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Data Quality Challenges using Artificial Intelligence during Software Feature Prioritization for New Product Development

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ABSTRACT:

Artificial intelligence is increasingly used by organizations during software development for creating data-driven decisions. This supports prioritizing software features during new product development. Organizations use AI systems for analyzing large volumes of information, which depends on their ability to handle extensive data sets. This is also practised using technologies enabled with AI. The decision-making process becomes ineffective when organizations face data-related challenges due to low data quality.

The study examines how the data quality issues associated with using artificial intelligence are impacting the software feature-prioritization decision-making process during the new product development stage. The study focuses on existing research based on AI-supported data quality and decision-making process for prioritizing software features.

The research involves a qualitative methodology, following semi-structured interviews with ten professionals who have experience in AI-supported feature prioritization. The research used thematic analysis to study the data, which reveals patterns about decision-making and data quality problems. The findings indicate lower quality data, resulting in the use of AI-generated insights, leading to problems in decision-making for software feature prioritization outcomes, feature ranking, resource allocation and product schedules. The results indicate how AI systems function for decision-making, which involves human inputs.

The study demonstrates the effectiveness of AI-based decision-making as it is required in the organizations for maintaining higher data quality standards. The focus at organization level should be on having strong data governance and regulatory systems for serving strict guidelines and rules for the maintenance of data produced by AI used for feature prioritization.

KEYWORDS: Artificial Intelligence, Data Quality, Software Feature Prioritization, Decision-Making, New Product Development

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1. Introduction

1.1 Background

In organisations, decision-making has become crucial because there is a need to assess the information that provides evidence-based support for their strategic and operational decisions. Organizations can now analyze larger datasets for producing insights, which were difficult to establish previously through traditional and manual analysis methodologies, because machine learning, analytics, and natural language processing technologies have been advancing with AI-supported systems. Organizations can support multiple business areas by enhancing efficiencies for improving prioritization forecasting, and decision-making processes (Bader & Kaiser, 2019; Dwivedi et al., 2021).

The usefulness of AI has expanded in the software product development ecosystem as it is assisting with requirement analysis, customer feedback interpretation, software analytics, defect prediction, product planning activities and project planning as well. Organisations are using user reviews, behavioural logs, support tickets and market signals for determining their product priorities. Current trends show that product management practices have shifted away from intuition-based decision-making towards data-backed decision-making, which requires measurable evidence for supporting all the choices (Maalej et al., 2016; Ebert et al., 2019; McAfee & Brynjolfsson, 2012).

Feature selection represents one of the most critical areas in decision-making. Organizations continuously decide feature ranking improvements, bug fixes, and technical capabilities. New product development requires organisations to make product development-related decisions because the product development process involves high uncertainty, and historical data remains limited, but available resources face time constraints, budget and restrictions. With respect to engineering capacity through effective prioritization organizations can match customer requirements with business value and technical viability while decreasing waste and enhancing their product market position (Karlsson & Ryan, 1997; Berander & Andrews, 2005).

In the software feature prioritization process, the use of AI-generated information analyses customer feedback, patterns, groups together different requirements, performs forecasting, creates user needs and summarises. The value of AI-generated outputs depends on the data quality, which supports the system's previous studies. They demonstrate data quality dimensions. This includes accuracy, completeness, consistency, and timeliness for supporting dependable decision-making and analytical results (Wang & Strong, 1996; Pipino et al., 2002; Cai & Zhu, 2015).

While the AI systems produce inaccurate prioritization results and incorrect recommendations as they process data that contains misleading information, outdated data or inconsistent information, lacking contextual understanding. Organizations that work with software products will experience these implications because this will lead to the selection of incorrect features from their product line while failing to understand the criticality of their product requirements, which delays technical advancements, leading to the distortion of their resources. An AI-supported decision-making process has created a need to investigate how data quality problems impact the system performance during software feature prioritization in product development (Sculley et al., 2015; Sambasivan et al., 2021).

The thesis aims to investigate the quality of data generated by AI used in software feature prioritization and how organizations are using AI-generated data for their product development decisions.

1.2 Research Purpose

Artificial intelligence has become a common tool in the software product development process, creating fresh possibilities for organizations to enhance their decision-making process. Organizations now apply AI-generated data to evaluate customer feedback, recognise behavioural trends, and for forecasting predictions to establish their project priorities. Due to certain issues faced by the organization, the software feature process requires enhancements, and technical capabilities should be placed first because these developments impact their software feature prioritization work.

The study investigates how data quality problems influence artificial intelligence during software feature prioritization at early stages of new product development, which involves strategic prioritization decisions under high uncertainty.

Below are the objectives and main research questions

Main Research Question:

How does the quality of data associated with the use of artificial intelligence influence decision-making in software feature prioritization during the early stages of new product development?

Research Objectives:

1. To identify the key data quality challenges associated with the use of artificial intelligence in software feature prioritization.

2. To examine how data quality issues (such as biased, incomplete, or outdated data) influence decision-making in software feature prioritization.

3. To explore how product development teams interpret and use AI outputs when prioritizing software features during new product development.

The study aims to examine how information generated from AI tools is interpreted by professionals under specific conditions, focusing on the quality of data. Although past studies have focused on the benefits and capabilities coming from AI. This study collects qualitative data from semi-structured interviews as its only research method, while avoiding generalisation. The study aims to explain organisational practices of using AI-generated information for decision-making through empirical research.

1.3 Definition of key concepts

During this study, the key concepts represent an important part of the study. The thesis studies how data quality impacts the decision-making process for software feature prioritization for new product development. So this will help to understand the key concepts that guide the study. Theoretical definitions of the topic will help understand the subject better while creating a foundation that supports upcoming chapters.

The term artificial intelligence describes computer systems that create intelligent behaviour that matches human capabilities. The process involves learning from data, detecting patterns, making predictions, understanding language and supporting the decision-making process. Organizations have been using AI to improve the performance of automated systems and perform data analysis. The advanced AI systems can be seen as a decision-support tool as they produce insights and recommendation than replacing human involvement. As per the thesis, AI functions as a tool for organization used for analysing data generated from AI for feature prioritization and the evaluation process. (Dwivedi et al., 2021; Davenport & Ronanki, 2018).

AI adoption in software product development has risen because organizations gather user feedback, support ticket data, behaviour logs and market indicators, which serve as their data collection sources. The AI systems enable faster data processing of extensive data collection, which helps decision makers find hidden patterns that could not be visible through manual analysis. The effectiveness of AI systems operates directly through the availability of top-quality data, which functions as their system input. In the study, the major functions are both technology capability and decision support system, which rely on reliable information for their operational value (Maalej et al., 2016).

The determination of data quality occurs when assessment results determine whether the data meets its intended usage requirements. High-quality data needs to meet certain requirements, which include accuracy, consistency, timely delivery, completeness of relevant information and reliable performance. Data quality holds significant value as people are relying on data insights. The analysis results will become unreliable when the data contains old or missing information, which can give conflicting information (Wang & Strong, 1996).

Data quality remains important for AI systems as these systems rely on data for their input. Users will distrust predictions and recommendations that use poor-quality data for software feature prioritization. As this needs to be collected from various internal and external sources, which raises the possibility of major data problems, such as inconsistency and incompleteness. The thesis identifies the data quality as a critical factor that determines how effectively information is generated and can assist in decision-making processes (Pipino et al., 2002; Cai & Zhu, 2015).

The software feature prioritization process involves assessment of software features together with their enhancements, bug resolution and technical needs for determining their importance level. Organizations face restrictions with time, financial resources, and development capabilities, which prevent them from implementing all requested features at once. Organisations use prioritization for determining which features need immediate attention and which features can be executed later based on their priority (Karlsson & Ryan, 1997).

During the new product development stage, with regard to the process, organizations use for creating new products or implementing transformative changes for their existing product lines, the process involves certain fundamental stages, which include opportunity identification, creation of concepts, subsequent development of both design and testing, as well as product launch. The objective of new product development establishes customer value while enhancing the company's competitive strength in the market (Cooper, 2019).

1.4 Structure of the study

The thesis is distributed within 5 significant chapters in a manner that progresses logically from the initial research statements to the conclusions.

Chapter one shows research background, objectives, questions, concept definition and the structure overview of the thesis. The chapter describes how artificial intelligence has become a major decision-making tool while demonstrating that software feature prioritization during new product development requires higher-quality information for proper functioning.

The literature review appears in chapter two, which studies all the relevant academic research that focuses on the artificial intelligence decision-making process and its difficulties. Focusing on the methods for software feature prioritization as well as the process for new product development. The role of data quality shows the gaps in the research and the conceptual framework.

The research methodology used in the thesis appears in Chapter Three. The chapter provides information about research methods that include data gathering, participant selection, and data analysis through thematic analysis. Each chapter values research credibility through its assessment of the study based on reliability and trustworthiness.

For chapter four, the study reflects the results obtained through the interviews. The chapter introduces the main themes identified through the analysis and explains how participants experience data quality challenges using AI outputs for software feature prioritization during product development.

In chapter five, the study presents the results through discussion, practical experience, implications and study limitations for future research needs and study conclusion. The research findings demonstrate the connection to existing literature, while the study demonstrates their theoretical impacts through its final results about how data quality affects artificial intelligence during software feature prioritization in new product development.

2 Literature review

2.1 Overview of Artificial intelligence for decision-making

Organizations have increased their engagement with AI for the software development process, and the dependency on AI has increased significantly for decision-making within organizations. Certainly, growth in fields like data analytics and machine learning has enabled organizations to integrate with larger data sets to extract insights for making managerial decisions. Technologies that are integrating with AI are largely used to automate business processes and for analysing data that helps in getting insights, which supports decision-making at an organizational level (Davenport & Ronanki, 2018).

As larger organizations are turning towards analysing large-scale data, they are seemingly adapting to use patterns to come up with significant insights. With the help of machine learning and pattern detection techniques, organisations are able to interpret large-scale data using algorithms. This helps organizations to improve their decision-making capabilities using insights from data. (Davenport & Ronanki, 2018).

The growth of integrating algorithms among organizations has helped in decision-making with the help of algorithmic ecosystems. Hence, decision-making in an algorithmic way defines the computational values to help process information related to decisions at the workplace (Bader & Kaiser, 2019). With the help of machine learning, technologies are being developed, where the rise of the integration of algorithms within the workplace has significantly increased the decision-making processes. These integrations are helping organizations come up with recommendations and analyze data for making strategic and operational decisions. (Bader & Kaiser, 2019).

With the increase in AI systems, some suggested research reflects how helpful AI is for supporting decision-making rather than replacing humans. Although AI technologies provide insights that are analytical and some information that is predictive in nature, which eventually helps the managers during the evaluation and decision-making. In such a context, a collaboration between AI and humans can be seen, where AI helps with human decisions rather than replacing them (Dwivedi et al., 2021).

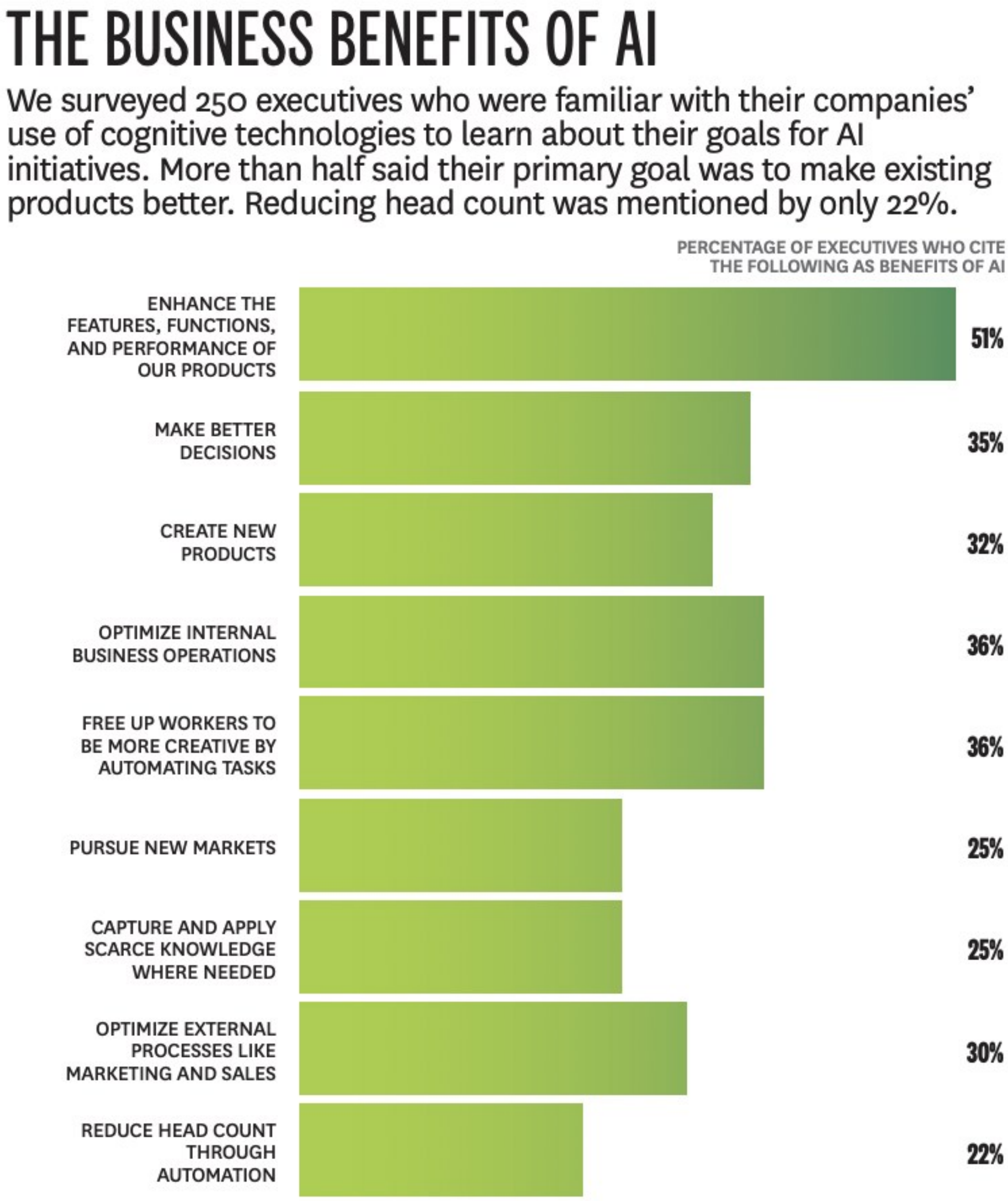

Figure 1. Business benefits of AI initiatives (Davenport & Ronanki, 2018).

