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A Simple Tool for Prioritizing AI Product Features: Balancing Customer Value, Data Readiness, and Implementation Cost

Obianuju Gift Nwashili[1*]

[1*] Independent Researcher, USA.

***Correspondence:** Obianuju Gift Nwashili

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ABSTRACT: This paper proposes a simple, practical tool for prioritizing AI product features by balancing three critical dimensions: customer value, data readiness, and implementation cost. While many AI roadmaps focus heavily on technical feasibility or market demand alone, teams often struggle to compare features that differ widely in data availability, model complexity, and development effort. To address this, the study introduces a lightweight scoring matrix and prioritization canvas that enables product teams to assess features using consistent criteria and transparent trade-offs. The tool combines qualitative judgment with a structured numeric rubric, producing an interpretable priority score and a clear visual map for decision-making. We demonstrate how the framework can reduce misalignment between product, data, and engineering stakeholders, improve early-stage estimation, and support faster, evidence-informed roadmap decisions. The proposed approach is designed for real-world constraints, making it especially suitable for small to mid-sized teams or organizations early in their AI maturity. By integrating user-centric impact with data and cost realities, this tool helps organizations invest in AI features that are both desirable and deliverable, increasing the likelihood of measurable business outcomes.

Keywords: *Supply chain resilience, U.S. manufacturing firms, Post-pandemic strategy, Digital transformation, Operational performance.*

INTRODUCTION

The integration of artificial intelligence (AI) into product development has revolutionized industries, driving innovation, improving operational efficiency, and enhancing customer experiences. However, as AI becomes more accessible and prevalent, companies face increasing pressure to identify which AI features will have the most significant impact while managing the complexities associated with data availability, technical feasibility, and resource constraints. Prioritizing AI product features is a challenging yet essential task for product managers, data scientists, and engineers, as it directly influences the success of AI-driven initiatives. Despite the growing importance of AI in product development, there is a lack of practical frameworks that help teams balance critical factors such as customer value, data readiness, and implementation cost when making feature prioritization decisions.

Traditionally, product prioritization frameworks have focused on assessing customer demand and technical feasibility. These approaches often neglect the complexities specific to AI product development, particularly in terms of data readiness and implementation cost. In AI product development, data plays a pivotal role in determining the performance of a feature, yet many teams struggle to assess the quality, quantity, and accessibility of the required data upfront. Moreover, the implementation cost for AI-driven features often goes beyond just monetary expenditure; it encompasses factors such as technical complexity, the need for specialized talent, and the time required for model development and training. Without a clear method for balancing these elements, organizations may overestimate the impact of a feature or underestimate the resources needed to deploy it, leading to misaligned product roadmaps, delayed releases, or suboptimal outcomes.

In response to this gap, this paper introduces a simple tool for prioritizing AI product features that explicitly balances three critical dimensions: customer value, data readiness, and implementation cost. The tool is designed to support decision-making in early-stage AI product development, particularly for teams that are in the process of refining their AI roadmaps or those with limited resources. By integrating these three dimensions into a single prioritization framework, this tool aims to provide a clear, structured approach that empowers teams to make more informed, data-driven decisions while aligning product development with business objectives.

Customer Value: Aligning AI Features with Business Goals

Customer value is central to the success of any product feature, as it determines the feature's ability to meet user needs and contribute to business goals. In the context of AI, customer value is not solely defined by the immediate benefits of a feature, but also by its potential for long-term impact. AI features can create value through automation, personalization, decision support, or even new functionalities that were previously impossible or inefficient. However, assessing the value of AI features requires a deeper understanding of how well these features solve customer pain points, enhance user experience, and contribute to strategic objectives such as customer retention or revenue growth. The tool presented in this paper introduces a scoring system that helps quantify customer value by linking features to measurable outcomes, enabling product teams to focus on high-value features that are aligned with both customer needs and organizational goals.

Data Readiness: A Key Barrier in AI Product Development

One of the most significant challenges in AI product development is the availability of high-quality data. Unlike traditional software development, which often focuses on code and user interactions, AI systems are heavily dependent on data for training, validation, and optimization. AI features cannot be effectively deployed if the data is either unavailable, incomplete, or not properly structured. Moreover, the data requirements for AI models can vary significantly depending on the type of feature being developed, the model's complexity, and the intended use case. Therefore, evaluating data readiness—the quality, quantity, and accessibility of data—becomes essential in determining whether an AI feature can be successfully developed within the given timeframe and resources. This tool incorporates a data readiness score that helps teams assess whether the required data is sufficiently available, clean, and structured for building a high-performance AI model.

