity and contextual understanding lead to innovative and user-centric designs[20].
- Limitations: Requires a long time and is susceptible to inconsistencies, mostly in huge teams[21].

AI-Driven Techniques:
- Process:AI tools, such as generative design and machine learning, analyze past design data to suggest templates, free up creatives, and generate multiple design alternatives[23][24].
- Strengths: Fast, data-driven, and have the ability to produce merchandising designs that humans might not have envisioned[23].
- Limitations: AI-generated designs may not be limited to the exact elements that human designers bring to the table. It can be difficult to explain why AI is being used[24].AI-generated designs improved prototyping speed by 3x but were rated 20% less user-friendly than human designs.[25]

3. **Implementation Phase**
Traditional Methods:
- Process: Developers manually issue, review, and correct the code, which often requires a fair amount of time and effort [26][27].
- Strengths: Full control over quality code and compliance with project requirements [27].
- Limitations: Human error, time-consuming, and other important procedures [26].

AI-Driven Techniques:
- Process: AI-powered tools, such as code completion assistants (e.g., GitHub Copilot that developers use Copilot wrote code 35% faster but introduced 25% more security vulnerabilities without manual review[28]) and static code analyzers, automate code generation, debugging, and optimization [29][30].
- Strengths: Naturally reduces errors, raises productivity, and ensures code quality through your testing and optimization [29].
- Limitations: AI-generated code may lead to weaknesses or compromises in meeting project requirements without human oversight [30].

4. Testing and Quality Assurance Phase

Traditional Methods:

- Process: Manual testing is work-intensive, wasting time, and susceptible to human issues[31][32].
- Strengths: Human testers can recognize usability problems and edge cases where automated tools might be absent [32].
- Limitations: Ineffective for huge-scale ventures and lacks comprehensive examination coverage [31].

AI-Driven Techniques:

- Process: AI automates assay instances, detecting defects, experimenting, and performing. Tools such as visual testing and log analysis provide real-time insights [33][34].
- Strengths: quick more effective, and includes comprehensive testing coverage. AI can forecast potential defects for needed tests [33].
- Limitations: Demands high-quality training data, and may lose marginal cases that testers of humans would seize [38].

5. Deployment and Maintenance Phase

Traditional Methods:

- Process: Deployment is manual, and maintenance is reactive, often depending on user comments to recognize matters[35][36].
- Strengths: Human supervision guarantees that deployments line up with user assumptions [36].
- Limitations: assets-intensive and susceptible to detains in matter resolution [35].

AI-Driven Techniques:

- Process: AI allows predictive maintenance by examining performance metrics to expect defeats. Automated bug exposure tools supply real-time control and solutions [37][38].
- Strengths: Proactive problem determination, decreased downtime, and sleeker deployments [37].
- Limitations: Demands notable computational resort and high-standard data for precise forecasts [38].

However, Number of Case studies present AI-driven deployments reduced downtime by 40% but increased ethical concerns in healthcare and finance sectors[39].

Table 1. compare the optimization of SDLC phases using traditional methods and AI-powered approaches

SDLC Phase	Traditional Methods	AI-Driven Techniques	Comparison
Requirements Gathering	- Manual stakeholder interviews and workshops. - Time-consuming and prone to errors.	- NLP extracts requirements from communication logs. - Faster and scalable.	**Effectiveness:** AI is faster but may lack depth. **Quality:** AI ensures consistency but may misinterpret nuances.
Design	- Manual brainstorming and design creation. - Relies on human creativity.	- Generative design and ML suggest templates. - Automates repetitive tasks.	**Effectiveness:** AI speeds up design but lacks creativity. **Quality:** AI improves consistency but may miss details.
Implementation	- Manual coding and debugging. - Prone to human error.	- AI tools (e.g., GitHub Copilot) automate coding and debugging. - Reduces errors.	**Effectiveness:** AI speeds up coding but requires human validation. **Quality:** AI improves code readability and reduces bugs.
Testing	- Manual testing is labor-intensive. - Limited test coverage.	- AI automates test case generation and defect detection. - Comprehensive coverage.	**Effectiveness:** AI is faster and more scalable. **Quality:** AI improves coverage but may miss edge cases.
Maintenance	- Reactive issue resolution based on user feedback. - Resource-intensive.	- Predictive maintenance anticipates failures. - Proactive and efficient.	**Effectiveness:** AI reduces downtime. **Quality:** AI improves reliability but requires human oversight.