2.1.1 Artificial intelligence in software product development decision-making

As part of software product development, there has been a significant increase in the integration of artificial intelligence within the products to help with the decision-making process. In many organizations, the engineering teams are moving towards a data-driven approach from an intuition-based one, especially in situations where the organization is dealing with large data volumes to prepare decisions aiming for product evolution, design, and requirements. Data-driven engineering requirements help the stakeholders to use the user feedback and software details to back decisions related to requirements during the development period (Maalej et al., 2016).

In requirements engineering, the feasibility of having data for decision-making enables prioritizing and identifying the required features at critical stages. Organizations can get insights through user-generated information, such as app reviews and logs; this data can help with requirement prioritization. For this situation, RE-SWOT enables the process of traditional engineering through user feedback and analysis of the competitors to help with requirement evaluation (Dalpiaz et al., 2019). Processes like these help to contribute to better decision-making in software ecosystems.

Since organizations operating on large-scale data have been acquiring insights from complex data, which has been possible with the advancements in fields like machine learning and artificial intelligence, including data science. These processes help the software development phases with better decision-making for pattern identification. One of the examples states how deep learning emerged as a massive way to produce prediction results for interpreting and analysing large-scale data (Zhang et al., 2018). The organization can predict and analyze the quality of software with data science-enabled methods, which also helps with the decision-making aspect. (Ebert et al., 2019).

The transformation of practices related to decision-making within software development due to big data has increased. Nowadays organizations are less dependent on experience, intuition, or any other factor; rather, they are relying on insights that are evidence-based. It's seen that organizations tend to improve their performance and aspects of strategic decisions with a data-driven decision-making approach. (McAfee & Brynjolfsson, 2012).

Human decision-making gets better with the involvement of AI, despite continuous advancement with AI technologies, although it cannot replace human involvement, it helps with improvements. Human interaction and contribution continue to remain vital for interpreting the data outputs and making decisions, especially in uncertain and complex environments. The research on AI with human involvement, it has shown how AI systems get better and more effective when they are made for human support rather than replacing humans. (Amershi et al., 2019)

To summarise, AI plays a vital role in decision-making and enhancing this process, which includes data-driven insights in software product development. This helps in improving strategic planning and refining requirement analysis for bettering it. With the integration of data-driven techniques and a mixture of AI, there is a shift in the software engineering ecosystem in decision-making.

2.2 Challenges and limitations of artificial intelligence in decision-making

Organizations deal with many limitations and challenges in the adoption of artificial intelligence for decision-making in software development. One of the major challenges remains the adoption of data-driven decisions, likely transforming and becoming challenging for organizations. The transformation for the adoption of data-driven processes by the organization can be difficult and require significant efforts and implementation by the decision-making process and leadership (McAfee & Brynjolfsson, 2012).

Secondly, a major limitation reflects the quality of managing the data across the organization. As AI systems operate on large data sets, this data is at times incomplete and unstructured. For software development, information collected via logs, reviews, and other feedback actually requires extensive refining for the data that are being processed before they can be used; hence, this increases the difficulty for decision-making (Maalej et al., 2016).

The constraints are present due to complexities in the technical aspect. In software engineering, data science techniques need advanced infrastructure and analytical tools. The integration of such techniques into the present development ecosystems can be challenging, especially for companies that lack expertise or resources in the related domain (Ebert et al., 2019).

In addition, the interpretation of data can be risky at times, considering outputs coming from data-driven architecture. These patterns used for identification can give misleading information when dealing with large datasets, especially when there is a failure in distinguishing between different correlations. These risky speculations can impact decision-making in a negative way, as the output coming from AI systems is not evaluated properly (McAfee & Brynjolfsson, 2012).

One of the major limitations is the shortage of professionals with the right skills. Expertise in domains like data science can help increase the effectiveness of AI systems, and organizations face challenges, while hiring process and gathering such talents, which in a way creates challenges in the right implementation of decision systems coming from AI (McAfee & Brynjolfsson, 2012).

Finally, it's not possible to replace human involvement in the decision-making process. Therefore, human involvement remains an essential fact for navigating through difficult situations and managing decisions and uncertainties, especially in unpredictable environments and dynamic spaces (Amershi et al., 2019).

2.3 Software Feature Prioritization in New Product Development

2.3.1 Overview and Traditional Approaches of Feature Prioritization

For new product development, software feature prioritization remains an essential phase. Especially at an early stage of product development, as it enables the success of the product. This refers to the process of ranking software components and performing evaluation, at the same time focusing on the requirements, which are based on the feasibility scale, and business value importance at a systematic level. Although there remain certain constraints, such as the development scale, time, and the budget values. During this scenario, organizations should focus on making strategic decisions to determine the priorities of the features to be implemented and have a roadmap. An effective process of prioritization sets up better alignment between the needs of the customer and the functionality of the product. Therefore, this results in a better product delivery that creates value and adds an advantage for remaining competitive (Karlsson & Ryan, 1997).

As part of the traditional process of building products, software feature prioritization has a reliance on approaches that are stakeholder-driven, where the decision-making process remains influenced by the customers, product managers, and developers. Many such techniques are being produced to support this ecosystem, which has focused on prioritization that is based on value and decision-support processes, like the analytic hierarchy process (AHP), helping in evaluating multiple criteria for features (Karlsson & Ryan, 1997). As in the current practice methods, which are MoSCoW specific, widely used for categorising features based on their importance and the parameter of urgency. (Wiegers, 1999). Therefore, these methods have a better decision-making process and enable organizations to have better implementation efforts and balance business.

Even though the use of the above-mentioned practices and methods has helped organizations as they are widely used, traditional approaches are somewhat limited due to their reliance on subjective judgment. Where decisions are based on biases caused by stakeholders, based on varied experiences and organizational politics. Therefore, these elements can cause inconsistencies and volatility in the feature prioritization. Furthermore, considering the changes in technologies over time cause complexity in software systems and their growth, it gets relatively difficult for the stakeholders to assess the impact and values of the features precisely, which results in an increased number of constraints. This also suggests the fact that although traditional processes do offer a very helpful base, they are not entirely sufficient for supporting decision-making for dynamically changing development environments and complex phases (Berander & Andrews, 2005).

Table 1. Decision type validation.

Decision Type	Situations in product development process	How AI can assist
Identifying opportunities	Customer needs not met	Can help analysing large scale data
Feature prioritization	Feature ranking process	Assess features and support with ranking features
Allocating resource	Budget and resource management	Forecasting workload based on feature information
Planning release	Feature launch timeline	Performing timeliness analysis using multiple factors
Risk assessment	Technical and market evaluation	Detecting anomalies for predicting risks
Customer segregation	New feature user selection	Identifying usage patterns
Post deployment enhancement	Improvement factor	Analysing metrics, reviews and signals

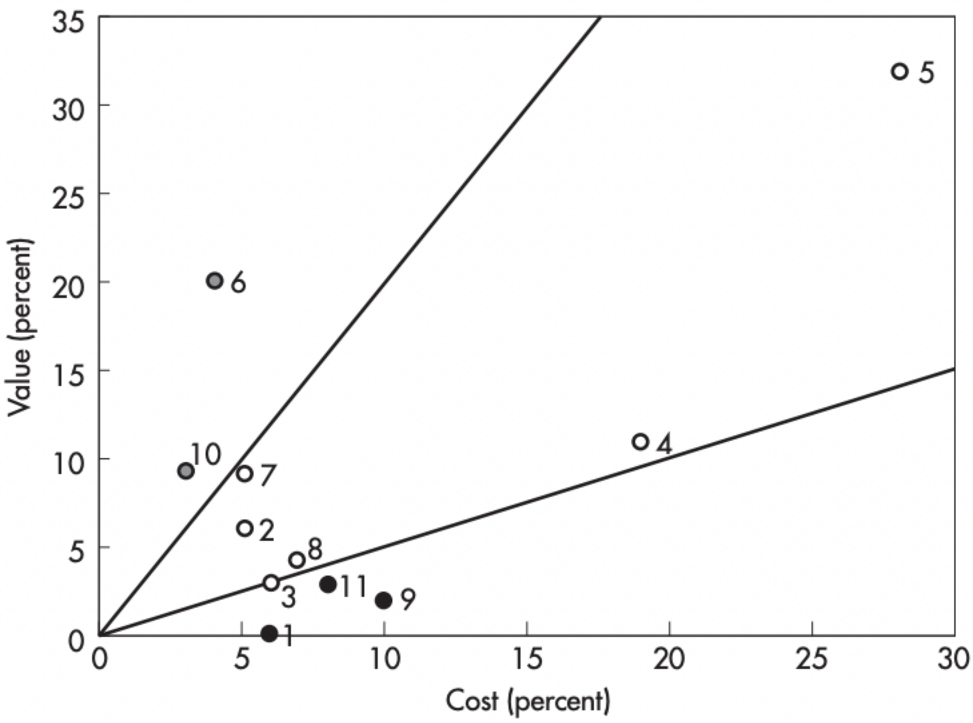

Figure 2. Cost–value diagram (Karlsson & Ryan, 1997).

2.3.2 Challenges and Evolution Toward Data-Driven Prioritization

There are many prioritization techniques currently. However, the software feature prioritization process remains challenging and a complex process. The major challenge is coming from the conflicts due to the stakeholder perspective based on their interests and choices. Additionally, this difference arises because different stakeholders practice different prioritization techniques, which are also based on their own calculations, evaluations, and perspectives. At an early stage of software product development, it's evident as there remains an uncertainty in the requirements as they are changing, which makes it difficult for accurately estimating the features and their impact considering their estimated value; therefore, all these components increase the complexity coming from decision-making (Racheva et al., 2010).

One of the major challenges that certainly intensifies these challenges is the resource constraints, because organizations should focus on continuously mapping the priorities under the right budget values and given time duration. The software development environment functions dynamically, requiring continuous assessments of priorities as many parameters keep evolving with time, such as technological components, customer needs, and market situations. All these factors overall reflect the limitations of experience-based and static practices of prioritization, thus emphasizing the adoption of evidence-based decision-making methods (Berander & Andrews, 2005).

Based on the abovementioned limitations, there has been a shift towards approaches based on data-driven aspects for feature prioritization. As organizations use various parameters for supporting their decision-making process, which involves information that comes from various sources, market analytics, user feedback, and logs. With the help of data-driven processes, the engineering team is able to help stakeholders to focus on decisions for prioritization based on empirical evidence instead of intuition. Therefore, this helps in enhancing transparency and improving objective aspects (Maalej et al., 2016). Additionally, it could be said that this shift signifies a transformation process in how prioritization decisions are managed within the product development cycle.

While the decision-making process is enhanced by data-driven approaches, they also come with challenges that are related to data interpretation and practices. The outcomes of these approaches are largely dependent on the quality and reliability of the data, as poor-quality data generates inconsistencies with respect to insights for making decisions related to prioritization. Thus, the increasing dependency on data shows how data quality can influence the decision-making process and how important it is to have an understanding of it for making the right choices. This also calls for the need for evaluation and examination of artificial intelligence systems, which are directly or indirectly involved in software feature prioritization, as discussed in the following.

2.4 Decision-making process for feature prioritization

Decision-making can be understood as an organised procedure which consists of multiple steps instead of viewing it as one distinct choice the organizational environment requires decision makers to follow systematic decision-making process which begins with problem recognition and ends with solution confirmation and structure decision-making helps organizations achieve better results because they increase understanding and uniformity while delivering better results to Messi situations with multiple decision factors and uncertain situations (Lunenburg, 2010; Nutt, 2008; Taherdoost & Madanchian, 2024). The perspective holds particular importance for software feature development because organizations must prioritise features by assessing various opportunities while their resources remain restricted for a specific time, budget and development capacity limits.