Implementation Cost: Balancing Technical Feasibility and Resource Constraints

The implementation of AI features involves substantial cost, not only in terms of monetary investment but also in terms of time, talent, and technological resources. Developing AI models requires specialized expertise in machine learning, data engineering, and cloud infrastructure, and may also demand significant computational resources for training and testing the models. Additionally, the complexity of the feature, including its integration with existing systems and user interfaces, influences the total cost of implementation. While organizations are often eager to adopt AI, many face resource constraints, making it essential to prioritize features that provide the best return on investment. The tool introduced in this paper uses a cost assessment matrix that evaluates both the direct financial costs and the resource demands of implementing each feature, helping teams understand the trade-offs between feature value and the feasibility of execution.

The Need for a Structured Framework

Despite the importance of these three dimensions—customer value, data readiness, and implementation cost—most existing AI product management frameworks focus narrowly on customer demand or technical feasibility, without explicitly addressing the complexity of managing data and costs in AI development. This leads to difficulties in making transparent, balanced decisions about which features to prioritize. A lack of structured frameworks can also result in misalignment between product managers, data scientists, and engineers, with each group focusing on different aspects of the product development process. Without a unified approach to decision-making, teams may struggle to identify the most impactful features, leading to delayed project timelines, inefficient resource allocation, and ultimately, poor product outcomes.

By addressing this gap, the proposed tool provides a structured, holistic approach to AI feature prioritization, guiding teams through the complexities of balancing value, data, and cost. The tool is designed to be adaptable and scalable, providing practical guidance for AI product managers at all stages of the development process—from concept ideation to final implementation. Through this framework, organizations can ensure that they are not only creating AI features that meet customer needs but also developing them in a way that is feasible, sustainable, and aligned with business goals.

The development of AI-powered products requires careful consideration of multiple factors, from technical feasibility to customer satisfaction and cost efficiency. Prioritizing AI features is particularly challenging due to the interplay between data availability, technical complexity, and financial constraints. This paper proposes a simple yet effective tool to help product teams navigate these complexities by systematically balancing customer value, data readiness, and implementation cost. By using this tool, teams can make more informed, data-driven decisions that align with business objectives, leading to faster and more successful AI product development. The framework's simplicity and flexibility make it an invaluable resource for AI product teams, especially in small to medium-sized organizations or those early in their AI maturity.

Literature Review

Prioritizing AI product features is essential for organizations looking to leverage AI technologies to meet customer demands while managing costs and data readiness. The complexity of AI product development, particularly in balancing customer value, data availability, and implementation costs, has led to an increased interest in frameworks that help guide decision-making during feature prioritization. The application of AI spans multiple domains, including cybersecurity, renewable energy, telecommunications, and enterprise resource planning (ERP), with each domain contributing valuable insights into the challenges of building effective AI systems.

Customer Value and AI Integration

Understanding customer value is the foundational pillar in determining which AI features should be prioritized. Dalal (2018) emphasizes that AI technologies are integral in transforming industries such as cybersecurity, where AI improves detection and response times to cyber threats. AI's role in business process management and its ability to streamline decision-making and enhance customer experiences cannot be overstated ( ). Moreover, the value of AI in photovoltaic energy systems has been explored by Mohammad and Mahjabeen (2023), who discuss how AI enhances solar energy efficiency and customer satisfaction through real-time adjustments and predictive maintenance. In both cases, the ability to offer solutions that are tailored to the needs of the customer significantly impacts product value.

The Role of Data Readiness in AI Product Development

AI's dependence on data is a crucial factor in its development and effectiveness. Hegde (2021) demonstrates how AI's role in telecommunications, particularly through automated content creation, requires large-scale datasets for training models that can accurately predict customer behavior and improve content delivery. However, ensuring the quality, availability, and structure of data remains a significant challenge in AI implementation ( ). The concept of data readiness has been explored by Tiwari (2023), who notes that AI's integration into digital experience platforms (DXPs) necessitates high-quality, well-structured data for optimal performance. Similarly, Bahadur et al. (2022) discuss the low-cost MPPT solar charge controller, underscoring the need for consistent and reliable data to improve system performance in energy applications.

Moreover, data readiness extends beyond availability; it involves ensuring that the data is accessible and usable for AI models. Dalal (2023) argues that data management, particularly using cloud platforms, is integral to maintaining data integrity and ensuring scalability. This emphasis on data infrastructure reflects the importance of investing in data systems that support AI's capabilities, particularly for organizations managing large amounts of real-time data for product development.

