An Industrial Case Study of Human and AI-generated System Requirements

by

Mozhdeh Rahmanpour

(Under the Direction of Beshoy Morkos)

Abstract

Defining system requirements in engineering design has always been challenging and complex. This research explores the potential for Large Language Models to support and enhance requirements development. A mixed-methods approach is employed to explore this potential, combining quantitative surveys and qualitative interviews with industry professionals who manage requirements. The original data set consisted of human-created system requirements, which were compared to AI-generated requirements that were assessed for completeness using four criteria: specificity, functionality, target values, and verifiable. The interviews provided valuable insights into current workflows and the common challenges faced in requirement definition, and also the potential benefits and limitations of AI solutions. The results indicated that AI-generated requirements can help make the process more manageable and act as a collaborative partner for human engineers. Although AI may miss some important details, there is still significant potential for its improvement to create models capable of accurately defining requirements.

Index words: [Design Requirements, Artificial intelligence, Natural Language Processing, GPT]

An Industrial Case Study of Human and AI-generated System Requirements

by

Mozhdeh Rahmanpour

B.S., Arak University of Technology, 2019

A Thesis Submitted to the Graduate Faculty of the

University of Georgia in Partial Fulfillment of the Requirements for the

Degree.

Master of Science

Athens, Georgia

2024

An Industrial Case Study of Human and AI-generated System Requirements

by

Mozhdeh Rahmanpour

Major Professor: Beshoy Morkos

Committee: R. Benjamin Davis
Ramana Pidaparti

Electronic Version Approved:

Ron Walcott
Dean of the Graduate School
The University of Georgia
December 2024

Dedication

"The roots of education are bitter, but the fruit is sweet."

— Aristotle

To my dear parents, whose unwavering support and encouragement allowed me to pursue my dreams and study abroad. Your belief in me has been my greatest strength.

And to my wonderful sister, whose constant support and love have inspired and comforted me throughout this journey.

Acknowledgments

First and foremost, I would like to express my deepest gratitude to Dr. Beshoy Morkos for providing me with this incredible opportunity. His support, wisdom, and guidance have been invaluable to my ongoing professional growth. I would also like to thank Dr. R. Benjamin Davis, and Professor Ramana Pidaparti for their consistent and constructive critiques, which have helped keep me on the right path. Additionally, I appreciate my lab mates, and my friend Dr. Farzan Shenavarmasouleh for their insightful contributions.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Requirement engineering and generating requirements for designing a mechanical system have recently attracted attention [1]. In engineering design, requirements are crucial for determining the project's intent or purpose, and requirement definition and elicitation are essential stages. These stages are among the most difficult steps in designing a system. A designer's workflow to create requirements significantly impacts the project's success and the associated costs [2], [3]. The reason for many system design failures is that the requirements are not managed effectively [3]. Requirements define stakeholders' needs, including users, customers, suppliers, developers, and manufacturers. The requirement elicitation purposes formulate statements that identify the design's essential attributes, characteristics, capabilities, or functions [4]. Requirements are the primary steps that need to be taken because the other design phases depend on requirements. For example, requirements are essential for generating ideas, evaluating, and selecting concepts [2]. Generally, design is a complex and dynamic process, and system requirements are not fixed; they change over time and throughout the process [5]. Designing a system can increase efficiency by understanding and analyzing the requirement documents and generating requirements correctly [6]. What is the requirement for a system? A requirement of a system is a specific need or expectation that the system must meet to satisfy its users or stakeholders. Requirements can be expressed in various forms, such as functional, non-functional, performance, and usability requirements. Functional requirements describe the specific features and functions that the system must perform to meet the needs of its users. The requirement needs to be clear and complete to ensure that the system will work correctly and that everyone is working toward the same goals and objectives.

In addition to the key role of requirements in designing a system, extracting and documenting requirements are another side that must be considered of the challenges that exist during this process. In most cases, humans define and develop the requirements, which is overwhelming and intensive work. So, what if AI can help us?

As technology advances, AI is integrated into many areas, including requirements engineering [7]. The focus of using Artificial Intelligence (AI) in design is to make systems smarter by learning how to help systems represent and manage a real-world understanding [8]. AI can explore a considerable amount of data and identify trends and patterns that can help to develop a system. For example, one of the ways that AI can play a role is Natural Language Processing (NLP).NLP is a well-known method in artificial intelligence and computational linguistics [9]. NLP techniques can be used to analyze text data such as customer feedback, requirements documents, and user manuals to identify common themes and requirements that need to be addressed by the system.

Regarding the importance of designing a requirement, there is a question of whether AI can help with designing requirements in addition to humans. The features of a good designer, such as creativity, speed, accuracy, and adaptability, should be addressed by any AI tool that wants to be considered an AI designer, also AI can be defined as the capability of a machine to imitate human intelligence, using algorithms inspired by human behavior to solve problems [10].

The purpose of this study is to find out the human and AI interaction in a high-level view of the design process. More specifically, the research's objective is to explore the integration of artificial intelligence (AI) in defining requirements for engineering design. Findings suggest that the current practice of defining requirements is primarily a human-intensive activity, relying on the expertise and experience of individuals. The goal is to enhance this process by leveraging AI to generate requirements autonomously. The approach involves developing an AI system to create initial requirements based on available data and knowledge. By incorporating AI in the requirement definition phase, the goal is to improve the efficiency and effectiveness of the design process while ensuring that the resulting requirements adequately address the desired outcomes. The research also wants to identify any potential gaps or missing elements in the generated requirements, thereby facilitating further refinement and improvement of the AI-powered requirement generation approach. This ultimately yields the following research questions:

RQ1: How may AI assist humans in defining system requirements?

RQ2: How complete were the requirements generated by AI?

RQ3: Can experts recognize the difference between AI-generated and human-generated content?

Figure 1.1 displays a logic model of this research and indicates where each research question is addressed in the overall process. This study can be divided into several different phases, the first phase of this research involved exploring the existing literature and methodology to understand how AI, in particular natural language processing (NLP) could improve the requirement engineering process, by examining various approaches to the goal is to see how AI can alleviate the tradition human methods of defining requirements and making the process more efficient. Following that, the research moved on to creating a model that can generate requirements regarding the problem description that is used as input. After that the AI model was trained and validated using this processed data, ensuring that the model could reliably generate requirements that meet the needs of stakeholders. After developing AI-generated requirements, it is necessary to focus on evaluating AI-generated requirements to see the completeness and the potential of the AI in generating requirements that is done in this study through some surveys and interviews. This research phase helped to understand how effective an AI system could be in replicating human-like decision-making and where is lacking. These assessments furnished valuable findings on the role of AI in requirements generation, demonstrating what strengths and limitations this area of AI has. The study was concluded by assessing expert perceptions of AI integration in the requirements engineering process, adding to the general understanding of how AI might improve the efficiency and effectiveness of engineering design.

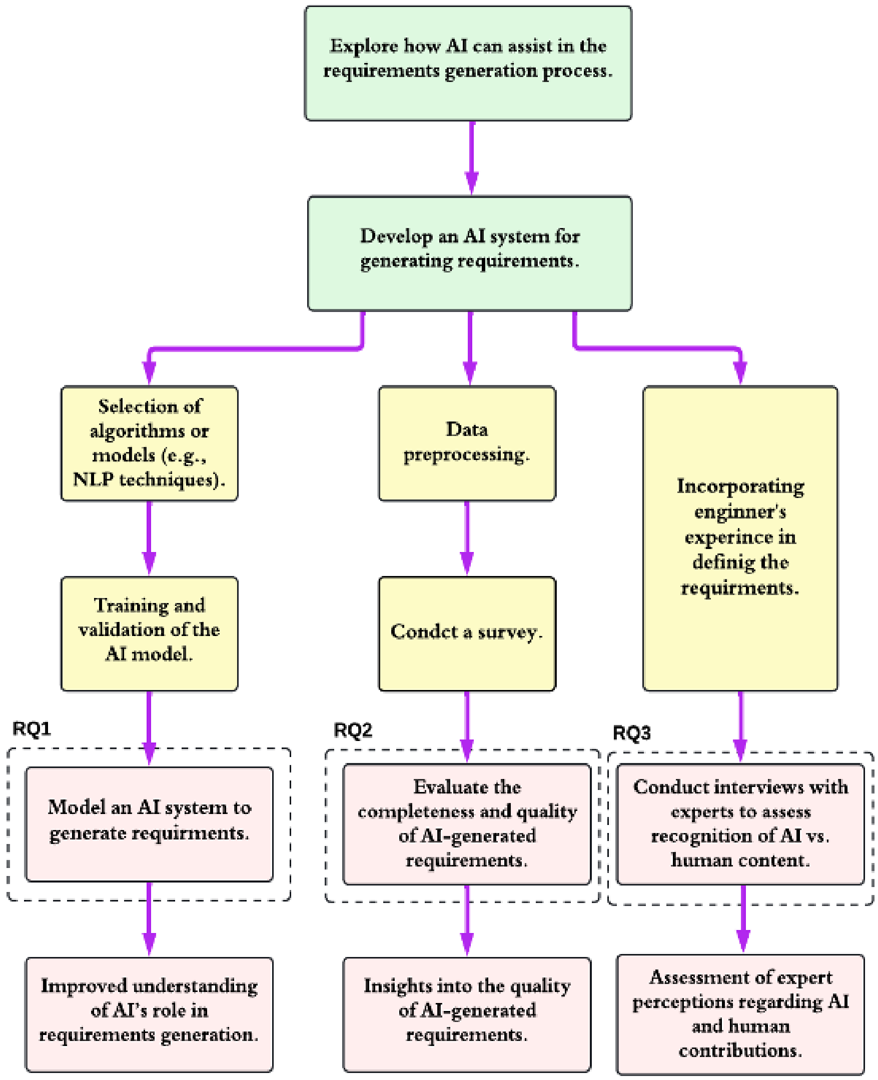


Figure 1.1: Logic Map of the Research

To wrap up the objective of this research is to explore how AI can be integrated into the process of defining requirements for engineering design. Traditionally, this task is carried out by humans, relying heavily on their expertise. This study improves the process by using AI to autonomously generate initial requirements based on available data. By doing so, the goal is to make the design process more efficient and effective. Additionally, this research will examine any gaps or missing elements in the AI-generated requirements, helping to further refine the approach.

Chapter 2

Literature Review

This thesis explores the intersection of human expertise and artificial intelligence (AI) in the process of defining requirements for engineering design. As requirements are significant in the design process, the proper elicitation and development of requirements lead to the project's success [11]. On the other hand, because of the advanced growth of technology, particularly artificial intelligence, expectations exist regarding how AI can be beneficial. AI technologies have a lot of ability to make many parts of requirements engineering effective, such as gathering requirements, analyzing requirements, making sure they are correct, and managing requirements. Machine learning algorithms, natural language processing techniques [7].

This section includes a summary of the literature review of relevant works to explore the history of requirements in engineering design; section 2.1 covers how engineering requirements have evolved from traditional, document-driven to new methods and the vital role of defining the requirements for designing a system. Section 2.2 covers different approaches for extracting and classifying the requirements. Section 2.3 This section examines the integration of AI technologies into the requirements engineering process, focusing on how AI can assist in generating. The last section, 2.4, discusses the potential and limitations of Generative AI in making requirements engineering.

2.1 Requirements in Engineering Design

The process of defining requirements is crucial in engineering design, as the process ensures that products meet functional, performance, and user needs. This section begins by discussing the design of an engineering system, followed by the role of requirements in engineering design, and concludes with an exploration of the potential of AI in this process.

2.1.1 Engineering System Design

People have always designed things. One of the most basic characteristics of humans is their ability to create tools and other objects to fulfill specific needs. [12]. Designing has a long history among people, particularly engineers. The primary responsibility of engineers is to utilize their scientific and engineering expertise to solve technical problems and refine solutions to meet the requirements and constraints [13]. The engineering design process often requires changes to a product's design during development. These changes may be made to enhance the product or to fix design issues [11]. One of the important steps is to have a defined design procedure that finds good solutions. This procedure must be flexible and, at the same time, capable of planning, optimizing, and verifying [13]. Many of the process activities depend on the status of requirements [14]. Fulfillment requirements have a strong connection with a clear and optimized process. Due to the design's dynamic and iterative nature, the continuous evolution of requirements is also possible [15]. Therefore, gathering requirements is an important part of the design process because requirements tell us what functions a system needs to do and what features the system should have [16]. Complex engineering design includes multiple types of data, and a successful project needs to follow a process to make sure that the system can be developed in an optimized way [17]. One well-ordered model is named SE-V. Systems Engineering (SE) is a top-down approach that involves understanding needs, exploring solutions, and refining the solution while addressing the whole problem [18]. This model indicates that a complex systems engineering process involves five levels of decomposition (concept development, system-level design, subsystem design, detailed design, and component development), specification, and integration testing [17].

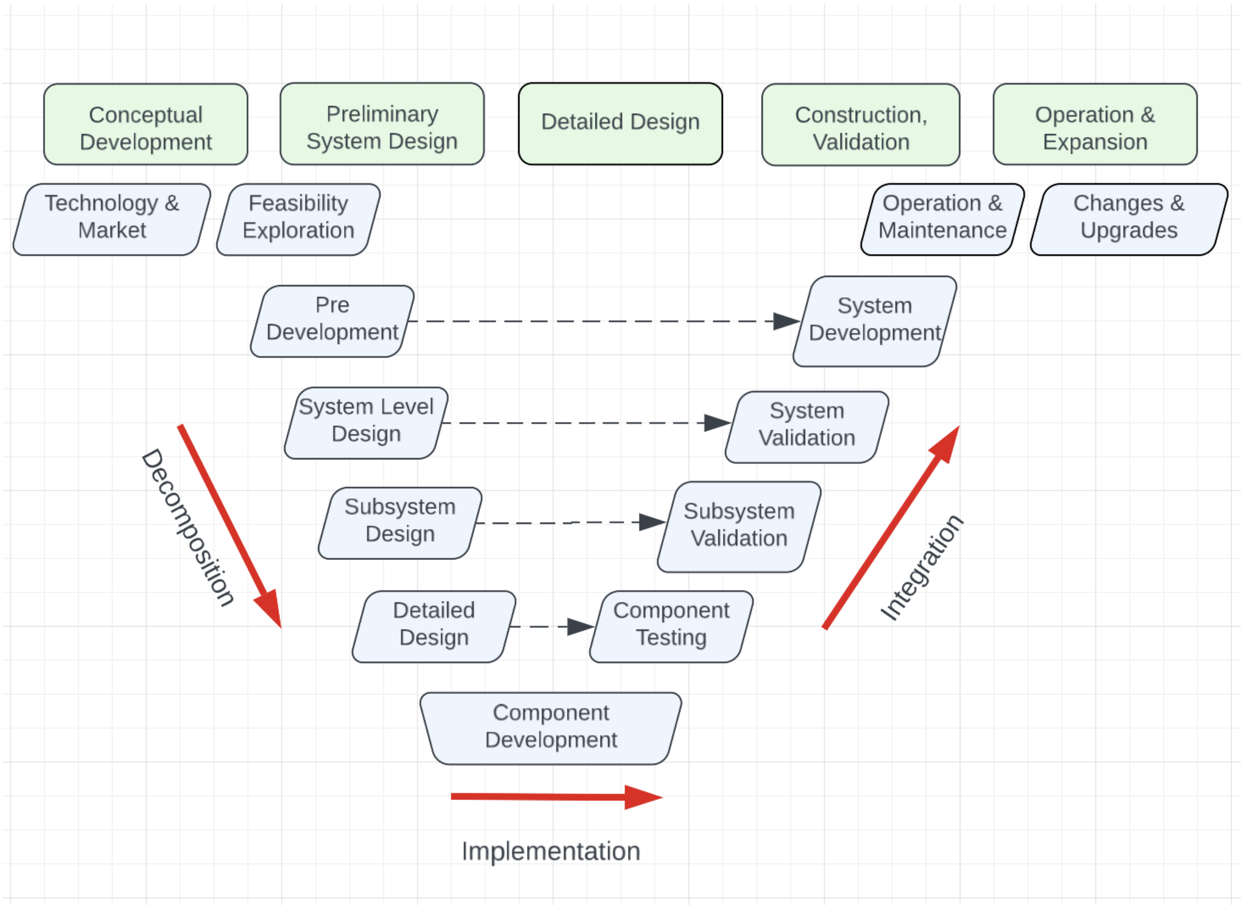


Figure 2.1: Top-down system Engineering Process

Requirements help engineering designers understand and meet stakeholder needs through specifications that detail functional and nonfunctional features [19]. These are typically documented in requirement statements and organized hierarchically to clarify design goals and relationships. The hierarchical lists often include details such as origin, responsible party, justification, verification methods, and any changes made [20]. Requirements are defined as the purpose, goals, constraints, and criteria associated with a design project. These requirements may range from the initial functional requirements to the detailed specifications [5]. Requirements documents for complex systems may include thousands of individual requirements formulated through interdisciplinary collaboration and expressed in natural language by various stakeholders [21]. A complete requirement should address the user's needs or achieve an object, which could be a condition or capability to satisfy a standard or specification also, there should be documentation to represent specification [22]. Specifying high-quality requirements is challenging but manageable. Learn key characteristics of good requirements to spot and fix defects conveniently. Understanding these principles helps improve requirements and reduce errors [23]. Some of the trait's requirements must be specific, traceable, realistic, measurable, stable, and consistent with other requirements and others [24]. A product's quality is defined by the requirements met. Requirements also serve as a benchmark to assess both existing solutions and new concepts [25]. Requirements are one of the original documents of any design project, which is generated in early stages and developed through time [26]. Requirements are an important part of the design process because they are the first thing the client and artist discuss. They are introduced early on after the job is made clear, and they guide the design and are always updated. When more detailed requirements are met, meaning that the design is moving forward and getting close to finished [13], [26].Figure 2.2 illustrates this flow:

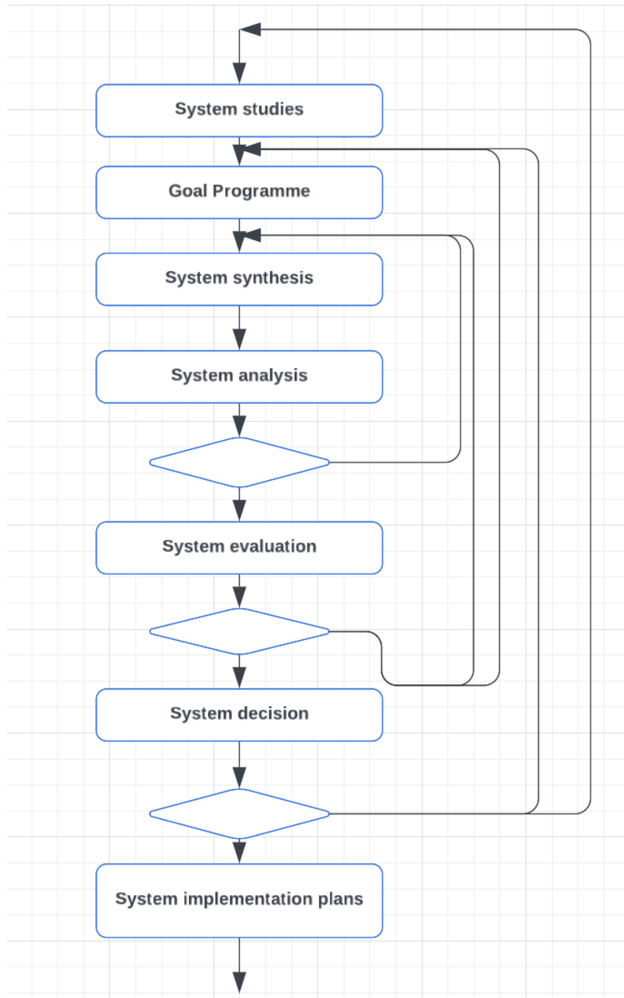


Figure 2.2: Iterative Systems Theory Model for Design

The NASA Systems Engineering Handbook provides a guideline for generating requirements and describes the appropriate usage of common terminology found in requirements, such as "shall," "should," or "will") [27]. The NASA Systems Engineering Handbook includes a checklist of recommendations for writing a good requirement. The checklist suggests that designers use "shall" for explicit requirements, "should" for goals, and "will" for facts or declarations of purpose. Following are some more of the handbook's recommendations:

- Requirements should be stated positively(e.g., use"shall"instead of"shall not")with correct grammar and spelling.
- Requirements should convey one thought with a single subject and predicate.
- Indefinite pronouns, ambiguous words, and unverifiable terms should be avoided.

Consistent terminology should be used throughout the document [28], [29].

Example product requirements specified by NASA are detailed in Table 2.1.

Table 2.1: Example of properly formatted requirements

General Requirements Structure
The system shall operate at a power level of ...
The software shall acquire data from the ...
The structure shall withstand loads of ...
The hardware shall have a mass of ...