The multistep decision-making process model helps to explain how features should be prioritised, the decision-making process from existing literature shows connected steps. This starts with problem definition and ends with final decision validation. (Taherdoost & Madanchian, 2024).

The first process requires problem identification for identifying issues and opportunities. Several challenges are faced during this process, that involves usability issues and customer issues. The second stage requires analysis that focuses on identifying the practical conditions that any selected feature must meet, such as budget-related information, technical feasibility, planned release schedules, and available development resources. The third stage is about goal formation, which defines what the organization seeks to achieve through the prioritization process. Organizations commonly aim to enhance user experience, boost customer retention, facilitate revenue growth, decrease operational expenses and improve the strategic market position. The decisions are improved by setting goals and working with constraints (Lunenburg, 2010).

The next phase focuses on identifying the possible solutions as part of generating alternatives and structuring them into an organised solution framework. The process of generating alternatives includes creating a complete inventory of all the possible software features, repairing defects, and system integration workflow enhancements. Organization proceed to select evaluation criteria after they have completed the process of identifying the alternatives because they need to create standards for assessing their available choices. The most common evaluation criteria include customer value, strategic implementation of effort, urgency requirement, technical risk assessment and expected return on investment. After that, the organisations select their decision-making approach for evaluating different alternatives. A structured approach helps organisations, which they use for evaluating multiple criteria during this time (Saaty, 1988; Triantaphyllou, 2000)

The next steps focus on final testing of different options while establishing the ultimate priority choices. The initial phase of this process requires organizations to establish evaluation standards that they will use to compare competing product features. The typical assessment criteria range from customer value, implementation effort, urgent needs, technical risk and strategic management. The next step requires organizations to choose a decision-making tool by selecting the appropriate method that they will use for assessing their options. The decision context complexity determines which method organizations will choose from, from simple ranking methods and scoring models to multi-criteria approaches. The evaluation process begins when the team assesses various options by applying the established standards through the chosen assessment technique in a contemporary product development environment. Artificial intelligence assists through these phases for analysing customer feedback and predicting upcoming demands, and detecting customer behavioural patterns. The final step is validating, which requires decision makers to establish when their chosen priorities can remain achievable while staying in tune with business schools and their original objectives until they complete the implementation process (Taherdoost & Madanchian, 2024).

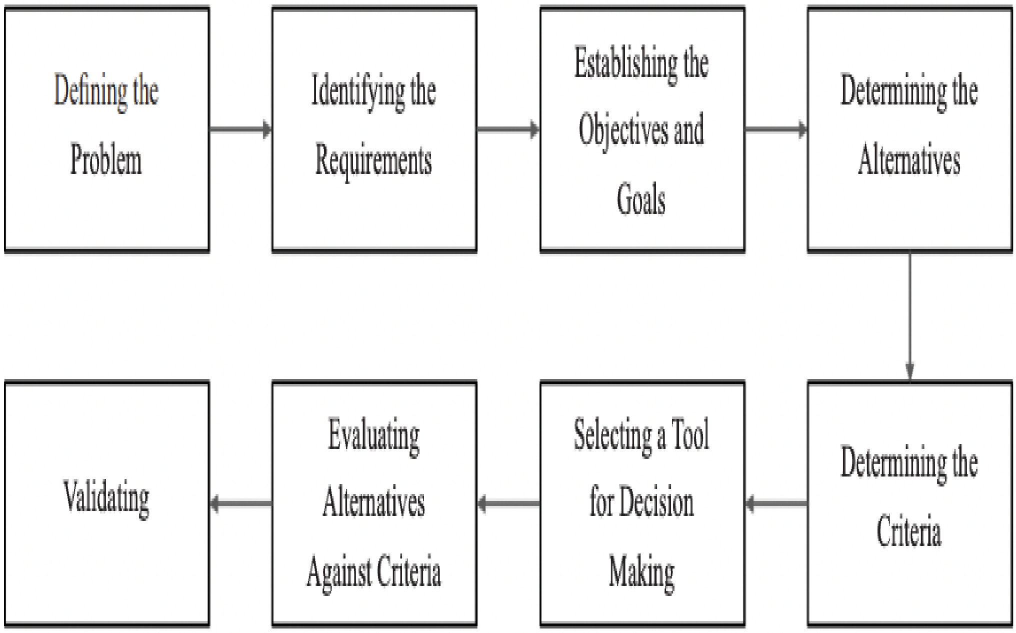

Figure 3. Decision-making process steps adapted from Taherdoost and Madanchian (2024).

2.5 Artificial Intelligence in Software Feature Prioritization

The software development processes have come across increasing complexity, with the transition of prioritizing features and methodologies as the major limitation. This has enabled organizations with the adoption of artificial intelligence in order to support the decision-making phases. As the research suggests in previous sections, decisions based on prioritization are likely to be influenced by stakeholder interests, uncertainty, and resource-related constraints. In addition to this, an important part of product innovation has been accomplished with the help of AI, especially in environments where sudden changes are taking place and based on the requirements of users (Verganti et al., 2020). In addition, with the help of systems that have integrated AI, organizations can now configure large sets of data and support from their insights, making it more structured and making decisions that are prioritized based on evidence (Raisch & Krakowski, 2021).

During software feature prioritization, the data sources are enhanced by using artificial intelligence techniques that align with the user feedback system, verifying logs and historical data used for the development process. These data-driven phases in software engineering focus on having a systematic way to analyze the data to help decision prioritization and evaluation of requirements. (Menzies & Zimmermann, 2013). Additionally, the empirical studies reflect the importance of software analysis in managing information from a large set of data in improving the product development methodologies and decision-making process (Buse & Zimmermann, 2012). Organizations following these approaches prefer intuition-based feature prioritization and decision-making based on a data-driven approach.

AI methodologies have integrated with natural language processing, complex software, and machine learning. Therefore, these integrations have improved the capabilities of organizations to draw information from complex data. While machine learning models are capable of identifying patterns among large data, at the same time, they enable predictions based on the insights for the impact of features and any important value. A valuable context is the predictive analysis, essential for helping with decision-making and evaluation among the alternatives for the engineering teams (Buse & Zimmermann, 2012). In addition to this, techniques such as sentiment analysis are also integrated into the user feedback, which enables companies to understand the user priorities and organize features (Zhang et al., 2018).

In terms of feature prioritization using AI technologies, act as a primary decision-making support parameter rather than having autonomous decisions. The research based on AI and human interaction reflects that systems that integrate with AI are beneficial when they value human judgment by generating insights, which enhances the quality of the decision being made (Amershi et al., 2019). Also, decision-making is based on algorithm studies, as the importance is mostly on insights generated by humans and interpreting the outcome to ensure the decisions remain in line with the goals of the companies

(Bader & Kaiser, 2019). Therefore, the integration of human-generated insights and AI remains essential for solving problems in complex environments.

With the mentioned advantages, software feature prioritization with the integration of AI possesses many challenges. One of the major bases of AI systems is reliance on data. As AI systems are dependent on the analysis and training of data, the data quality is directly dependent on the information generated. Additionally, challenges based on data-related issues or inconsistent data can lead to inaccuracy during the predictions, leading to inaccurate decision-making on prioritization. Therefore, the challenges coming from AI models make it harder for the stakeholders to move ahead with the outcomes produced by these systems, impacting the transparency.

Due to the increase in dependency on AI-generated approaches during software feature prioritization, it reflects the importance of data in the decision-making process. The companies are depending on insights that are generated with the help of AI, which indeed helps in maintaining the data reliability and quality and for effective prioritization and the outcomes based on them. This explains, quality of data is crucial but can be concerning, as it plays a critical role in software product development, driving decision-making methodologies. Therefore, it's important to assess the quality of data and the outcomes of AI-based information used for decision-making, as discussed.

2.6 Data Quality for AI-based decision-making

2.6.1 Overview of the concept of Data Quality

Data quality means how data meets its purpose by reflecting its significance during decision-making phases and any analytical activity. Data quality becomes an essential part as it remains a vital part of product development, because the software feature prioritization decision-making process relies on the data that is coming from the interaction of users and software feedback and behaviour. Lower-quality data can often show up with low-quality insights being generated, which results in inadequate user assessment needs and also leads to bad decision-making during prioritization (Pipino et al., 2002). The important parameters consist of timeliness, consistency, completeness and accuracy. These parameters impact the effectiveness of decision-making. As data accuracy indicates, how data is interpreted in real-world scenarios. The term completeness depicts the data availability for analysis. At the same time, consistency confirms the authenticity of the dataset for not having misleading information. Timeliness shows whether the data is relevant. These parameters are vital for the software feature prioritization phase, because access to correct information is an important key for making the right decision. (Cai & Zhu, 2015).

As the researchers have pointed out, the quality of data is multi-dimensional, that is developed requiring both contextual values and technical aspects, as the quality of data is assessed using a certain decision evaluation-based environment (Madnick et al., 2009). The stakeholder process has reliance over the data to be examined over requirements and reflecting on the priorities. Therefore, the software development process needs a multi-dimensional perspective.

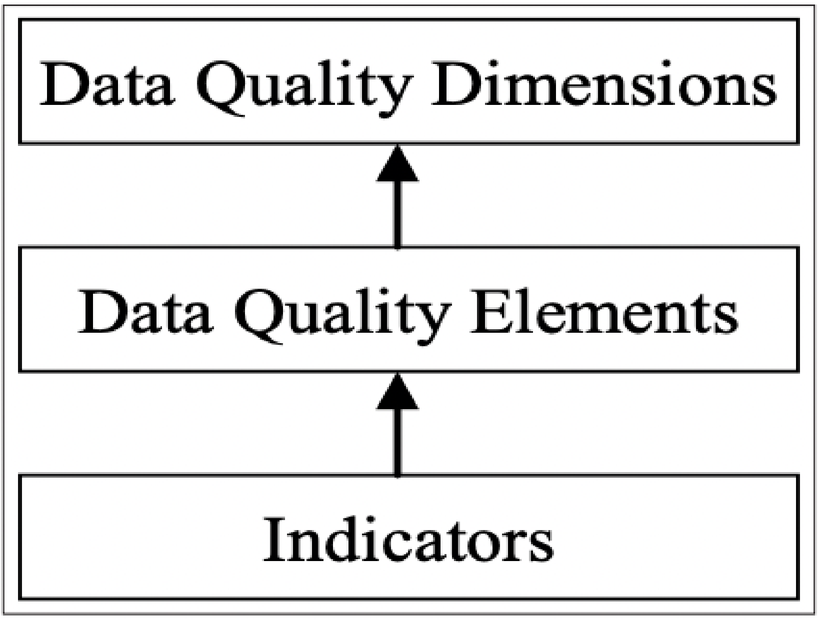

Figure 4. Data quality framework (Cai & Zhu, 2015).

2.6.2 Data Quality role in Artificial Intelligence Systems

Data challenges have arisen significantly due to the limitations based on algorithmic structure in the machine learning ecosystem. The studies portray that the AI systems are run closely with the quality of data and the data being used for training (Halevy et al., 2009). As data, the data is coming from many different sources e.g. analytical engines, logs and the same information is being utilised during software product development. Therefore, generating the right quality of data becomes challenging at different stages of product development.

The research based on AI determines that the improvement of the quality of data can bring improvements in the outcomes of these models, especially with predictive analytical systems for the decision-making process (Sambasivan et al., 2021). This also reflects the significance of the quality of data required during the feature prioritization phase.

2.6.3 Data Quality Challenges in Artificial Intelligence Systems

Maintenance of high data quality among the AI systems poses many challenges. Major issues are due to biased data, as the dataset does not map the current population, which leads to lower-quality outcomes and decisions that are not in support (Mehrabi et al., 2021). Data that tends to be biased can happen because of numerous reasons, such as due to data collection processes that are not adequately performed, sampling issues or any inequalities while mapping data. This can severely impact the decision coming from the AI system

One of the major problems remains with the missing information and incomplete ones as well. Considering the real-world situation, where certain information related to data is present, this can impact the performance of machine learning systems and training of data (Little & Rubin, 2019). The capabilities of AI systems are also impacted due to a missing dataset, which leads to problems related to prediction and outcomes for decision-making.

The inconsistency due to data quality poses several challenges, especially in situations where data is taken from multiple sources. It gets complex for AI systems to formulate information when the data has quality issues, inadequate values and unstructured information (Katal et al., 2013). In addition, the problem of data drifting can be caused by the distribution of information changes with time, which can lead to lower reliability of AI models when dealing with dynamic environments (Gama et al., 2014).

The highlighted challenges can create complexity while dealing with the quality of data being used by AI systems. Therefore, there is a need to emphasize on having structure data governance process and evaluation process to ensure data reliability and maintenance of data quality.

