Using AI to Improve the Problem Definition of Information Systems Development

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Abstract- This study explores the role of artificial intelligence (AI) in the early stages of information systems (IS) development, specifically in identifying system problems for system improvement and in finding solutions to problems that arise during the system's lifecycle. The current study begins by reviewing traditional methods such as interviews, questionnaires, and modeling, highlighting their limitations in today's complex and data-rich environments. The research adopts a descriptive methodology and combines a review of relevant literature with structured interviews with systems analysts to investigate the benefits and challenges of AI-based tools such as machine learning, natural language processing, and anomaly detection. The study's findings reveal that while AI significantly enhances the accuracy, speed, and scalability of problem identification, its adoption faces challenges such as data quality issues, tool complexity, lack of training, and ethical concerns. The study concludes that integrating AI with - rather than replacing - human expertise provides the most effective approach to identifying IS problems, paving the way for the development of a more accurate, adaptive, and user-friendly system.

Index Terms- problem definition phase, systems development, AI tools.

I. Introduction

Defining a problem through systems analysis involves a comprehensive study of the situation to clearly identify, understand, and describe the problem or opportunity at hand. This initial phase of systems analysis aims to clearly define the problem and gain stakeholder buy-in, which forms the basis for subsequent phases by defining objectives, the current status, and specific information requirements for a future solution. The goal is to understand the problems within an existing system or process to propose improvements or a new system that can effectively address these challenges (Liu, 2021).

The problem-definition phase (requirements elicitation and initial specification) is foundational to IS development: errors here frequently cascade into late design changes, cost overruns, or project failure. Traditional elicitation tools—structured and unstructured interviews, questionnaires, workshops, use-case diagrams, and document analysis, have been the backbone of practice and education for decades. However, these methods face scalability and subtlety challenges when projects involve large stakeholder sets, extensive documentation, or ambiguous socio-technical contexts. Recent research explores AI methods (NLP, ML, and generative AI) to automate, augment, or accelerate parts of the elicitation and specification pipeline.

The identification process involves recognizing the type and complexity of the problem, understanding user needs, and considering organizational and technical challenges. This ensures that the developed system addresses real issues and fits its intended context. Developing a successful information system begins with identifying and thoroughly understanding the underlying problems, which often requires addressing complexity, engaging users, and maintaining flexibility (Aleryani, 2024).

Conventional Approaches to Information Systems Problem Identification

Problems can range from well-structured (clear objectives and requirements) to unstructured (unclear objectives and requirements). Most real-world IS projects are complex, involving both human/social and technological factors, and often fall into the "complex problem" category (Swanson, 2021; Avison & Taylor, 1997). Some problems are defined by high user interaction or uncertain user requirements, which require flexible and adaptive development approaches (Avison & Taylor, 1997).

Traditional methods for identifying information system problems are grounded in statistical and mathematical modeling, with a strong emphasis on data analysis, error interpretation, and structured problem-solving strategies. These approaches provide a robust foundation for accurately defining and addressing IS problems, though they may require adaptation for complex or evolving systems.

Systems analysts have traditionally used methods such as interviews, questionnaires, observations, document analysis, brainstorming, workshops, models, prototyping, and root cause analysis to identify problems in information systems. While these methods are valuable, each has significant drawbacks. For example, interviews and questionnaires can yield biased or incomplete data, especially if stakeholders are unclear or uninvolved. Observation can alter behavior, and document analysis may rely on outdated material. Group methods such as brainstorming and focus groups risk the dominance of particular voices or conflicting viewpoints. Tools such as checklists may overlook unique problems, and prototyping can prematurely shift the focus to solutions. Root cause analysis, despite its methodology, may miss broader systemic problems if it targets the wrong symptoms. These drawbacks typically arise from human bias, communication barriers, outdated information, or the complexity of the system under study (Liu, 2021).
Some methods emphasize human factors, such as resource management, which concentrates on aspects like attention and perception in system operation and design. Lastly, analysis and elaboration involve dissecting information and establishing connections among data elements to deepen understanding and generate comprehensive insights. (Ljung, et al., 2019 ; Gubarev, & Romanenko, 2023).
In addition, (Aleryani, 2024) listed the key challenges in requirements definition include communication barriers, as clients often lack technical knowledge, making it difficult to clearly articulate their needs to systems analysts. Additionally, stakeholder needs are often conflicting and constantly changing. Choosing the appropriate extraction technique is often based on personal preference, rather than methodological criteria or project-specific needs. Traditional methods, such as interviews and questionnaires, are no longer able to keep up with the speed and complexity of modern projects, especially in digital environments.