2.1.2 Requirements Engineering

Requirements engineering (RE) is a systematic process that includes repeatedly working and analyzing the problem to find a verifying and accurate solution [22]. The term "requirements engineering" (RE) is widely used in the software engineering (SE) field to indicate the organized management of requirements, which express the needs and constraints that contribute to the solution of some real-world problem [30]. In recent years, requirements engineering (RE), a sub-field of software engineering (SE), has garnered significant attention for its applications in AI. RE involves activities focused on identifying and communicating the purpose of a software-intensive system and understanding the contexts in which RE will be used [31]–[33].

RE focuses on identifying the goals for the intended system, translating these goals into specific services and constraints, and assigning responsibilities for these requirements to agents such as humans, devices, and software [34]. As systems engineering developed, the need for RE became obvious, but new methods were required to address emerging technologies [30].

Requirements engineering (RE) is concerned with the elicitation, analysis, specification, validation, and management of requirements. RE is also well known for contributing to the improvement of software development quality, as well as decreasing the risks of budget overruns, delays, and project failures [35]. However, the lack of effort and resources in RE leads to significant challenges in later stages of development, such as inconsistent, incomplete, and incorrect requirements, which become increasingly difficult to resolve [36]. As AI for Requirements Engineering (AI4RE) grows, AI-powered solutions help RE activities by saving time, reducing complexity, and minimizing human effort. This also benefits other development processes of testing, product quality, and project planning [37].

Human-AI (HAI) interaction design is an area of study focused on understanding design principles that enable humans to interact with intelligent tools and agents [38]. The goals of AI research involve knowledge representation, reasoning, automated planning, learning, natural language processing, perception, robotics, and general intelligence [10].

AI is increasingly enhancing requirements engineering by improving activities such as elicitation, analysis, validation, and management, ensuring software systems meet user expectations and quality standards. Additionally, natural language processing techniques facilitate the extraction of requirements from various sources [7]. Researchers are studying the implementation of Artificial Intelligence (AI) assistance within various engineering design stages, including concept space exploration and generation, [39], [40]. concept evaluation [41], prototyping [42], manufacturing [43], and process management of teams [44].Further, research involving 1500 companies found that human-AI collaboration resulted in considerable performance improvements [45], [46]. AI will become embedded within the future workforce. To handle this technological and organizational shift, fundamental research is needed to address key challenges related to how humans and AI can most effectively interact [47].

The integration of AI and optimization fields will significantly enhance the capabilities of computational design tools because design problems involve both symbolic and numeric elements [48]. AI is transforming design by helping engineers quickly explore new ideas and optimize solutions. It improves efficiency, precision, and adaptability in mechanical systems, driving innovation across many fields [49]. The Artificial Intelligence-based smart system is broadly utilized in the mechanical engineering design sector [8].

2.2 Software Management in Requirement Engineering

Software requirements engineering (SRE) is the process of identifying and documenting the features a software system needs to meet user expectations. This involves defining functionalities that enable the system to perform its intended tasks and translating user requirements into a software requirements specification document (SRSD). Requirements engineering also aligns the software system with the organization's goals, ensuring that the system helps achieve desired outcomes [50].

In the context of software development achieving success in any project, software requirements management is crucial. This involves capturing and documenting what the software should do, also ensuring that all stakeholders have a clear understanding and agreement on these requirements. Proper management prevents misunderstandings and ensures that the final product meets the intended goals and user needs.

Furthermore, software requirements include details about user needs or contract specifications that are formally imposed. The reuse of software requirements is studied and explained benefits in two ways: (i) reducing the time needed for requirements analysis, and (ii) identifying reusable code and test artifacts with similar requirements, leading to early reuse in the development cycle [51], [52].

Software development is a technological task and a complex social process that heavily depends on effective communication among all stakeholders. The success of a project closely relies on how well these communications are managed. Effective software requirements management must be a collaborative effort due to the complex communication involved. This communication's effectiveness depends on the similarity between the environments of the sender and receiver and the ongoing dialogue between stakeholders from diverse disciplines with varying expertise, interests, and objectives [53]–[55].

Generally, five key factors for project success are: (1) user involvement, (2) executive management support, (3) clear requirements, (4) proper planning, and (5) realistic expectations. The third factor directly relates to requirements, while the others involve gathering stakeholder input. Conversely, the top five indicators of project challenges are (1) lack of user input, (2) incomplete requirements, (3) changing requirements, (4) lack of executive support, and (5) technical incompetence. Two of these are linked to requirements [56].

The goal of software systems Requirements Engineering (RE) is to identify stakeholders and their needs, document requirements, and ensure successful implementation. Customers are often seen as the most important stakeholders because they fund the system [57], [58].

Requirements management encompasses tasks such as organizing and documenting requirements, tracking and controlling their evolution, and their visualization and presentation [59]. Thus, effective requirements management is key to avoiding product failure, as poor management is often a major reason why products fail. The most important part of managing requirements is ensuring everyone communicates well.

Requirements management tools help with this by allowing organizations to define, document, and store requirements in one place. Tools similar to Rational Suite Analyst Studio, RDT 3.0, RTM Workshop 5.0, and Telelogic DOORS are designed to improve communication and keep everyone on the same page throughout the project [60].

Requirements management (RM) is a part of requirements engineering (RE) that focuses on managing changes, keeping track of requirements, controlling versions, and monitoring their status. RM tools support the management of the requirements database and any changes made to the requirements [61].

Requirements management tools are essential for tracking changes and organizing requirements. Most of these tools are designed for single projects, but efficient product development requires reusing components and artifacts to keep costs low for new projects [62].

Managing software requirements requires regular communication among stakeholders with different backgrounds, expertise, interests, and goals. This complexity calls for various techniques to define requirements clearly. Research demonstrates that collaboration between developers and users can enhance knowledge sharing, uncover hidden requirements, clarify expectations, help find errors early, and improve planning and decision-making [54], [55].

The goal of the requirements management activities is to elicit and specify the requirements. Missing or incorrect requirements can have negative effects on the success of the product, which is widely recognized [63].

As software evolves, requirements can change due to new information, technological updates, or shifting user needs. To keep the software useful and effective, it's important to manage these changes in an organized way throughout its life.

Software changes for various reasons, such as fixing faults, adding new features, or restructuring for future updates [64]. Changing requirements is a major reason for these changes, as requirements can shift from the start of the project until they become obsolete [65]. To address software failures caused by poor requirements, related disciplines have grown, and AI techniques in the requirements phase are making a significant impact on improving software development [66].

One of the important challenges that software products face today is generating perfect requirements. As software products are changing and evolving, there is always a need to create new requirements [33].

One application of requirements engineering could be developing and maintaining software in an organized way to provide high efficacy [67].

Software requirements are a common area among users, customers, and stakeholders that must be shaped at the beginning stage of the project. In earlier decades, software requirements were collected manually using formal or informal methods, which had disadvantages such as extensive workload, time management, and cost estimation. Currently, technology helps in this process. Some software requirement tools mentioned in the study include MARAMA AI, ARM, TIGER Pr, C&L, etc. [68].

Software requirement specifications elaborate on the functional and non-functional requirements, design artifacts, business processes, and other aspects of a software system. Complete and accepted software requirement specifications provide a shared understanding and agreement of what a software system should do and why [69].

Requirements Management tools have evolved significantly over time [1]. Today's software can automate many parts of gathering and analyzing requirements, making the process faster and more accurate. They also help people work together effectively by offering easy ways to communicate and keep track of information.

Ultimately, during the development process, the requirements themselves evolve and undergo several modifications. This reflects why researchers address the software process as a dynamic socio-technical system, involving the coordination of interdisciplinary approaches and skill sets, such as defining user needs and developing solutions for the needs. Thus, requirement management plays a critical role at the intersection of sustaining the clarity of the process and communicating efficiently between participants involved in measuring success [70], [71].

To wrap up, effective software requirements engineering is crucial for successful software development. software requirements engineering involves capturing, documenting, and managing requirements while ensuring clear communication among all stakeholders. Advances in tools and AI have improved how we handle these tasks, making tasks less complex to manage changes and meet project goals. By using these tools and fostering collaboration, organizations can enhance the quality and success of their software projects.

2.3 Application of AI in Requirements

Requirement elicitation is a crucial process in product development. Various traditional techniques, including interviews, meetings, and brainstorming sessions, are employed to gather accurate and specific requirements [72]. The process involves "a set of activities that must allow for communication, prioritization, negotiation, and collaboration with all the relevant stakeholders"[73].

While traditional requirement elicitation techniques are important, they can be time-consuming, error-prone, and potentially confusing. In contrast, AI excels in handling substantial datasets, automating tasks, and facilitating processes, making data especially valuable for large-scale, repetitive, or data-intensive projects [74].

AI is increasingly enhancing requirements engineering by improving activities such as elicitation, analysis, validation, and management, ensuring software systems meet user expectations and quality standards. Additionally, natural language processing techniques facilitate the extraction of requirements from various sources [7].

The integration of AI and optimization fields will significantly enhance the capabilities of computational design tools because design problems involve both symbolic and numeric elements [48]. AI transforms design by helping engineers quickly explore new ideas and optimize solutions. AI improves mechanical systems' efficiency, precision, and adaptability, driving innovation across many fields[49].

Researchers are studying the implementation of Artificial Intelligence (AI) assistance within various engineering design stages, including concept space exploration and generation [39], [40], concept evaluation [41], prototyping [42], manufacturing [43], and process management of teams [44]. Further, research involving 1500 companies found that human-AI collaboration resulted in considerable performance improvements [27], [45]. AI will become embedded within the future workforce. To handle this technological and organizational shift, fundamental research is needed to address key challenges related to how humans and AI can most effectively interact [47].

AI-based techniques are now widely integrated into software systems, helping companies enhance performance and cut costs [73]. Typically, various elicitation techniques are employed, chosen based on time and cost limitations, the nature and accessibility of information sources, the company culture, and the desired outcomes [75]. However, applying traditional requirements engineering practices to complex or unpredictable systems has brought about new challenges [76].

The Artificial Intelligence-based smart system is broadly utilized in the mechanical engineering design sector [8]. Implementing AI offers significant benefits, such as providing a comprehensive guide for engineers and researchers in automated validation, management, and prioritization [77]. Studies highlight AI's potential in requirement elicitation, by identifying three steps: filtering data, classifying text by stakeholder groups, and categorizing technical issues [78].

Other research explores a variety of AI techniques, including automated data processing and scalability, that enhance the elicitation process [74]. Another approach uses machine learning to simplify elicitation and boolean metrics for less challenging evaluation, reducing bias from dominance hierarchies, a strategy from the Analytic Hierarchy Process (AHP) to address scalability issues [79].

One key aspect is AI's role in requirement prioritization. Traditional techniques are often human-intensive and face issues such as overlapping outcomes, scalability problems, and inaccuracy. AI can address these challenges by employing algorithms such as Genetic Algorithms, Fuzzy Logic, Ant Colony Optimization, and Machine Learning, which improve the efficiency and accuracy of prioritizing requirements [9].

The other aspect that could be considered is requirement Analysis which is a key aspect of requirements engineering (RE). A systematic review of 61 studies explored automated techniques in RE, with 25 using machine learning, 21 adopting deep learning, and 9 utilizing transfer learning. Six studies proposed ensemble models combining multiple techniques. The review highlights recent AI advancements in RE, emphasizing the potential for AI to enhance decision support and intelligent systems in RE and software engineering [80].

Requirements elicitation is favored over "capture" to avoid the notion that requirements can be collected with less effort. The choice of elicitation techniques depends on time, resources, and the type of information needed, ranging from traditional methods such as interviews to group techniques, prototyping, model-driven approaches, cognitive methods, and contextual techniques [32].

Requirements elicitation is a collaborative process between the analyst and stakeholder, crucial for gathering project information. Despite its importance, the process is prone to errors, with vague and ambiguous requirements often causing misunderstandings among developers. This challenge is heightened by the need for precise requirements in modern software development, where evolving products frequently introduce new demands. Numerous studies aim to prevent these elicitation errors, ensuring clearer definitions and descriptions for enhanced insight [33], [81], [82].

Despite requirement elicitation, the other concern that needs to be considered is the requirements validation. A requirements validation role is ensuring that software requirements are complete, consistent, and aligned with user needs. While the validation process is important to confirm that the requirements accurately reflect the user's needs, the process can be challenging when performed manually because the process requires significant effort, time, cost, and accuracy, which can lead to errors. Various validation techniques, such as prototyping, animation, and reviews, are employed to verify the correctness of the requirements [67], [83], [84].

There are many studies around this concept. One study mentioned that validation methods could be a simulation, trial, model-centered validation, and expert opinion [85]. Requirements validation is essential in software development as it helps eliminate conflicts among requirements in the software requirements specification. By identifying and resolving errors early, requirements validation prevents late-phase costs [83], [86].

Overall, the integration of AI into requirements represents a trans formative advancement in the field. leveraging AI technologies can lead to improving the accuracy, efficiency, and scalability of requirements elicitation and management. AI's ability to process significant data sets, and automate repetitive tasks, could be helpful in this area.

2.4 Generative AI

Artificial Intelligence (AI) is the theory and development of computer systems that can perform tasks that normally require human intelligence [85]. AI can be defined as creating machines or computers that can think and behave similarly to human beings. Whenever there is a need to make complex judgments, computers can't replace humans. But with the help of artificial intelligence, computers can be trained to think and behave similarly to humans do [87].

The development of large language tools, such as Chat GPT and other chatbots, has indicated the potential of AI in understanding text and creating natural language responses [88]. This capability is powered by neural networks and machine learning, which focus on generating new content based on learning from previous data and identifying patterns. One of the most important of these is large language models (LLMs). LLMs are neural network models designed to process sequential data. In recent years, AI development has gained attention with tools such as Chat GPT, GitHub Copilot, and DALL-E, which are generative AI techniques capable of generating new content [89].

Generative AI's ability to create diverse types of content can be illustrated through its various applications. Generative AI can create various types of content, including text, audio, images, videos, and even 3D models [90].

Generative AI systems can help create new content and also assist humans as smart question-answering systems [78]. In other words, these generative tools can produce sensible-sounding language in various contexts [91].

Regarding engineering design, generative AI is transforming how engineers approach problem-solving. The methods behind generative AI include several innovative techniques. Generative AI can be divided into several methods. One of the methods is generative adversarial networks (GANs), which found initial success with convincing image synthesis performance [92], [93]. Variations Auto-Encoders (VAEs) and Generative Adversarial Networks (GANs) are classical deep generative models that were used for generating images with relative success [94].

In the context of brain network computing, generative AI can be used to reconstruct the topological connectivity of brain networks [92]. Generative AI can enhance creativity and innovation in generative art, musical composition, and aesthetic design, although there are challenges and ethical considerations associated with its implementation [95].

The practical application of generative AI in design is exemplified by generative design systems. A generative design system uses AI to transform a conceptual design into various options. The designer selects a preferred option, and AI then suggests the best materials based on function and cost [96].

Generative AI could be implemented in generative design by using AI algorithms to create novel and unique designs that could go further than what humans can achieve alone. In engineering, there might be a way to generate all possible solutions that meet specific objectives and constraints defined by humans. These methods employ various techniques, such as genetic algorithms, variations autoencoders, generative adversarial networks, and large language models [97].

The impact of generative AI applications extends to routine tasks and more advanced creative processes. The latest generative AI applications can handle routine tasks such as data organization, but their headline-grabbing ability to write text, compose music, and create digital art has encouraged consumers to try these applications out [98]. Generative AI can facilitate the automation of monotonous and time-consuming tasks in various domains, including healthcare [90], [99].

The other aspect of generative AI can be seen in industries, where the fast pace of growing artificial intelligence (AI) affects industries and societies. The most common example is ChatGPT, which can create human-like text that has advanced significantly due to improvements in natural language processing (NLP) and deep learning [100]. As we move toward Industry 4.0, which focuses on automation, and Industry 5.0, which emphasizes human-AI collaboration, generative AI is becoming increasingly important. ChatGPT improves communication and creativity between humans and machines, helping with tasks such as collaborative design, research, and decision-making [101].

In Industry 5.0, collaboration between humans and AI, such as Chat GPT, is essential. These AI systems are transforming sectors such as manufacturing by acting as virtual assistants to workers and optimizing supply chains with real-time updates. As Industry 5.0 and Society 5.0 develop, AI models such as Chat GPT are expected to bring significant innovations, enhancing human abilities and driving progress in many areas [100], [102], [103].

One other ability of Chat GPT is making communication in different parts of the system, which can be helpful in the supply chain. chat GPT can handle tasks such as processing orders, tracking shipments, and giving real-time updates. In Industry 5.0, AI can act as a virtual assistant, helping workers by providing quick answers, troubleshooting, and real-time training, which boosts their skills and productivity [22], [104].

AI has brought challenges and opportunities in many areas, such as technology (information processing), business (decision-making and automation), education (personalized learning), healthcare (AI diagnosis), and the arts (human-centered design) [90], [105].

Generative AI tools such as Bard, Chat GPT, and others can create advertising content, digital marketing strategies, chatbots, blog posts, and sales training. Before AI, innovations such as the Meta-verse were popular for promotion [90], [106].

In manufacturing, generative AI can be used to explore and implement optimal solutions, generating new outputs based on functional specifications and costs. In retailing, the Internet has enabled companies to conduct their retail operations online through e-commerce [90].

Generative AI tools are becoming more common, but they bring unique design challenges. As people use these technologies more, there's a need for guidance on creating user-friendly experiences that ensure safe and effective use. While advancements in machine learning, such as GANs [107], [108], VAEs [109], and transformers [110], have helped spread AI adoption, most efforts have focused on improving the technology itself [111].

However, less attention is paid to the human side of AI interaction. Users now need to learn new skills, for instance, crafting precise prompts, to get the best results from generative AI [111].

Users can interact with generative AI models through various interfaces, with prompting a key skill. These tools have applications in fields such as education, healthcare, and business. However, it's important to recognize AI's limitations and challenges, including bias, transparency, hallucination, misuse, and societal impact [112].

Effective interaction with generative AI requires skillful prompting. Prompt engineering is essential for generative AI, helping to create accurate and meaningful results. It's important in areas such as entrepreneurship, art, science, and healthcare, and newer GPT models present how prompts improve understanding of user needs [113].

Chat GPT exemplifies this trend with its advanced conversational capabilities, resulting in more context-aware and detailed user interactions. Similarly, DALL-E 3's ability to produce images from text descriptions blend linguistic comprehension with visual creation [114], [115].

Generative AI could be helpful to teach machines to recognize patterns in vast datasets, allowing machines to create new content. This can be used in art, entertainment, design, and scientific research, producing realistic images, music, video game characters, and aiding drug discovery. Generative AI is essential for content creation, data enhancement, simulation, penalization, design assistance, and scientific exploration, helping to bridge gaps and explore new possibilities in various fields [116].

Generative Adversarial Networks (GANs) had many challenges during their early development, especially with training problems such as divergence and model collapse. Training divergence happens when the GAN's generator and discriminator don't balance properly, causing unstable outputs. Despite these issues, GANs have become a key technique in generative AI[117].

Transformers, introduced by Vaswani et al., revolutionized generative AI by enabling tasks, for example, machine translation and language generation [109]. They are the basis for models such as GPT, which generates coherent text, and BER, used for understanding and processing language [110]. Other generative AI models, such as Variations Autoencoders (VAEs) and Diffusion Models, have been developed to enhance AI capabilities, with VAEs focusing on encoding and decoding data, and Diffusion Models improving upon GANs for enhanced performance [117]–[119].

AI, especially generative AI and large language models such as Chat GPT, excels in repetitive and data-driven tasks. AI is strong in language comprehension and can engage in human-like conversations. However, humans contribute creativity, empathy, and common sense [120], [121]. Human-AI collaboration works well because AI and humans complement each other's strengths and weaknesses, making the collaboration possible to tackle tasks more effectively together [120], [122], [123].

Despite its advancements, generative AI faces some challenges. Although generative AI is popular worldwide, it still has issues, for instance, lower accuracy, doubtful quality of generated content, and a lack of transparency in how it works [124], [125].

Seeing generative AI as a data-driven tool rather than a perfect solution helps set realistic expectations and avoids disappointment when results fall short [126].

The benefits that GAI can offer to companies are uncountable, for instance, cost reduction and enhanced workforce productivity through task automation because generative AI models rely on large language models, reducing the need for manual intervention [127].

These models are usually trained on extensive datasets that include web content, books, social media, and encyclopedias, though the training process and data size can vary by chatbot. OpenAI's Chat GPT uses deep learning and language models in the GPT architecture, greatly improving chatbot abilities [128].

We have observed instances where transformer-based large language models have been used in requirements to perform topic modeling [6], [129], functional studies [20], and joint embedding [130]. However, many studies are still required to determine the role of LLMs in requirements and how they can be used to support requirements elicitation, reasoning, and management.

