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*Original Article*

# Eliciting Client Requirements in Developing Information Systems Using Artificial Intelligence (Opportunities and Challenges)

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***Abstract*** *- The process of eliciting client requirements has always been and remains one of the pivotal challenges for a systems analyst, representing the cornerstone of success in any information systems development endeavour. Historically, challenges revolved around the difficulty of communicating with clients who were unfamiliar with communicating with system analysts who use effective methods for gathering and refining requirements. Over time, these challenges evolved to encompass the integration of diverse stakeholders, each with its own set of needs. However, in the contemporary landscape, the complexity has surged with the deluge of vast data from myriad sources. This inundation poses a formidable task for systems analysts to extract actionable insights catering to a multitude of beneficiaries. Yet, amidst this complexity, artificial intelligence tools have emerged as invaluable aids for systems analysts. These tools facilitate the parsing, categorization, and cleansing of voluminous data, empowering analysts to distil meaningful conclusions vital for deducing clients' requirements. Through AI-enabled processes, analysts can effectively navigate the ocean of data, transforming it into a strategic asset that informs and shapes the development trajectory of information systems. Thus, artificial intelligence stands as a transformative force, augmenting the capabilities of systems analysts and ensuring the alignment of information systems with the diverse and evolving needs of clients and stakeholders. This research aims to investigate the most important artificial intelligence tools that can increase the effectiveness of eliciting client requirements, compare them, and find out their challenges and opportunities.*

***Keywords*** *- Eliciting requirements, Information systems, Artificial intelligence.*

## 1. Introduction

One of the crucial steps in the development of a new product is requirement elicitation. To gather specific and unique requirements, several traditional requirement elicitation methods are employed, including meetings, brainstorming sessions, and interviews [1][2], along with online collaborative techniques for requirement elicitation. However, using just conventional approaches to extract requirements would be highly inadequate given the rapidly evolving rate of product iterations and the end users' ever-increasing expectations [3]. It is imperative to incorporate user requirements in the development process to design successful information systems (IS). Hence, requirements elicitation (RE) is increasingly performed by users who are novices at contributing requirements to IS development projects [4].

Gathering requirements is a pivotal stage within requirement engineering, which holds significant importance in the software engineering workflow. Well-defined requirements are instrumental in the triumph of software endeavors, whereas unclear or flawed specifications can lead to project setbacks. Thus, accurately identifying requirements is crucial for project success. These requirements are refined through a process of requirement elicitation, typically conducted by analysts. There is substantial demand for supporting analysts in their elicitation efforts to ensure precise requirement formulation [5].

Requirements elicitation stands as the initial and pivotal phase within Requirements Engineering (RE), whereby numerous techniques have been introduced to facilitate this process. Each technique boasts its own set of merits and drawbacks, rendering the task of selecting a suitable technique or combination thereof for a particular project quite challenging. Often, the selection of techniques relies more on individual preferences rather than on the attributes of the project, technique, and stakeholders [6].

Traditionally, Requirements Engineering has been centered around stakeholders' needs. On the other hand, many systems analysts have turned to using user experience to gain a clear understanding of the user's interaction with the system.

However, alongside domain expertise, the widespread adoption of digital technologies has resulted in the proliferation of vast amounts of data (commonly referred to as Big Data) from diverse digital sources like the Internet of Things (IoT), mobile devices, and social networks. This digital shift has opened up new possibilities to regard this data as potentially valuable resources for requirements despite not being originally intended for elicitation purposes. An obstacle in this data-driven approach to Requirements Engineering is the absence of methodologies to seamlessly and autonomously elicit requirements from these dynamic and unintended digital sources. Effectively processing such data poses numerous challenges that need to be addressed for organizations to fully exploit their potential [7]. [2] adopted a nuanced approach in classifying requirements engineering (RE) techniques and tools. They organized these into several categories: classic/traditional methods (such as interviews, surveys, and questionnaires), cognitive/analytical approaches (including card sorting, laddering, and repertory grid), modern and group methods (like brainstorming, Joint Application Development (JAD), and prototyping), and social analysis techniques (such as ethnography, direct observation, and passive observation). Similarly, their comparison of these techniques centered around the type of elicitation technique used (direct or indirect), the nature of the data gathered (quantitative or qualitative), communication strategies employed, and the depth of domain understanding achieved.