Challenges in Problem Identification

Information system (IS) problems are complex and multifaceted, encompassing technical, organizational, and human factors (Swanson, 2021; Rudakova, 2023 ; Aleryani, 2009). Gaps in understanding user needs, business processes, or technical limitations often obstruct accurate problem identification. Moreover, the absence of a clear and structured problem definition can result in system development that is misaligned with actual requirements (Kautz, et al., 2007; Swanson, 2021). Additionally, ensuring that systems remain adaptable to evolving environments and capable of integrating with other systems continues to present an ongoing challenge (Rudakova, 2023).
To address these challenges, it is crucial to involve users directly in the early stages of system development, as their participation helps clarify actual needs and ensures that the system targets real problems (Sims, 1992) Maintaining ongoing dialogue among stakeholders, developers, and users is equally essential for refining the understanding of the problem as development progresses (Kautz, et al. 2007). Furthermore, selecting development methodologies that are appropriately aligned with the specific nature of the problem can significantly improve project outcomes (Avison & Taylor, 1997; Kautz, et al. 2007). One of the most significant problems in identifying system problems is that "real problems were not reported." The lack of proper documentation and problem identification was also a serious weakness. This directly contributed to the failure of the system development project, as lessons were not learned from the previous system, costs and efforts were wasted, and the same mistakes were repeated (Aleryani, 2009).

The Role of AI in Addressing Information System Problems

Artificial intelligence (AI) is increasingly used to identify and address problems within information systems (IS). AI enhances the ability to detect, analyze, and solve IS issues, but also introduces new complexities and challenges. AI can significantly improve problem identification in information systems by automating data analysis, enhancing decision support, and streamlining information management, though it also brings challenges related to data quality, transparency, and integration.
Traditional information systems face significant challenges due to the ever-increasing volume and complexity of data. Artificial intelligence has emerged as an effective solution to address these challenges through adaptability and intelligent decision-making. Data can provide valuable insights to automate repetitive tasks and improve operations (Mimi,2024).
Artificial intelligence uses machine learning and natural language processing to analyze massive amounts of data, detect anomalies, and identify shortcomings or errors in information systems processes (Johnson et al., 2022; Sudhamsu et al., 2023, Von 2021). Moreover, AI systems can also predict potential failures or bottlenecks, enabling proactive problem resolution (Johnson et al., 2022). AI also provides insightful recommendations and insights, helping organizations identify and address complex or unstructured issues that may not be apparent through traditional analysis.

Artificial Intelligence (AI) enhances problem identification in information system (IS) development by integrating diverse tools that complement each other across the analysis process. Machine learning (ML) establishes the foundation by detecting patterns in system logs, transactions, and user behavior, while also predicting potential failures and classifying requirements to reduce ambiguity (Xu et al., 2009). Building on this, anomaly detection algorithms refine the analysis by flagging irregularities in system performance or user activity, ensuring that hidden issues are identified before they escalate (Chen et al., 2021). To address unstructured information, Natural Language Processing (NLP) extracts insights from user feedback, tickets, and requirement documents, highlighting concerns or inconsistencies that traditional methods may miss. NLP also powers chatbots, which interact dynamically with stakeholders, clarifying requirements and capturing emerging problems in real time (Ryciak et al., 2022; Surana et al., 2019). These conversational agents transform problem elicitation into a continuous, adaptive process that complements static interviews and questionnaires (Obafemi-Ajayi et al., 2025).
Complementing text-based analysis, log analysis tools and deep learning (DL) models handle the massive streams of system data. Log analysis automates the detection of errors, bottlenecks, and anomalies, while DL architectures such as RNNs and LSTMs learn contextual dependencies in log sequences, enabling accurate anomaly detection and root cause identification at scale (Chen et al., 2021). To manage