In summary, Artificial Intelligence (AI), especially generative AI, is revolutionizing how machines perform tasks traditionally requiring human intelligence. Generative AI, powered by technologies such as large language models (LLMs), generative adversarial networks (GANs), and transformers, can create diverse content, including text, images, and music. This is widely used in fields of engineering, manufacturing, healthcare, and entertainment to enhance creativity, automate tasks, and improve decision-making. Despite its capabilities, generative AI faces challenges such as bias, transparency, and quality issues, but AI continues to drive innovation, particularly in collaborative human-AI interactions.

Chapter 3

Methodology

This chapter outlines the methodology used in this research to explore the integration of AI in defining engineering design requirements. Section 3.1 begins with an overview of how requirements were generated for designing a system, setting the foundation for the study. Following this, Section 3.2 details the data collection process, which includes gathering both the original data set and additional data created through AI. This section also covers the insights gained from participant interviews, which provided valuable context and deeper understanding. Section 3.2 then shifts focus to the participants, describing their roles, their selection, and their contributions to the research. Finally, Section 3.3 explains how the data was analyzed using both qualitative and quantitative methods. These methods were carefully chosen to thoroughly examine the data and provide a complete and balanced understanding of the research findings.

3.1 Overview of the requirements

This section provides an overview of the process used to generate the requirements for designing a system. Generating accurate and comprehensive requirements is an important phase in the design process because these requirements define the scope and direction of the project [11], [25]. In this research, requirements were generated through a combination of traditional methods, such as the document that is provided by stakeholders or extracts from books, alongside AI-driven tools that assisted in defining requirements. The process involved gathering initial input from stakeholders, analyzing the inputs to see how the inputs can be refined, and examining if AI has the potential to generate requirements and ensure that they are aligned with the project's objectives.

3.2 Data Sets

3.2.1 Human-Generated Data Set

Engineering documents and specifications provide important details, such as technical specifications, design guidelines, standards, and industry best practices. For this research, several documents and specifications are obtained from a company focused on automotive valves. These documents include a list of 214 requirements and functional specifications that engineers and experts from related industries put together.

The requirements cover various aspects such as technical specifications, dimensions, materials, appearance, and safety factors, all of which are essential for ensuring the equipment meets industry standards. The requirements differ in detail; some provide extensive explanations and specific numerical values, while others are more brief and general.

From the full list of 214 requirements, 30 are selected randomly using Microsoft Excel's random function. This method ensures that the sample is unbiased and fairly represents the human-generated requirements.

The number of 30 requirements is chosen because the AI model used in this study is capable of generating only 30 accurate requirements before the outputs become repetitive. To keep the comparison between human and AI-generated requirements fair, this same number is used. Additionally, working with an immense set of requirements could have made the process more complicated and increased the chances of errors, making the smaller sample size more practical for this study.

3.2.2 AI-Generated Data set

A list of 30 requirements was created by humans using documents provided by the company. To determine if AI can produce similar requirements, GPT-4, an AI model from OpenAI, is employed. This involves using natural language processing (NLP) to generate requirements from a problem description derived from the available company information.

The process begins with developing a detailed problem description based on the company's specifications, project description, and other relevant documents. This problem description includes essential technical details, functional requirements, and objectives related to the product, which in this case are automotive valves. The purpose of this description is to clearly and accurately represent the design challenge, which is crucial for AI to generate meaningful requirements.

Following the development of the problem description, the AI model is trained to produce requirements. During this training, several factors are considered to ensure the model generates high-quality requirements.

The AI is trained to be creative, offering innovative solutions while also maintaining accuracy to align with technical standards. Consistency is emphasized to ensure that the generated requirements reflect the problem description and adhere to the company specifications. Additionally, relevance is important to ensure the requirements are applicable within the context of the automotive valve industry.

Once the model is trained, the problem description is used as input for the AI, which then generates a set of 30 requirements. These AI-generated requirements are designed to be directly comparable to the human-generated ones to allow for a fair comparison between the two sets of data.

To implement this process technically, Python code was developed to automate the interaction between the problem description and the GPT-4 model. This code, included in the appendix, facilitates the smooth input of the problem description and manages the output of the generated requirements, making the process repeatable and verifiable by others.

To generate requirements using AI, several steps are needed:

1. **Set Up the API**: The API is made to take input related to design specifications and return requirements generated by GPT-4. This ensures that the AI stays focused on creating the correct design requirements.

2. **Choose the Right Tools**: A suitable programming language and framework are selected to support the API and work with GPT-4.

3. **Generate Requirements**: GPT-4, using its understanding of language and engineering, creates the initial design requirements. These are based on the problem description, which is made from the company's documents and specifications.

The major steps in generating the AI requirements are: Define the Data Needed: The necessary data is identified, based on the company's documents and specifications.

1. **Prepare the Data**: The data is cleaned and formatted so that GPT-4 can use the data. This involves converting the information into text and organizing the text for the model.

2. **Build the API**: The API is built to allow input and output for GPT-4, so the API can generate the design requirements.

3. **Review the Requirements**: The AI-generated requirements are reviewed and compared to the human-generated ones to ensure they are accurate and meet the necessary criteria.

3.3 Data Collection

Different ways of gathering data are important because how the information is collected affects the methodology and analytical approach applied by the researcher [131], [132].

Some of the data collection methods are as follows:

- **Surveys**: Surveys can gather information from numerous groups of people and are good for collecting demographic data that describes the group being studied. [133] Surveys are great for collecting people's opinions, attitudes, beliefs, or knowledge from a specific group.

- **Interviews**: interviewing is "a valuable method for exploring the construction and negotiation of meanings in a natural setting". That is, the value of interviewing lies in that the interview builds a holistic snapshot, analyzes words, and reports detailed views of informants; the interview also enables interviewees to 'speak in their voice and express their thoughts and feelings [134]Interviews involve one-on-one conversations with people to gather information using a set of prepared questions or topics. These conversations are often recorded and written down. The data from interviews can be used to identify patterns, create theories, or develop models.

Other methods also exist but they are not used in this research such as Focus groups such as observation and Textual or content analysis [135]. In this study, there are two distinct data sets. The first is the original data set, which we call the human-generated data set, created by engineers and industry experts. The second is the AI-generated data set, produced by artificial intelligence based on the input and criteria provided.

3.3.1 Survey

To set up the survey, each participant was given ten requirements: five were human-generated, and the other five were AI-generated. Participants were then asked to rate each requirement from -2 (strongly disagree) to +2 (strongly agree) based on the following four items, which evaluated the completeness of the requirements. The survey was conducted through Qualtrics, a platform approved and provided by UGA. Each participant received a unique set of requirements, different from those given to others.

3.3.2 Interview

Despite new research methods, face-to-face interviews are still popular and are used in 70–90% of social research projects [136]. Interviews can be used in descriptive studies and qualitative studies. They can be unstructured in which the content is controlled by the study participant or structured in which the content is similar to that of a questionnaire, with the possible responses to questions that are carefully designed by the researcher [137].

The objective of this interview was to gather expert opinions on the integration of AI in defining requirements for system design, as well as to explore any practical experiences with implementing AI in requirements engineering. Additionally, the interviews sought to assess the potential future role of AI in improving the generation of design requirements.

The interviews utilized a semi-structured format, focusing on specific topics while allowing flexibility for detailed and in-depth responses. Most of the questions were open-ended to facilitate comprehensive answers. The interviews were conducted using Qualtrics, a user-friendly platform endorsed by the University of Georgia (UGA). In total, five participants were interviewed, all of whom were engineers with experience in design or manufacturing and familiarity with requirements engineering. Each interview included seven questions and lasted approximately 20 minutes. The interviews were conducted virtually via Zoom.

This paragraph outlines the development of the interview questions. The interview process begins by asking participants about their familiarity with AI and whether they use any AI tools in their work. If participants are familiar with such tools, they are asked to explain their experiences. If not, they are asked to provide their predictions on the potential future integration of AI in defining requirements.

For the data management with the consent of all participants, the interviews were recorded and organized systematically. These recordings were then transcribed into text to facilitate analysis, as textual data is required for the data analysis process. All ethical considerations were addressed before the interviews. Participants provided consent to record the sessions and were instructed to avoid mentioning any company or individual names to maintain anonymity. There were no significant limitations or challenges encountered during the interviews beyond participant availability.

The following questions were posed to the participants:

1. Can you provide an overview of your role and responsibilities in the design process with respect to system requirements?
2. Who is involved in the process of generating design system requirements?
3. Could you describe the typical workflow for collecting and documenting design requirements in your organization?
4. What approaches or software do you use to identify and prioritize design requirements?
5. What challenges do engineers often face in requirements management?
6. How do you think AI can help address the challenges related to requirements management?
7. What's your view on AI integration in engineering design and its potential to replicate tasks currently done by engineers?

The responses from the interviews were analyzed using thematic analysis, and the results will be presented in Chapter 5.

3.4 Participants

3.4.1 Interview Participants

The industry has seen major changes and progress in recent years. Industry 4.0 covers many changes that can improve the current industrial system [138]. So The Interview included five engineers who were chosen because of their experience in design and manufacturing and their knowledge of engineering requirements. The invitations and interview instructions were sent via email. Each participant consented to participate in the study, understanding the purpose and agreeing to have their responses recorded.

To protect their privacy, all interviews were anonymous, and recordings were stored securely. The data was only accessible to authorized personnel. Although the study involved a small group of five participants, their expertise provided valuable insights into the use of AI in requirements engineering. The careful selection and management of participants ensured that the information gathered was relevant and useful.

Ethical guidelines were followed carefully to keep participants' information confidential and to ensure the data remained secure throughout the study.

3.4.2 Survey Participant

For this part of the study, two groups of participants were selected. The first group consists of 10 graduate students who work daily with various AI applications, while the second group includes 10 industry engineers who are experts in engineering design. The purpose is to compare how these two groups evaluate AI-generated requirements, with the graduate students providing insights from their experience with AI, and the engineers contributing their expertise in design requirements.

3.5 Data Analysis

The data in this research is analyzed using both qualitative and quantitative methods. These approaches provide different but complementary views, with qualitative analysis focusing on participant insights and quantitative analysis measuring variables. These methods were chosen to fully address the research questions and work with the types of data collected.

Research typically involves three main approaches: quantitative, qualitative, and mixed methods. Quantitative research focuses on testing theories by analyzing numerical data, whereas qualitative research involves collecting interview data, observations, and experiences from subjects in the research inquiry [139].

Both of these approaches have advantages and limitations. The decision of whether to choose either method is dependent on the nature of the project, the type of information needed, the context of the study, the data you want to collect, and the type of available data [140]. For this research, both methods were used to get a complete view of the topic. Because the study involves complex real-world issues, a case study approach was chosen. This method allows for a detailed look at the context and combines different types of data collection, making the method a good fit for this research.

Case study research methodology is effective in examining individual, group, organizational, and social phenomena [141]. It allows for analyzing a topic in its real-life context and using various methods to gather information from one or more individuals, groups, or organizations. Case studies can be conducted with a single case or multiple cases. They can be categorized as exploratory, explanatory, or descriptive based on their approach and implementation [140].

3.5.1 Qualitative

As mentioned above here Qualitative research methods were utilized in this study as they are useful for exploring and understanding any emerging research problem. Qualitative research methods involve observing people in their natural settings and conducting interviews [142]. The other kind of qualitative research rather than interviews could be surveys, focus groups, conversational analysis, observation, and ethnography [143].

The purpose of interviewing industry experts is to provide a detailed look at their views and experiences with AI technology and how it can be used in defining requirements. For the interviews, questions were prepared, and participants were identified according to the standard described in section 3.3. The interviews were scheduled and conducted over 40 days, depending on the participants' availability. Detailed information about the interview structure is provided in section 3.2.3. The data collected from the interviews were transcribed and analyzed using NVivo software, which is effective for managing and visualizing qualitative data.

The analysis involved coding the responses to identify key themes and patterns. The results are presented through various graphs and plots to illustrate these themes. NVivo was used to analyze the interview data because it helps organize and manage qualitative data effectively. The software allows for creating coding relationships, such AS parent-child structures, which made it more straightforward to find key themes in the interview responses. By using NVivo, the data was coded systematically, helping to identify important patterns in participants' views on AI and its role in defining requirements.

3.5.2 Quantitative

Quantitative methods work well with deductive approaches, where a theory or hypothesis helps shape the research variables, goals, and specific questions [143]. In the quantitative research process, data collection is a critical step. The quality of the collected data significantly influences the accuracy and validity of the study's outcomes or findings [137].

The objective of this survey was to collect quantitative ratings to assess how AI-generated requirements compare to human-generated ones in terms of clarity, functionality, target value, and verifiable. The goal was to evaluate the effectiveness and completeness of AI-generated requirements and identify any differences or recognition issues between AI and human-generated requirements. In this study, a survey was administered to two distinct groups of participants: 10 students and 10 industry experts. The survey comprised 10 requirements in total, with 5 of these requirements generated by AI and the remaining 5 created by humans. To ensure unbiased responses, the requirements were presented randomly, so participants could not distinguish between the AI-generated and human-generated requirements.

The sample size for this study consisted of 10 students and 10 industry experts. This choice was made based on the need to gather diverse perspectives while remaining manageable within the study's constraints. To capture both academic and practical insights, the study included an equal number of students and industry experts. Regarding the literature review, these questions are finalized to be asked. Each requirement was evaluated based on four questions:

1. The requirement clearly references a component or system.
2. The requirement of a function.
3. The requirement includes a target value.
4. The requirement is verifiable.

The 5-point scale facilitates to measurement and comparison of opinions on AI-generated and human-generated requirements. By analyzing the ratings, we could see how effective, clear, and complete the requirements were and find any differences between requirements. Each requirement in the survey was evaluated using a 5-point rating scale, designed to capture the participants' opinions on various aspects of the requirements. The scale was as follows:

-2: Strongly Disagree

-1: Disagree

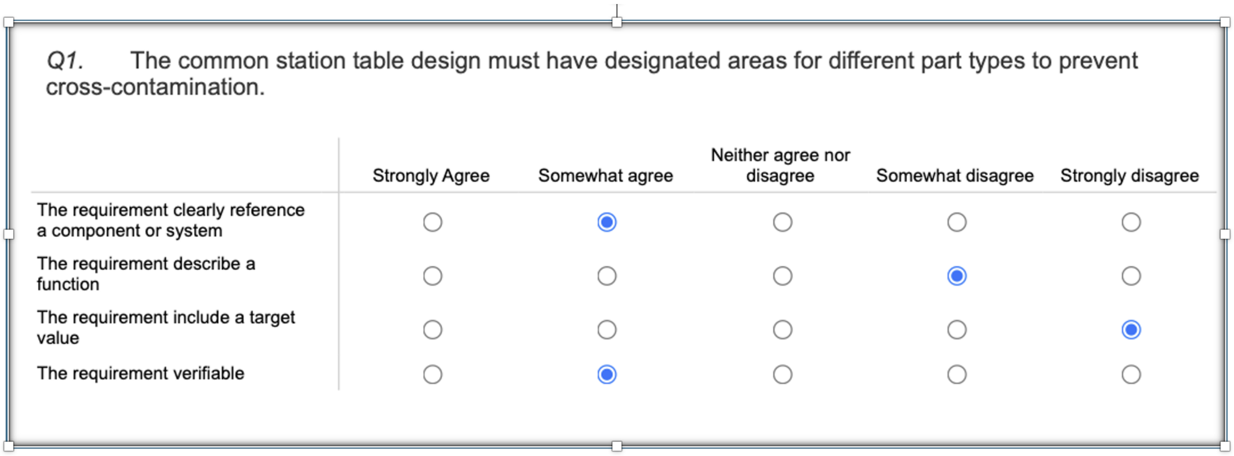
0: Neutral

+1: Agree

+2: Strongly Agree

This scale allowed participants to express their level of agreement or disagreement with each statement regarding the requirements. An example of a requirement used in the survey is provided below.

For the quantitative data, methods such as t-tests and averages were used to compare AI-generated and human-generated requirements. These analyses were done in Excel for easy calculations and data handling. Python was also used to create visualizations, making the data more clear to understand. The Python code, illustrated in the appendix, helped generate graphs and charts to better present the results.



Q1. The common station table design must have designated areas for different part types to prevent cross-contamination.

	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	○	●	○	○	○
The requirement describe a function	○	○	○	●	○
The requirement include a target value	○	○	○	○	●
The requirement verifiable	○	●	○	○	○

Figure 3.1: Example of Survey Format and Question Structure Used in Study

Chapter 4

Results

Chapter Four presents the findings of this research, focusing on both quantitative and qualitative data collected during the study. The results are organized into two sections: survey data from engineers and, followed by insights gathered through interviews with engineers.

This section explains the results of the study discussed in Chapter 3. To gain more data, a mixed methods approach is used where the qualitative and quantitative data are collected. A survey collects quantitative data based on evaluation questions related to requirements—some of which are human-generated, while others are AI-generated. The results of this method are presented in section 4.1. The second method involves gathering qualitative data through interviews, aiming to capture participants' opinions regarding the integration of AI in defining requirements for design systems. The findings from this approach are detailed in section 4.2. These methods help to understand how people view and assess both AI-generated and human-generated requirements. By presenting these results, this chapter directly addresses the research question of whether AI can enhance the process of generating design requirements in engineering.

The quantitative data, gathered from engineers and graduate students, will be presented using descriptive statistics such as averages and percentages. Graphs and tables will be used to provide visual representations of these findings. Statistical comparisons between the responses of different groups will also be highlighted where relevant.

The qualitative data from interviews will be analyzed and presented in the form of key themes and patterns. There are some chats and tables to visualize the relation (similarities or differences) among participants's responses.

4.1 Quantitative Data Result

To evaluate the effectiveness of both human-generated and AI-generated requirements, a study was conducted with student participants. Each participant received ten randomly selected requirements—five created by humans and five by AI without informing them of their origin. For each requirement, they were asked to rate four key items:

Item 1: The requirement clearly references a component or system.

Item 2: The requirement of a function.

Item 3: The requirement includes a target value.

Item 4: The requirement is verifiable.

It is important to note that the evaluation metrics presented here were developed based on an exhaustive search of papers related to requirements evaluation[144].

The data demonstrates the average rating for each question, with scores ranging from -2 to 2. To compare the performance of human-generated and AI-generated requirements, the results were separated: **AI-generated** data is represented in **blue**, and **human-generated** data is represented in **orange**. To simplify the comparison, the mean of all collected data was calculated.

4.1.1 The mean of Data

The mean (average) is a commonly used method in data comparison, as the average provides a central value that summarizes the data. A summary of the student participants is displayed in the table, with detailed comparisons in the bar graphs, which display the average ratings for each question across all ten **graduate student** participants.

	AI-Generated		**Human-Generated**	
	X bar	SD	X bar	SD
Item 1	1.38	0.72694	1.22	0.62147
Item 2	1.06	0.7306	0.92	0.73151
Item 3	-0.08	1.46727	-0.06	1.07103
Item 4	1.06	0.4115	0.80	0.63944

To illustrate the detailed responses to all items, bar charts can be used to present students' responses to each of the items.

I1: The requirement references a component or system.

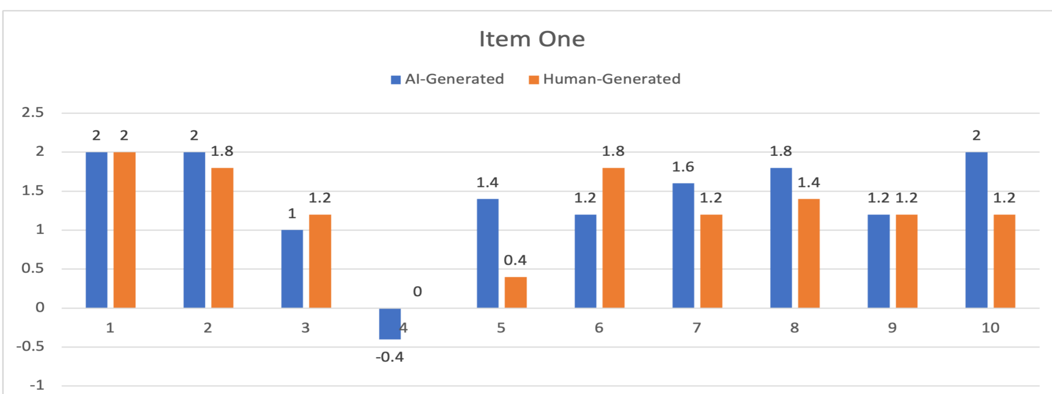


Figure 4.1: The answer of all students to item one

I2: The requirement of a function.