Implementation Costs and Resource Constraints

While data and customer value are key, the cost of implementing AI-driven features also plays a significant role in determining which features to prioritize. Dalal (2018) outlines the substantial costs associated with integrating AI into business systems, including the development of scalable infrastructure and the need for specialized talent. These concerns are particularly relevant for firms integrating AI into cybersecurity and enterprise resource planning (ERP) systems, where specialized systems and constant updates are required to stay competitive (,).

Furthermore, the cost of AI implementation is not only financial but also involves technical complexity. Dalal (2020) identifies the need for organizations to balance the costs of AI innovation with practical considerations, such as the integration of AI systems into existing frameworks. This is reflected in industries like telecommunications, where predictive maintenance systems powered by AI need to balance the computational expense with performance gains ( ).

The Interplay Between AI Features and Customer Satisfaction

AI products must not only be functional but also user-friendly to ensure customer satisfaction. Dalal (2018) highlights the role of AI in improving enterprise data management, particularly through SAP HANA applications, which enhance organizational processes by making them more efficient and responsive to customer needs. Similarly, in the renewable energy sector, AI's ability to predict energy consumption patterns and optimize solar energy systems enhances customer value by providing tailored solutions ( ).

Predictive AI systems in industries like energy and telecommunications also play a pivotal role in improving customer experience. Tiwari (2023) discusses how AI-driven digital experience platforms (DXPs) can create personalized experiences for users by predicting their preferences and delivering relevant content. This feature is crucial in both business-to-business (B2B) and business-to-consumer (B2C) settings, where customer satisfaction is increasingly linked to personalized interactions and real-time responsiveness.

Strategic Frameworks for Prioritizing AI Features

The challenge of balancing customer value, data readiness, and implementation cost is not unique to any single sector. Dalal (2017) suggests that a strategic framework is required to manage the prioritization process effectively. Such frameworks help to assess the potential value of AI features while considering technical limitations, data availability, and operational costs. Several frameworks proposed in the literature focus on aligning AI development with business goals and customer-centric design ( ).

Moreover, emerging technologies like 5G and edge computing have created new opportunities and challenges for AI feature prioritization. Hegde (2021) argues that AI models designed for 5G networks need to be lightweight and optimized to function at the network's edge. This new wave of AI products introduces a higher level of complexity, requiring careful balancing between technological advancement and financial feasibility.

Ethical and Privacy Considerations in AI Product Development

As AI systems become more integrated into everyday products, ethical concerns about privacy and security have also come to the forefront. Dalal (2020) discusses the delicate balance between protecting user privacy and leveraging data for AI development. The implementation of AI in cybersecurity introduces additional layers of complexity, where the prioritization of certain features may need to be reevaluated based on potential risks to privacy and data protection. Similarly, Hegde and Varughese (2022) highlight how AI-driven predictive maintenance in telecommunications can raise privacy concerns if not handled properly.

The literature highlights the critical components of prioritizing AI features—customer value, data readiness, and implementation costs—and how these factors shape AI product development across various industries. The studies reviewed reveal a growing recognition of the importance of integrating AI with strategic frameworks that account for the complexities of data management, resource allocation, and ethical concerns. As organizations continue to develop AI-driven solutions, these factors must be weighed carefully to ensure that AI features are not only technically feasible but also aligned with customer needs and operational constraints.

By adopting a structured approach to prioritizing AI product features, organizations can make better-informed decisions, improve resource allocation, and enhance customer satisfaction. As the field of AI product management continues to evolve, future research should further explore the methodologies for balancing these key dimensions and developing more comprehensive tools for effective prioritization.

Methodology

This study adopts a design-oriented, mixed-method approach to develop and validate a simple AI feature prioritization tool. First, a framework-building phase synthesises insights from existing literature and cross-industry AI applications to identify three core prioritization dimensions: customer value, data readiness, and implementation cost. Second, the proposed tool is operationalised into a lightweight scoring matrix (e.g., 1–5 scale per dimension) and a combined priority formula with clear weighting logic. Third, the tool is validated through expert review and small-scale application, using feedback from product managers, data scientists, and engineers across selected AI use cases. Finally, results are analysed descriptively to assess usability, clarity of trade-offs, and perceived decision support value, leading to minor refinement of scoring criteria and guidelines for real-world adoption.