the volume and complexity of modern IS environments, Big Data platforms (Hadoop, Spark, Splunk) process distributed datasets, uncovering systemic inefficiencies and allowing real-time anomaly detection through streaming analytics (Ahmad et al., 2023). Finally, Cloud AI services extend these capabilities by offering scalable, pre-trained solutions for anomaly detection, NLP, and predictive analytics, making advanced tools accessible to distributed teams without heavy infrastructure investments (Baghdasaryan et al., 2024). Together, these AI-driven approaches form a complementary ecosystem: ML and anomaly detection uncover hidden patterns, NLP and chatbots capture stakeholder needs, DL and log analysis provide deep insights into complex behaviors, while Big Data platforms and cloud services ensure scalability and accessibility. This synergy transforms IS problem identification from a fragmented, manual process into a proactive, adaptive, and data-driven practice.

Key Challenges and Considerations

Effective AI relies on high-quality, well-integrated data. Poor data can lead to inaccurate problem identification. Many AI models, particularly deep learning systems, are "black boxes," making it difficult for users to understand how problems are identified, which can reduce confidence in AI-based solutions (Johnson et al., 2022; Von Eschenbach, 2021).Therefore, successful problem identification often requires combining AI capabilities with human expertise, especially in complex or ambiguous cases (Johnson et al., 2022).

Moreover, some of the challenges facing AI tools include bias and inaccuracy in AI models. Machine learning and natural language processing models may suffer from biased training data, inaccuracy resulting from the use of informal language or ambiguous terminology, and overreliance on past behaviors that may not reflect future needs. Integrating IoT or big data analytics also requires significant investments in infrastructure and qualified personnel. Additionally, privacy and security risks raise ethical and regulatory concerns. (Aleryani, 2024).

Another challenge in using AI tools is the expertise required by systems analysts. Using AI tools require systems analysts to possess a strong understanding of algorithms for text analysis, machine learning, and natural language processing, along with the ability to operate specialized AI platforms for data collection and analysis. Analysts must be skilled in managing large and diverse datasets—including emails, social media data, and transaction logs, and in applying data cleaning and preparation techniques. They should be capable of interpreting AI-generated outputs within the system context, assessing the reliability of results, and distinguishing meaningful patterns from misleading ones. Furthermore, analysts must translate AI-driven insights into clear, precise, and actionable system requirements. A thorough understanding of data privacy, information security, and the ethical implication of algorithmic bias is also essential when using AI tools (Johnson et al., 2022) ; (Gu, et al., 2024; Habiba, et al., 2024); (Yousefi, et al., 2025)

II. RESEARCH METHODOLOGY

Defining the information system problem under study is a vital and foundational step in the analysis process. The more precise and clearly articulated the problem statement is, the smoother and more efficient the subsequent system analysis and design phases will be. The issue at hand may stem from an existing deficiency within the system, or it may not constitute a problem at all but rather reflect a client's request for enhancement or development. In some cases, the problem may be vaguely identified or misunderstood by the stakeholders, or what is perceived as the problem might actually be a symptom of a deeper, underlying issue that has gone unnoticed. At times, the problem may even arise from differing perspectives on system operations or conflicting opinions among stakeholders. Therefore, establishing a clear, accurate, and comprehensive definition of the problem or the request presented to the systems analyst is essential to ensure a solid and effective starting point for the analysis.

Research Questions

1. What are the main factors that contribute to inaccurate or unclear problem definitions in information systems analysis?
2. What are the most effective AI tools for supporting systems analysts during the problem definition phase? (benefits and challenges)

Research Methodology

This research employs a descriptive methodology designed to accurately and comprehensively define the problem under investigation. It focuses on examining the challenges that arise when system-related problems are articulated in vague or inadequate terms, drawing on an extensive review of the relevant literature. Building on these insights, the study explores a range of artificial intelligence (AI) tools that can assist systems analysts in achieving a more precise and effective problem definition. To complement the information from the literature review, structured interviews will be conducted using a carefully developed set of questions to capture the perspectives of systems analysts with varied expertise. Ultimately, this research aims to demonstrate how AI techniques can enhance clarity, minimize ambiguity, and reduce the risk of misinterpretation during problem identification in systems analysis.