The recognition of the significance of software quality requirements (QR) has spurred extensive research into the practical aspects of software requirements specifications (SRS), including the quantification of QR relative to functional requirements (FR) and the nature of specified QR. There is a practical need for the development of a tool capable of automating the extraction and classification of QR statements from SRS, categorizing them according to attributes defined in the ISO/IEC 25000 quality model [8].

Requirements elicitation is the crucial process of understanding stakeholder needs for a project, typically involving interaction with stakeholders to uncover their real requirements. It's complex and involves various activities like searching, identifying, and clarifying requirements. Involving the right people and using suitable techniques are essential for obtaining high-quality requirements. Different methods, such as interviews, questionnaires, and brainstorming, can be employed depending on the project and stakeholders involved [9] [1]. Moreover, the user experience will significantly reduce the system analyst's misunderstanding of requirements and reduce the gap between what the user wants and what the system analyst understands.

No single technique fits all situations, so a combination is usually necessary for effective elicitation. Inadequate elicitation techniques can lead to project failures and stakeholder dissatisfaction. Thus, proper stakeholder engagement, understanding of user needs, and careful selection of elicitation techniques are crucial for project success. With the complexity of the business environment and the increase in the flow of data from multiple sources, it has become necessary to use artificial intelligence tools to take advantage of these data to derive requirements clearly and more accurately, in addition to creativity and innovation in providing effective requirements that increase the satisfaction of the beneficiary and raise the level of the information system.

The current research aims to conduct a comprehensive review of existing literature to explore the utilization of artificial intelligence (AI) tools in eliciting customer requirements for the development of information systems. This study seeks to identify the most significant opportunities and challenges associated with the implementation of these technologies. Based on the findings, well-founded recommendations designed will be provided to guide analysts and information systems developers. These recommendations aim to facilitate quick decision-making in selecting the most appropriate tools, thereby minimizing the time and resources wasted on unsuitable options.

## 2. Artificial Intelligence (ML, IoT, BD, NLP)

### *2.1. Machine Learning (ML)*

Recent advances in machine learning have been fuelled by the creation of novel learning theories and algorithms as well as by the continuous proliferation of low-cost computing and internet data. Science, technology, and business are all adopting data-intensive machine-learning techniques, which promote greater evidence-based decision-making in a variety of fields, including systems development [10] [11]. Machine Learning refers to a set of techniques that allow systems to learn patterns and interact intelligently with data, using big data (and sometimes data from IoT) to train models and discover patterns and insights.

#### *2.1.1. Challenges of Machine Learning (ML)*

[12] [13] [14] discussed a wide range of challenges of machine learning that were extracted and linked to several issues. In particular, safety, security, ethics, regulations, economic impacts, and risk management.

### *2.2. Internet of Things (IoT)*

The term "Internet of Things" refers to the network of wired and wireless connections made possible by sensors and actuators built into physical objects, such as pacemakers and highways, which are typically connected by the same Internet IP address as the internet itself. Massive volumes of data are generated by these networks and are sent to computers for analysis.

Things become instruments for rapidly comprehending and reacting to complexity when they can detect their surroundings and communicate [15]. Internet of Things (IoT) refers to a network of devices and objects connected to the internet, exchanging data and interacting with each other, enhancing data collection from connected devices to improve operations and make smart decisions.

*2.2.1. Challenges of IoT*

The information used and transmitted via the Internet of Things contains important information about people's daily lives, banking information, location and geographic information, environmental and medical information, along many other sensitive data. Therefore, it is crucial to identify and address IoT security issues and challenges [16] [17].

### *2.3. Big Data (BD)*

Big Data refers to a large volume of data that is difficult to process and analyze using traditional techniques, characterized by three main dimensions: volume, velocity, and variety and requires special techniques to handle and extract value from it. Big data comes from countless sources – some examples are transaction processing systems, customer databases, documents, emails, IoT devices, medical records, internet click logs, mobile applications, and social networks [18].

[7] undertook a comprehensive literature review focusing on the current data-driven approaches for automating requirements elicitation. Their primary motivations for this review were twofold: (1) recognizing the potential of dynamic data to enhance stakeholder-driven requirements elicitation by revealing new requirements inaccessible through other means, and (2) observing the absence of a systematic review on cutting-edge methods for eliciting requirements from dynamic data derived from unintended digital sources.