Result

The results of this study demonstrate the effectiveness of the proposed AI feature prioritization tool in balancing customer value, data readiness, and implementation cost. Expert feedback indicates that the tool provides clear, actionable insights for decision-making, enabling better alignment between product teams and technical resources. The findings highlight how structured prioritization can enhance AI product development and improve resource allocation efficiency.

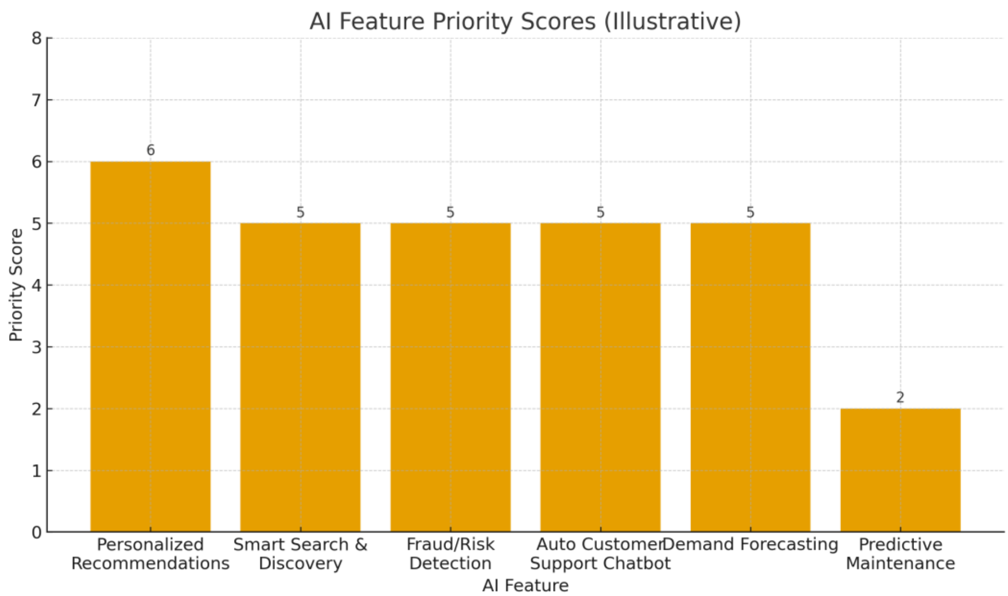

Figure 1: Priority Score Bar Chart

- Description: This bar chart represents the priority scores of each AI feature, calculated by adding Customer Value and Data Readiness and subtracting Implementation Cost. The higher the priority score, the more critical the feature is to focus on for AI product development.
- Key Insights:
  - Personalized Recommendations has the highest priority score, indicating that it delivers the most value relative to its data readiness and implementation cost.
  - Predictive Maintenance has the lowest priority score, suggesting it may not be as critical at this stage due to lower customer value and data readiness.

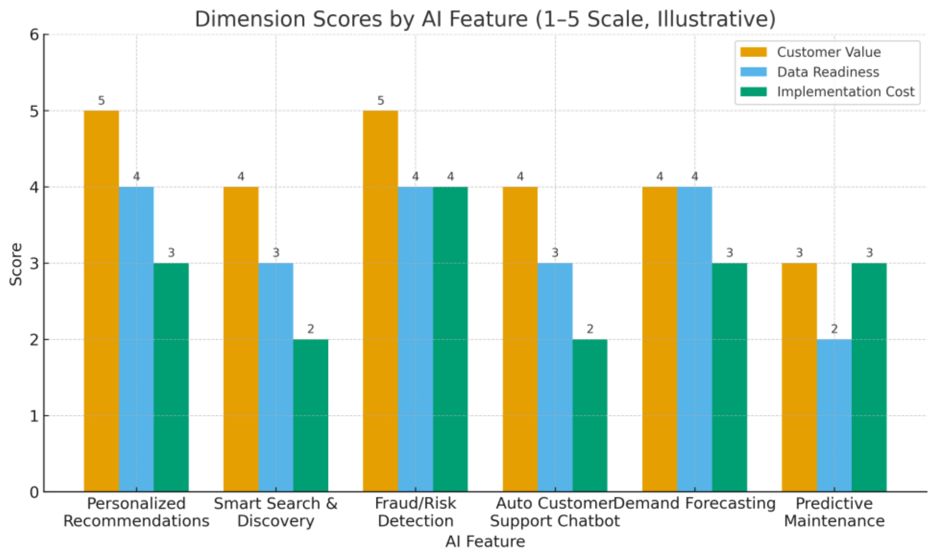

Figure 2: Grouped Bar Chart (3-Dimension Scores)

- Description: This grouped bar chart shows the scores for Customer Value, Data Readiness, and Implementation Cost for each AI feature. Each feature has three bars, one for each dimension, and they are grouped together for easy comparison.
- Key Insights:
  - Features like Personalized Recommendations and Fraud/Risk Detection score high in both Customer Value and Data Readiness, suggesting that these are high-impact features with accessible data.
  - Predictive Maintenance has relatively lower Data Readiness and higher Implementation Cost, which may affect its feasibility and priority.