2.6.4 Impact of Data Quality on Decision-Making

The decision-making process is impacted due to the quality of information generated by AI systems. Data quality demonstrated the capabilities of organization for generating accurate information for supporting effective decision-making. At the same time, lower-quality data can result in inaccurate outcomes, inadequate conclusions impacting the outcomes of decision-making (Redman, 1998).

The use of lower-quality data can lead to many problems that are faced by the stakeholders, making them less reliant on insights generated from AI systems (O'Neil, 2016). Such a situation can impact the way AI adoption is taking place and lower the effectiveness with respect to the decision-making process. Additionally, for improving the decision-making process, it's important to accommodate a higher quality of data, at the same time leads to an increase in stakeholder confidence for relying on AI systems.

Therefore, the quality of data can be positioned as an important factor in the decision-making process, especially when it's generated with the help of AI systems. The companies are dependent on AI systems for operating complex processes for decision-making and emphasize on handing data quality problems. This context remains relevant with respect to software feature prioritization, at times when the decisions are dependent on insights generated by a data-driven process, which calls for the need to examine the quality of data with a focus on detail.

2.7 Research Gap

In the software development cycle, the integration of AI has created great products. However, due to the quality of data utilised for decision-making, especially with respect to new product development during software feature prioritization, there is a limited understanding. Existing researchers have been spending most of their time focusing on AI systems and the way data is forecasted and managed. The research shows how the AI systems have created decisions based on which feature is prioritized and the ranking of the features based on priority. The findings from the study show the impact of data quality on the decision-making process, but there have been limited studies on assessing the data quality, whether it's uncertain or partially available (Sculley et al., 2015).

The software feature prioritization process requires assessment of features from the decision makers for competing and having multiple evaluation criteria. This enables business values, customer requirements, technical possibilities and their implementation. The current process has received improvements through the implementation of AI-based solutions that utilize analysis of data. However, studies have focused on the usage of data instead of the evaluation of the actual assessment of data quality. Research demonstrated that the analytical results have been compromised, while some research uses lower-quality data, consisting of incomplete and inconsistent types. At the same time, these data remain biased, yet there exists a gap in how these data quality problems have been impacting the decision-making process during the software feature prioritization (Khoshgoftaar & Seliya, 2004).

A noticeable gap has been identified for new product development during software feature prioritization, which requires decision-making under conditions of extreme uncertainty. New product development during early stages needs to handle changing requirements as organization lacks historical data, while users and the market should evolve. Organization now use AI-supported systems for making better prioritization choices. The existing literature fails to examine how data quality restriction controls AI-supported decision-making processes that the organization use for prioritization at early stages of new product development. As the decisions predict the product development and resource management for business success (Cooper, 2019).

During software feature prioritization for new product development, it operates as a technical method built on requiring human decision-makers to interpret AI-based data. The AI system enabled the prioritization from the ability to analyze extensive data. At the same time, the decision-makers require the assessment of the system results in a real-world scenario. The current research reflects the importance of human and AI interaction, which has failed to investigate the processes that are required by decision-makers for assessing AI recommendations, while they doubt the precision and accuracy of the data. The research has also identified how the quality of data has problems from information generated by AI, as it impacts the feature prioritization during NPD for decision-making (Jarrahi, 2018).

The prior research reflects how AI-based data methods improve prioritization processes, but the researchers fail to investigate the negative impacts that come from incomplete information. Research has shown that poor data quality leads to incorrect insights, which cause organizations in the selection of incorrect features for their products, leading to wastage of time and resources. The existing research about organizations, existing in a restricted form because companies maintain their data quality problems as hidden when they conduct AI-based software feature prioritization during new product development.

The research gap requires resolution through studies that examine how data quality in artificial intelligence impacts the software feature prioritization process during new product development projects. The research gap requires analysis that identifies how data quality issues impact the prioritization processes, and how the decision-makers understand that the AI-generated information in environments where the data changes frequently during new product development. The study will help the field by demonstrating how data quality impacts AI decision support for software feature prioritization in new product development.

2.8 Conceptual Framework

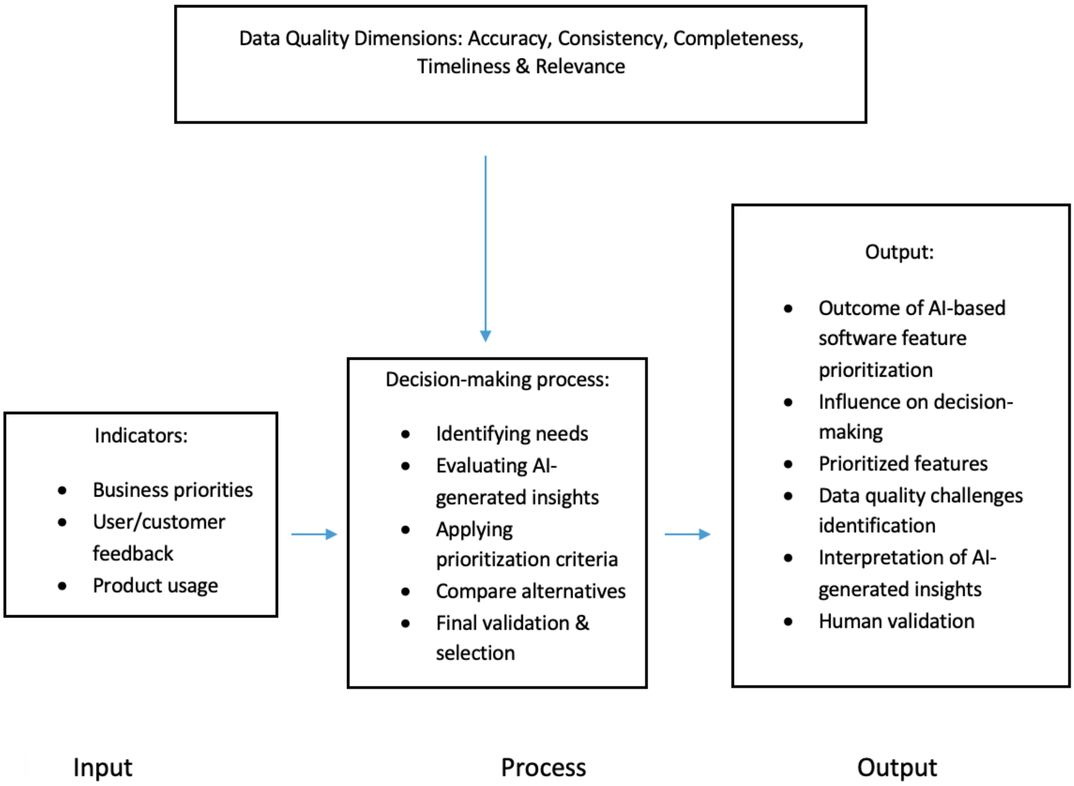

Figure 5. Conceptual framework structure for the study.

In the conceptual framework, the study aims to illustrate how decision-making using AI outputs is affected by data quality dimensions in software feature prioritization. The framework contains three stages, which are interconnected and include input processing and output, as shown in Figure 5.

As the input phase gathers essential business indicators together, forming the main sources for information that will guide the feature prioritization process. The inputs are effective when data quality dimensions achieve the right parameters as displayed in Figure 5, having accuracy, completeness, timeliness, consistency and relevance for checking the data reliability for analysis (Wang & Strong, 1996).

This process involves utilising artificial intelligence for processing data, helping in decision-making for complex feature prioritization phases (Davenport & Ronanki, 2018).

The framework shows the decision-making process involving a structured method starting with need identification, moving to assessing AI outputs, prioritization criteria, mapping and comparing alternatives, before proceeding to the final selection stages. This will highlight how AI can assist with analytical work, while keeping human intervention essential. The results show how humans are interpreting results that contribute to decision-making for software feature prioritization in new product development stages. The framework demonstrates how data quality dimensions impact decision-making processes, which results in different feature prioritization outcomes for AI-supported environments.

2.9 Summary of Literature Review

As per the details in the literature review, during decision-making in software product development for software feature prioritization, there is a higher dependency on data coming from artificial intelligence systems. There is a significant increase among companies depending on the insights provided by AI-generated systems. These datasets are also drawn from large information systems. At the same time, they are indeed helping with the decision-making process. Additionally, the quality of decision-making from these data sources depends on the quality of data, which has a significant influence on making reliable decisions during new product development.

The findings illustrate that, during early stages of new product development for the process of software feature prioritization, it remains a critical phase as the decision-making process is dependent on the data quality and needs the involvement of stakeholders. Additionally, there can be resource-related constraints and uncertain situations that influence the decision-making phase. Although the adoption of data-driven methodologies supporting AI has given noticeable improvement during the software feature prioritization process. However, uncertainty arises due to the quality of data, that are inconsistent and biased. This can end up giving unreliable output for the data coming from AI systems. Therefore, the above-mentioned scenarios can impact the outcomes of the decision-making process and the overall software development process.

With the increasing number of companies integrating artificial intelligence for their software development process, the details from the literature reflect limited information on the quality of data coming from AI outputs used during new product development, and how they are impacting decision-making, especially for the software feature prioritization process. This proves the existing gap and how crucial it is to examine the quality of data coming from AI. These data are used for decision-making, especially for software feature prioritization as it is one of the critical phases of the software development process and holds a greater importance for long-term reliance on running a stable product. Therefore, it’s evident there is a strong need to study these gaps.

3 Methods

3.1 Research Approach

The study follows qualitative research for examining how artificial intelligence and the quality of data have been impacting the decision-making processes during the software feature selection. In the initial phases of product development, qualitative research methods help to discover the ways people behave and tend to make their decisions, purely based on their interpretation and understanding of organisational situations coming from their experiences. The current study investigates how the experts are assessing the insights generated from AI systems. Although qualitative research methodology allows for exploring AI outputs by analysing the process (Creswell & Creswell, 2018; Saunders et al., 2019).

AI has become an important tool for decision-making as well as for processing large volumes of data and establishing project-related priorities. Although AI can certainly improve the efficiency and operational speed of the companies, the value depends on the type of foundational data due to inaccurate, incomplete or biased data, as their outcome results in issues, leading to poor management choices. The previous studies have reflected that technical skills and strong data foundations involving human judgment are necessary for achieving successful AI implementation. (Davenport & Ronanki, 2018; Dwivedi et al., 2021).

In the software feature prioritization process, examining data quality plays a vital role in making decisions that impact resource distribution, customer value creation, market situations, product capabilities, and new product development. Prioritization needs decision-making based on multiple factors, which include product development feasibility, user demands, cost and the requirements for product development organizations that are dependent on AI-generated recommendations that are usually generated from lower-quality data. Most of the difficulties appear while trying to prioritise the customer requirement decisions, related results depend on a few essential data qualities that include data such as complete data, timely data delivery and relevant information (Wang & Strong, 1996; DeLone & McLean, 2003).

The study followed an exploratory qualitative approach for achieving objectives. The focus will be on using exploratory research while studying a phenomenon that has not been fully understood, and existing research fails to document all the practical experiences. The existing literature on artificial intelligence adoption has rapidly increased, but the study focuses on how practitioners deal with data quality issues, with AI-based software feature prioritization for new product development being less frequent. Therefore, the study investigates the issues and practical solutions related to decision-making methods through its exploratory design by focusing on gathering information from professionals who have extensive experience in this field (Saunders et al., 2019; Myers, 2020).

The aim is to evaluate the social interaction among people and their own understanding of the things that are established by organisational reality and what people tend to observe. The thesis aims to present different meanings for the terms such as "trustworthy AI", "high quality data", and "useful recommendation" according to participant's background and their previous work experience, as well as their specific company environment, ranging from professionals to evaluate AI outputs through their specific job responsibilities and their decisions. The orientation of the study helps the researchers to investigate various perspectives for software feature prioritization, instead of accepting one universal understanding of the technology (Bryman & Bell, 2015).

A semi-structured interview process has been followed because the data collection approach gives a combination of structured elements and flexible elements. The research objectives establish predefined themes with respect to alignment for open-ended questions that enable the participants to elaborate on their practical experiences and specific concerns by providing detailed explanations. A set of standardised questionnaires is planned for documenting specific knowledge that people provide because they offer a general view of emerging technologies. The interview method helps to investigate hidden knowledge, decision-making methods and the actual practices that the organisations use for implementing AI during the product development process (Kvale & Brinkmann, 2015; King et al., 2019).

Following a qualitative research methodology, this study aims to achieve its research goals. The research provides a detailed analysis of how professionals evaluate and assess the quality of data and their ways of interpreting AI results, as well as the impact on software feature prioritization for new product development. The research presents context-specific knowledge while emphasising experiences coming from relevant people who exist in the development field that also combines technical systems and human judgement.

3.2 Data Collection and Sample

3.2.1 Data Collection

The collection of data involved empirical data through semi-structured interviews with professionals who were a part of the software product development and software feature prioritization process. Semi-structured interviews were chosen because they enabled the study to be theme-specific while allowing participants to share their personal experiences and professional views on decision-making with respect to software feature prioritization and the culture of the company. The research method allows a detailed investigation of both organizational decision-making process and the implementation of technology procedures based on their practices (Kvale & Brinkmann, 2015; Saunders et al., 2019).