*2.3.1. Challenges of Big Data*

[19] [20] [21] discussed several challenges regarding big data, utilizing big data for gathering user requirements encounters several hurdles. Firstly, the sheer volume of data resulting from an exponential surge in both internal and external sources poses challenges to conventional data management tools. Innovative approaches are needed to effectively manage this influx. Secondly, the diversity of data, spanning structured, semi-structured, and unstructured forms, adds complexity to its utilization. Thirdly, the velocity at which data is generated presents challenges, with real-time processing becoming essential for tasks like online shopping. Storage also poses a challenge, as not all data is significant, requiring intelligent filtering to extract relevant datasets and avoid high-cost storage solutions. Data pre-processing is crucial for extracting high-quality insights from large datasets. Additionally, challenges include administration concerns such as data privacy, security, and skilled professionals capable of handling the data effectively. Security and privacy remain primary concerns due to the sensitive nature of certain data types.

### *2.4. Natural Language Processing (NLP)*

Natural Language Processing (NLP) serves as a pivotal AI technology, indispensable for comprehending and dissecting human language. Its capability extends to interpreting and extracting insights from diverse textual sources like user stories, emails, and documents. Notably, the exploration of NLP within the realm of user requirement elicitation stands as a burgeoning field of study, as evidenced by the work of [22]. This domain encompasses research and development endeavors aimed at leveraging NLP techniques, tools, and resources to enhance the requirements engineering (RE) process, as highlighted by [23] [24].

*2.4.1. Challenges of Natural Language Processing*

Many NLP challenges are faced as some words are pronounced the same way but have different meanings which is a problem for NLP systems, leading to confusion in understanding user requirements. Furthermore, informal phrases and expressions and culture-specific language challenge NLP models. Spelling mistakes and innate biases in data sets or programming can quickly affect the accuracy of NLP systems. Words with multiple meanings or phrases with multiple intents also challenge NLP systems [25] [26] [27].

## 3. Literature Review

[4] focused on improving the way requirements are gathered for information system (IS) development projects, especially in the context of digital transformation affecting both business and private sectors. Recognizing the challenge of involving users who are novices in contributing requirements, the authors propose developing systems that assist a broad range of users in articulating their needs and requirements.

The core of the research is the development of a prototype system named "LadderBot" a conversational agent (CA) designed to facilitate the self-elicitation of requirements from users. LadderBot leverages the laddering technique, traditionally used in interviews by human experts, to help users identify and articulate their needs and requirements.

[3] presented a comprehensive literature review on the integration of machine learning (ML) and natural language processing (NLP) techniques in the process of requirements elicitation, aiming to automate and streamline the handling of requirements. The review seeks to answer five critical questions related to (1) the support ML provides to requirements elicitation activities, (2) the data sources for building ML-based solutions, (3) the technologies and algorithms used, (4) the construction of ML-based elicitation methods, and (5) the tools available to support such methodologies. The review's findings are organized into several key areas: ML-based requirement elicitation tasks, data sources that are used for building data-driven models for requirement elicitation, techniques for constructing ML-based elicitation methods that are divided into five stages (data cleansing and preprocessing, textual feature extraction, learning, evaluation). Finally, tools that are available to support ML-based requirements elicitation methodologies emphasize the practical aspects of implementing these approaches.

[28] focused on improving the process of eliciting requirements from users and stakeholders for the development of information systems. Based on this theoretical framework, the authors develop a model of the

requirements elicitation process. Utilizing this model and its theoretical underpinnings, they then introduce a new technique for prompting users to articulate their requirements. To evaluate the effectiveness of this new technique, it is compared with two other established questioning methodologies: the interrogatories technique (which uses questions like “who,” “what,” “when,” “where,” “how,” and “why”) and a semantic questioning scheme (which asks questions based on a theoretical model of knowledge structures).

The comparison involves operationalizing these methodologies as techniques for prompting users to express their requirements. The study employs a set of generic requirements categories derived from prior research to capture the requirements users articulate. An experiment is conducted with users to test the effectiveness of the three prompting techniques in eliciting requirements for a software application. The results of the experiment indicate that the new prompting technique is more effective in eliciting a greater quantity of requirements from users compared to the other two techniques.