2. Advantages and Disadvantages of AI-Driven Approaches

Advantages and Disadvantages of AI-driven approaches are identified in terms of three aspects which are production, effectiveness, and quality as shown in Table 2.

Advantages:

- Production: Automate repetitive missions, which speeds up the development procedure and decreases human effort [29].

- Effectiveness: supplies data-driven perceptions, enhancing decision-making and issue-solving [33].
- Quality: Decreases mistakes and secures consistency resulting in higher-quality outputs [37].

Disadvantages:

- Production: Over-dependence on AI can result in a lack of human supervision and creativity [24].
- Efficiency: Models of AI demand high-standard data and may have difficulties dealing with unclear or unique issues [18].
- Quality: AI may miss edge cases or issues of usability that person testers might recognize[32].

Table2. Advantages and Disadvantages of AI-Driven Approaches

Aspect	Advantages	Disadvantages
Production	- Automates repetitive missions. - Accelerate the development process.	- Over-dependence may decreaseperson oversight. - May lack creativity.
Effectiveness	- Data-driven insights develop decision-making. - Scalable for huge ventures.	- Demands high-standard data. - have difficulties dealing with unclear or unique issues..
Quality	- Decreases mistakes and secures consistency. - upgrades test coverage and reliability.	- May miss edge cases or usability problems. - AI-generated outputs may lack nuance.

3. Impact on the Human Role in the SDLC

There are two types of effects that resulted from AI-powered technologies in the human role in the SDLC, positive effects and negative effects as shown in Table 3.

Positive Effects:

- Creativity: AI increases human creativity by supplying innovative resolutions and automating repeated missions [29].
- Problem-Solving: AI examines data to recognize patterns, allowing humans to center on complex challenges [11].
- Decision-Making: AI supplies data-driven insights, boosting the accuracy and effectiveness of decisions [33].

Negative Effects:

- Creativity: Over-reliance on AI may stifle human creativity and innovation [24].
- Problem-solving: AI may face difficulty with fuzzy or unique issues that demand human intuition [18].
- Decision-Making: The AI-driven resolution reached may lack ethical and emotional considerations [38].

Irreplaceable Human Role:

- Humans stay important for supplying context, ethical judgment, and creativity.
- AI tools should complement, not substitute, human knowledge [38].

Table3. The Impact on the Human Role in the SDLC

Aspect	Positive Effects	Negative Effects
Creativity	-AI enhances human artistry by providing innovative resolutions.	-Over-reliance on AI may stifle human innovation.
Problem-Solving	- AI recognizes patterns, allowing humans to focus on complex challenges.	-AI may struggle to solve a complex or unique problem that requires human intuition.
Decision-Making	- AI suppling data-driven insights, developing accuracy and efficiency.	-Decisions driven by artificial intelligence may lack ethical and emotional considerations.

III. Results and Discussion

Three questions were identified to imply the comparison process between traditional methods and AI-driven approaches in the software development lifecycle (SDLC) which are:

Q1.How do traditional methods and AI-powered techniques compare in terms of optimizing the SDLC phases?

There are five stages in SDLC and the comparison part done in terms of effectiveness and quality between traditional methods and AI-powered techniques in each stage.