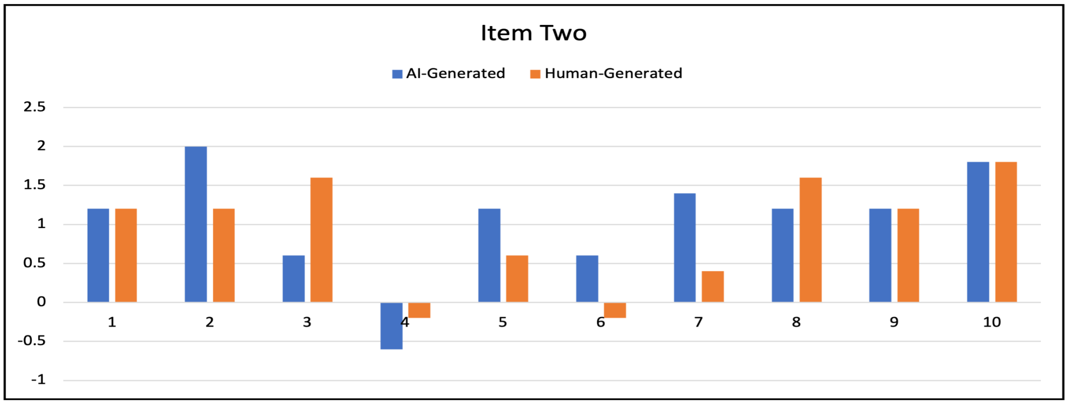


Figure 4.2: The answer of all students to item two

I3: The requirement includes a target value.

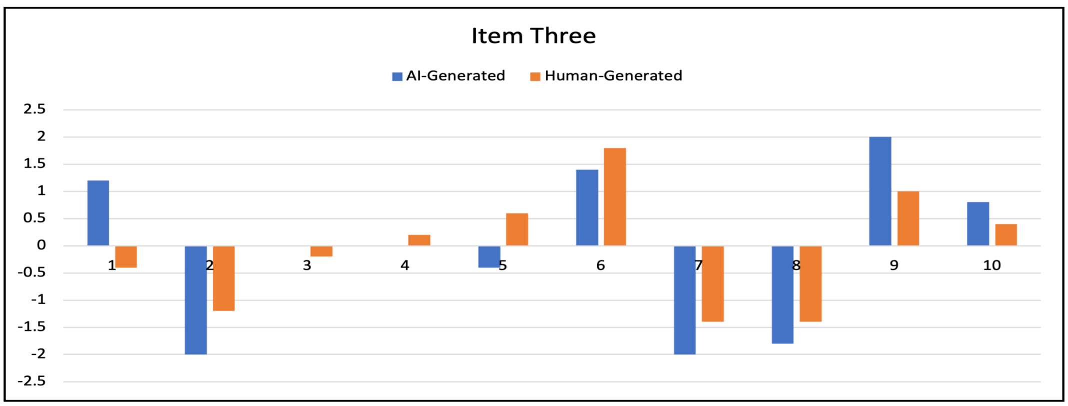


Figure 4.3: The answer of all students to item three

I4: The requirement is verifiable.

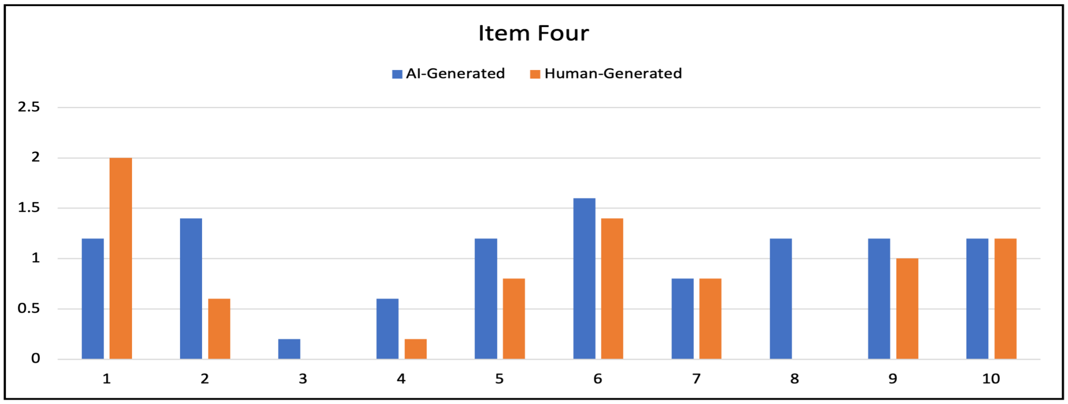


Figure 4.4: The answer of all students to item four

There is the same data collection from industry people (engineers), a summary of the engineer participants is illustrated in the table, with detailed comparisons in the bar graphs, which display the average ratings for each question across all ten **engineer** participants.

	AI-Generated		Human-Generated	
	X bar	SD	X bar	SD
Item 1	1.62	0.56921	1.08	0.50067
Item 2	0.98	0.90652	1.0	0.74833
Item 3	-0.36	1.31925	-0.1	1.00333
Item 4	0.94	0.76623	0.92	0.535

To illustrate the detailed responses to all items, bar charts can be used to demonstrate engineers' responses to each of the items.

I1: The requirement references a component or system.

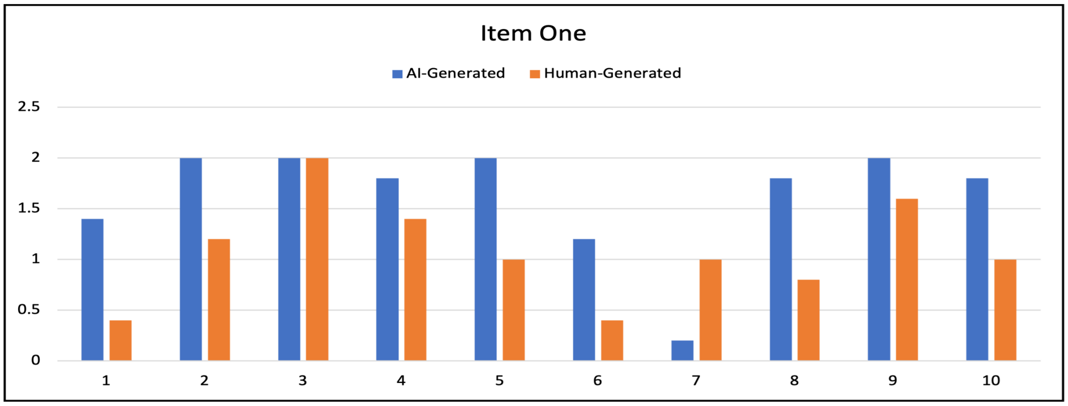


Figure 4.5: The answer of all engineers to item one

I2: The requirement of a function.

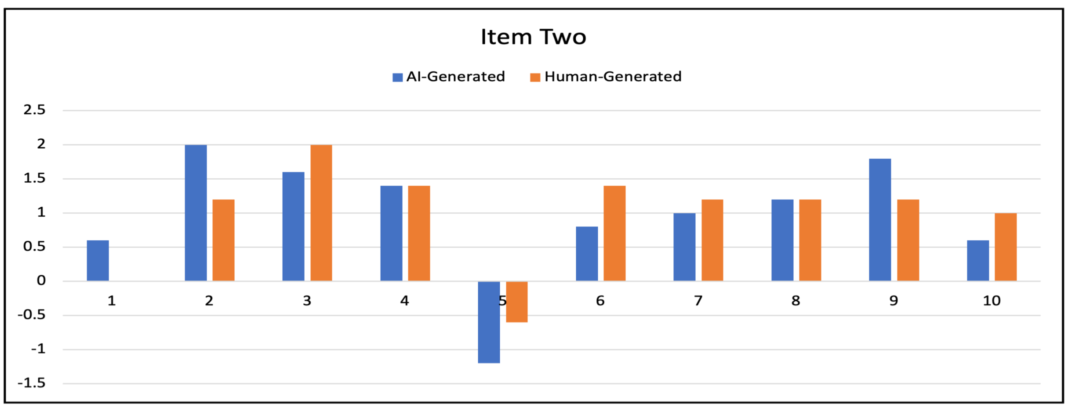


Figure 4.6: The answer of all engineers to item two

I3: The requirement includes a target value.

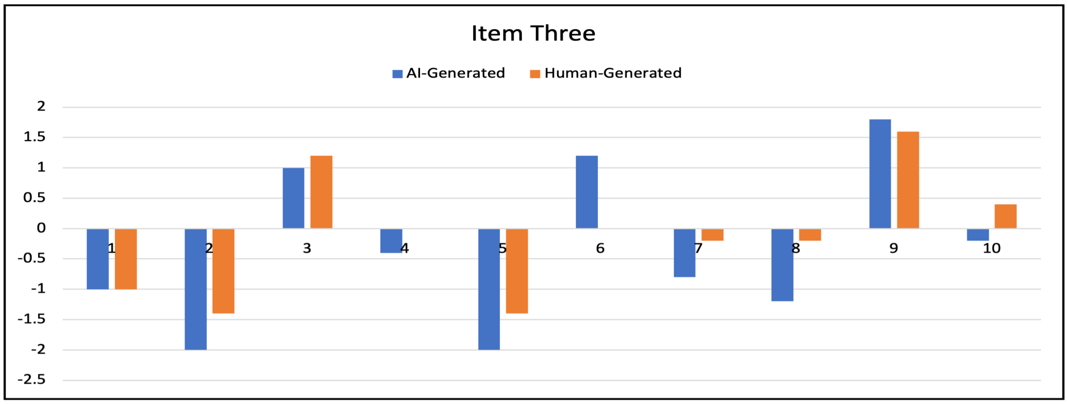


Figure 4.7: The answer of all engineers to item three

I4: The requirement is verifiable.

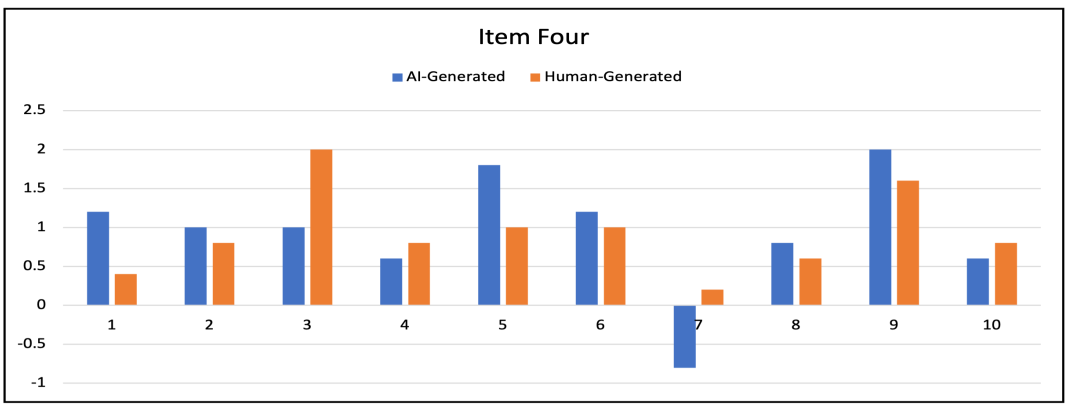


Figure 4.8: The answer of all engineers to item four

4.1.2 t-test comparison

The other method that can be implemented for analyzing data is a t-test. A t-test is a statistical method used to determine if there is a significant difference between the means of two groups. In each case, the t-test helps researchers and analysts conclude whether the differences between groups are statistically significant. Due to the importance of the t-test, for each item, a t-test is done, and here is the result.

Students Analysis:

T-test	I1	I2	I3	I4
P(T=t) two-tail	0.298159	0.513090	0.928056	0.198825

Engineers Analysis:

T-test	I1	I2	I3	I4
P(T=t) two-tail	0.005436	0.922685	0.245012	0.9203381

In the **student's** t-test For all four items (I1 to I4), the p-values are more than 0.05, indicating that there are no statistically significant differences between the paired means of Variable 1 and Variable 2 in each question. This suggests that the changes in the variables are not significant enough to conclude that there is a meaningful difference in the means.

The **engineer's** t-test I1 demonstrates a significant difference between the paired means of Variable 1 and Variable 2, indicating that there is a meaningful difference in the means.

I2, I3, and I4 do not present significant differences between the paired means of Variable 1 and Variable 2, indicating that there are no meaningful differences in the means for these items.

After analyzing the data from graduate students and engineers separately, comparisons can be made using graphs that indicate the average ratings from each group. Another comparison involves analyzing both engineers' and graduate students' data together. Python code, provided in the appendix, was used to visualize this comparison.

The graph illustrates that AI-generated requirements received higher ratings than human-generated ones, except for I3. Both graduate students and engineers gave positive ratings to AI-generated requirements for I1, I2, and I4, with engineers rating I1 particularly high. However, both groups rated I3 poorly for both types of requirements.

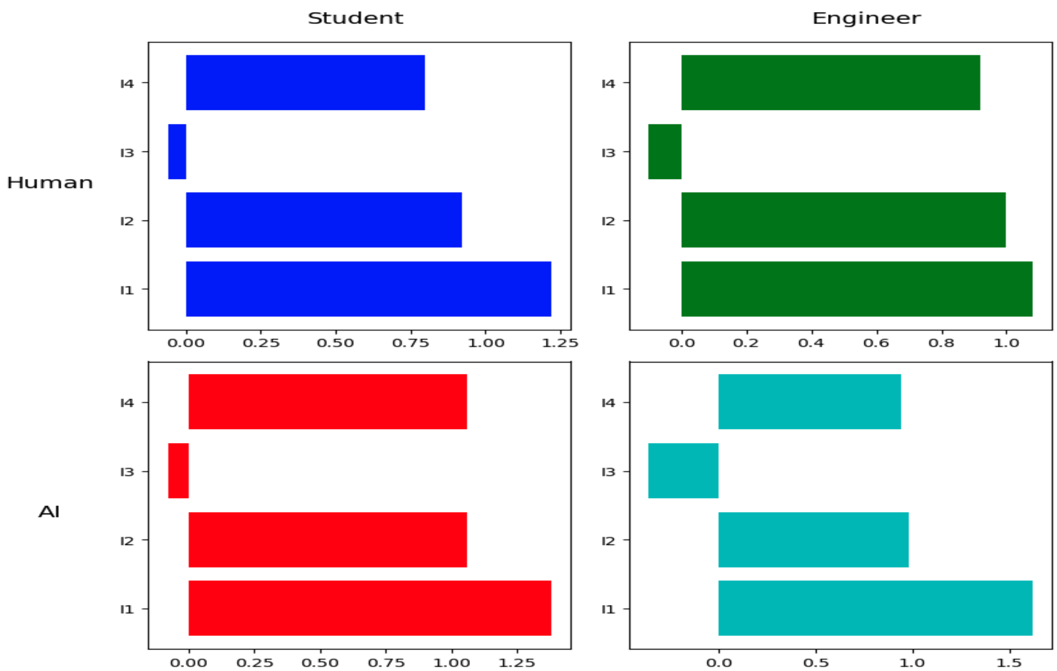


Figure 4.9: Comparison of Ratings: Students Vs. Engineers, Human Vs. AI-Generated Requirements

4.2 Qualitative Data Results

To collect additional data, interviews were conducted with experts with manufacturing and design experience, specifically in defining system requirements. The structure of the interviews is discussed in section

3.2.3 For data gathering, all interview recordings were transcribed into text using Restream, and the qualitative data was analyzed with NVivo. This process involved coding the data, identifying correlations between responses, and developing themes. Five participants, each with different roles, took part in this study, and their responses to various questions are presented here. There is a code book in the appendix that could be used as a reference for the following code.

In this study, with the help of NVivo, codes were generated, and visual mapping was used to illustrate the relationships between participants' responses. As this research employs thematic analysis, some themes have emerged from the interview responses.

To introduce the participants involved in the interviews, the following word frequency illustration represents who took part in the study. As illustrated in the figure, the participants were mechanical engineers working in manufacturing or design fields.

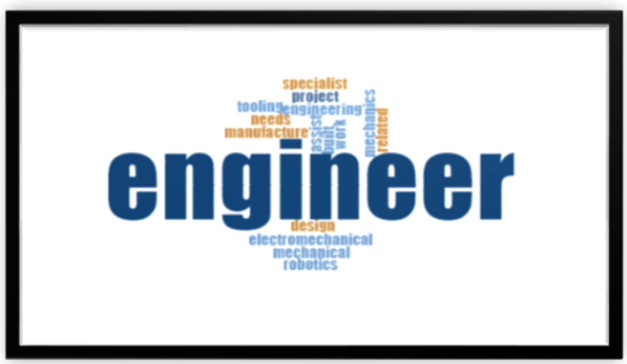


Figure 4.10: Word cloud of participant's roles

All participants are professionals from leading U.S. companies in aerospace, defense technology, automation and motion control solutions, and other multidisciplinary mechanical engineering firms. Their job roles include manufacturing engineer, mechanical engineer, electromechanical engineer, and robotics specialist. On average, they have over 10 years of experience in designing requirements.

1. Workflow

One of the interesting questions asked of the participants was to describe a typical workflow for collecting and documenting design requirements in their organization. The responses varied due to differences in their roles, company policies, and organizational goals. Five distinct workflows were identified as described below.

Workflow-1

Figure 4.11: Process Workflow: Visualizing Key Phases and Flow of Activities

Workflow-2

Figure 4.12: Process Workflow: Visualizing Key Phases and Flow of Activities

Workflow-3

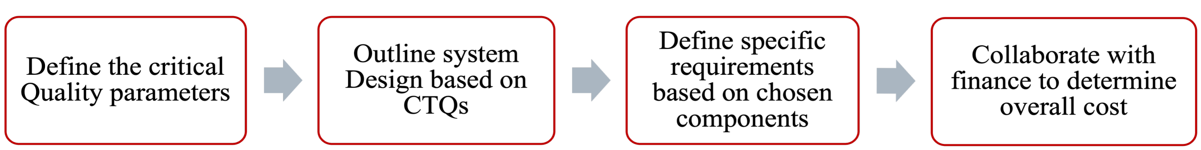


Figure 4.13: Process Workflow: Visualizing Key Phases and Flow of Activities

Workflow-4

Figure 4.14: Process Workflow: Visualizing Key Phases and Flow of Activities

Workflow-5

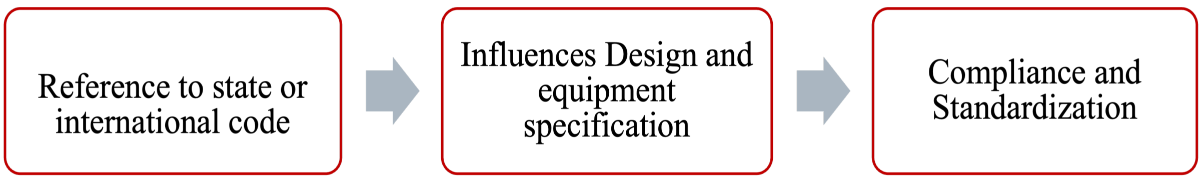


Figure 4.15: Process Workflow: Visualizing Key Phases and Flow of Activities

Theme 1: Structured Process for Requirement Definition

Workflows follow a clear, step-by-step process for defining requirements, including scope definition, technical specifications, and final review. Supporting steps: "Define Scope of Work," "Compile Specifications and Requirements," "Final Review."

Theme 2: Collaborative Involvement

Many workflows involve various departments, such as technical experts, marketing, finance, and quality engineers, indicating the need for teamwork. Supporting steps: "Assign Technical Experts," "Collaborate with Finance," "Report to Quality Engineers."

Theme 3: requirements based on regulations

Some workflows focus on meeting regulatory standards or industry codes, which affects the development of specifications. Supporting steps: "Reference to State or International Code," "Influences Design and Equipment Specifications."

Theme 4: Adaptation Based on Company Goals

Workflows vary depending on company policies and goals. Supporting steps: "Marketing Defines CTQ Parameters," "Reference to State or International Code.

Summary: By defining these themes, you'll provide a structured, thematic analysis of the workflows. Each theme will help you explain the underlying patterns in how requirements are defined, and how roles, company goals, and regulatory standards influence the process.

2. Challenges and solutions

Another question asked participants about their experiences with challenges in defining requirements and how they dealt with the challenges. They were also asked whether they thought AI could help address these challenges and what potential solutions AI might offer to assist engineers in the requirements definition process.

AI Challenges

Theme 1: Challenges in Requirement Gathering and Management

Handling multiple requirements and maintaining accurate information can be overwhelming. Supporting challenges: "Covering all requirements" "a significant amount of information" "Different configurations"

Theme 2: Accuracy and Completeness of Requirements

Getting detailed, accurate requirements is challenging, especially as they change over time. Supporting challenges: "Wrong requirements" "Not detailed enough" "Requirements changed over time"

Theme 3: Early Definition and Scoping Issues

Defining requirements early and ensuring proper scoping can be difficult. Supporting challenges: "Initial scoping" "Defining requirements early"

Theme 4: Collaboration and Communication

Clear communication and collaboration are needed to ensure requirements are understood and accurate. Supporting challenges: "Collaborating to clarify requirements"

Theme 5: Safety

Ensuring safety is integrated into requirements and design processes. Supporting challenge: "Safety"

AI Solutions

Theme 1: AI for Management and Standardization

AI helps manage extensive data sets, ensures requirements align with standards, and standardizes language. Supporting solutions: "Ensure the database includes system standards, and AI consistently references the database." "Standardize language in requirement generation." "Scan and filter guidelines."