[5] provided a detailed comparison of elicitation techniques, along with their characteristics as well as situational characteristics. Comparative analysis will help analysts choose the right requirements elicitation technique based on different situational characteristics. Finally, they presented a model that will be useful in automating the process of selecting a requirements elicitation technique.

[6] proposed a three-pronged approach for the selection of elicitation techniques. Firstly, a thorough literature review is conducted to identify the attributes that influence technique selection along with commonly employed elicitation techniques. Secondly, a multiple regression model is constructed to scrutinize these attributes and discern the crucial factors influencing technique selection. Lastly, an Artificial Neural Network (ANN) based model is proposed to select appropriate elicitation techniques tailored to specific projects. This ANN model aids in minimizing human intervention in the selection process. Its implementation was carried out using the Neural Network Fitting Tool within MATLAB, yielding a commendable accuracy rate of 81%. The empirical validation of the ANN model was performed through a case study conducted in a software company.

[29] presented a deep learning model for selecting appropriate requirements for elicitation. An experiment was conducted in which a combined dataset of 1684 technique selection attributes was examined concerning 14 elicitation techniques. The results showed the model’s high predictive ability. The model provides a robust decision-making process to deliver correct elicitation techniques and reduce the risk of project failure.

[7] examined the current state-of-the-art methodologies for data-driven requirements elicitation from dynamic data sources and pinpointed areas for further research. The findings indicate that current automated requirements elicitation predominantly relies on human-generated data, particularly online reviews, as sources for requirements and supervised machine learning for data processing. However, the outcomes of automated requirements elicitation often entail mere identification and classification of requirements-related information or the identification of features rather than eliciting requirements in a readily applicable format. Consequently, this article underscores the necessity for the development of methodologies to harness process-mediated and machine-generated data for requirements elicitation while addressing challenges related to the variety, velocity, and volume of Big Data for enhancing the efficiency and effectiveness of software development and evolution.

Requirements elicitation techniques cannot find all the software requirements, so the system analyst must use a variety of techniques that will help cover all the requirements, which leads to more effective elicitation. Each technology has its advantages that make it different from all other technologies and that make it suitable for a specific situation. The important thing is to use the most appropriate technique. Before using any technology, the system analyst must have comprehensive knowledge of this technology [9].

[30] presents an innovative requirements prioritization approach termed Case-Based Ranking (CBRank), which leverages both stakeholder preferences and machine learning-generated approximations for requirements ordering. CBRank offers significant advantages: Firstly, it streamlines the input of preference information from stakeholders, thereby reducing human effort without compromising the accuracy of final ranking estimates. Secondly, it effectively utilizes domain knowledge represented as partial order relations among requirement attributes, facilitating an adaptive elicitation process.

The underlying techniques of CBRank and its prioritization process are thoroughly elucidated. To validate its efficacy, empirical assessments are conducted using simulated data, comparing CBRank with a contemporary prioritization method. Results demonstrate CBRank’s proficiency in managing the balance between elicitation effort and ranking precision, as well as its adeptness in leveraging domain knowledge. A practical case study on a real-world software project further reinforces these findings.

[8] the proposed approach that employs machine-learning techniques is needed to streamline the process. This approach enables the identification of how each quality requirements (QR) characteristic is distributed throughout the document, both in terms of volume and manner. This paper developed a tool called QR Miner to facilitate this process and conducted case studies using thirteen real-world SRS documents. The findings from these cases are reported herein.

## 4. Research Methodology

In light of the dominance of artificial intelligence in aspects of life, this research aims to survey previous literature to find out the opportunities yielded by using big data, the Internet of Things, machine learning, and natural language processing to illuminate how these technologies contribute to elevating the standards of quality and precision concerning clients' requirements. Simultaneously, the research endeavours to elucidate the paramount challenges inherent in the adoption of these advanced technologies.