The process for the interview involved a comprehensive interview guide, which was created from the research objectives and focused on research questions. The identified themes from the literature review helped in focusing on the study. The main areas included artificial intelligence applications, data quality problems and the process for selecting features during the software feature prioritization process. The research has used 12 interview questions during interview discussions, while the complete interview guide can be found in Appendix 1. The interviews were conducted online, which were individual interviews that lasted between 30 and 60 minutes each. The study required participants, and for each interview, their consent was taken. The research documented the responses of each participant’s with their permission, and the transcription for each interview was taken into consideration for systematic analysis.

The research has considered purposive sampling for selecting participants who had specific expertise and experience in making decisions for product development, and focusing on priorities. The qualitative study has used purposive sampling for selecting respondents who had the expertise to provide detailed information related to the studied phenomenon (Patton, 2015). The contacted participants for the research were gathered based on professional connections and contacts in the software industry, focusing on the software development process. The study sample has included 10 professionals who have worked both in product and service-based organisations with relevant experience using AI.

Table 2. Participants overview.

Interview	Interviewee code	Experience (Years)	Organization Type(Product/ Service/Both)	AI usage	Decision Involvement (Primary Decision Maker/Contributes to Decisions)
1	P1	8	Both	Yes	Both
2	P2	15	Both	Yes	Both
3	P3	8	Both	Yes	Both
4	P4	6	Product	Yes	Primary
5	P5	6	Product	Yes	Contributes to decisions
6	P6	7	Both	Yes	Primary Decision Maker
7	P7	9	Both	Yes	Both
8	P8	10	Product	Yes	Both
9	P9	12	Product	Yes	Both
10	P10	11	Product	Yes	Primary Decision Maker

For the research, a specific group of participants were selected because of the professional experience that would enable them to deliver valuable insights and information about the AI-based software prioritization process and describe more about data quality issues from their perspective. The collection of data included common themes emerging from the interview process, which provided the right information for the research work. The qualitative research requires an adequate sample for evaluation of its relevance and richness, as well as assessing information (Creswell & Creswell, 2018; Guest et al., 2020; Braun & Clarke, 2021).

3.3 Data Analysis

The research was followed using thematic analysis to examine the data collected from the interviews. Thematic analysis is a qualitative method used for identifying, analysing, and interpreting patterns of meaning from a set of information (Braun & Clarke, 2006). The study required this method as its purpose was to determine and investigate how AI-generated information faces quality challenges and impacts the decision-making process for software feature prioritization during new product development. Thematic analysis helped in studying the participant's experiences and their decision-making choices, as the study used semi-structured interviews and a comprehensive set of questionnaires.

With the help of Braun and Clarke's six-phase process, which included 6 steps that started with data familiarisation and ended with the creation of a report (Braun & Clarke, 2006; Braun & Clarke, 2022). The conducted analysis was done manually without using any analytical software tool for qualitative data analysis. The research conducted involved transcript reading, highlighting, coding, comparing and grouping activities and themes. The manual method was chosen for examining the interview transcripts while studying each participant's answers.

The analysis process has followed the research objectives and conceptual framework directed towards three main areas of investigation: data quality problems, the impact of low-quality data on making decisions for software feature prioritization and the methods used by the teams to use and understand the AI outputs. From the analysis, the aim is to identify patterns from interview data. The coding process was guided by research objectives, keeping it flexible for analysing data and insights. The responses from the participants revealed stronger themes for human validation and domain expertise, as well as contextual governance. The research analysis uses a flexible approach using thematic analysis to maintain its alignment with the purpose of the research, while maintaining a flexible interpretation from the participants during the interview.

The study has applied coding during the extraction of information and to analyze the recorded data, which included actual statements made by the participants involved in the interview process. The initial codes contain references for incomplete data, outdated information context, as well as misleading software feature prioritization, at the same time, recommendations for adding human checks for assessing the raw data coming from AI. The research has combined similar codes into broader themes. The research has classified data-related codes with respect to data quality challenges, while codes about ranking and false urgency, as well as resource constraints and road map distortion where classified under the impact of poor quality of inputs.

The final version interpreted from themes by interviewing the participants produces the following results : (1) Insights generated from AI are being impacted due to data quality challenges (2) Software feature prioritization decision-making process is influenced by lower-quality AI inputs,(3) Information generated from AI tools used as decision support, (4) Interpreting AI-generated information for software feature prioritization requires human involvement and domain knowledge. (5) AI-based software feature prioritization is shaped by contextual and governance conditioning. These themes establish the structure and the research for presenting the final results.

The document presents an analysis of all the transcript extracts and the initial codes and candidate themes, as well as reviewing notes and final theme definition, which provides trustworthy and transparent information. The research looks at direct transcript lines during the process of coding and how they are linked to the research objectives by reviewing the candidate themes through the complete analysis based on the dataset. The practices help to establish credibility and trustworthiness using thematic analysis (Nowell et al., 2017).

The information displayed in Table 3 shows the analysis process of interpreting and transforming interview data into codes, categories and final themes. The structure reflects how participant’s responses are mapped with the identified themes for establishing a direct link between the findings and data. Thematic analysis shows the reliability and credibility of this approach.

Table 3. Data structure for thematic analysis.

Quotes based on data	Codes	Category	Themes
“The data is never complete.” (P2)	Incomplete data	Data-quality	Insights generated from AI are being impacted due to data quality challenges
“AI may only see partial or sanitised information…” (P6)	Partial Data	Data-quality	Insights generated from AI are being impacted due to data quality challenges
“data quality problems can lead to incorrect or misleading prioritization decisions” (P4)	Misleading prioritization	Decision impact	Software feature prioritization decision-making process is influenced by lower-quality AI inputs
“AI helps us summarise the information and group similar themes faster” (P10)	AI summarization	AI usage pattern	Information generated from AI tools used as decision support
“final prioritization is usually done by product managers after validation” (P4)	Human decision	Decision control	Interpreting AI-generated information for software feature prioritization requires human involvement and domain knowledge
“the output still needs to be checked against business direction, threat sensitivity, customer	Human Interpretation	Decision control	Interpreting AI-generated information for software feature prioritization requires human

commitments and platform constraints" (P8)			involvement and domain knowledge
If AI insight cannot be traced back… it should not influence prioritization" (P6)	Traceability	Governance Control	AI-based software feature prioritization is shaped by contextual and governance conditioning
"final choices must remain with accountable stakeholders" (P8)	Accountability	Governance Control	AI-based software feature prioritization is shaped by contextual and governance conditioning

Figure 6 shows the collective research process followed during the study from the initial phase of methodology, data collection, interpreting the interviews using transcription, thematic analysis, theme generation and final results.

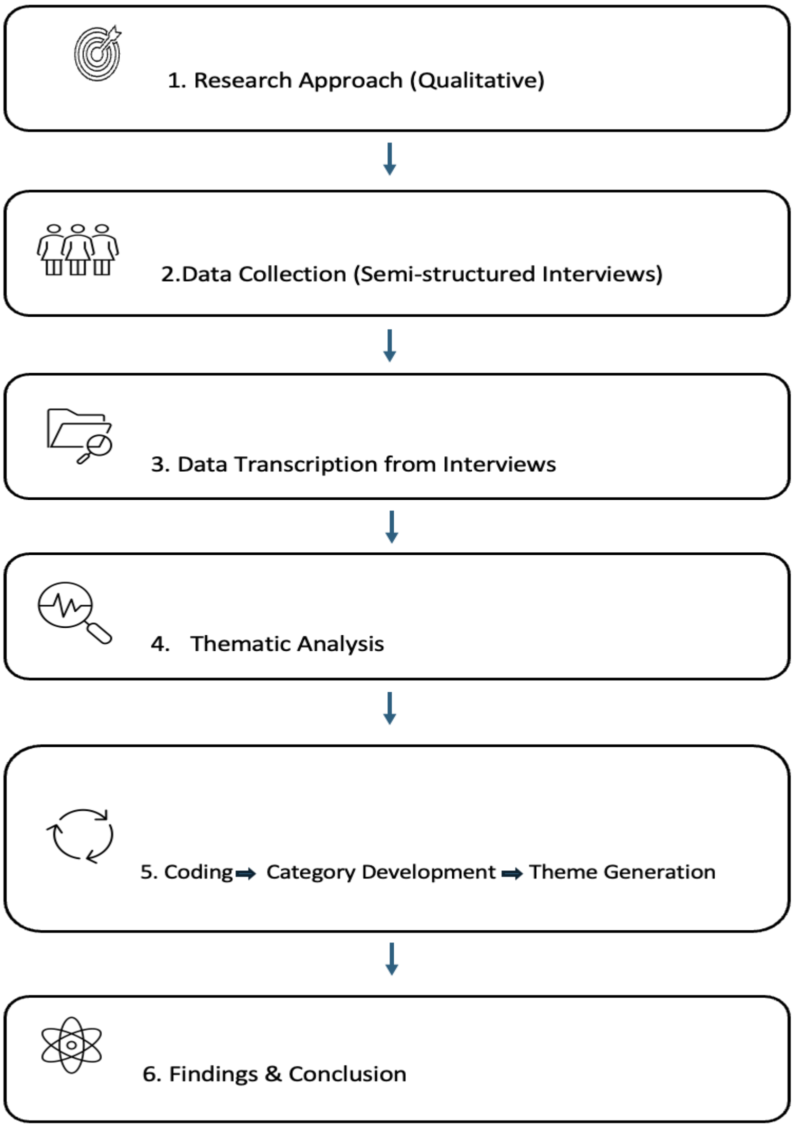

Figure 6. Research process.

3.4 Reliability and trustworthiness

The outcome of the research demonstrates assessing research reliability through the trustworthiness assessment instead of statistical measurement methods. Lincoln and Guba (1985) have proposed essential criteria which should be used in the research for evaluation of qualitative research, such as dependability, credibility, transferability and confirmability. The research used these criteria for achieving research transparency and maintaining better process control through rigorous research methods.

In the research credibility refers to the ability to demonstrate views of participants involved in the interview process and their believability the study was able to achieve credibility through semi structured interviews which helped participants in delivering detailed information and their experiences with AI-generated insights and data quality during software feature prioritization the interview questions where designed for meeting research objectives for maintaining consistent core themes throughout the process the analysis process used the exact extracts from the transcripts during the coding process for maintaining the authenticity of participants original language thematic analysis needs specific elements because research credibility exists through established links between coding and data for theme development (Nowell et al., 2017).

The research findings have focused on transferability that enables their application to the related study settings. The qualitative nature of this study prohibits statistical generalization as its research goals focus on analytical and contextual understanding (Saunders et al., 2019). The demonstrated participant's data, based on professional background and organisation type, as well as AI experience, contributing to the decision-making role, enhances the transferability of the study results. This allows the readers to decide whether the research results apply to software product development and AI-based software feature prioritization in similar situations.

The research work requires dependable research throughout. The study establishes its dependable results following continuous research documentation, which was maintained during the analysis process. The document contained transcript extracts together with initial codes and candidate themes, as well as review notes. The analysis proceeded through Braun and Clarke’s thematic analysis process, which included six phases. The research documented the whole transition from participant statements to codes and themes. The research process achieves systematic traceability by using this method.

The study has involved extracts from the interview sessions with transparent coding and theme development for aligning with research objectives, and the final themes were tested against the complete data set. The study practices the establishment of credibility, transferability and dependability for qualitative thematic analysis (Lincoln & Guba, 1985; Nowell et al., 2017; Saunders et al., 2019).

4 Key Findings

The details in the following chapter display the findings segregated from interview data using thematic analysis. The findings have used the conceptual framework as established in section 2.8. This makes the base of the following results, which present research outcomes through a structured theory-based presentation. The essential components of the framework appear in the themes, which include data quality, AI-supported information, dimensions, decision-making, human validation, interpretation, governance factors and related information that determine decision outcomes. The study establishes a relationship between the theoretical framework through its study and empirical findings.

4.1 Insights generated from AI are being impacted due to data quality challenges

This thematic element reflects the initial phase of the conceptual framework, which determines the conceptual framework that examines the data for quality dimensions that include timeliness, contextual relevance, completeness and consistency. The study showcases the challenges of data quality issues and how it influences software feature prioritization for AI-generated information.

The theme demonstrates that the accuracy of information generated from AI depends on the quality of the input data. From the interviews, with respect to the participants, incomplete data, missing context, outdated information, inconsistent data, fragmented information and even the presence of hallucinated output. The key challenges to the reliability of AI outputs used for software feature prioritization were impacted by these problems.

Due to limited data, tasks remained unfulfilled because of incomplete data and the related restrictions participants involved during the interview process elaborated that

AI tools often do not receive the full information needed for understanding a product issue or feature-related information.

Participant P2 stated, "The data is never complete."

Participant P7 stated, "The data is not fully available."

Participant P5 stated, "Data and AI-generated insights do not provide the complete context when the underlying data is incomplete or outdated."