Theme 2: AI for Enhancing Requirement Accuracy

AI improves accuracy by identifying key elements, and root causes, and evaluating tool effectiveness. Supporting solutions. "Identify root causes. "Evaluate tool effectiveness. "Identify key elements.

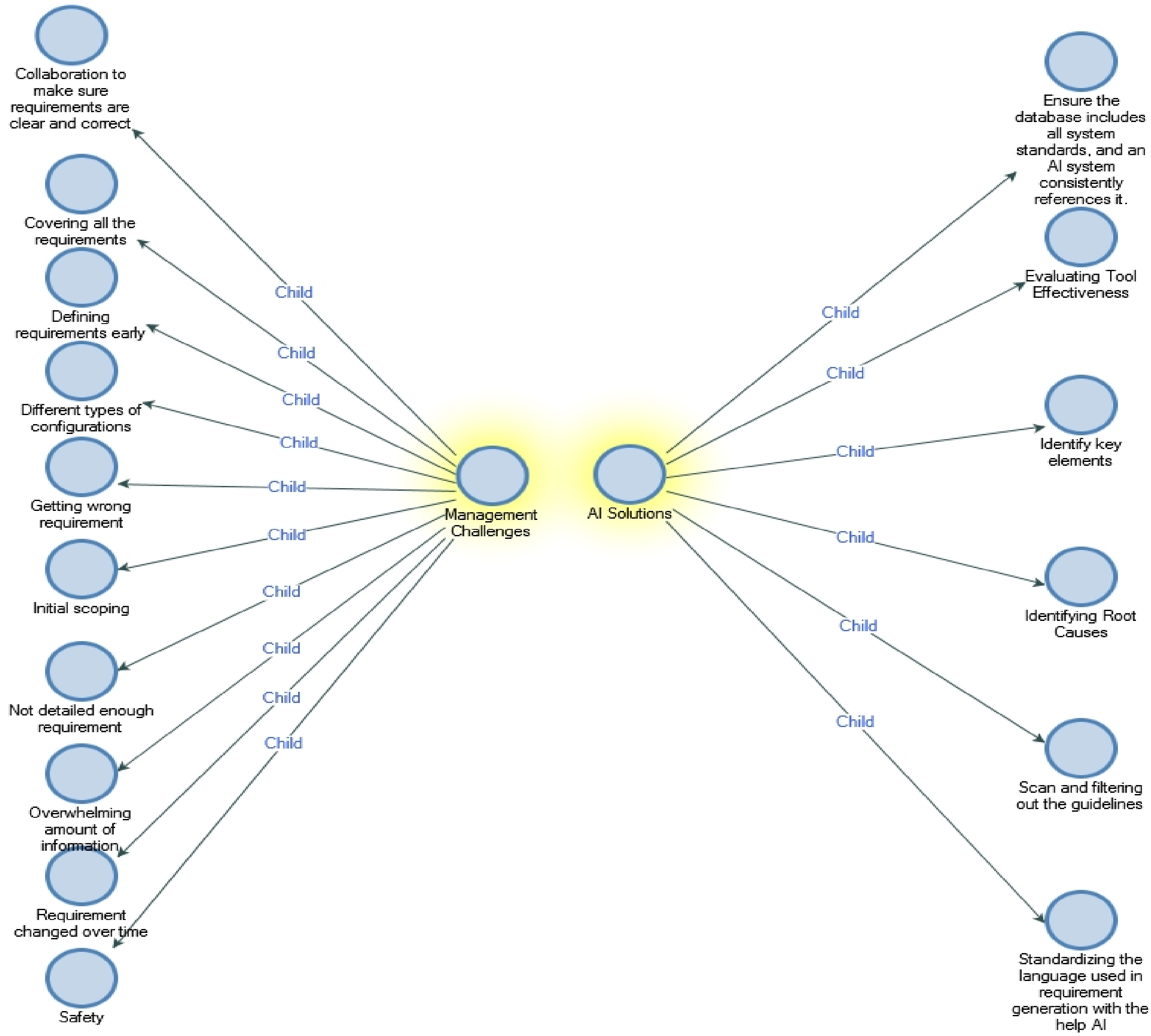


Figure 4.16: Challenges and AI-Solutions

Some additional visualizations were made for other interview questions, but they didn't define any important findings. For instance, no specific tools were mentioned when participants were asked if they knew of any software or tools for the design requirements process. Instead, they pointed to general standards and specifications that engineers typically use.

Chapter 5

Discussion

This chapter discusses the results of this thesis. Section 5.1 explains how the results answer the research questions. Section 5.2 covers the trend and findings of the implementation of this study. Finally, Section 5.3 presents recommendations derived from this work. Limitations for this thesis are then presented in Section 5.4.

5.1 Research Questions

RQ1: How may AI assist humans in defining system requirements?

One of the important goals of this research is to explore how AI can help humans define system design requirements. To do this, the study first looked into the potential of AI and Natural Language Models (NLM) such as GPT. Using documents and specifications provided by a company, these inputs were given to the GPT model, which then generated a set of requirements. A key part of this process was understanding how to create prompts, meaning how to interact with AI and structure the model properly.

In this research, all available documents were used to create a problem description of the system or product. This description was given to the GPT model, which was asked to generate 30 requirements.

The AI-generated requirements were then evaluated, as described in Chapter 4, by gathering opinions from two groups of participants—graduate students and expert Engineers. For comparison, the original set of human-generated requirements was also included.

To evaluate the AI-generated requirements, a survey was designed based on the structure explained in the previous chapter. The survey focused on four key factors: referencing a component, functionality, including target values, and verifiable. These factors were chosen based on the literature review. While there are many ways to assess requirements, these four were considered important for this study. Participants rated the requirements based on these factors, which provided results to help answer the first research question.

The results suggest that AI-generated requirements are similar to human-generated requirements based on participants' ratings. In most cases, the AI-generated requirements received slightly higher ratings, indicating that AI has the potential to help define requirements. However, the p-value indicates that there is no significant difference between the two, meaning AI is not necessarily better. AI can still be a helpful tool when used with human input. AI-generated requirements can support human efforts in defining system requirements, providing similar results in some cases, though further improvement of AI models might be needed to address specific weaknesses presented in the ratings.

RQ2: How completely did AI generate requirements?

The second research question focuses on evaluating the completeness of AI-generated requirements compared to human-generated ones. Completeness, in the context of requirements engineering, can be assessed using various frameworks and criteria. However, this research focused on four specific dimensions to evaluate the completeness of the generated requirements: (1) whether the requirement refers to a specific component, (2) whether the requirement addresses functionality, (3) whether the requirement includes a target value, and (4) whether the requirement is verifiable.

As explained in Chapter 4, the four items were used in the survey to see how well the AI-generated requirements matched human expectations in terms of completeness. Each item looks at a different part of the requirements to indicate how well the AI understood what was needed. For example, requirements that mention specific components are important to make sure the system is clearly defined and all necessary parts are considered. The AI's ability to include these references was compared with human-made requirements to see if there were any gaps or similarities. Functionality is another important part. Functionality ensures that the system's actions and operations are clearly explained. The AI-generated requirements were reviewed to see how well they described what the system needs to do and if they captured the goals.

The gathered data indicates that AI-generated requirements performed well in terms of completeness. For most items, the average rating for AI-generated requirements was higher than for human-generated ones, suggesting that AI has the potential to produce complete requirements. However, for the third item, which involves the target value, the human-generated requirements were more complete than the requirements generated by AI.

RQ3: Can experts recognize the difference between AI-generated and human-generated content?

The third research question asks whether experts can recognize the difference between AI-generated and human-generated requirements. Based on the results of the study, the engineers' ratings of the requirements—based on the four key items—were similar for both AI-generated and human-generated content. The experts couldn't differentiate between the requirements created by AI and the requirements written by humans, suggesting that they could not readily distinguish between the two. This indicates that AI-generated requirements can closely resemble human-generated ones in terms of perceived quality and completeness.

An interesting point to note is that when engineers were unaware of which requirements were AI-generated, they viewed AI as a potential tool for generating requirements. However, when asked in interviews whether they saw AI as a helpful tool shortly, most said no. This may be because AI hasn't yet made enough progress in the industry. While there are some examples of AI usage in industry today, there is still a gap in fully developing and implementing AI for broader use in requirement generation.

5.2 Trends and Findings

The comparison between the two sets of requirements demonstrates that AI can generate requirements with reasonable accuracy, but these requirements may lack domain-specific insights that human engineers include based on their expertise. In comparing the graduate student's data with engineers' data, both engineers and students have close averages for human-generated requirements (0.725 for engineers, 0.720 for students). This suggests that, in terms of quality or performance metrics, there is little difference between how students and engineers assess or generate requirements manually.

For both groups, Item 3 (I3) demonstrates a negative score in the human-generated category, meaning both students and engineers rated or generated requirements that performed below expectations in this case. Students had a higher average (0.855) for AI-generated requirements than engineers (0.795). This suggests that students may have found AI-generated requirements more beneficial or efficient in their context, while engineers were slightly more critical of the AI's output.

When comparing the two groups, both students and engineers rated AI-generated requirements similarly to human-generated ones. Engineers were generally more critical, especially in I3, while students were more positive about AI-generated requirements in some areas. As there was no significant difference in ratings between the two groups, the result suggests that AI can help in defining system requirements and can produce results similar to the requirements from humans. For I1, engineers rated AI-generated requirements higher (1.62) than students did (1.38). This could reflect that, in specific tasks, engineers see more significant benefits from AI-generated content, particularly in the areas where AI can assist with technical or domain-specific tasks.

A considerable gap was found in Item 3 (I3), where engineers rated AI-generated requirements lower (-0.36) compared to students (-0.08). This difference suggests that engineers found AI particularly weak in addressing specific, possibly more detailed aspects of requirements in this area. Item 3, which evaluates requirements based on whether they include specific target values, posed a significant challenge for participants. Both engineers and students had difficulty recognizing or creating requirements with precise values, indicating that this is an area where both human and AI systems may need additional support.

The interviews indicated that each participant had a different way of defining requirements, influenced by their company's structure. They talked about challenges in designing systems and defining requirements and suggested ways AI could help. Their ideas included making sure AI uses the right system standards, helps find root causes, checks how well tools work, and uses clear language. They also suggested that AI could help find key parts of the requirements, scan guidelines, and provide more organized support for the process.

5.3 Recommendation

The results indicate that AI has the potential to generate requirements that are similar to the requirements created by humans, with participants rating requirements closely. However, there is still a need to train AI models to improve their ability to produce more technical and specific requirements. One challenge participants mentioned was that requirements are often written differently by different teams and for different projects. To solve this, using AI to make the wording of requirements more consistent across an organization is suggested. A standardized vocabulary would make requirements clearer and more consistent, help teams work together better, and make the requirements more manageable to move projects from one phase to the next.

Based on the expert engineer's suggestions, AI can play a significant role in managing a database that includes all system standards, allowing the AI to reference these standards as needed. Additionally, AI can be used as a tool to scan and filter requirements according to specific guidelines. Another recommendation is to leverage AI's ability to handle Extensive amounts of requirements and data, enabling AI to manage requirements in various ways, such as ensuring completeness, consistency, and compliance with industry standards.

One more suggestion could be that AI systems should incorporate relevant guidelines, standards, and regulations into the requirements generation process. By consistently referencing these materials, AI could help ensure that all generated requirements meet industry standards and comply with legal or regulatory requirements. To get the most out of AI for generating requirements, it's important to have a feedback loop between the AI and engineers. By regularly collecting feedback on what works and what does not, the AI can learn and improve. Integrating real-time feedback into AI tools would enable engineers to make rapid adjustments while allowing the AI to learn from these changes, resulting in improved outcomes.

5.4 Limitations

While this study provides valuable insights, several limitations should be considered. Only 30 AI-generated requirements were used, resulting in repetitive outcomes and possibly not reflecting AI's full potential for generating diverse requirements. Additionally, the limited number of participants may not represent the broader engineering community, which restricts how widely the findings can be applied. Using surveys and interviews can introduce biases, such as inaccurate responses or people giving answers they think are expected, which could affect the data.

Additionally, the study focused on how engineers interact with AI-generated requirements, possibly missing other important factors in the requirements process. Time limits and the study's scope may have also reduced the depth of analysis in some areas. Future research should include more participants, look at a wider range of AI-generated requirements, and consider factors such as company culture and industry practices for a broader understanding of AI's role in defining requirements.

Chapter 6

Conclusion

Managing the substantial number of requirements and the challenges that arise in generating the requirements will become more manageable with the improvement of advanced tools used in designing complex systems. While many current systems can still rely on the hard work of expert engineers in requirements engineering (RE) and systems engineering to manually handle these tasks, this approach is not expected to work well on a broader scale without extra tools and new methods. In this study, the importance of artificial intelligence (AI) in this process was discussed. The study involved comparing human-generated requirements with AI-generated requirements using surveys. This research also pointed out the real difficulties that engineers face in the real world and how AI could help solve the problems. The goal of this study was to find out how AI can assist humans in generating requirements by training an AI model to act as a co-worker for engineers. This AI is capable of managing and analyzing significant amounts of data, helping to ensure that no important information is missed.

Here are some key findings from this research: The figures illustrated in the results and the trends discussed show that both groups of participants—graduate students and expert engineers—provided almost the same average ratings for the requirements, regardless of whether they were created by humans or AI, meaning that there wasn't a significant difference noticed between the two groups of requirements, suggesting that AI has the potential to create system requirements just similar to humans do. Another important point from the surveys is that while AI can generate requirements, the completeness of these requirements was also a concern. To check this, four different criteria were used to see how complete the AI-generated requirements were. To gather more data, both quantitative and qualitative methods were used. Along with the survey, interviews were conducted with experts to learn more about the actual process of defining requirements and the challenges they face in real-world industry projects. The findings were interesting because the workflows varied slightly depending on the specific goals and policies of each company. Still, some of the challenges mentioned by experts could potentially be solved with the help of AI.

At the end of the interviews, experts were asked how they saw AI as a potential tool for assisting in the generation of requirements. Most expressed some hesitation, noting that while AI has potential, there is still a long way to go before AI can be fully integrated into industry practices. Interestingly, despite this skepticism, the results from the surveys indicate that these same experts rated AI-generated requirements similarly to human-generated ones, and many were unable to distinguish between the two. This finding suggests that AI may already be closer to becoming an effective tool in requirement generation than many industry professionals realize.

For future work in this research, there is a benefit to exploring how AI can be further developed and refined to improve its effectiveness in generating requirements. This could involve testing different AI models and algorithms to see which ones produce the most accurate and complete requirements. Additionally, future studies could focus on expanding the sample size and including a wider range of industries to better understand how AI can be adapted to various engineering fields. There is value in investigating how AI can be integrated into existing workflows to enhance collaboration between human engineers and AI tools, ensuring that AI-generated requirements meet industry standards and expectations. Finally, conducting long-term studies to assess the impact of AI on the requirements generation process in real-world projects could provide insights into its practical applications and benefits.

Appendix A

The Code for Problem description

```
f = open("Problem description of Pier burg.txt", 'r')
text = f.read()

print(text)

import openai

# Your OpenAI API key
api_key = ""
openai.api_key = api_key  # Set your actual API key here

preprompt = "you are an agent that get a system problem description\
         and generate 30 more highly detailed requirements"
```

```
f = open("Problem description of Pier burg.txt", 'r')
sr = f.read()
prompt = f"{preprompt}\nsystem requirements: {sr}\nRequirements: "

try:
    response = openai.ChatCompletion.create(
        model="gpt-3.5-turbo",  # Use the appropriate chat-based model
        messages=[
            {"role": "system", "content": "You are a helpful assistant."},
            {"role": "user", "content": prompt},
        ],
    )
    result = response['choices'][0]['message']['content']
    print(result)
except openai.error.OpenAIError as e:
    print(f"OpenAI API Error: {e}")
```

Appendix B

Comparison of Rating

```
import matplotlib.pyplot as plt
import numpy as np

# Sample data for the bar charts
x = np.arange(4)
categories = ['I1', 'I2', 'I3', 'I4']
y1 = [1.22, 0.92, -0.06, 0.8]
y2 = [1.08, 1, -0.1, 0.92]
y3 = [1.38, 1.06, -0.08, 1.06]
y4 = [1.62, 0.98, -0.36, 0.94]

# Create a 2x2 grid of subplots
fig, axs = plt.subplots(2, 2, figsize=(8, 8))
```

```
# Bar chart 1
axs[0, 0].barh(np.arange(len(categories)), y1, color='b')
#axs[0, 0].set_title('Bar Chart 1')
#axs[0, 0].set_xlabel('X-axis label 1')
axs[0, 0].set_yticks(np.arange(len(categories)))
axs[0, 0].set_yticklabels(categories)

# Bar chart 2
axs[0, 1].barh(np.arange(len(categories)), y2, color='g')
#axs[0, 1].set_title('Bar Chart 2')
#axs[0, 1].set_xlabel('X-axis label 2')
axs[0, 1].set_yticks(np.arange(len(categories)))
axs[0, 1].set_yticklabels(categories)

# Bar chart 3 (horizontal)
axs[1, 0].barh(np.arange(len(categories)), y3, color='r')
#axs[1, 0].set_title('Bar Chart 3')
#axs[1, 0].set_xlabel('X-axis label 3')
axs[1, 0].set_yticks(np.arange(len(categories)))
axs[1, 0].set_yticklabels(categories)

# Bar chart 4 (horizontal)
axs[1, 1].barh(np.arange(len(categories)), y4, color='c')
#axs[1, 1].set_title('Bar Chart 4')
#axs[1, 1].set_xlabel('X-axis label 4')
```

```
axs[1, 1].set_yticks(np.arange(len(categories)))
axs[1, 1].set_yticklabels(categories)


# Add a label for the entire first row
fig.text(0, 0.75, 'Human', ha='center', fontsize=14)

# Add a label for the entire second row
fig.text(0, 0.25, 'AI', ha='center', fontsize=14)

fig.text(0.3, 1, 'Student', ha='center', fontsize=14)
fig.text(0.8, 1, 'Engineer', ha='center', fontsize=14)

plt.subplots_adjust(left=0.1, top=0.9)
plt.tight_layout(rect=[0.05, 0, 1, 0.99])

# Show the plot
plt.show()
```

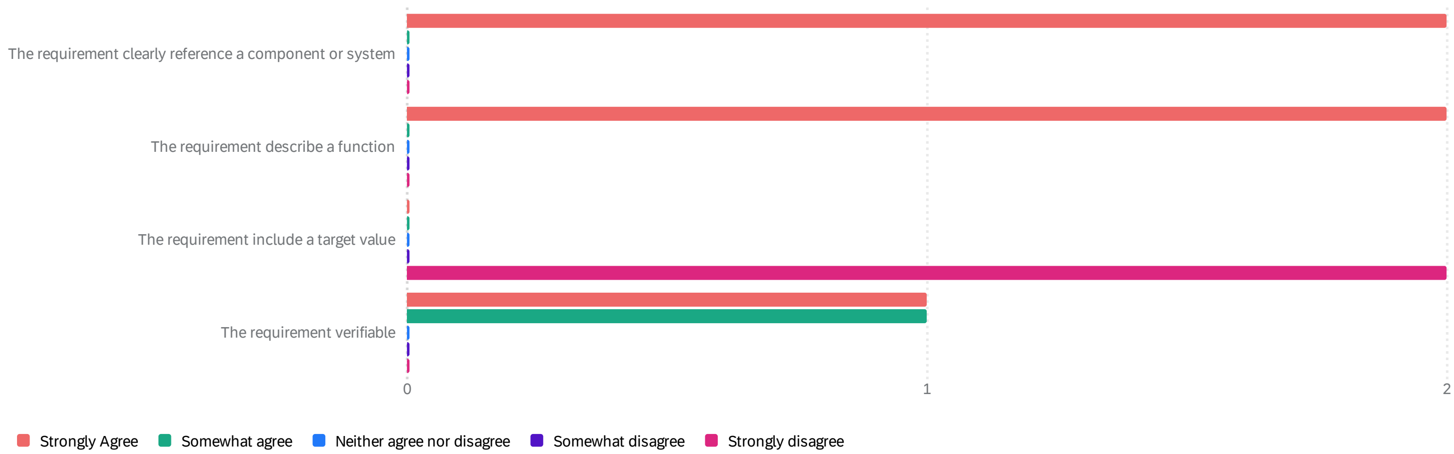
Appendix C

Sample Of Survey

Student two / Page 1

Responses: 5

6. The pass/fail lights must be visible from all stations and provide instant feedback on product quality 2



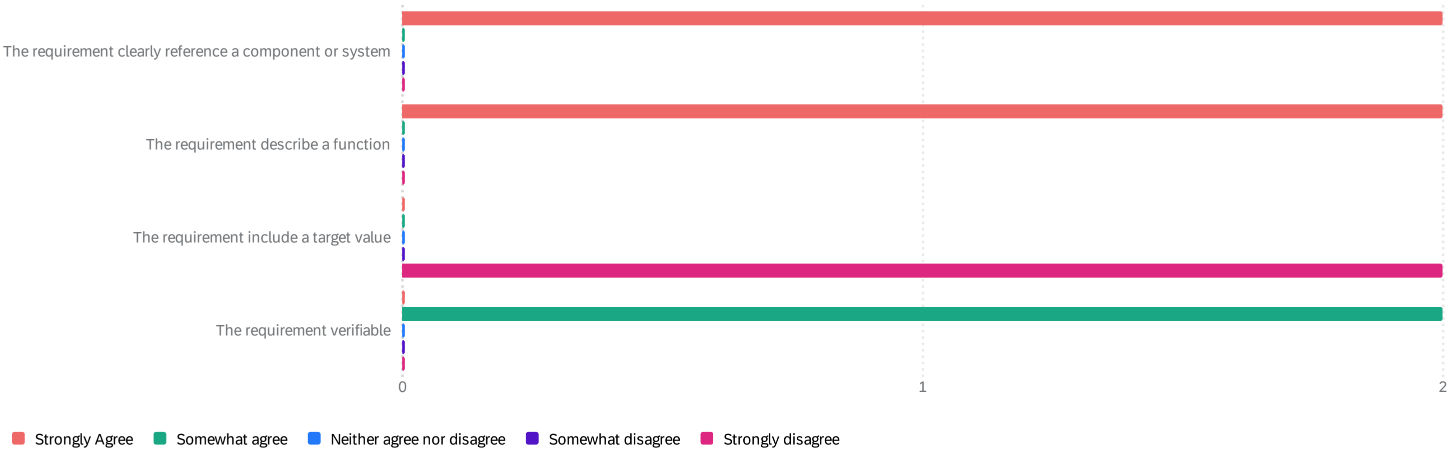
6. The pass/fail lights must be visible from all stations and provide instant feedback on product quality 2