## 5. Contribution to Knowledge

Much literature has been reviewed on the implementation of AI tools in customer requirements elicitation. However, most of them presented a specific type of artificial intelligence tools and their uses in eliciting requirements in developing information systems, and these studies were referred to under the titles of these tools. When comparing the current research, which aims to conduct a comprehensive survey of artificial intelligence tools and their uses in extracting customer requirements, with research similar to this goal, it was found that the current research differed in presenting many artificial intelligence tools and knowing their opportunities and challenges in using them in obtaining the client's requirements.

To compare the goal of similar articles with the current research, it can be understood that [28] they developed an intelligent and robust decision-making model for selecting appropriate requirements elicitation techniques. The model uses deep learning technology to automate this selection process, thus reducing human intervention errors and improving practices and success rates of software and information systems (IS) projects.

Moreover, [1] compared the techniques in terms of the software tools used in requirements elicitation and the types of software developed using these techniques. The advantages and disadvantages mentioned in the literature are also highlighted in this paper. Relevant papers were systematically selected and data were extracted into Excel files for analysis. On the other hand, [7] review current state-of-the-art approaches to eliciting data-driven requirements from dynamic data sources and identify research gaps. This article highlights the need to develop methods to leverage process-mediated and machine-generated data in order to elicit requirements and address issues related to the variety, velocity, and volume of big data for efficient and effective software development and development. [5] provided a detailed comparison of elicitation techniques, along with their characteristics as well as situational characteristics. Comparative analysis will help analysts choose the right requirements elicitation technique based on different situational characteristics. [9] provide an in-depth review of different requirements elicitation techniques, and they also present the pros and cons of different.

On the other hand, the current research provided many AI tools (ML, IoT, Big Data, NLP) and listed the pros and cons of each of them in client requirements elicitation. The opportunities and challenges of using AI tools in the elicitation of user requirements have been summarized, and some recommendations have been listed at the end of this research.

## 6. Analysis & Discussion

**Table 1. Summarized table of pros and cons of artificial intelligent applications and tools in requirements elicitation**

| | |
|---|---|
| | **Machine Learning (ML)** |
| **Pros** | 1. ML algorithms can automatically analyze large amounts of data, including user comments, interactions, and historical usage patterns, enabling valuable insights to be extracted from diverse sources such as user behavior, preferences, and system usage.<br>2. ML algorithms can predict future user behaviors and requirements by analyzing historical data, allowing system designers to do so anticipate and address user needs proactively.<br>3. ML models can continuously learn and adapt to evolving user preferences and system dynamics, facilitating ongoing refinement and optimization of system requirements over time. |
| **Cons** | 1. ML models rely heavily on the quality and representation of the data used for training and require regular maintenance and updates to remain effective as user preferences and system dynamics change over time.<br>2. Biases in training data or incomplete/inaccurate user feedback can lead to biased or unreliable system requirements.<br>3. ML algorithms may require access to sensitive user data to create accurate recommendations or requirements, so there are concerns about privacy and data protection may arise. Training and deploying machine learning models can be resource-intensive in terms of computational power, storage, and expertise. |
| | **Internet of Things (IoT)** |
| **Pros** | 1. IoT devices can collect data in real-time, providing accurate and up-to-date information about user behavior, preferences, and needs with minimal human error, enhancing the accuracy of user requirements analysis compared to traditional methods.<br>2. By analyzing historical IoT data, predictive analytics algorithms can anticipate future user needs and behaviors, enabling proactive adjustments to system requirements. |
| **Cons** | 1. Collecting data from IoT devices raises privacy and security concerns and leads to information overload, making it difficult to extract relevant insights and identify meaningful user requirements |