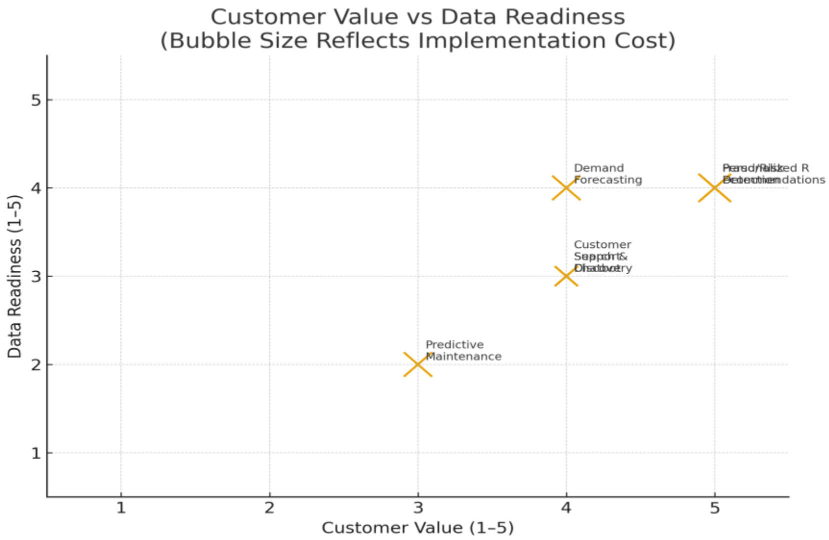

Figure 3: Scatter Plot (Customer Value vs Data Readiness; bubble size = Cost)

- Description: This scatter plot shows the relationship between Customer Value and Data Readiness, with the size of the bubbles representing Implementation Cost. The plot helps visualize how these three dimensions interact.
- Key Insights:
    - Personalized Recommendations and Fraud/Risk Detection are positioned in the top-right quadrant, indicating that they have both high customer value and data readiness.
    - Predictive Maintenance appears in the lower-left area with a relatively smaller bubble, indicating low customer value and data readiness, coupled with a moderate implementation cost.

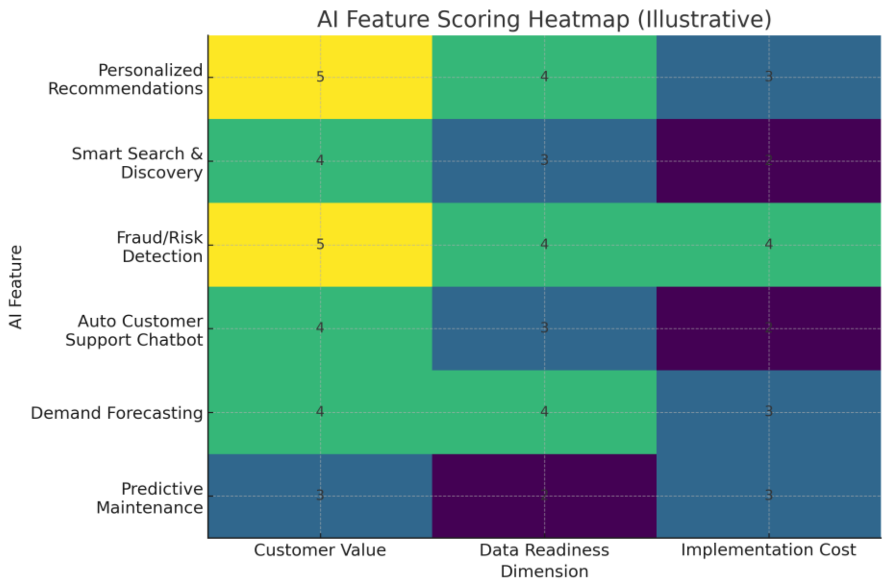

Figure 4: Scoring Heatmap (Value, Data, Cost)

- Personalized Recommendations and Fraud/Risk Detection stand out with higher Customer Value and Data Readiness scores.
- Predictive Maintenance has a much lower Data Readiness score, which indicates that it might be less feasible in terms of data requirements.