6. The pass/fail lights must be visible from all stations and provide insta...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	2	0	0	0	0
The requirement describe a function	2	0	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	1	1	0	0	0

6. The pass/fail lights must be visible from all stations and provide instant feedback on product quality 2

6. The pass/fail lights must be visible from all stations and provide insta...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.00	1.00	1.00	2
The requirement describe a function	1.00	1.00	1.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	1.50	1.00	2.00	2

30. The C-MORE brand HMIs must have a secure user authentication system to prevent unauthorized access. 2



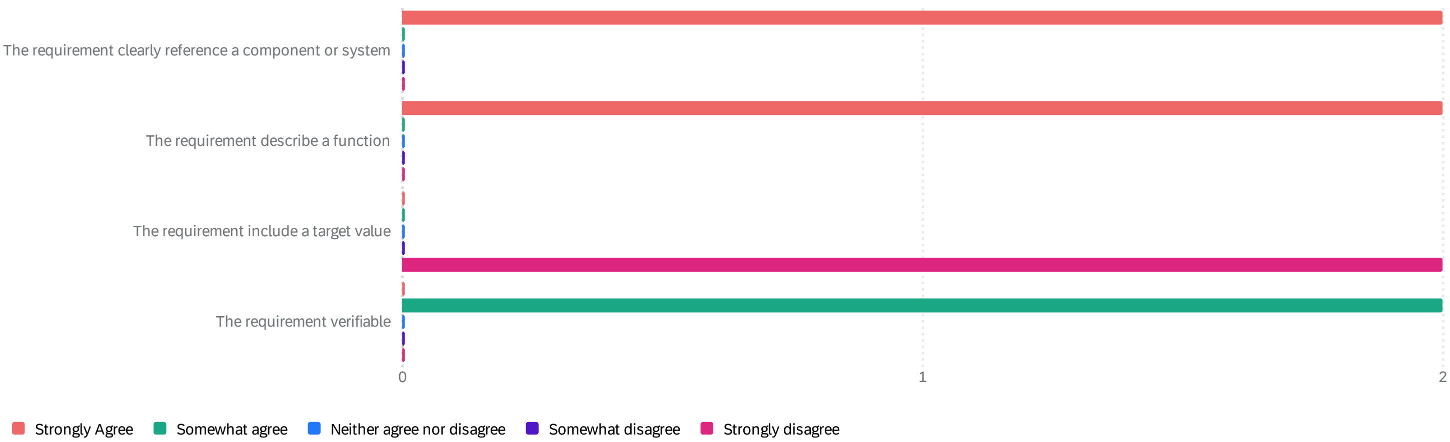
30. The C-MORE brand HMIs must have a secure user authentication system to prevent unauthorized access. 2

30. The C-MORE brand HMIs must have a secure user authentication system to...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	2	0	0	0	0
The requirement describe a function	2	0	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	0	2	0	0	0

30. The C-MORE brand HMIs must have a secure user authentication system to prevent unauthorized access. 2

30. The C-MORE brand HMIs must have a secure user authentication system to...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.00	1.00	1.00	2
The requirement describe a function	1.00	1.00	1.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	2.00	2.00	2.00	2

14. The Cogent Data man 2D barcode scanners must have a high scanning speed to minimize production bottlenecks. 2



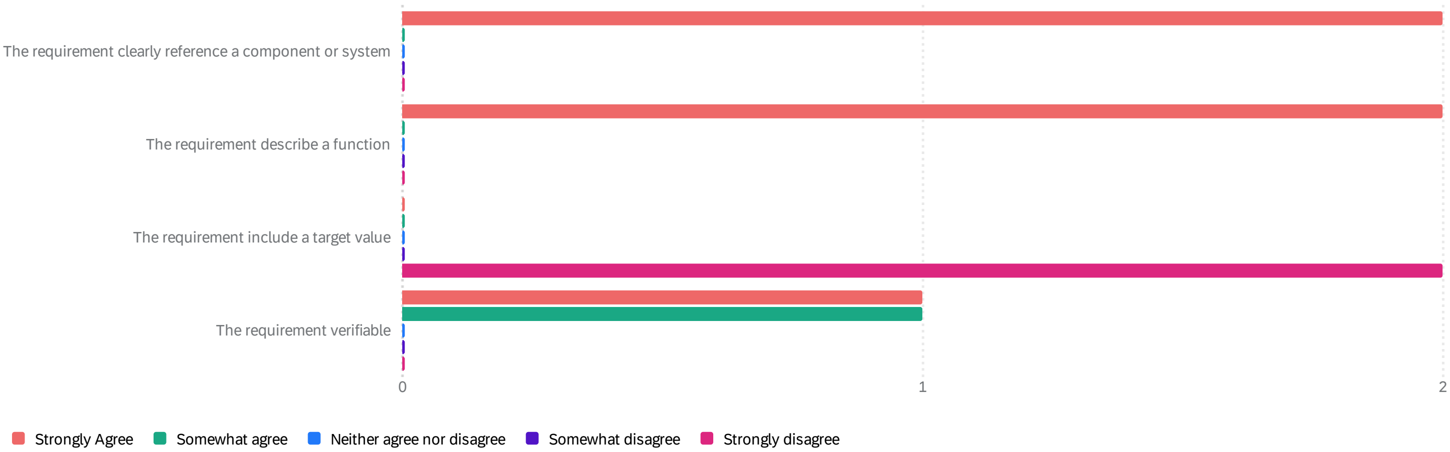
14. The Cogent Data man 2D barcode scanners must have a high scanning speed to minimize production bottlenecks. 2

14. The Cogent Data man 2D barcode scanners must have a high scanning speed...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	2	0	0	0	0
The requirement describe a function	2	0	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	0	2	0	0	0

14. The Cogent Data man 2D barcode scanners must have a high scanning speed to minimize production bottlenecks. 2

14. The Cogent Data man 2D barcode scanners must have a high scanning speed...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.00	1.00	1.00	2
The requirement describe a function	1.00	1.00	1.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	2.00	2.00	2.00	2

20. The PLC-controlled stations must have the ability to record and analyze data for process improvement 2



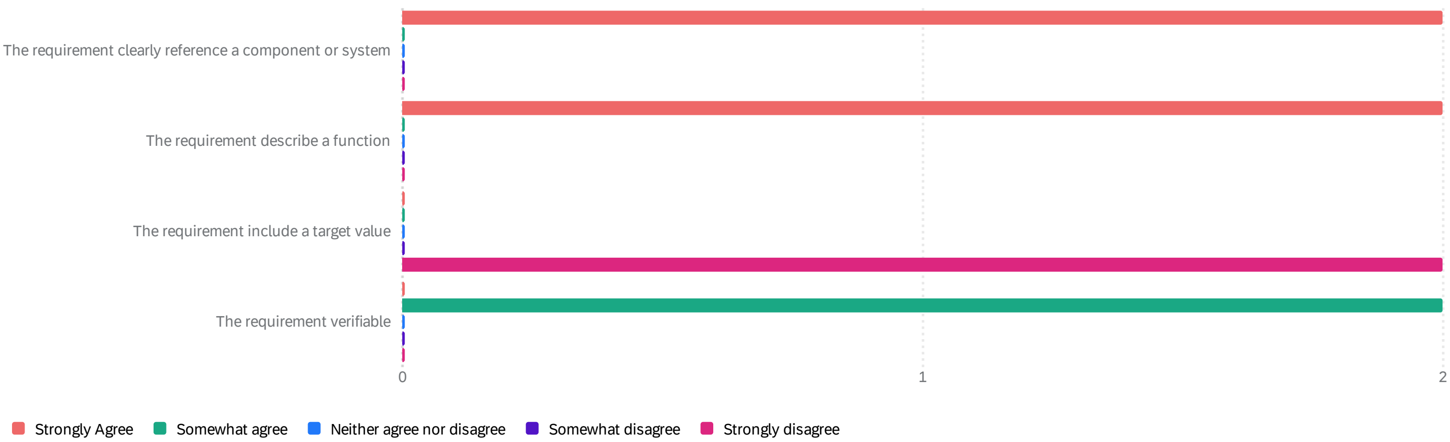
20. The PLC-controlled stations must have the ability to record and analyze data for process improvement 2

20. The PLC-controlled stations must have the ability to record and analyze...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	2	0	0	0	0
The requirement describe a function	2	0	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	1	1	0	0	0

20. The PLC-controlled stations must have the ability to record and analyze data for process improvement 2

20. The PLC-controlled stations must have the ability to record and analyze...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.00	1.00	1.00	2
The requirement describe a function	1.00	1.00	1.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	1.50	1.00	2.00	2

18. The fluorescent lighting must have a long lifespan and be energy efficient. 2



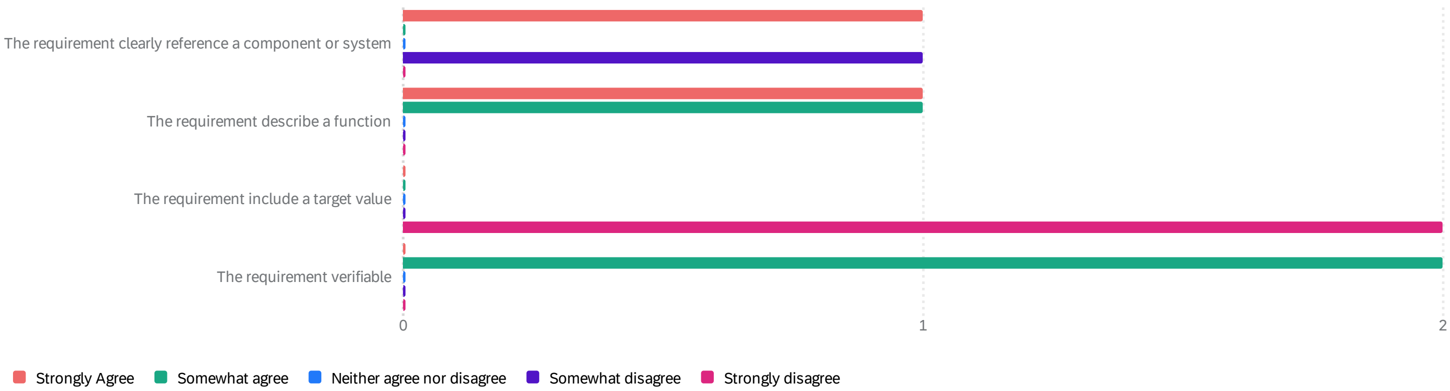
18. The fluorescent lighting must have a long lifespan and be energy efficient. 2

18. The fluorescent lighting must have a long lifespan and be energy effici...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	2	0	0	0	0
The requirement describe a function	2	0	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	0	2	0	0	0

18. The fluorescent lighting must have a long lifespan and be energy efficient. 2

18. The fluorescent lighting must have a long lifespan and be energy effici...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.00	1.00	1.00	2
The requirement describe a function	1.00	1.00	1.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	2.00	2.00	2.00	2

43. all error messages must be displayed on the HMI fault information must be as detailed as possible error messages shall not block the HMI all functions of the HMIs Hall remain accessible and operable even with an error message present a bad operation must be signalized by a red light, a good operation by a green light. 2



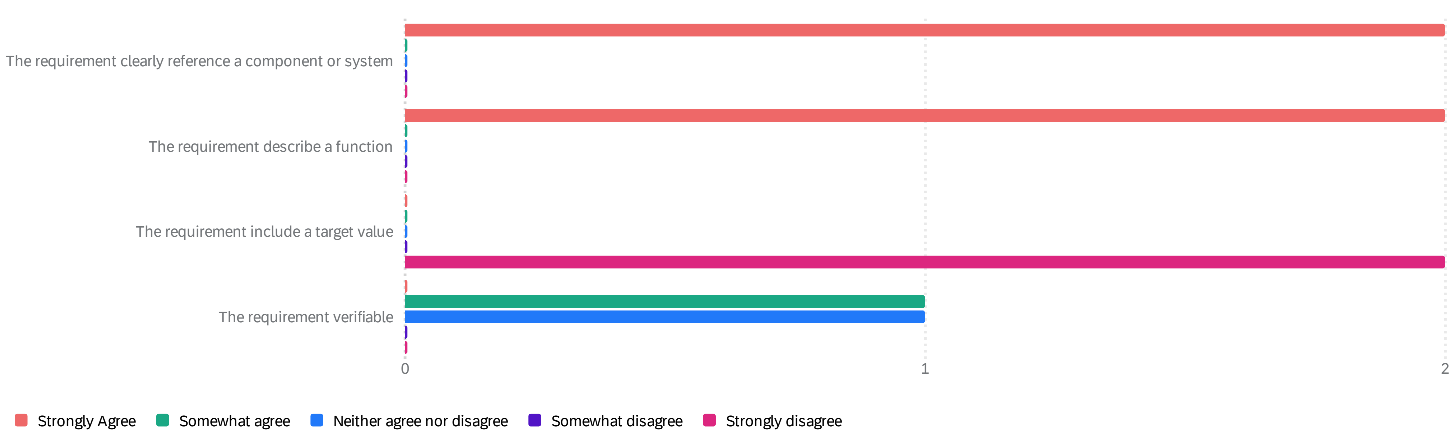
43. all error messages must be displayed on the HMI fault information must be as detailed as possible error messages shall not block the HMI all functions of the HMIs Hall remain accessible and operable even with an error message present a bad operation must be signalized by a red light, a good operation by a green light. 2

43. all error messages must be displayed on the HMI fault information must...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	1	0	0	1	0
The requirement describe a function	1	1	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	0	2	0	0	0

43. all error messages must be displayed on the HMI fault information must be as detailed as possible error messages shall not block the HMI all functions of the HMIs Hall remain accessible and operable even with an error message present a bad operation must be signalized by a red light, a good operation by a green light. 2

43. all error messages must be displayed on the HMI fault information must...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	2.50	1.00	4.00	2
The requirement describe a function	1.50	1.00	2.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	2.00	2.00	2.00	2

185. if pallet with tags and no part barcode are used for tracking, the conveyor belt must be guarded by a transparent cover to prevent unauthorized access. 2



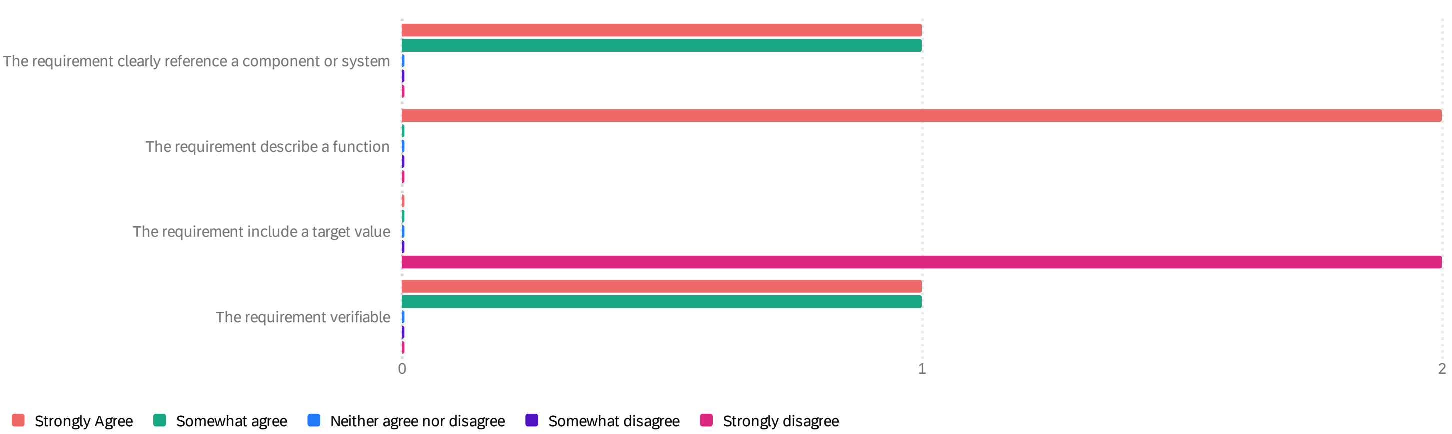
185. if pallet with tags and no part barcode are used for tracking, the conveyor belt must be guarded by a transparent cover to prevent unauthorized access. 2

185. if pallet with tags and no part barcode are used for tracking, the con...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	2	0	0	0	0
The requirement describe a function	2	0	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	0	1	1	0	0

185. if pallet with tags and no part barcode are used for tracking, the conveyor belt must be guarded by a transparent cover to prevent unauthorized access. 2

185. if pallet with tags and no part barcode are used for tracking, the con...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.00	1.00	1.00	2
The requirement describe a function	1.00	1.00	1.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	2.50	2.00	3.00	2

122. equipment controls shall have a high-speed modem for offsite accessed by system integrator to support troubleshooting and upgrades system integrator to coordinate equipment and protocol with Pier burg information technology officer. 2



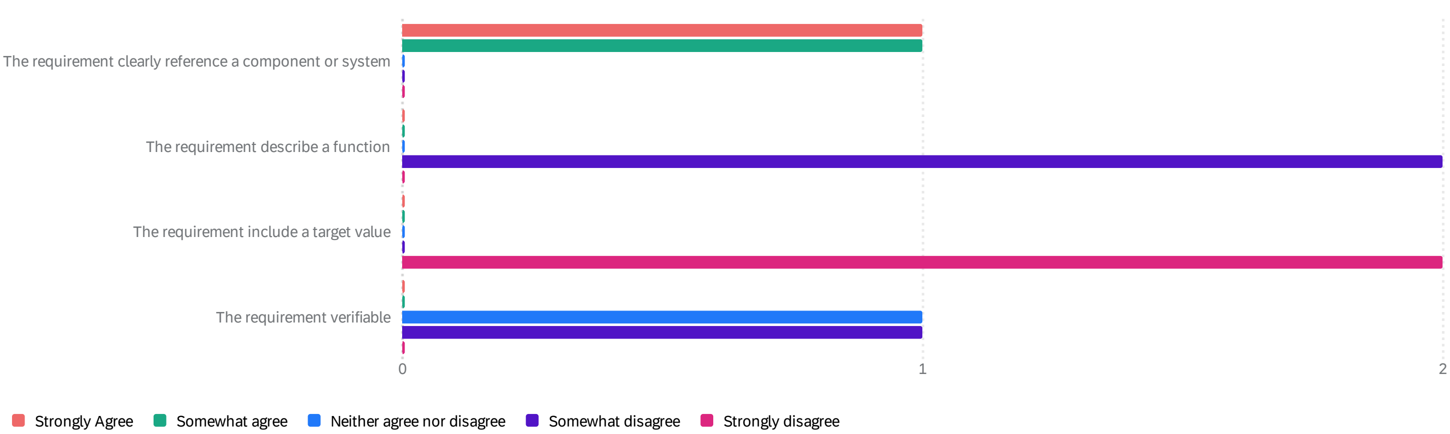
122. equipment controls shall have a high-speed modem for offsite accessed by system integrator to support troubleshooting and upgrades system integrator to coordinate equipment and protocol with Pier burg information technology officer. 2