Starting with the requirement-gatheringphase, AI-driven approaches are more efficient for huge-scaleventures but may lack the depth of understanding provided by human analysts[17]. While Traditional methods ensure better alignment with stakeholder expectations, AI improves consistency and reduces errors in data extraction

[16]. The next stage is design, AI speeds up the design process and ensures consistency, but human oversight is necessary to ensure designs meet project-specific needs [23]. It also improves design quality by leveraging data-driven insights, but human creativity remains irreplaceable for addressing unique challenges [21].
Moving to the implementation phase, AI significantly speeds up coding and debugging but requires human validation to ensure accuracy and security[29]. AI improves code quality by reducing errors and enhancing readability, but human expertise is essential for complex problem-solving[27]. In the testing and quality assurance phase, AI-driven testing is more efficient and scalable, but human testers are essential for exploratory testing and usability evaluation [33]. AI improves test coverage and defect detection, but human intuition is critical for identifying subtle issues [32].
Finally, AI-driven maintenance is more proactive and efficient in the deployment and maintenance phase, but human oversight is necessary to address complex issues[36]. It improves system reliability and reduces downtime, but human expertise is essential for strategic decision-making[35].

Q2. What are the primary advantages and disadvantages of AI-driven approaches in terms of production, effectiveness, and quality compared to traditional methods?
Advantages and Disadvantages of AI-driven approaches were identified in terms of three aspects which are production, effectiveness, and quality.Beginning with advantages: Automate repetitive missions, which speeds up the development procedure and decreases human effort regarding Production [29]. In the Effectiveness part AI-driven approaches supply data-driven perceptions, enhancing decision-making and issue-solving [33]. In terms of quality, it decreases mistakes and secures consistency which results in higher-quality outputs [37].
On the other hand, some disadvantages were identified which are: over-dependence on AI can result in a lack of human supervision and creativity in terms of Production [20]. Meanwhile, models of AI demand high-standard data and may have difficulties dealing with unclear or unique issues regarding efficiency [18]. Last on is Quality issue where AI may miss edge cases or issues of usability that person testers might recognize [32].

Q3. How do AI-powered technologies affect the human role in the SDLC, particularly in terms of creativity, problem-solving, and decision-making?
There were two types of effects that resulted from AI-powered technologies in the human role in the SDLC, positive effects and negative effects in terms of creativity, problem-solving, and decision-making:
Firstly positive effects, AI increases human creativity by supplying innovative resolutions and automating repeated missions regarding creativity [23]. Meanwhile, in Problem-Solving, AI examines data to recognize patterns, allowing humans to center on complex challenges [11]. The last positive impact is decision-making where AI supplies data-driven insights, boosting the accuracy and effectiveness of decisions [33].
In terms of negative effects, on creativity, over-reliance on AI may stifle human creativity and innovation [24]. Moving to problem-solving, AI may face difficulty with fuzzy or unique issues that demand human intuition [18]. In decision-making, the AI-driven resolution reached may lack ethical and emotional considerations [38].

IV. Conclusion

Adding artificial intelligence (AI) to the software development life cycle (SDLC) is a vast opportunity to fix the issues with old ways of doing things that aren't working well or are limited. This paper shows that AI-based methods, like natural language processing (NLP) and predictive analytics, can significantly develop quality, productivity, and efficiency at many phases of the software development lifecycle (SDLC). In requirements gathering, AI refines steadiness and reduces mistakes, while in design, it speeds up processes and ensures data-driven insights. During implementation, AI accelerates coding and debugging, and in the testing phase increases coverage and fault detection. Finally, in maintenance, AI enables proactive and efficient system management.

However, the paper confirms the significance of balancing AI automation with human skills. While AI excels at automating repeated missions and supplying data-driven perceptions, human creativity, intuition, and ethical considerations stay irreplaceable, especially in labeling unique challenges and securing stakeholder alignment. The advantages of AI-driven approaches, such as increased efficiency and decreased mistakes, must be weighed as opposed to possible drawbacks, including over-dependency on AI, challenges with unclear issues, and the risk of stifling human innovation.

Finally, AI-operated technologies are expected to revolutionize the software development life cycle by customizing processes and improving results. However, his successful implementation requires a collaborative approach that takes advantage of the strength of both AI and human expertise. Future research should focus on developing outlines that integrate AI in the software development life cycle, preserving the important role of human decisions and creativity in software development. By doing this, the software industry can get more scalability, accuracy, and innovation in providing high-quality product solutions.Also explore longitudinal case studies of AI-integrated SDLC in industry settings."

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