As per information received from the participants, the results demonstrate AI outputs present partial information about the actual user experience and product, due to incomplete data results in output that appears useful but fails to represent the complete situation behind the feature. It was also reflected that the outdated information becomes a major obstacle to their work. Participants clearly explained that historical or old data may not reflect the current product infrastructure or regulatory situation as per customer needs.

According to Participant P1, "If we completely rely on historical data that does not reflect the current infrastructure or scale, the insights may not be useful."

According to Participant P4, "We also received outdated information from AI."

According to Participant P8, "A pattern that appeared important a few months ago may no longer reflect current customer risk."

As per information from the participants, they indicated that AI-generated information becomes outdated during the situation, underlying data becomes outdated. This is critical for software feature prioritization as user behaviour and system conditions also product goals with respect to customer needs undergo rapid changes.

Another critical piece of information encountered was missing background information. Participants observed that AI tools tend to produce results that lack understanding of the complete business scenario, technical detailing and regulatory information as per user needs.

Participant P2 stated, " Most of the time, AI does not provide enough context."

Participant P6 stated, " One major issue is that the information available to AI may not include the full regulatory context behind a feature request."

Participant P10 stated, " If that background is missing, the AI output may appear logical but still miss the underlying cause."

The study also reflects that AI-generated information can create logical results, which lack critical background information. Participants considered context to be necessary for correctly understanding results generated from AI.

It was also indicated that the AI outputs were disrupted by people providing information that was delivered irregularly and inconsistently. Some participants explained that there were times when data was not aligned across the tools, teams, or among the systems.

According to Participant P3, "There have been moments when the data was inconsistent."

Participant P7 stated, "Numbers from different tools, such as analytics and CRM systems, do not align."

Participant P8 stated, "Relevant information often exists in fragments."

These statements reflect that trust in AI-generated information decreases when information exists in multiple platforms and systems or comes from different sources that present opposing information or can be conflicting.

The participants also described the situation in which people are given an uneven representation of information. Certain signals reflected strongly in the data due to their visibility, not because they tend to be essential.

Participant P8 said, "Some signals get more visibility simply because they are louder."

Participant P10 stated, "Smaller schools, individual learners, or less vocal users may have important problems, but these may not appear strongly in the available information."

AI outputs tend to show more visible problems, which people often report, rather than showing the crucial user requirements that users keep to themselves

Finally, the participants talked about hallucinated outputs generated from AI as well as incorrect information persisting in the AI-generated outputs. The participants demonstrated that they did not consider the AI outputs to be trustworthy without a certain level of verification.

4.2 Software feature prioritization decision-making process is influenced by lower-quality AI inputs.

This theme focuses on demonstrating how decision-making elements with respect to the conceptual framework, and how AI-generated information impacts outcomes of software feature prioritization. The study proves the accuracy of the decision-making and the effectiveness of the quality of insights generated from AI tools that involve inaccurate or inconsistent data.

With respect to the second theme, which demonstrates how lower-quality information generated from AI influences the decisions for software feature prioritization. Whereas the first theme described the different data quality challenges that exist, this theme explains how these challenges impact the process of software feature prioritization. The participants also described how teams tend to make incorrect decisions while selecting features for the development process and incorrectly assessing the importance of tasks, and at times misuse development resources and create product development problems when they rely on insights generated from AI, which can also be because data is incomplete, weak or may be misleading.

> *Participant P1 stated, "Sometimes situations can be misleading prioritization due to incomplete data."*
>
> *Similarly, Participant P4 stated:*
>
> *"Data quality problems can lead to incorrect or misleading prioritization decisions"*

From the statements, it can be seen how the initial prioritization process can be disrupted due to lower-quality AI inputs because they can make certain features seem more crucial and urgent than their actual importance. The problem exists because both AI-generated outputs and the data quality used for generating the output need to be of value.

The participants elaborated on the inputs to be of poor quality, which may lead teams to rely on wrong features, as *P5 indicates:*

> *"The team may end up focusing on the wrong issue or misjudging the urgency of a feature."*

P3 also connected poor data quality with the risk of selecting features that users may not actually need:

> *"Choosing features that customers do not actually want"*

The study demonstrates that the use of poor-quality information generated from AI impacts the decision-making process. Decision makers will focus on different metrics instead of the actual user requirements. The software feature prioritization process becomes difficult as teams will waste time and resources on features that AI-generated outputs mark as important, but also which do not provide any real value to customers or products, as this can be risky.

Another outcome of research, which showed that participants had trouble determining the ranking of the features because they lacked proper assessment criteria. The participants demonstrated that their evaluation of the features during the prioritization process changed when they encountered low-quality or incorrect evidence coming from AI.

> *According to Participant P7, "A feature may be ranked higher or lower based on signals that are not fully reliable."*

P10 raised a similar concern in relation to visible but potentially misleading feature needs:

> *"The recommendation may push us toward building more teacher dashboard features, while on the student side may show difficulties that are hidden."*

The given information highlighted reflects how lower-quality AI information can influence the software prioritization process by making some features more needy due to their visibility, while lowering the visibility of other features. Due to this, the software feature prioritization ranking process can get unbalanced, and teams may fail to understand or detect this problem.

The participants also pointed out risks based on false information. P8 reflected how weak information can manipulate recommendations, which can lead to inaccurate information

> *Participant P8 observed, "Weak inputs can produce highly polished but misleading recommendations.*"

The same participant also noted:

> *"A capability may appear more urgent than it actually is across the broader user base.* (P8)"

The recommendations generated from AI show a structured appearance, yet can be misleading and unreliable, as they might be presenting false information. Teams that are quickly trusting the AI-generated information will choose to work on features on which the AI outputs present as an urgent need, but which actually lack priority for the overall user base, this might impact prioritising the features.

Also, the lower-quality of information generated from AI can lead to wastage of development activities as well as resource-related issues. As per P3:

> *"Poor data quality can lead to wasted development resources."*

P10 made a similar point:

> *"The team may spend engineering effort on features that appear useful on paper, but do not improve learning outcomes."*

Based on the evidence from the extracts, it demonstrates how AI-generated information related to prioritization can lead to major problems for the engineering teams related to improper usage, which can be that the teams may use resources for building features that do not address real-time issues, which occurs because software feature decisions depend on flawed or deceptive information generated from AI.

The participants were able to establish a connection between the inputs and the negative outcomes due to lower-quality information, which can lead to engineering road map changes and project work delays. P5 has indicated weaker insights and road map planning delays.

> *As per Participant P5, "Poor data quality can affect the road map planning, release focus and, in some cases, customer satisfaction."*

P10 described how important technical work may be delayed:

> *"We may delay important technical work such as improving assessment reliability, content delivery speed, mobile performance, classroom session stability, and accessibility improvements."*

The research shows that strategic priorities can be impacted due to the quality of AI input data used in this process. The impacts of these issues extend beyond feature prioritization as it impacts road map development, technical priority settings, release and user experience.

The overall information related to the theme demonstrates how software feature prioritization gets affected by lower-quality AI-generated inputs because these inputs create misleading priorities that lead to incorrect feature ranking, false urgency, wasting resources and disrupting the development road map. Participants also described AI outputs as being neither neutral nor fully trustworthy. The study has discovered that organisations receive more benefits from AI-supported prioritization when they use strong input data, which enables their decision-making choices, as the use of lower-quality AI input during the feature prioritization process results in the team moving away from product goals, technical priorities and actual user needs.

AI-based decision-making involving human intervention presents ultimate choices on output results, which artificial intelligence systems provide for deciding on product-related requirements. The system helps users by providing file functions that include trend identification, summarisation, demand forecasting, feedback clustering, and finding alternative recommendations. People with contextual knowledge and professional judgment abilities hold the decision-making power (Amershi et al., 2019).

The concept matters because organizations limit AI system functions for creating products through decisions made by professionals. Organisations use AI technology for enhancing operational performance and study results, while human experts confirm output validity through their validation-supported decision-making through its application for AI outputs for prioritizing software features in the development phase for new product development (Bader & Kaiser, 2019).

4.3 Information generated from AI tools used as decision support

The themes display the usage of insights generated by AI for the software feature prioritization process guided by the conceptual framework. The AI systems support by providing assistance in information processing and analysing work instead of acting as a direct or autonomous decision-maker.

Information with respect to the third theme demonstrates how organizations are using AI-generated information to assist with their decision-making. The interviewees explained how AI is eventually functioning as a tool that lets users perform activities such as creating summaries, developing discussion materials, discovering patterns, and generating helpful recommendations. The participants also explained that they did not consider information generated from AI to be an independent element that determines feature priority decisions directly.

The participants shared that AI systems function as a vital tool helping organizations during prioritization process. P2 explained how AI functions for assisting:

> *According to Participant P2, "AI is more or less like a helping hand."*
>
> *Participant P7 similarly explained:*
>
> *"They are mostly treated as supporting inputs during feature prioritization."*

The given statements also demonstrate that information coming from AI receives attention, yet it does not stand as the primary source of truth, as this data is used as an element that supports the decision makers in reaching up to final results.

Participants have identified that information generated from AI reflects more suggestions and recommendations.

Participant P3 stated, "I treat it more as suggestions rather than decisions."

P4 shared a similar view:

"I treat AI-generated insights as recommendations rather than facts."

The study also discovers that participants have been using AI to develop their thought process, as they treated those results as temporary solutions or supporting ones. AI-generated information served as a foundation for decision-making. Participants needed to assess and interpret the results before using them for prioritization.

The second best way AI was assisting the participants as it involves its capacity for enabling teams to gather information, create summaries and structure their formats.

As per Participant P5, "The AI-generated insights are usually helpful in summarising large amounts of information."

P8 also stated:

"AI tools help us summarize and cluster the inputs more quickly"

The response is coming from the participants demonstrates that AI tools reduce the time for preparation because they enable faster product feedback data and support, which means that the teams used AI-generated information for establishing a definite starting point for prioritization related discussions.

The participants discussed how AI serves a valuable purpose between preparing and conducting their discussions.

Participant P5 said, "These insights support the discussion but do not make the decision on their own."

P9 similarly explained:

"AI helps prepare and support the discussion."

These statements indicate that information generated from an AI is useful for both ongoing prioritization meetings and for the preliminary stage, yet its presence cannot substitute for actual meeting dialogues. This information enables teams to detect ongoing issues or potential problems while they assemble their proof and develop their enquiries, yet their decision-making process requires more information that sometimes an AI tool cannot produce.

Participant P8 stated, "I usually treat them as a starting point that needs verification from other sources."

Participant P9 also explained:

"I interpret AI-generated insights as a starting point for investigation rather than a final priority decision."

The AI-generated content serves as an initial analysis tour, which is generally a starting point. The output of information generated may help the teams towards a pattern or an issue, but further validation or checks are required, as this could influence the final outcome-based decisions.

The theme further shows how AI-generated information functions as a tool for the software feature prioritization process. According to its primary use in software product development, the participants who were using AI for creating, generating and preparing materials. Their ideas considered that AI-generated information helps in assisting, but they did not accept it as the ultimate decision-making source. The study depicts how AI tools help in enhancing prioritization preparation efficiency, but actual prioritization requires human interpretation and validation, plus decision-making that involves multiple stakeholders.

4.4 Interpreting AI-generated information for software feature prioritization requires human involvement and domain knowledge.

The following themes integrate the conceptual framework with human participation and its various components, balancing product requirements and human assessments for understanding AI-generated information used for feature prioritization. The study presents a framework that shows how domain knowledge and human validation checks enable human interpreters to work with AI-generated outcomes.

Focusing on the fourth theme that indicates how human understanding is needed for interpreting the contents generated from AI tools, which are used by participants during the software feature prioritization process. The professionals involved in the interview process have helped to understand the usage of AI-generated information. The current outcomes need validation and interpretation to align with product requirements and have a better understanding of products to help with AI outcomes.

The interview also revealed that the software feature prioritization decision-making process remains under human verification. The participants asserted that AI should not take over the role of human decision makers, as they cannot fully rely on AI for software feature prioritization-related decisions.

> *As per Participant P1, "The final decision is always made by a human."*
>
> *According to Participant P2, "You should make your own decisions based on what you see."*
>
> *Participant P3 said, "You are ultimately the person who makes the decision at the end."*

The participants have perceived that AI-generated content can be inaccurate sometimes, but at the same time, it can be valuable. There was a need for additional checks and having additional resources to achieve their objectives. Human involvement was important because software feature prioritization requires people to make decisions about what features should receive higher importance based on their understanding of the product market and user requirements.

Participants have established certain validation procedures that are required for proofing before AI-generated content can be used for software prioritization work. The expectation from P4 showed that:

> *Participant P4 stated, "We always validate the insights against other data sources and stakeholder input before making the final decision."*
>
> *Similarly, P6 stated:*
>
> *"AI-generated insights must be reviewed against approved evidence before influencing software feature prioritization."*

The participants also reflected on how data generated from AI is not directly accepted, participants tend to check and verify the data generated from various sources, as well as stakeholders, before it can be used for the software feature prioritization process.

An important parameter for understanding information generated from AI can be perceived as domain knowledge.