III. LITERATURE REVIEW

The study by Steyvers & Kumar (2024) examines human–AI complementarity, emphasizing that the best outcomes emerge when human judgment and AI capabilities are combined. The authors stress that effective collaboration requires humans to discern when AI outputs are reliable and when they may be misleading, especially since AI predictions often overlook contextual, ethical, or dynamic factors. They argue that identifying system problems cannot be fully delegated to machines; instead, it must be a collaborative process involving human insight, calibrated mental models, and supportive interfaces. Ultimately, AI should be seen not only as a predictive tool but as a partner that helps frame and refine the questions driving decision-making. Steyvers and Kumar's, 2024 ensured that, despite its computational power, AI remains fundamentally limited in one crucial aspect: its ability to understand and define the problem it is solving. highlighted this issue, emphasizing that effective AI-assisted decision-making relies not only on algorithms, but on the dynamic interaction between human cognition and machine computation, particularly in the first and most critical phase of any decision process: defining the system's problem.

This systematic literature review (Stoykova, & Shakev, 2023) explores the adoption of AI in management information systems (MIS), analyzing 60 key studies selected from nearly 4,000 publications between 2006 and 2023. The authors categorize AI applications into areas such as intelligent process automation, predictive analytics, natural language processing, and machine learning. They also examine deployment platforms, identifying the current preference for cloud solutions, while highlighting the growing interest in edge computing and federated learning for their privacy and reliability benefits. The review confirms that most AI contributions to MIS still stem from practical case-based lessons, rather than guidelines or formal frameworks. It also reveals that AI delivers value primarily through process automation, analytical insights, and cognitive interaction, such as virtual assistants and chatbots. However, challenges remain, particularly regarding data privacy, ethical concerns, workforce resistance, and the lack of unified business strategies for integrating AI.

Sarker (2022) aims to help academics, professionals, and decision-makers understand how AI can be applied to create intelligent, automated systems across diverse fields. The paper classifies AI into five types—analytical, functional, interactive, textual, and visual—and outlines ten key techniques, including machine learning, neural networks, data mining, fuzzy logic, and expert systems. These approaches support applications in healthcare, business, cybersecurity, agriculture, and smart cities. The study presents AI not only as a set of tools but as a foundational approach for shaping future intelligent systems, urging ongoing research and innovation. For systems analysts, it highlights how AI can enhance clarity, precision, and depth in defining system problems.
The first tool is a natural language processing (NLP), which helps analyze unstructured text data (such as user feedback, help center logs, and emails). This tool identifies recurring issues, sentiment trends, and user-reported issues that may not have been formally documented. The second tool is automated anomaly detection, which can identify unusual patterns in system logs, performance metrics, or transaction data. Automatic anomaly detection (AAD) can identify abnormal behavior that may indicate underlying system failures or inefficiencies. The third tool is an AI-powered process mining tool, which can analyze and visualize actual system workflows based on event logs. It can detect bottlenecks, anomalies, and inefficiencies in current processes. The fourth tool is machine learning predictive analytics, which predicts system failures, performance degradation, or user behavior. It anticipates potential problems before they become critical, supporting proactive identification. The fifth tool is AI-powered chatbots and virtual assistants, which gather real-time insights from users and support teams and engage stakeholders in structured conversations to uncover hidden or emerging system issues.

The researcher (Aleryani, 2024) explores how Artificial Intelligence (AI) tools specifically Machine Learning (ML), Internet of Things (IoT), Big Data (BD), and Natural Language Processing (NLP) can enhance the process of eliciting client requirements in the development of information systems. It underscores that traditional requirement elicitation methods (interviews, brainstorming, workshops) are becoming insufficient due to increased system complexity, evolving user expectations, and the massive influx of data from various sources.
Ryciak et al., 2022 explored the use of natural language processing (NLP) techniques to analyze log files for anomaly detection. It emphasizes the importance of logs in monitoring system behavior, diagnosing errors, and identifying problems. Traditional methods for log analysis struggle to keep pace with the increasing complexity and volume of system logs. The study applies NLP techniques, such as TF-IDF, word embedding, and clustering, to represent and analyze log data. The results demonstrate that NLP-based methods can significantly improve the identification of unusual patterns and support problem detection in system development and maintenance.