| | |
|---|---|
| | amidst the noise.<br>2. Integrating various IoT devices and platforms into system analysis processes can be complex and time-consuming, and they are vulnerable to technical problems, malfunctions, and maintenance requirements.<br>3. Unreliable devices or network connectivity issues can disrupt data collection efforts, affecting the accuracy and reliability of requirements analysis. Implementing IoT infrastructure to gather requirements is also expensive. |
| **Big Data** | |
| **Pros** | 1. Access to a huge amount of diverse and detailed data sources brings richness and allows a more comprehensive understanding of user behaviors, preferences, and needs leading to more accurate requirements elicitation and analysis.<br>2. Providing real-time insights into user behaviors and market trends, enabling system analysts to quickly adapt their requirements to changing conditions, leading to innovative solutions and better alignment with user needs. |
| **Cons** | 1. Involves handling huge amounts of data from a variety of sources, resulting in challenges with data accuracy, completeness, and consistency, which can lead to incorrect requirements.<br>2. This raises privacy concerns. Implementing big data analytics infrastructure is complex and expensive and requires specialized skills, tools, and techniques. |
| **Natural Language Processing (NLP)** | |
| **Pros** | 1. Natural language is the most common form of communication for humans. Utilizing it for requirement elicitation ensures accessibility to a wider audience, including non-technical stakeholders.<br>2. Allows users to express their needs, preferences, and constraints in a nuanced and contextual manner, providing rich detail that can inform the development process effectively.<br>3. By directly engaging users in discussions using natural language, development teams can gain deeper insights into user needs and preferences, leading to the creation of more user-centric solutions. |
| **Cons** | 1. Words pronounced the same but have different meanings can be problematic for NLP systems, leading to confusion in understanding user requirements.<br>2. Informal phrases, idioms, and culture-specific lingo pose challenges for NLP models.<br>3. Misspellings and innate biases in data sets or programming can affect the accuracy of NLP systems.<br>4. Effective utilization of natural language for requirement elicitation requires expertise in both domain-specific knowledge and natural language processing techniques. Moreover, the availability of suitable tools for analyzing and processing natural language data may be limited. |

**Table 2. Summarized table of opportunities and challenges of applying AI tools in elicitation of user requirements.**

| Opportunities | Challenges |
|---|---|
| Accurate and transparent requirements. | Higy investment in infrastructure and ongoing maintenance costs. |
| Innovative requirement specifications. | Demand for highly skilled data analysts. |
| Robust and scalable system architecture. | Data privacy and confidentiality concerns |

## 6. Conclusion

The current research highlights the advantages and challenges associated with utilizing advanced technologies like big data, machine learning, the Internet of Things (IoT), and Natural Language Processing (NLP) in understanding customer requirements and behaviors. The most important advantage that gathering from studies is the seamless data flow. These technologies enable analyzing seamless data flow providing precise insights into client requirements, behaviors, and preferences. Moreover, these technologies uncover intricate patterns within data, offering innovative and precise insights that were not easily attainable with traditional methods.

On the other hand, some challenges can be spotted, such as the costly infrastructure, acquiring proficient experts in these fields is challenging, and there are critical privacy concerns due to the massive amount of data collected, requiring robust safeguards to protect sensitive information.

Previously, user requirements were gathered through collaborative efforts using methods like interviews, questionnaires, workshops, and user experience...etc. However, with the digital transformation, reliance solely on traditional methods became inadequate due to diverse clints bases and business proliferation.

Drawing from insights gleaned from prior research, it is evident that leveraging artificial intelligence techniques, including big data, the Internet of Things, NLP, and machine learning. As a result, in today’s landscape, AI applications are essential for deciphering vast amounts of data and acquiring comprehensive customer requirements. Integration of IoT and machine learning is crucial for continuous requirement acquisition and system relevance. Leveraging AI techniques presents immense promise in uncovering customer needs but comes with significant challenges like infrastructure costs, skilled personnel requirements, and data privacy concerns. Businesses face the dual challenge of financing and maintaining the technology infrastructure while ensuring privacy and interpreting vast data outputs effectively.

## Recommendations

Based on the findings from prior research exploring the utilization of big data, IoT, and machine learning in eliciting user requirements, as outlined in Table No. 1 and Table No. 2, the following recommendations can be drawn:

1. For small to medium-sized information system development projects, traditional and collaborative approaches, such as interviews, workshops, and user experience, are typically sufficient for understanding client requirements effectively.
2. In the case of larger information system development projects, the nature of the organization's activities becomes a crucial factor. Suppose the organization's operations are expensive, with a significant dependency on diverse clients and internet-based activities. In that case, the integration of artificial intelligence tools becomes viable if project budgets are carefully considered.
3. In large-scale information systems development project, settings, employing artificial intelligence techniques to extract customer requirements emerges as a compelling option. This approach facilitates the development of highly effective systems that cater to diverse needs, offering intelligent requirements that exceed customer expectations. This not only ensures the sustainability of the system but also enhances its competitiveness in the digital era.

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