> *Participant P5 said, "Data needs interpretation because numbers alone do not always explain the business context or customer reality"*
>
> *P7 stated this more directly:*
>
> *"Domain understanding is more important."*

The responses based on the comments state how information generated from AI cannot prove the importance of feature prioritization and how it affects the product quality.

The responses focused on having human interpretation for the data and how important it is for staying aligned with business and product-related goals.

The following information demonstrates that the AI outputs fail to provide a complete explanation because they cannot reveal the reason for feature importance, highlighting the people who will experience its effects and its relationship to the overall product framework. The data requires human expertise to interpret its meaning and connect the findings to business value and customer experience, as well as product objectives.

The participants have identified cross-checking commercial tasks for conducting their interpretation work.

> *As per P8, "The actual prioritization happens through human review and cross-functional discussion."*
>
> *P9 similarly stated:*
>
> *"The feature ranking depends on verified financial data."*
>
> *P10 added:*
>
> *"Reliability comes from cross-checking, source awareness, and human review, not only from the tool alone."*

The statements show that dependable prioritization needs. AI-generated data combined with rightly verified information under humour human assessment and operational team discussion, the feature-related decision process required this particular aspect because it involves financial and technical as well as customer and regulatory factors.

Based on the overall responses, the theme demonstrates that human capabilities and specialised knowledge are essential for assessing AI-generated information as well as for data focusing on software development priorities, particularly for the software feature prioritization process. AI tools can support the process by producing summaries and identifying patterns. Participants consistently viewed human judgment as necessary and a validation check for final decision-making. The research indicates that people with appropriate expertise must review and understand the AI-generated data before it is used for the software feature prioritization decision-making process.

4.5 AI-based software feature prioritization is shaped by contextual and governance conditioning.

The theme demonstrates how governance systems and contextual attributes from the conceptual framework create an environment that organisations, regulatory bodies and product teams use to determine AI-generated information that is used for decisions during software feature prioritization. The decision-making process uses data and AI outputs as its base while balancing external and contextual factors.

As per the fifth theme demonstrates that AI-based software feature prioritization relies on specific conditions and governance frameworks for the feature prioritization process. The participants did not support AI-generated information, as it cannot be used across all the product environments. The regulatory context requires AI-generated information for undergoing more stringent control and validation process, together with the right traceability requirements, before it can be used for determining feature prioritization.
In certain situations, AI systems showed their limitations because they failed to understand all aspects of feature requests the problems became most apparent in situations that required safety measures or which followed specific regulations.

According to Participant P2, "Corner cases are often left out when we use AI."

Participant P6 said, "One major issue is that the information available to AI may not include the full regulatory context behind a feature request."

The AI-generated information fails to capture vital contextual information. According to the comments, the software feature prioritization process involves a deeper understanding of how AI outputs will frame feature requests, but the actual request requires a definite assessment of safety and compliance, as well as operational elements.

As stated with respect to the core issues of governance and traceability emerging as essential elements, P6 has pointed out that AI-generated information cannot fully help with software prioritization until the sources of information have undergone checks and a certain level of validation.

> *Participant P6 has stated, "If the AI-generated insight cannot be traced back to approved evidence, it should not influence feature priority."*

Some regulated environments require AI-generated information with traceable sources, which can act as proof of the accuracy of the result, and need to demonstrate usefulness, but it requires validation through established evidence before it can influence decisions for the prioritization process.

Participants have elaborated that software feature decisions are determined by the existing risk assessment process together with active regulatory requirements.

> *Participant P7 said, "Regulatory and risk-related features are usually prioritized first."*

The methodology indicated for software feature prioritization combines both AI-generated and user needs for the system, acting as the primary basis. Certain situations require organizations to prioritise risk-related and regulatory obligations instead of working on product enhancement and features that improve user convenience.

The requirement for security and business operations, and customer obligations, together with platform restrictions, served as essential conditions for the project. P8:

Participant P8 stated, "Those outputs still need to be checked against business direction, threat sensitivity, customer commitments and platform constraints."

The information demonstrated a complete product and business environment that AI-generated content needs to be evaluated according to the error-generated output, which shows a feature as important, but the actual value of the feature depends on how it relates to business operations, customer requirements, security requirements and technical system limitations.

The financial environment requires participants to recognise the weak or incomplete AI-supported information, which can lead them to make incorrect decisions about which projects to prioritise.

Participant P9 shared, "A wrong product decision can affect customer funds, subscriptions, and refunds across the platform."

P9 has also pointed out the need for checking information produced by AI-based on safety and approval checks:

P9 also shared, "I first check whether the information shared by the AI tool is approved and safe."

Responses to the comment indicate how AI-based prioritization needs enhanced governance for financial and sensitive product situations. The process requires validation and at most control because any incorrect feature decisions will lead to direct customer repercussions.

Primarily 3 major factors are important in education products: academic value, privacy and technical feasibility, as these were marked as important.

Participant P10 stated, "The actual feature prioritization still depends on product goals, technical feasibility, academic value, privacy rules and human review."

Information from AI-generated output, depending on the product context for which it has been created, educational products require software feature prioritization to rely on factors that AI systems identify and on the feature's ability to achieve certain learning outcomes, safeguard the privacy of users while maintaining both academic standards and meeting the technical criteria.

Based on the overall themes demonstrated, AI-based software feature prioritization needs contextual as well as governance rules to make its operational decisions. Participants have found AI-generated information useful when the correct interpretation was applied for product regulatory, financial, technical and educational contexts. The study demonstrates that trust in AI-supported prioritization depends on information characteristics, which include approved status, safety features, traceability and compliance with product environment governance standards.

5 Discussion and Conclusion

5.1 Discussion based on findings

This study has investigated how data quality problems impact AI-generated information during software feature prioritization for new product development. The research outcomes reflect how AI-generated information supports feature prioritization work, but its effectiveness depends on a few factors that include the quality of base data, human expert participation or human intervention, as well as the specific organizational environment used for decision-making.

The major findings were that the problems with data quality led to decreasing trust in AI-generated outcomes. The participants reported difficulties with data that was not complete and came up with inaccurate information, which was not current and with data that was not properly organised. Based on the sources provided, different information, representation and situations where essential contacts were missing. The current findings support earlier research, which shows that AI systems require higher quality, and there is a need for complete and relevant data to produce useful results. AI systems create information that seems structured and believable. When source data is weak, it lacks some essential information. The software feature prioritization requires some vital information as it enables decision-making based on detailed knowledge about products, customers, and technical aspects.

Another key finding shows that AI systems that receive lower-quality data input tend to make incorrect decisions for prioritization. The participants explained how inaccurate data leads to policy recommendations that create urgency and incorrect feature ranking, leading to delays with respect to decisions, as well as distortion for the project road map and instabilities with resources. The research shows how organization face negative outcomes from bad data and lower-quality information coming from AI systems. It decreases their technical work outcomes, lowers the quality of the teams and disrupts how they prioritise the features that they can see while they ignore more important strategic requirements and foundational needs for their work.

The next key finding showed how organizations use the AI-generated information for resisting the decision-making process, but do not use it as a basis for making decisions. Participants described AI as a helpful tool that helps in producing summaries, feedback, aligning repetitive work, and developing recommendation systems. The participants believe that AI should not make software development priority decisions, especially related to software feature prioritization. The evidence also reflects how AI technology currently works for human decision-making capabilities in a complicated product environment, as compared to its ability to replace human judgment.

From the study, it was discovered that human knowledge and domain expertise continue to function as vital components for working. The participants in the study pointed out that they needed to perform validation activities and cross-check stakeholder discussions and certain contextual assessments or needed expert evaluation, before they could rely on AI-generated data to make prioritization related choices for software feature prioritization as they require both analytical work as well as additional activities. The process requires stakeholders to balance customer value and technical viability, business objectives, project dependencies and regulatory requirements, and future business plans. The process of managing these trade-offs needs human interpretation skills.

Based on the research gaps, the issues were addressed by providing empirical evidence, which shows how data quality problems impact the AI-based decision-making process during prioritizing software features at the initial stages of new product development. The study outcomes showcase organisations experience limitations when there are data quality-related issues, despite previous studies that focused on demonstrating AI abilities being beneficial. As AI outputs become unreliable due to their inaccuracy and inconsistency in processing the data, this results in difficulties prioritizing the features.

The research shows that AI functions as a decision support system because it needs human validation and domain expertise for contributions to decisions. The research demonstrates how governance and contextual factors control the practical usage of insights generated from AI, which has been identified in prior research. The research demonstrates how regulatory, contextual, and governance factors control the AI-generated information, which has received limited study. The study provides a detailed understanding through practically implemented challenges and theoretical assumptions.

Overall, the study helped in discovering that contextual factors, together with governance frameworks, determine how people trust AI systems for task prioritization. Participants from regulated domains such as financial and edtech recognised traceability, privacy, accountability and risk awareness as essential requirements. The research shows that editing information needs to be studied together with its organizational context. AI-generated outputs require higher governance standards in high-risk situations before they can be used for decision-making.

From the overall findings, the outcomes demonstrate that artificial intelligence improves software feature prioritization methods through its ability to create better operational procedures and supporting information. The most beneficial use of AI-generated information occurs when it assists the decision makers by presenting its initial data for their work, and helping with the final prioritization process requires human judgment and validation checks.

The research findings show AI-based prioritization systems can achieve full potential when organizations combine their technical capabilities for understanding contextual information contributing to decision-making. The findings support earlier research, which showed human interpretation and organisation ecosystems are essential for the decision-making process for AI-supported environments (Jarrahi, 2018; Amershi et al., 2019).

5.2 Discussion on the conceptual framework based on empirical findings

Table 4. Empirical findings based on interpretation.

Components from Framework	Empirical Findings	Conceptual Framework Implication
Data Quality	Data quality influences all the stages of prioritization based on AI-generated insights. According to the participants from the interview inaccurate, inconsistent and outdated impact the data quality produced by AI.	Quality of data influences all the phases of software feature prioritization.
AI insights usage	Acts as decision support, assessing and analyzing information	Insights generated from AI can be used as decision-support.
Decision-making	Operates as part of an iterative process, needs more checks due to data limitations	Instead of a following a sequence for prioritization process, findings indicate the process involves feedback and iterative steps supported by assessments, validation and discussions.
Human Interpretation	Important for validation and interpretation of data from having domain expertise and better contextual knowledge.	Human validation and checks can be considered as a vital component rather than a supporting element
Governance and context	Assists with contextual constraints, regulatory information, technical analysis, risk assessment contributed to using AI	Governance remains important for guiding the usage of AI generated information under certain conditions and setting up rules/guidelines.
Outcomes of Software Feature Prioritization	Feature prioritization can be impacted due to low-quality data and mislead prioritization. Assessments and validation checks required for AI generated information are necessary to improve feature prioritization quality.	The outcomes from feature prioritization process is seen to be dependent on combined parameters such as AI-generated insights, data-quality, governance, regulatory factors, human involvement and judgment.

The information based on the findings examines the conceptual framework when assessed based on the empirical evidence. The findings demonstrate that theoretical elements from the framework for real-world situations for software feature prioritization supported by AI.

As presented in Table 4, the empirical results explain the interpretation of the conceptual framework. The outcomes show a mixed and dynamic system rather than a single linear structure. The data quality influences all stages of software feature prioritization than just being a part of the initial stages. The reflected findings have supported past studies, which have focused on data quality, effectiveness of AI systems, as well as the decision-making process (Wang & Strong, 1996; Cai & Zhu, 2015).

The AI systems function as a decision support tool and enables to analyze data, but do not enable it to make direct judgments for decision-making without human involvement.

This supports the previous findings that show how artificial intelligence supports human decision-making choices and helps in enhancing the decisions in a complex environment (Amershi et al., 2019; Raisch & Krakowski, 2021). The research demonstrates that the decision-making processes operate as a repeating cycle that needs verification and checks for validating data-related issues and uncertain situations. Existing studies have demonstrated that AI-supported decision-making processes require human supervision and validation through multiple rounds of testing to maintain accountability and reliability (Jarrahi, 2018; Dwivedi et al., 2021).

According to the findings, based on the interview results and the literature, while focusing on new insights from the correlation among the factors mentioned in Table 4. It is evident as quality of data affects all the stages of feature prioritization. The study shows the framework parameters and their relevance to decision-making for maintaining a better decision-making process (Wang & Strong, 1996). As per the study, AI functioned as decision support rather than replacing human decision-making capabilities (Raisch & Krakowski, 2021).

The findings have shown human validation as an essential part of the evaluation of recommendations produced by AI. The study demonstrates that software feature prioritization needs understanding of the domain and contextual information (Amershi et al., 2019). Additionally, the study discovered that contextual and regulatory factors determined the practical application of AI-generated information, for feasibility analysis, setting up priorities and privacy regulation (Dwivedi et al., 2021).

Overall, the outcomes of the study for the software feature prioritization process are dependent on certain factors such as AI-generated information, quality of data, human decision checks and governance information. The empirical findings have achieved the goal of refining the existing conceptual framework by an AI-supported interrelated model instead of a linear sequence.