122. equipment controls shall have a high-speed modem for offsite accessed...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	1	1	0	0	0
The requirement describe a function	2	0	0	0	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	1	1	0	0	0

122. equipment controls shall have a high-speed modem for offsite accessed by system integrator to support troubleshooting and upgrades system integrator to coordinate equipment and protocol with Pier burg information technology officer. 2

122. equipment controls shall have a high-speed modem for offsite accessed...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.50	1.00	2.00	2
The requirement describe a function	1.00	1.00	1.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	1.50	1.00	2.00	2

76. individual module and or system operations can be plc controlled if the data transfer, collection, and management is pc based and does not slow down the speed of the system. 2



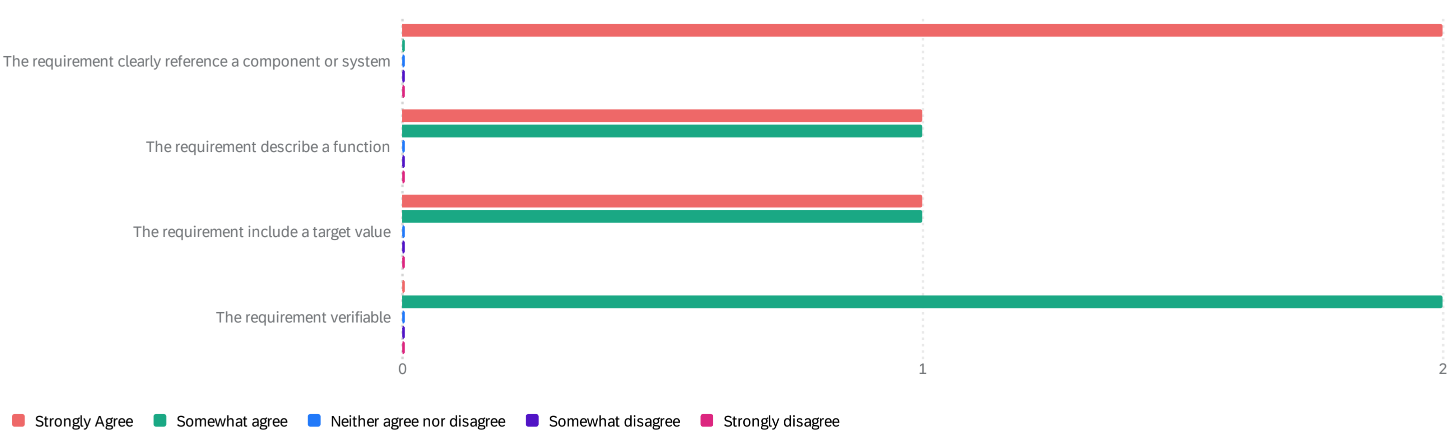
76. individual module and or system operations can be plc controlled if the data transfer, collection, and management is pc based and does not slow down the speed of the system. 2

76. individual module and or system operations can be plc controlled if the...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	1	1	0	0	0
The requirement describe a function	0	0	0	2	0
The requirement include a target value	0	0	0	0	2
The requirement verifiable	0	0	1	1	0

76. individual module and or system operations can be plc controlled if the data transfer, collection, and management is pc based and does not slow down the speed of the system. 2

76. individual module and or system operations can be plc controlled if the...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.50	1.00	2.00	2
The requirement describe a function	4.00	4.00	4.00	2
The requirement include a target value	5.00	5.00	5.00	2
The requirement verifiable	3.50	3.00	4.00	2

188. all workstations will be equipped with adequate lighting for operators a minimum of 2 lights (4 ft florescent lights) is requested per workstation unless limited by workstation design lux requirements should be considered depending on the type of activity performed at stations. 2



188. all workstations will be equipped with adequate lighting for operators a minimum of 2 lights (4 ft florescent lights) is requested per workstation unless limited by workstation design lux requirements should be considered depending on the type of activity performed at stations. 2

188. all workstations will be equipped with adequate lighting for operators...	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The requirement clearly reference a component or system	2	0	0	0	0
The requirement describe a function	1	1	0	0	0
The requirement include a target value	1	1	0	0	0
The requirement verifiable	0	2	0	0	0

188. all workstations will be equipped with adequate lighting for operators a minimum of 2 lights (4 ft florescent lights) is requested per workstation unless limited by workstation design lux requirements should be considered depending on the type of activity performed at stations. 2

188. all workstations will be equipped with adequate lighting for operators...	Average	Minimum	Maximum	Count
The requirement clearly reference a component or system	1.00	1.00	1.00	2
The requirement describe a function	1.50	1.00	2.00	2
The requirement include a target value	1.50	1.00	2.00	2
The requirement verifiable	2.00	2.00	2.00	2

Appendix D

Sample Of Interview

Can you provide an overview of your role and responsibilities in the design process with respect to system requirements?

Who is involved in the process of generating design system requirements?

Could you describe the typical workflow for collecting and documenting design requirements in your organization?

What approaches or software do you use to identify and prioritize design requirements?

What challenges do engineers often face in requirements management?

How do you think AI can help address the challenges related to requirements management.

What's your view on AI integration in engineering design and its potential to replicate tasks currently done by engineers?

→

Appendix E

Code Book

Role Overview: • Manufacturing engineering • Mechanical engineering • Electromechanical engineering • Robot specialist	**Role Overview**: Can you provide an overview of your role and responsibilities in the design process with respect to system requirements?
Involved Parties/ Process Participant • Mechanical Engineer • Electrical Engineer • Automation Engineer • Production engineer • Quality engineer • Marketing • Safety engineer • Architect	**Involved Parties/ Process Participant:** Who is involved in the process of generating design system requirements?
Workflow Description: • 1. Define Scope of Work 2. Categorize the Scope 3. Assign Technical Experts 4. Develop Technical Specifications 5. Compile Specifications and Requirements 6. Add Additional Requirements 7. Fulfillment. • Identify Issues, Report to Quality Engineers, Determine Tool Solutions, Draft and Optimize Tool Design, Finalize Design. • 1.Marketing defines Critical to Quality (CTQ) parameters.2. Outline system design based on CTQs. 3. Define specific requirements based on chosen components 4. Collaborate with finance to determine overall costs. • Requirements Collection, Technology Selection, Validation, Project Execution, Final Review. • Reference to state code or international code guides requirements. Influences design and equipment specifications. Important for compliance and standardization in the process.	**Workflow Description:** Could you describe the typical workflow for collecting and documenting design requirements in your organization.

Tools/ Software: • No Specific Software • Standard/norms/template • Only a website to track • No requirement software	**Tools/ Software:** What approaches or software do you use to identify and prioritize design requirements.
Challenges: • Covering all the requirements • Overwhelming amount of information • Different types of configurations • Safety • Getting wrong requirement • Not detailed enough requirement • Requirement changed over time • Initial scoping • Defining requirements early • Collaboration to make sure requirements are clear and correct	**Challenges:** what challenges do engineers often face during requirement generating.
AI Solutions: • Ensure the database includes all system standards, and an AI system consistently references it. • Identifying Root Causes • Evaluating Tool Effectiveness • Standardizing the language used in requirement generation with the help AI. • Identify key elements. • Scan and filtering out the guidelines.	**AI Solutions:** How do you think AI can help address the challenges related to requirements management.
The Potential of AI in doing human task: • It will not replace by human soon. • Can not replaced regarding safety matters, safety should check with humans. • It cannot be replaced the creativity of humans. • AI can generate a Python script to make a CAD model. • Still a long way from having AI replace what we do.	**The Potential of AI in doing human task:** What's your view on AI integration in engineering design and its potential to replicate tasks currently done by engineers.

Appendix F

Requirements

Comparing AI-Generated with originals requirements:	
AI-generated	**The originals requirements**
1. The PLC-controlled stations must have the ability to operate independently and in sync with each other.	76. individual module or system operations can be controlled if the data transfer, collection, and management is compute-based and does not slow down the speed of the system.
2. The C-MORE brand HMIs must have an intuitive interface for easy control and monitoring of the assembly line.	47. all system parameters (times, limits, rates) will be editable through the user interface (password protected).
3. The shared HMIs between stations must allow operators to communicate and coordinate effectively.	45.all actuators (servos, pneumatic cylinders) must be operable through the user interface.

4. The sliding troughs with guide rails must be designed to minimize friction and ensure precise and smooth product transfer.	1. the standard concept for transfer systems is in-line without transfer lifts (counterclockwise) each station shall run independent from the others single part is processed operation is from one side and material flow by roller conveyors flow (asynchronous) a station is a line location where a racks from the other side direct to the operation zone details and other concepts (e.g. control elements) will be discussed during the quote and design phase.
5. The Cogent Data man 2D barcode scanners must be able to accurately read and interpret barcodes at each position.	185. if pallet with tags and no part barcode are used for tracking, the conveyor belt must be guarded by a transparent cover to prevent unauthorized access.
6. The pass/fail lights must be visible from all stations and provide instant feedback on product quality.	43. all error messages must be displayed on the user interface fault information must be as detailed as possible error messages shall not block the user interface. all functions of the user interface shall remain accessible and operable even with an error message present a bad operation must be signalized by a red light, a good operation by a green light.

7. The common station table design must include clear labeling and organization for efficient part storage.	36.all wires must be labeled per electrical print at all termination points, including terminal blocks, connector plugs.
8. The guarding system must be designed to meet safety regulations and prevent accidents.	32. guarding shall protect equipment from damage that may occur during routine floor sweeping and mopping practices.
9. The fluorescent lighting must be adequately bright and evenly distributed throughout the assembly line area.	97. all data is stored in a database on a computer-basis data shall be imported automatically into spreadsheet format file from the database system and have the capability to pulled easily from the data based onto a backup system or tape backup system for supplied database of the system provider pulling data shall not impact the availability performance of the operations or stations status indicator at every station must be mounted for good visibility (top down: red-yellow-green).

10. The shared mounting approach must be adjustable and allow for easy installation and removal of equipment.	11. replacement and or maintenance of all perishable tooling shall be designed to permit ease of removal and installation utilizing minimum tools and technical skills.
11. The PLC-controlled stations must have built-in error detection and recovery mechanisms.	65. the user interface will need to have a password-protected manual function that will allow the control system time to be changed this will help to correct for minor time adjustments, such as daylight savings time changes.
12. The C-MORE brand HMIs must have customizable display options for different operator preferences.	214. work instruction holders must be installed on each station unless operator work instructions are incorporated into user interface.

13. The sliding troughs with guide rails must be able to handle products of varying sizes and weights.	154.A quick dump gate should be constructed into any bowl that is designed to run more than one style or size of part.
14. The Cogent Data man 2D barcode scanners must have a high scanning speed to minimize production bottlenecks.	122. equipment controls shall have a high-speed modem for offsite accessed by system integrator to support troubleshooting and upgrades system integrator to coordinate equipment and protocol with Pier burg information technology officer.
15. The pass/fail lights must have a clear and distinct visual indication for easy identification	85. there must be a manual function to test all station lights (stack lights, good bad lights, etc.) at one time to detect for defective bulbs.
16. The common station table design must include anti-slip surfaces to prevent accidents and product damage.	152. freestanding bowl support tables should have heavy-duty adjustable mounting feet for final alignment at set up.

17. The guarding system must allow easy access for maintenance and troubleshooting purposes.	32. guarding shall protect equipment from damage that may occur during routine floor sweeping and mopping practices.
18. The fluorescent lighting must have a long lifespan and be energy efficient.	188. all workstations will be equipped with adequate lighting for operators a minimum of 2 lights (task lighting) is requested per workstation unless limited by workstation design requirements should be considered depending on the type of activity performed at stations.
19. The shared mounting approach must have robust locking mechanisms to ensure stability during operation.	174. no process shall require operator vigilance to ensure stability and capability.

20. The PLC-controlled stations must have the ability to record and analyze data for process improvement	76. individual module and or system operations can be system controlled if the data transfer, collection, and management is computer based and does not slow down the speed of the system.
21. The C-MORE brand HMIs must have multi-language support for diverse operator backgrounds.	
22. The sliding troughs with guide rails must be designed to minimize noise and vibration during product transfer	
23. The Cogent Data man 2D barcode scanners must be able to withstand dust, dirt, and vibration without compromising performance	158.vents and dirt discharge ports are required to eliminate dirt and foreign particles from reaching escapement.
24. The pass/fail lights must have a user-friendly interface for easy configuration and calibration	24. supplier will design equipment to eliminate calibrations and adjustments.
25. The common station table design must have designated areas for different part types to prevent cross-contamination.	152. freestanding bowl support tables should have heavy-duty adjustable mounting feet for final alignment at set up.

26. The guarding system must include emergency stop buttons within easy reach of operators	8. equipment shall recover from fault situations and emergency stop situations automatically when a reset sequence is requested from the user interface total time from request to ready shall not exceed some seconds.
27. The fluorescent lighting must have uniform color temperature to prevent visual fatigue.	21. equipment shall detect tooling type features equipment shall alarm if tooling is installed incorrectly or if the wrong tooling is installed the tooling should have visual indicators to facilitate change over.
28. The shared mounting approach must allow for easy adjustment of equipment height and angle.	152. freestanding bowl support tables should have heavy-duty adjustable mounting feet for final alignment at set up.

29. The PLC-controlled stations must have real-time monitoring and reporting capabilities for efficient maintenance scheduling.	65. the user interface will need to have a password-protected manual function that will allow the control system time to be changed this will help to correct for minor time adjustments, such as daylight savings time changes.
30. The C-MORE brand HMIs must have a secure user authentication system to prevent unauthorized access.	185. if pallet with tags and no part barcode are used for tracking, the conveyor belt must be guarded by a transparent cover to prevent unauthorized access.

References

[1] J. M. McLellan, B. Morkos, G. G. Mocko, and J. D. Summers, "Requirement modeling systems for mechanical design: A systematic method for evaluating requirement management tools and languages," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, vol. 44113, 2010, pp. 1247–1257.

[2] S. Joshi, B. Morkos, P. Shankar, J. D. Summers, and G. M. Mocko, "Requirements in engineering design: What are we teaching?" *Tools and methods for competitive engineering*, vol. 1, no. 38, pp. 1319–1326, 2012.

[3] J. D. Summers, S. Joshi, and B. Morkos, "Requirements evolution: Relating functional and non-functional requirement change on student project success," in *International design engineering technical conferences and computers and information in engineering conference*, American Society of Mechanical Engineers, vol. 46346, 2014, V003T04A002.

[4] B. Morkos, P. Shankar, and J. D. Summers, "Predicting requirement change propagation, using higher order design structure matrices: An industry case study," *Journal of Engineering Design*, vol. 23, no. 12, pp. 905–926, 2012.

[5] B. Morkos, J. Mathieson, and J. D. Summers, "Comparative analysis of requirements change prediction models: Manual, linguistic, and neural network," *Research in Engineering Design*, vol. 25, pp. 139–156, 2014.

[6] C. Chen, J. Mullis, and B. Morkos, "A topic modeling approach to study design requirements," in *International design engineering technical conferences and computers and information in engineering conference*, American Society of Mechanical Engineers, vol. 85383, 2021, V03AT03A021.

[7] I. M. Siddique, "Harnessing artificial intelligence for systems engineering: Promises and pitfalls," *European Journal of Advances in Engineering and Technology*, vol. 9, no. 9, pp. 67–72, 2022.

[8] A. J. Obaid and S. Sharma, "Recent trends and development of heuristic artificial intelligence approach in mechanical system and engineering product design," *Saudi Journal of Engineering and Technology*, vol. 5, no. 2, pp. 86–93, 2020.

[9] M. W. Anwar, I. Ahsan, F. Azam, W. H. Butt, and M. Rashid, "A natural language processing (nlp) framework for embedded systems to automatically extract verification aspects from textual design requirements," in *Proceedings of the 2020 12th International Conference on Computer and Automation Engineering*, 2020, pp. 7–12.

[10] H. Salehi and R. Burgueño, "Emerging artificial intelligence methods in structural engineering," *Engineering structures*, vol. 171, pp. 170–189, 2018.

[11] P. H. Hein, V. Menon, and B. Morkos, "Exploring requirement change propagation through the physical and functional domain," in *International design engineering technical conferences and computers and information in engineering conference*, American Society of Mechanical Engineers, vol. 57052, 2015, V01BT02A051.

[12] N. Cross, *Engineering design methods: strategies for product design*. John Wiley & Sons, 2021.

[13] G. Pahl, W. Beitz, J. Feldhusen, K.-H. Grote, *et al.*, *Engineering design: a systematic approach*. Springer, 1996, vol. 3.

[14] B. Morkos, S. Joshi, J. D. Summers, and G. G. Mocko, "Requirements and data content evaluation of industry in-house data management system," in *International design engineering technical*

conferences and computers and information in engineering conference, vol. 44113, 2010, pp. 493–503.

[15] B. Morkos, S. Joshi, and J. D. Summers, "Investigating the impact of requirements elicitation and evolution on course performance in a pre-capstone design course," *Journal of Engineering Design*, vol. 30, no. 4-5, pp. 155–179, 2019.

[16] P. Shankar, B. Morkos, D. Yadav, and J. D. Summers, "Towards the formalization of non-functional requirements in conceptual design," *Research in engineering design*, vol. 31, pp. 449–469, 2020.

[17] S. D. Eppinger, N. R. Joglekar, A. Olechowski, and T. Teo, "Improving the systems engineering process with multilevel analysis of interactions," *Ai Edam*, vol. 28, no. 4, pp. 323–337, 2014.

[18] P. Ruiz-Minguela, V. Nava, J. Hodges, and J. M. Blanco, "Review of systems engineering (se) methods and their application to wave energy technology development," *Journal of Marine Science and Engineering*, vol. 8, no. 10, p. 823, 2020.

[19] S. Hansen, N. Berente, and K. Lyytinen, "Requirements in the 21st century: Current practice and emerging trends," in *Design Requirements Engineering: A Ten-Year Perspective: Design Requirements Workshop, Cleveland, OH, USA, June 3-6, 2007, Revised and Invited Papers*, Springer, 2009, pp. 44–87.

[20] J. Mullis, C. Chen, B. Morkos, and S. Ferguson, "Deep neural networks in natural language processing for classifying requirements by origin and functionality: An application of bert in system requirements," *Journal of Mechanical Design*, vol. 146, no. 4, p. 041 401, 2024.

[21] A. E. Gärtner, D. Göhlich, and T.-A. Fay, "Automated condition detection in requirements engineering," *Proceedings of the Design Society*, vol. 3, pp. 707–716, 2023.

[22] K. Pohl, *Requirements engineering: An overview*. Citeseer, 1996.

[23] D. Firesmith, "Specifying good requirements," *Journal of Object Technology*, vol. 2, no. 4, pp. 77–87, 2003.

[24] C. B. Keating, J. J. Padilla, and K. Adams, "System of systems engineering requirements: Challenges and guidelines," *Engineering Management Journal*, vol. 20, no. 4, pp. 24–31, 2008.

[25] P. Htet Hein, B. Morkos, and C. Sen, "Utilizing node interference method and complex network centrality metrics to explore requirement change propagation," in *International design engineering technical conferences and computers and information in engineering conference*, American Society of Mechanical Engineers, vol. 58110, 2017, V001T02A081.

[26] B. Morkos and J. D. Summers, "Requirement change propagation prediction approach: Results from an industry case study," in *International design engineering technical conferences and computers and information in engineering conference*, vol. 44090, 2010, pp. 111–121.

[27] S. J. Kapurch, *NASA systems engineering handbook*. Diane Publishing, 2010.

[28] R. Shishko and R. Aster, "Nasa systems engineering handbook," *NASA systems engineering handbook/by Robert Shishko; with contributions by Robert Aster...[et al.]; edited by Randy Cassingham.[Washington, DC?]: National Aeronautics and Space Administration,[1995]*, vol. 6105, 1995.

[29] NASA, "Appendix c: How to write a good requirement," no. 2024b, 2024. [Online]. Available: `https://www.nasa.gov/reference/appendix-c-how-to-write-a-good-requirement/`.

[30] H. Belani, M. Vukovic, and Ž. Car, "Requirements engineering challenges in building ai-based complex systems," in *2019 IEEE 27th International Requirements Engineering Conference Workshops (REW)*, IEEE, 2019, pp. 252–255.

[31] K. Liu, S. Reddivari, and K. Reddivari, "Artificial intelligence in software requirements engineering: State-of-the-art," in *2022 IEEE 23rd International Conference on Information Reuse and Integration for Data Science (IRI)*, IEEE, 2022, pp. 106–111.

[32] B. Nuseibeh and S. Easterbrook, "Requirements engineering: A roadmap," in *Proceedings of the Conference on the Future of Software Engineering*, 2000, pp. 35–46.