(Collins, et al., 2021) reported that Artificial Intelligence (AI) has attracted growing attention from the Information Systems (IS) research community in recent years. However, concerns have emerged that AI research may face the same challenge of limited cumulative knowledge building that has previously affected IS research. To address this issue, this study conducts a systematic literature review of AI-related research in IS published between 2005 and 2020. The search process yielded 1,877 studies, of which 98 were identified as primary studies. From these, key themes relevant to the study were synthesized. The contributions of this work include: (i) identifying the reported business value and contributions of AI, (ii) outlining both research and practical implications for AI use, and (iii) proposing a research agenda that highlights future opportunities for AI research.

(Baghdasaryan et al., 2024) said that the core problem lies in the inefficiency of customer support in modern cloud environments, where resolving issues often takes days or even weeks. The key challenge is reducing the mean time to resolution, but the scale and complexity of cloud systems make this difficult without intelligent solutions. Current limitations include slow resolution times, underutilized knowledge, and data challenges. Thus, the aim of the research problem is how to develop an intelligent recommender system leveraging large language models and cross-customer data to quickly connect new issues with relevant prior solutions, thereby shortening resolution time and enabling proactive or even self-service support.

(Surana et al., 2019) said; software requirements constitute the foundation of high-quality software development, with all subsequent stages dependent on their accuracy and clarity. Requirements elicitation, a critical aspect of requirements engineering, is often laborintensive and error-prone, particularly when managing large volumes of requirements. To mitigate these challenges, we propose an automated approach that leverages an intelligent conversational chatbot powered by Artificial Intelligence and Machine Learning. The chatbot engages stakeholders in natural language to elicit formal system requirements and automatically classify them into functional and non-functional categories.

IV. ANALYSIS AND DISCUSSIO

First: Analyzing the System Analysts Interviews

Questions were designed on a Google Form and posted on LinkedIn with an invitation to information systems analysts. After a month, only eleven responded, with diverse experiences, and were considered for inclusion to gain information from the actual work of systems analysts. The questions were as follows:

1. Have you ever encountered difficulty or ambiguity in accurately defining the problem? If yes, what do you believe are the reasons for this ambiguity?
2. Have you ever used AI tools to help you understand or identify a system problem? If yes:
    a. What tools have you used?
    b. What benefits have you gained from using them?
    c. What challenges or limitations have you encountered while using them?
3. If no: What are the reasons preventing you from using them currently?
4. From your perspective, can AI tools improve the accuracy and speed of identifying system problems? And why? What are the most important tips or steps you recommend for systems analysts to ensure they arrive at a clear and accurate definition of the system problem under study?

The answers were retrieved and analyzed as follows:

Table 1

Analyzing Interviews

Factors	Novice Analysts	Mid-Level Analysts	Experienced Analysts
Tools & Methods	Structured interviews, questionnaires, basic visual tools (use case diagrams, flowcharts).	SWOT analysis, stakeholder analysis, requirements traceability matrices (strategic alignment).	Stakeholder workshops, BPMN, diagnostic tools (“Five Whys,” fishbone diagrams).
Challenges in Problem Definition	Unclear communication from end users.	Instability of requirements and changing customer needs.	Systemic complexity, legacy systems, poor documentation, conflicting stakeholder perspectives.
Use of AI Tools	Limited use, superficial understanding (e.g., chatbots).	Use of ML for log analysis and user behavior patterns.	Integrated AI use: anomaly detection, data visualization, predictive analytics (Power BI, Tableau, NLP).
Barriers to AI Adoption	Lack of training and experience.	Limited organizational access to AI tools.	Epistemologically, the reliability and interpretability of AI are without human verification.
Recommendations	Ensure clear communication, gather requirements carefully, verify client input.	Engage stakeholders, use visual modeling for shared understanding.	Continuous validation, detailed documentation, and ensuring traceability.