The framework introduces human interpretation as a new element that is required for examining AI outputs. The results provide a strong focus on highlighting how the organisation needs human expertise and situational understanding to interpret AI-generated information for decision-making (Bader & Kaiser, 2019; Amershi et al., 2019). The application of AI outcomes depends on organizational limitations and respective circumstances because they determine the actual usage of AI to generate information for significant outcomes.

Additionally, through the findings its reflecting how AI is utilised as decision-support rather than being a primary element. The study proves research findings that show that augmented AI systems use artificial intelligence for analysis while keeping human control over strategic judgment (Raisch & Krakowski, 2021). The framework also shows the need for human validation for data quality checks and assessment, being an essential part. The previous studies have shown trusting AI-supported organizational systems that have adapted validation processes and governance systems for achieving accountable systems (Dwivedi et al., 2021; Sambasivan et al., 2021).

The findings show how the conceptual framework operates through integration between data quality, human interpretation, AI usage and governing parameters, which reflects AI-based decision-making, governance and software feature prioritization. The current method of software feature prioritization process is AI-based and relies on shared collaborative decision-making among humans and AI systems instead of human control. The interview results have shown that AI systems provide rapid analytical functions, together with their ability to process extensive information and identify patterns. However, human involvement brings stakeholder understanding, contextual knowledge, and strategic assessment for decision-making capabilities. The study outcomes support previous findings, that demonstrates artificial intelligence operating to its maximum capacity in a complex environment for serving decision-making for assistance but not as an independent decision-maker (Jarrahi, 2018). The results have further reflected human expertise being essential for determining prioritization during uncertain situations.

Based on empirical findings show how the data quality dimensions interact with organizational inputs for producing AI insights, which require human checks throughout the software feature prioritization process. The framework established some major components that affect prioritization-based decisions, yet the details from the interview data revealed how these components remain active during all phases of the decision-making process. Participants reported multiple situations in which AI-generated recommendations needed validation through proper assessment activities and required stakeholder discussion and evaluation, as well as business review, before finalising the prioritization decision and establishing the same. This shows the need for AI-supported prioritization to be more adaptive, which occurs in repeated cycles instead of following a fixed process or set of technical tasks. The previous studies have investigated the decision-making process in organization under uncertain situations need higher level of assessment (Nutt, 2008).

The outcomes have established an essential connection between organizational trust and the utilization of AI tools. During the interview, participants have shown trust in AI systems for being traceable, maintaining transparency and having contextual understanding, as well as the ability to validate AI through recommendations from additional sources. Decision-makers have found AI-generated outputs to be beneficial when they can trace information and assess the recommendation against their needs for organizational priorities. The present literature has emphasized that the trust in such intelligent systems depends not only on technical performance but also accountability, explainability and reliability with the organization for decision support (Bader & Kaiser, 2019). The interview data shows that people have trusted AI-generated recommendations less when the system produces outcomes based on inaccurate and outdated information. The conceptual framework presents data quality dimensions both as technical requirements and trust mechanisms, which determine how well AI-powered prioritization systems will function with real-world scenarios.

Through the study, it’s seen that organizations need a process for software feature prioritization that involves both social and technical parameters. The study showed how governing systems, customer obligations, technical limitations, business priorities, and regulatory standards are combined to create a framework to perform the study. The previous research has studied the AI systems required human and organizational capabilities for functioning according to the findings (Amershi et al., 2019). The results of the study establish conceptual boundaries for showing that AI-based software feature prioritization needs to be investigated and studied beyond its technical capabilities. The process of prioritization functions as a complete socio-technical systems which organization use for making decisions through a specific context and the capacity for human users to interpret AI recommendation outcomes.

The data from the interview shows that data quality dimensions and organizational input indicators, together with AI-generated insights and human validation checks, continuously shape product-related decisions for new product development. Participants have emphasized prioritization, and reliability decreases due to inaccurate information, which affects resource allocation and decision outcomes. Earlier research on information quality has shown that organization experience weakened decision-making abilities due to poor-quality information (Wang & Strong, 1996; Pipino et al., 2002). The research results have demonstrated that data quality should be reviewed not only on technical grounds but also from strategic perspectives, as this impacts AI-based decision-making capabilities in software development.

Research studies, which currently existing demonstrates AI governance systems mechanism which integrates accountability by protecting against organizational risks that emerge from AI-based systems (Sambasivan et al., 2021).

The evidence based on empirical findings coming from the conceptual framework remains relevant because effective AI-based software feature prioritization depends both on data quality and technological capabilities, as well as human expertise for decision-making.

5.3 Practical Implications of Findings

The research findings demonstrate how organizations which use AI-generated data for certain practical benefits, such as getting base support for selecting software features by assessing available data. Organisations must understand the AI output with respect to the data quality, particularly dependent on the data that is used for training these artificial intelligence systems. Companies must establish data governance processes that include ongoing data set maintenance, system-wide data correction, and complete customer operational and product data collection before they can completely trust AI and information generated from it. The usability of AI outputs for software features becomes better when organisations improve their data quality assessment methods.

Organizations must use AI technology as a decision-making support or assistance tool that helps the engineering teams make their own decisions. The research shows that participants found value in AI technology because it helps them to summarise content, discover new patterns, and organises feedback and create discussion materials. The maximum value of AI technology for businesses comes from its use in preparing work and conducting analysis, while human decision makers remain responsible for making final choices for the prioritization process, as well as for decision-making.

The teams from different departments need to work together as the software development feature prioritization process requires product managers, engineers, stakeholders, customer support agents and domain specialists to decide which feature should be developed first. The organisation should implement a collaborative review process for elevating AI-generated information instead of accepting data without verification. This approach helps organisations make better decisions because it reduces misleading information and increases trust in their ultimate choices.

Working in a fast-paced, changing environment, information requires organisations to establish stronger control systems. Financial institutions and certain environments require traceability and privacy protection for evidence, validation and accountability. Certain operational activities, AI outputs need to undergo layers of assessments in those environments, as decision-making for software feature prioritization requires verification against established internal evidence.

The research results show how the organization needs to build their internal ability to teach AI literacy to the decision-making engineers, the product teams, and managers need to develop skills that allow them to assess outputs and verify data constraints for evaluating information, recommendations and making business decisions using AI-generated information. The growing use of AI tools for the software development process will make their skills increasingly essential for organisations.

5.4 Study Limitations and Future Research

Table 5. Identified limitations for future directions.

Limitations based on study	Future research expectations
10 interview sample size	Broader space for quantitative studies
Self-reported studies	Combining observation and mixed methods
Participants variation across industry	Industry oriented specified studies
Current AI tools findings	Advancing AI capabilities
No live observation	Capturing real events under case studies for real products

The findings in the research have certain limitations with regard to the study that affect the ability to interpret the results. The key study limitation and corresponding future research directions are reflected in Table 5. The current study establishes certain limitations with respect to the research that requires additional investigation for developing a better understanding of AI-generated information used in software feature prioritization for the decision-making process

The study involved semi-structured interviews conducted with 10 participants. The research method provided deep insights into the experiences of the participants. However, the findings had limited applicability as the number of study participants was small. The study aimed to create contextual knowledge instead of making generalisations, which aligns with the qualitative research methods (Saunders et al., 2019). Future studies should be able to examine the topic based on large-scale qualitative research involving broader participants

As part of the research self-reported data from the participants were used the interviews contributed in research by understanding people's perception and their experiences based on organizational behaviour process but interview results can be affected by how people remember things and how well they interpret their memories and their selective decisions for pointing to specific details with respect to future research enhancing existing evidences through studies that implement both direct observation methods together with internal company documents and research designs as well as interview techniques that could use multiple research methods.

The participants involved in the interview process belong to various professional fields and different workplace settings. The variety in the background for the participants spot essential insects, but the research discovered that different industries have used AI-generated data for software feature prioritization as well as determining which features research should need to investigate, particularly industry environments which include financial technology, healthcare and education technology, as well as manufacturing or any such highly controlled sectors.

The outcome of the findings has presented the implementation of organizations for using artificial intelligence tools for software development phases, as these technologies are being developed at a faster pace. The advancements in their capabilities, governance and business integrations keep evolving. It has been discovered that the organisational practices keep undergoing modifications very frequently. Deeper research needs to be executed for tracking the progress of AI-supported software feature prioritization that keeps undergoing frequent changes.

Overall, the study did not involve a real-time decision-making process for the software feature prioritization. The research was based on participants perception for establishing the findings. Future research could use case study approaches within product organizations to observe how AI generator information is discussed, validated and applied in the actual software feature prioritization process.

5.5 Conclusion

The findings from the study have investigated how data quality challenges impact the implementation of AI-based software feature prioritization during new product development. The study shows how AI-generated information is essential for organizations that need help with summarising data, identifying patterns, sorting the feedback, conducting meetings and prioritization the effectiveness of information generated from AI depends on the quality of the underlying data used for creating the outputs.

The study has also discovered all types of data, which include outdated, incomplete and inaccurate data that are weak and reduce the reliability of AI-generated information, resulting in inaccurate software feature prioritization for the decision-making process. The study has discovered how AI inputs, which are based on lower-quality data, create several issues and challenges, including incorrect feature ranking and false urgency, as well as disrupting the engineering road map and resource-related constraints. The results demonstrate that the quality of data functions as a vital part that enables organizations to execute AI supported process for making decisions.

The overall research portrays high-quality data together with proper governance mechanisms, and screening based on human monitoring can enable AI systems to improve the process for software feature prioritization for new product development. AI functions most effectively when it assists human judgment because this way it helps decision makers to stay on their original course for making any judgment. The study provides new insights into how organizations operate and handle AI-generated information for succeeding in their software feature prioritization process.

5.5.1 Addressing the Research Question

The studies show how the data quality of information generated from AI-based systems impacts decision-making for the software feature selection process during new product development. According to the study, data quality directly impacts both the reliability of AI-generated information and its benefits for software feature prioritization activities. The presence of inaccurate information, incomplete and outdated information will lead to errors with feature assessment. This impacts prioritizing features and resource management decisions. The research results demonstrate that organizations required higher quality data generated from AI-enabled systems to support the decision-making process during new product development (Wang & Strong, 1996).

The research results show that artificial intelligence can function as a decision support system during software feature prioritization rather than being a direct contributor. Human involvement, contextual understanding and stakeholder collaboration together can lead to better interpretation of AI results for maintaining an important role in decision-making for feature prioritization. The interview participants pointed out that organization should validate AI outcomes through internal checks and using business expertise.

The study indicates how governance mechanisms and organizational strategies combined with the right validation and regulatory practices, can determine how AI-generated information is used during new product development activities. The effectiveness of the AI-supported software feature prioritization process needs organizational governance, technical capabilities and human assessments.

5.5.2 Evaluation of Research scope and objectives

The study has successfully achieved its main objective by investigating how data quality impacts software feature prioritization decisions during new product development. The research has identified data quality issues, which include incomplete data and outdated data. The study showed how this can lower the trustworthiness of AI-generated information while decreasing the accuracy of prioritization decisions. The findings show that the organisation's decision-making process, while using poor quality data, impacts feature evaluation, resource-related constraints and roadmap planning.

The study investigated the ways product development teams interpret AI-generated outputs for making decisions for prioritizing feature. The findings showed how organizations use AI technologies for assisting decision-making instead of using AI for independent decision-making. The process of new product development requires human evaluation capabilities to assess and validate AI-generated content. This also requires domain expertise and contextual understanding with better-regulated systems for data governance before AI-generated recommendations can be used for software feature prioritization decisions.

There are multiple aspects based on this study that need to be investigated. The study has not evaluated the technical performance and the accuracy of the AI models within the software feature prioritization decision-making process. As the research was based on qualitative methodology focusing on interview data from a small participant group, it might lack a broader set of information for generalisation across the industrial ecosystem.

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Appendices

Interview Questions

1. How would you define the culture in your firm/organization?
2. In terms of data, including insights generated from AI, how are they used for software feature prioritization in your organization or previously?
3. What type of data quality issues have you experienced while using AI for software feature prioritization e.g. inconsistent, outdated or incomplete data?
4. How data quality problems related to AI outputs influence the decisions for software feature prioritization.
5. Can you give me a walk-through of the software feature prioritization decision-making process in your current or prior organization?
6. While prioritizing software features, what factors would you consider with respect to data and AI-generated information? For example, you can consider user needs, business value, technical feasibility, or data and AI outputs.
7. You may have recognized or heard from colleagues about data-driven decision-making. Can you please share one or two examples of what people think about the importance of data?
8. How are you ensuring that AI-generated insights used in decision-making for software feature prioritization were reliable?
9. How do you interpret AI-generated insights when making decisions for software feature prioritization?
10. How is the culture in your organization with respect to software feature

prioritization decisions, do they encourage AI driven decision-making? If so, what AI tools do you use?

11. From your experience, how are people in your organization who have been perceiving the importance of AI-generated insights for decision-making during software feature prioritization?
12. What are your views on product development data sharing with and from external partners, customers, and competitors within the broader ecosystem?