[33] R. Alkabour and O. Alrwais, "Ai techniques in requirements elicitation.," *J. Softw.*, vol. 18, no. 4, pp. 200–208, 2023.

[34] A. Van Lamsweerde, "Requirements engineering in the year 00: A research perspective," in *Proceedings of the 22nd international conference on Software engineering*, 2000, pp. 5–19.

[35] D. Dermeval *et al.*, "Applications of ontologies in requirements engineering: A systematic review of the literature," *Requirements engineering*, vol. 21, pp. 405–437, 2016.

[36] C. Arora, J. Grundy, and M. Abdelrazek, "Advancing requirements engineering through generative ai: Assessing the role of llms," in *Generative AI for Effective Software Development*, Springer, 2024, pp. 129–148.

[37] S. Arvidsson and J. Axell, "Prompt engineering guidelines for llms in requirements engineering," 2023.

[38] M. N. Shergadwala and M. Seif El-Nasr, "Human-centric design requirements and challenges for enabling human-ai interaction in engineering design: An interview study," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers, vol. 85420, 2021, V006T06A054.

[39] B. Camburn *et al.*, "Computer-aided mind map generation via crowdsourcing and machine learning," *Research in Engineering Design*, vol. 31, pp. 383–409, 2020.

[40] J. Koch, "Design implications for designing with a collaborative ai," in *2017 AAAI Spring symposium series*, 2017.

[41] B. Camburn, Y. He, S. Raviselvam, J. Luo, and K. Wood, "Machine learning-based design concept evaluation," *Journal of Mechanical Design*, vol. 142, no. 3, p. 031 113, 2020.

[42] M. L. Dering, C. S. Tucker, and S. Kumara, "An unsupervised machine learning approach to assessing designer performance during physical prototyping," *Journal of Computing and Information Science in Engineering*, vol. 18, no. 1, p. 011 002, 2018.

[43] G. Williams, N. A. Meisel, T. W. Simpson, and C. McComb, "Design repository effectiveness for 3d convolutional neural networks: Application to additive manufacturing," *Journal of Mechanical Design*, vol. 141, no. 11, p. 111 701, 2019.

[44] J. T. Gyory *et al.*, "Human versus artificial intelligence: A data-driven approach to real-time process management during complex engineering design," *Journal of Mechanical Design*, vol. 144, no. 2, p. 021 405, 2022.

[45] H. J. Wilson and P. R. Daugherty, "Collaborative intelligence: Humans and ai are joining forces," *Harvard Business Review*, vol. 96, no. 4, pp. 114–123, 2018.

[46] P. R. Daugherty and H. J. Wilson, *Human+ machine: Reimagining work in the age of AI*. Harvard Business Press, 2018.

[47] Z. Xu *et al.*, "Adaptation and challenges in human-ai partnership for the design of complex engineering systems," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers, vol. 87318, 2023, V03BT03A056.

[48] J. Cagan, I. E. Grossmann, and J. Hooker, "A conceptual framework for combining artificial intelligence and optimization in engineering design," *Research in Engineering Design*, vol. 9, pp. 20–34, 1997.

[49] S. Mondal and S. S. Goswami, "Rise of intelligent machines: Influence of artificial intelligence on mechanical engineering innovation," *Spectrum of Engineering and Management Sciences*, vol. 2, no. 1, pp. 46–55, 2024.

[50] D. Jitnah, J. Han, and P. Steele, "Software requirements engineering: An overview," *Penins. Sch. Comput. Inf. Technol. Monash Univ*, vol. 1995, 1995.

[51] G. Mussbacher and J. Kienzle, "A vision for generic concern-oriented requirements reuse re@ 21," in *2013 21st IEEE International Requirements Engineering Conference (RE)*, IEEE, 2013, pp. 238–249.

[52] M. Irshad, K. Petersen, and S. Poulding, "A systematic literature review of software requirements reuse approaches," *Information and Software Technology*, vol. 93, pp. 223–245, 2018.

[53] R. B. Adler, G. R. Rodman, and A. Sévigny, *Understanding human communication*. Oxford University Press Oxford, 2006, vol. 10.

[54] M. Lang and J. Duggan, "A tool to support collaborative software requirements management," *Requirements Engineering*, vol. 6, pp. 161–172, 2001.

[55] S. R. Faulk, "Software requirements: A tutorial," *Software Engineering Project Management*, 1995.

[56] O. O. Oduko, "Comparison of requirement management software," 2021.

[57] J. M. Coble, J. Karat, and M. G. Kahn, "Maintaining a focus on user requirements throughout the development of clinical workstation software," in *Proceedings of the ACM SIGCHI Conference on Human Factors in computing Systems*, 1997, pp. 170–177.

[58] V. V. Das, "Involvement of users in software requirement engineering," in *10th International Conference on Information Technology (ICIT 2007)*, IEEE, 2007, pp. 230–233.

[59] J. Rios, R. Roy, and P. Sackett, *Requirements engineering and management for manufacturing*. SME Society of Manufacturing Engineers, 2006.

[60] R. R. Sud and J. D. Arthur, "Requirements management tools: A quantitative assessment," 2003.

[61] A. Zainol *et al.*, "An investigation of a requirements management tool elements," in *2011 IEEE Conference on Open Systems*, IEEE, 2011, pp. 53–58.

[62] D. Beuche *et al.*, "Using requirements management tools in software product line engineering: The state of the practice," in *11th International Software Product Line Conference (SPLC 2007)*, IEEE, 2007, pp. 84–96.

[63] W. Song, "Requirement management for product-service systems: Status review and future trends," *Computers in Industry*, vol. 85, pp. 11–22, 2017.

[64] Mockus and Votta, "Identifying reasons for software changes using historic databases," in *Proceedings 2000 international conference on software maintenance*, IEEE, 2000, pp. 120–130.

[65] H. O. Ali, M. Z. Abd Rozan, and A. M. Sharif, "Change requirement management issues for a large software development projects," *Journal of Information Systems Research and Innovation*, vol. 5, pp. 63–69, 2013.

[66] S. Sharma and S. Pandey, "Integrating ai techniques in requirements phase: A," *Int J Comput Appl*, vol. 975,

[67] H. Al Qaisi, G. Y. Quba, A. Althunibat, A. Abdallah, and S. Alzu'bi, "An intelligent prototype for requirements validation process using machine learning algorithms," in *2021 International Conference on Information Technology (ICIT)*, IEEE, 2021, pp. 870–875.

[68] A. Shah, M. A. Alasow, F. Sajjad, and J. J. A. Baig, "An evaluation of software requirements tools," in *2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS)*, IEEE, 2017, pp. 278–283.

[69] M. Kamalrudin and S. Sidek, "A review on software requirements validation and consistency management," *International journal of software engineering and its applications*, vol. 9, no. 10, pp. 39–58, 2015.

[70] S. N. Khairuddin, A. Sarlan, and R. Ahmad, "Challenges in requirement management process: An overview," in *2021 International Conference on Computer & Information Sciences (ICCOINS)*, IEEE, 2021, pp. 120–124.

[71] T. Sedano, P. Ralph, and C. Péraire, "Software development waste," in *2017 IEEE/ACM 39th International Conference on Software Engineering (ICSE)*, IEEE, 2017, pp. 130–140.

[72] C. Cheligeer, J. Huang, G. Wu, N. Bhuiyan, Y. Xu, and Y. Zeng, "Machine learning in requirements elicitation: A literature review," *AI EDAM*, vol. 36, e32, 2022.

[73] K. Ahmad, M. Abdelrazek, C. Arora, J. Grundy, and M. Bano, "Requirements elicitation and modelling of artificial intelligence systems: An empirical study," *arXiv preprint arXiv:2302.06034*, 2023.

[74] V. S. Chomal, M. J. K. Patel, M. I. A. Shah, and M. B. T. Solanki, "Ai-driven software requirements elicitation: A novel approach,"

[75] D. Gobov and I. Huchenko, "Requirement elicitation techniques for software projects in ukrainian it: An exploratory study," in *2020 15th Conference on Computer Science and Information Systems (FedCSIS)*, IEEE, 2020, pp. 673–681.

[76] K. Ahmad, M. Bano, M. Abdelrazek, C. Arora, and J. Grundy, "What's up with requirements engineering for artificial intelligence systems?" In *2021 IEEE 29th International Requirements Engineering Conference (RE)*, IEEE, 2021, pp. 1–12.

[77] I. Harris, "The role of artificial intelligence in software requirement engineering," *International Journal of Advanced Engineering Technologies and Innovations*, vol. 10, no. 2, pp. 586–602, 2024.

[78] C. Rohleder, I. Kusumah, C. Salinesi, and M. Meier, "Ai-based requirement elicitation for product innovation in data-driven marketing a case study,"

[79] P. Avesani, C. Bazzanella, A. Perini, A. Susi, *et al.*, "Supporting the requirements prioritization process. a machine learning approach.," in *SEKE*, 2004, pp. 306–311.

[80] K. Kaur and P. Kaur, "The application of ai techniques in requirements classification: A systematic mapping," *Artificial Intelligence Review*, vol. 57, no. 3, p. 57, 2024.

[81] S. Sharma and S. Pandey, "Integrating ai techniques in requirements elicitation," in *Proceedings of International Conference on Advancements in Computing & Management (ICACM)*, 2019.

[82] N. R. Darwish, A. A. Mohamed, and A. S. Abdelghany, "A hybrid machine learning model for selecting suitable requirements elicitation techniques," *International Journal of Computer Science and Information Security*, vol. 14, no. 6, pp. 1–12, 2016.

[83] H. A. Bilal, M. Ilyas, Q. Tariq, and M. Hummayun, "Requirements validation techniques: An empirical study," *International Journal of Computer Applications*, vol. 148, no. 14, 2016.

[84] F. Fabbrini, M. Fusani, S. Gnesi, and G. Lami, "An automatic quality evaluation for natural language requirements," in *Proceedings of the Seventh International Workshop on Requirements Engineering: Foundation for Software Quality REFSQ*, Citeseer, vol. 1, 2001, pp. 4–5.

[85] L. Myllyaho, M. Raatikainen, T. Männistö, T. Mikkonen, and J. K. Nurminen, "Systematic literature review of validation methods for ai systems," *Journal of Systems and Software*, vol. 181, p. 111 050, 2021.

[86] A. Abran and J. W. Moore, "Guide to the software engineering body of knowledge: Trial version: A project of the software engineering coordinating committee," *(No Title)*,

[87] M. Agarwal and S. Goel, "Expert system and it's requirement engineering process," in *International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014)*, IEEE, 2014, pp. 1–4.

[88] M. Rahmanpour, F. Mozaffar, and B. Morkos, "Nsf/asme design essay competition 2023,"

[89] E. Brynjolfsson, D. Li, and L. R. Raymond, "Generative ai at work," National Bureau of Economic Research, Tech. Rep., 2023.

[90] K.-B. Ooi *et al.*, "The potential of generative artificial intelligence across disciplines: Perspectives and future directions," *Journal of Computer Information Systems*, pp. 1–32, 2023.

[91] Z. Epstein *et al.*, "Art and the science of generative ai," *Science*, vol. 380, no. 6650, pp. 1110–1111, 2023.

[92] C. Gong *et al.*, "Generative ai for brain image computing and brain network computing: A review," *Frontiers in Neuroscience*, vol. 17, p. 1 203 104, 2023.

[93] L. Regenwetter, A. H. Nobari, and F. Ahmed, "Deep generative models in engineering design: A review," *Journal of Mechanical Design*, vol. 144, no. 7, p. 071 704, 2022.

[94] Y. Wang, N. B. Damen, T. Gale, V. Seo, and H. Shayani, "Inspired by ai? a novel generative ai system to assist conceptual automotive design," *arXiv preprint arXiv:2407.11991*, 2024.

[95] J. Taylor, V. El Ardeliya, and J. Wolfson, "Exploration of artificial intelligence in creative fields: Generative art, music, and design," *International Journal of Cyber and IT Service Management*, vol. 4, no. 1, pp. 39–45, 2024.

[96] C. Hyunjin, "A study on application of generative design system in manufacturing process," in *IOP Conference Series: Materials Science and Engineering*, IOP Publishing, vol. 727, 2020, p. 012 011.

[97] J. Z. Clay *et al.*, "Engineering design thinking in the age of generative artificial intelligence,"

[98] M. Chui, E. Hazan, R. Roberts, A. Singla, and K. Smaje, "The economic potential of generative ai," 2023.

[99] R. Nishant, M. Kennedy, and J. Corbett, "Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda," *International Journal of Information Management*, vol. 53, p. 102 104, 2020.

[100] N. Rane, "Chatgpt and similar generative artificial intelligence (ai) for smart industry: Role, challenges and opportunities for industry 4.0, industry 5.0 and society 5.0," *Challenges and Opportunities for Industry*, vol. 4, 2023.

[101] W. Xiang, K. Yu, F. Han, L. Fang, D. He, and Q.-L. Han, "Advanced manufacturing in industry 5.0: A survey of key enabling technologies and future trends," *IEEE Transactions on Industrial Informatics*, vol. 20, no. 2, pp. 1055–1068, 2023.

[102] S. Grabowska, S. Saniuk, and B. Gajdzik, "Industry 5.0: Improving humanization and sustainability of industry 4.0," *Scientometrics*, vol. 127, no. 6, pp. 3117–3144, 2022.

[103] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, "Industry 4.0 and industry 5.0—inception, conception and perception," *Journal of manufacturing systems*, vol. 61, pp. 530–535, 2021.

[104] B. Rathore, "Future of textile: Sustainable manufacturing & prediction via chatgpt," *Eduzone: International*, 2023.

[105] F. Fui-Hoon Nah, R. Zheng, J. Cai, K. Siau, and L. Chen, *Generative ai and chatgpt: Applications, challenges, and ai-human collaboration*, 2023.

[106] Y. K. Dwivedi *et al.*, "Metaverse marketing: How the metaverse will shape the future of consumer research and practice," *Psychology & Marketing*, vol. 40, no. 4, pp. 750–776, 2023.

[107] I. Goodfellow *et al.*, "Generative adversarial nets," *Advances in neural information processing systems*, vol. 27, 2014.

[108] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2019, pp. 4401–4410.

[109] D. P. Kingma, "Auto-encoding variational bayes," *arXiv preprint arXiv:1312.6114*, 2013.

[110] A. Vaswani, "Attention is all you need," *Advances in Neural Information Processing Systems*, 2017.

[111] J. D. Weisz, J. He, M. Muller, G. Hoefer, R. Miles, and W. Geyer, "Design principles for generative ai applications," in *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 2024, pp. 1–22.

[112] L. Banh and G. Strobel, "Generative artificial intelligence," *Electronic Markets*, vol. 33, no. 1, p. 63, 2023.

[113] P. Korzynski, G. Mazurek, P. Krzypkowska, and A. Kurasinski, "Artificial intelligence prompt engineering as a new digital competence: Analysis of generative ai technologies such as chatgpt," *Entrepreneurial Business and Economics Review*, vol. 11, no. 3, pp. 25–37, 2023.

[114] H. Du *et al.*, "The age of generative ai and ai-generated everything," *IEEE Network*, 2024.

[115] D. Baidoo-Anu and L. O. Ansah, "Education in the era of generative artificial intelligence (ai): Understanding the potential benefits of chatgpt in promoting teaching and learning," *Journal of AI*, vol. 7, no. 1, pp. 52–62, 2023.

[116] B. Ramdurai and P. Adhithya, "The impact, advancements and applications of generative ai," *International Journal of Computer Science and Engineering*, vol. 10, no. 6, pp. 1–8, 2023.

[117] S. S. Sengar, A. B. Hasan, S. Kumar, and F. Carroll, "Generative artificial intelligence: A systematic review and applications," *arXiv preprint arXiv:2405.11029*, 2024.

[118] L. Mescheder, A. Geiger, and S. Nowozin, "Which training methods for gans do actually converge?" In *International conference on machine learning*, PMLR, 2018, pp. 3481–3490.

[119] A. Radford, "Improving language understanding by generative pre-training," 2018.

[120] G. Zhu, V. Sudarshan, J. F. Kow, and Y. S. Ong, "Human-generative ai collaborative problem solving who leads and how students perceive the interactions," *arXiv preprint arXiv:2405.13048*, 2024.

[121] K. van den Bosch, T. Schoonderwoerd, R. Blankendaal, and M. Neerincx, "Six challenges for human-ai co-learning," in *Adaptive Instructional Systems: First International Conference, AIS 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings 21*, Springer, 2019, pp. 572–589.

[122] J. M. Leimeister, "Hybrid intelligence," *Business & Information Systems Engineering*, vol. 61, no. 5, pp. 637–643, 2019.

[123] L. Memmert and E. Bittner, "Complex problem solving through human-ai collaboration: Literature review on research contexts," 2022.

[124] N. Wang, S. Li, C. Wang, and L. Zhao, "Current status and emerging trends of generative artificial intelligence technology: A bibliometric analysis," *Journal of Internet Technology*, vol. 25, no. 3, pp. 477–485, 2024.

[125] B. Zeng, S. Yang, and X. Yin, "Robotic relocalization algorithm assisted by industrial internet of things and artificial intelligence," *Journal of Internet Technology*, vol. 21, no. 5, pp. 1517–1530, 2020.

[126] F. García-Peñalvo and A. Vázquez-Ingelmo, "What do we mean by genai? a systematic mapping of the evolution, trends, and techniques involved in generative ai," 2023.

[127] L. Fan, L. Li, Z. Ma, S. Lee, H. Yu, and L. Hemphill, "A bibliometric review of large language models research from 2017 to 2023," *arXiv preprint arXiv:2304.02020*, 2023.

[128] P. Gupta, B. Ding, C. Guan, and D. Ding, "Generative ai: A systematic review using topic modelling techniques," *Data and Information Management*, p. 100 066, 2024.

[129] C. Chen and B. Morkos, "Exploring topic modelling for generalising design requirements in complex design," *Journal of Engineering Design*, vol. 34, no. 11, pp. 922–940, 2023.

[130] C. Chen, C. Carroll, and B. Morkos, "From text to images: Linking system requirements to images using joint embedding," *Proceedings of the Design Society*, vol. 3, pp. 1985–1994, 2023.

[131] S. Wright, B. C. O'Brien, L. Nimmon, M. Law, and M. Mylopoulos, "Research design considerations," *Journal of graduate medical education*, vol. 8, no. 1, pp. 97–98, 2016.

[132] A. Teherani, T. Martimianakis, T. Stenfors-Hayes, A. Wadhwa, and L. Varpio, "Choosing a qualitative research approach," *Journal of graduate medical education*, vol. 7, no. 4, pp. 669–670, 2015.

[133] P. A. Glasow, "Fundamentals of survey research methodology," *Retrieved January*, vol. 18, p. 2013, 2005.

[134] H. Alshenqeeti, "Interviewing as a data collection method: A critical review," *English linguistics research*, vol. 3, no. 1, pp. 39–45, 2014.

[135] E. Paradis, B. O'Brien, L. Nimmon, G. Bandiera, and M. A. Martimianakis, "Design: Selection of data collection methods," *Journal of graduate medical education*, vol. 8, no. 2, pp. 263–264, 2016.

[136] K. Riach, "Exploring participant-centred reflexivity in the research interview," *Sociology*, vol. 43, no. 2, pp. 356–370, 2009.

[137] V. Sadan, "Data collection methods in quantitative research," *Indian Journal of Continuing Nursing Education*, vol. 18, no. 2, pp. 58–63, 2017.

[138] L. Smith *et al.*, "Industry's take on challenges in the agricultural post-harvesting industry," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers, vol. 87295, 2023, V002T02A038.

[139] B. Schuebert, D. Shah, J. Mullis, F. Mozaffar, and B. Morkos, "The impact of covid-19 on mass personalization supply chain networks–a qualitative inquiry," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers, vol. 87332, 2023, V005T05A010.

[140] A. Rahman, "An empirical study on the role of requirement engineering in agile method and its impact on quality," 2015.

[141] M. Host and P. Runeson, "Checklists for software engineering case study research," in *First international symposium on empirical software engineering and measurement (ESEM 2007)*, IEEE, 2007, pp. 479–481.

[142] R. E. Gallardo-Valencia and S. E. Sim, "Continuous and collaborative validation: A field study of requirements knowledge in agile," in *2009 Second International Workshop on Managing Requirements Knowledge*, IEEE, 2009, pp. 65–74.

[143] M. Borrego, E. P. Douglas, and C. T. Amelink, "Quantitative, qualitative, and mixed research methods in engineering education," *Journal of Engineering education*, vol. 98, no. 1, pp. 53–66, 2009.

[144] A. Joshi, S. Kale, S. Chandel, and D. K. Pal, "Likert scale: Explored and explained," *British journal of applied science & technology*, vol. 7, no. 4, pp. 396–403, 2015.