To summarize Table 1. It can be realized that system analysts' approaches to problem definition evolve with experience. Novices rely on interviews, questionnaires, and simple diagrams, which provide structure but leave them vulnerable to unclear user communication. Mid-level analysts move toward strategic tools such as SWOT and stakeholder analysis, focusing on aligning business needs with solutions while struggling with unstable requirements. Experienced analysts use advanced methods like workshops, business process modeling, and root cause analysis, tackling systemic complexity, legacy systems, and conflicting stakeholder perspectives. AI tools are increasingly shaping this process, though their use differs by expertise. Novices experiment with simple chatbots, mid-level analysts apply machine learning to analyze logs and user behavior, while experienced analysts integrate anomaly detection, data visualization, predictive platforms, and natural language processing. Across all levels, AI is valued for its ability to process large data sets, reveal patterns, and highlight bottlenecks, but challenges remain. Structured data, setup effort, and the "black box" nature of many models limit trust. Barriers vary training gaps for novices, restricted access for mid-level analysts, and concerns about reliability for experienced ones. Second: Analyzing the challenges that often arise when using traditional methods and the capabilities of artificial intelligence in overcoming these challenges

Second: Answering Research Questions

Table no.2 below highlights the most significant challenges that often arise when using traditional methods to identify problems in information systems, as well as their underlying causes. It then explores key AI tools capable of addressing these limitations, enabling more accurate, clear, high-quality, and efficient identification of information systems problems. The table below answers the first and second questions

1. *What are the main factors that contribute to inaccurate or unclear problem definitions in information systems analysis?*
2. *What are the most effective AI tools for supporting systems analysts during the problem definition phase?*

Table 2
Analyze the capabilities of AI in problem identification in information systems development

Problem	**Traditional Tools**	**Why it May Occur (Q1)**	**AI Tools**	**How AI Helps in Problem Identification (Q2)**	**Sources**
Incomplete or vague problem definition.	Interviews, Questionnaires.	Stakeholders may not fully express or understand the problem.	NLP & Sentiment Analysis.	• Extracts hidden stakeholder concerns and sentiments from unstructured data. • Faster, richer data understanding.	Ryciak et al. , 2022
Biased information	Interviews, Observation	Subjective or filtered responses may skew the analysis	AI Chatbots	• Provide consistent, bias-reduced data collection from various users. • Efficient stakeholder interviews	(Gizzi, et al 2022; Obafemi-Ajayi, 2025).
Limited stakeholder involvement	Document Analysis, Meetings	Narrow input from limited users	Machine Learning (ML) Tools	• Helps validate problems across broader contexts and projects. • Access to best practices and benchmarks	Xu, et al., 2009; Johnson et al., 2022; Sudhamsu et al., 2023, Von 2021. Cheligeer et al

Difficulty handling complex data	Manual Data Analysis	Patterns in large datasets may be missed	Anomaly Detection	• Automatically detects irregularities or deviations in large datasets. • Early identification of root causes	Chen, et al., 2021
Over-reliance on assumptions	Brainstorming, Expert Judgment	Risks of missing actual root causes	Machine Learning (ML) Tools	• Enables scenario testing and root cause analysis. • Evidence-based decision making	Xu, et al., 2009; Johnson et al., 2022; Sudhamsu et al., 2023, Von 2021).
Resistance to change or withholding info	Interviews, Surveys	Fear or distrust may limit transparency	AI Chatbots NLP	• Encourages honest feedback through conversational AI. • Non-intrusive data collection	Ryciak, et al. , 2022
Lack of real-time data	Periodic Reports, Logs	Delay in identifying issues	Process Mining	• Captures and analyzes live data flows to detect problems earlier. • Accurate mapping of real processes	Xu, et al., 2009
Ambiguity in process understanding	Manual Mapping, Flowcharts	May not reflect actual workflows	Process Mining	• Creates real-time process models from digital footprints. • Accurate process visualization	Xu, et al., 2009
Poor traceability of issues	Documents, Meeting Minutes	Hard to track issues across systems or time	Machine Learning (ML) Tools	• Links data across time and departments for holistic view. • Better problem tracking	Xu, et al., 2009; Johnson et al., 2022; Sudhamsu et al., 2023, Von 2021
Time-consuming, error-prone analysis	All Manual Methods	Prone to delays and human errors	All AI Tools	• Automates analysis and reduces human workload and mistakes. Speed and accuracy.	

Table 3
The benefits and challenges of AI tools

AI Tools	**Benefits**	**Challenges**	**Sources**
• Machine Learning • Anomaly Detection Algorithms	Enhances precision in identifying root causes through data-driven analysis.	May yield inaccurate results if models are trained on biased or poor-quality data.	(Xu, et al., 2009; Johnson et al., 2022; Sudhamsu et al., 2023; Von 2021).

• Natural Language Processing • Log Analysis Tools	Automates data processing to quickly detect system issues and anomalies.	Requires significant computing power and real-time integration.	Ryciak, et al., 2022
• AI-powered Chatbots	Reduces manual work and increases analyst productivity.	Over-reliance may hinder analysts' critical thinking.	(Surana, et al. 2019)
• Deep Learning Models	Reveals hid den patterns and relationships that may not be noticed by humans.	Outputs can be complex and difficult to interpret without technical expertise.	Ahmad et al., 2023
• Big Data Platforms, • Cloud AI services	Effectively processes large and diverse datasets from multiple system components.	Requires scalable data infrastructure and integration frameworks.	(Baghdasaryan, et al., 2024; Poghosyan, et al. 2024; Ahmad, et al. 2023).

When discussing problem definition in systems development, researchers often mention processes (such as data mining, modeling, Knowledge Discovery, etc.) in conjunction with AI tools, because the processes may involve the use of AI techniques. However, in this paper, we will discuss AI tools themselves, regardless of the techniques that may be used with AI tools.
Using AI tools to identify problems during information systems development offers significant benefits, including improved accuracy, accelerated analysis, increased efficiency, and deeper insights. Tools such as machine learning algorithms, natural language processing, data mining platforms, and predictive analytics help automate and improve problem detection, particularly in complex or large-scale systems. These tools also support scalability and continuous learning, making them increasingly valuable in dynamic environments. However, challenges remain. Issues such as data bias, the complexity of interpreting AI outputs, high upfront costs, and the risks of overreliance on AI must be carefully managed. Effective use of AI also requires robust infrastructure, skilled professionals, and ethical oversight. AI tools have the potential to revolutionize problem identification in information systems, but their success depends on thoughtful implementation, ongoing evaluation, and the balanced integration of human judgment and machine intelligence.

CONCLUSION

The current study highlights the critical role of artificial intelligence (AI) tools in improving the problem definition phase of information systems (IS) development. Traditional methods such as interviews, questionnaires, and document analysis remain valuable, but they are often limited by human bias, incomplete stakeholder input, and the inability to process large or complex data. The findings demonstrate that AI tools, such as machine learning, natural language processing, anomaly detection, and process mining, offer significant benefits by enhancing accuracy, reducing ambiguity, and enabling faster and more comprehensive identification of system problems.
At the same time, the research emphasizes that AI adoption is not without challenges. Issues related to data quality, tool complexity, interpretability, ethical considerations, and organizational readiness may hinder effective implementation . This has been confirmed by (Collins, et al. 2021). The interviews with analysts further reveal that the successful use of AI depends on experience, training, and organizational support. Importantly, the study concludes that AI should not replace human expertise but rather complement it, and this is what (Stoykova, & Shakev, 2023) confirmed. The most effective approach is a hybrid one, where human judgment, contextual understanding, and stakeholder engagement are integrated with AI's computational power and scalability.
The use of artificial intelligence tools in information systems development should be aligned with the project's type, nature, and size. Small, well-defined projects with experienced analysts can rely on traditional methods. Medium-sized projects with extensive data and multiple stakeholders may benefit from a hybrid approach that combines traditional methods with selective AI tools. For large projects requiring complex data analysis, such as email and social media processing, AI tools become essential, provided the team has strong expertise in managing such data.
In summary, AI tools hold strong potential to transform the problem definition process in IS development, but their success depends on thoughtful adoption, continuous evaluation, and the balanced integration of technology with human insight. By leveraging this synergy, organizations can achieve more accurate, adaptive, and user-centered systems that are better aligned with real-world needs.

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