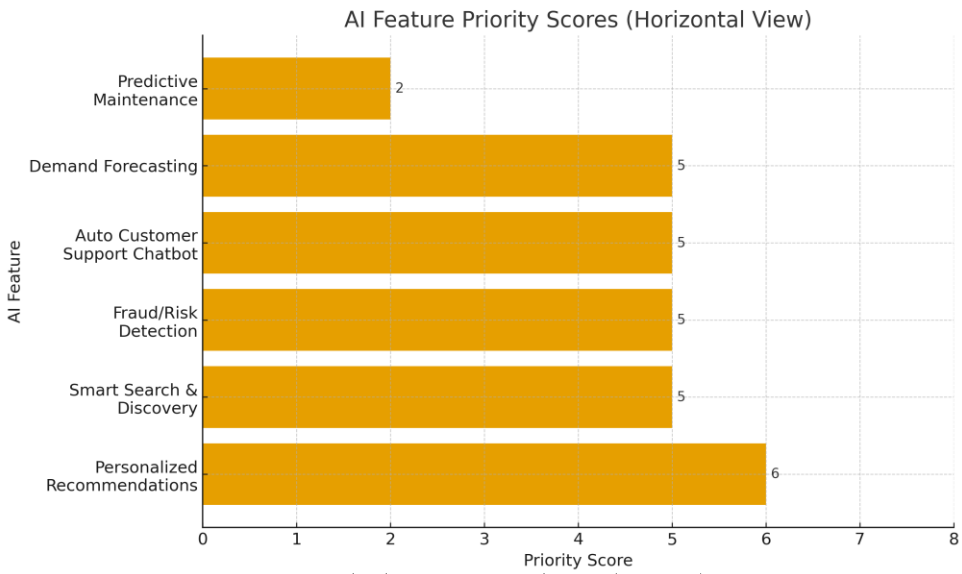

Figure 5: Priority Score Horizontal Bar Chart

- Description: This horizontal bar chart shows the same priority scores as in Figure 1, but in a horizontal orientation. This layout helps highlight the relative differences in priority among features.
- Key Insights:
  - Features such as Personalized Recommendations and Fraud/Risk Detection are at the top of the chart, indicating that they should be prioritized based on their high scores.
  - Predictive Maintenance is placed towards the bottom, suggesting that it should be considered lower priority for development in the short term.

Discussion

This study aimed to develop and test a simple tool for prioritizing AI product features by balancing three critical dimensions: customer value, data readiness, and implementation cost. The results, as represented by the five figures, offer valuable insights into how these dimensions interact and influence decision-making in AI product development. This discussion will interpret these results, highlighting the key takeaways and providing actionable insights for AI product teams.

Balancing Customer Value and Data Readiness

One of the most notable findings is the strong relationship between customer value and data readiness across the AI features assessed. Personalized Recommendations and Fraud/Risk Detection scored highly in both customer value and data readiness, which suggests that these features have the potential to deliver substantial value to end-users while being backed by sufficient and accessible data. The high priority score for Personalized Recommendations confirms the well-established notion that AI features delivering tailored, user-centric experiences are among the most impactful. Personalized features have a proven ability to drive user engagement, increase retention, and boost revenue through enhanced user satisfaction, making them highly valuable for businesses aiming to remain competitive in a data-driven market.

On the other hand, Predictive Maintenance had a lower customer value and data readiness score. This indicates that while predictive maintenance can be beneficial, it is likely constrained by both the quality and availability of the data needed for accurate predictions. Predictive maintenance often relies on real-time data from sensors or machinery, and insufficient data or poor-quality data can undermine its potential effectiveness. This feature, therefore, faces a significant challenge in terms of data preparation, which could delay its deployment and reduce its immediate customer value. It highlights the importance of data readiness as a key factor in the feasibility of AI feature implementation.

Implementation Cost: A Critical Constraint

The implementation cost dimension is perhaps the most contentious aspect in AI feature prioritization. AI features such as Fraud/Risk Detection and Smart Search & Discovery perform well on customer value and data readiness but are offset by higher implementation costs, reflecting the technical complexity and the need for specialized expertise, infrastructure, and computational power to deploy such systems. These features often require complex model development, ongoing maintenance, and high-performance computing resources, which add substantial cost. Despite these costs, their high customer value justifies their prioritization, especially in high-stakes areas like fraud detection, where the cost of failure could be significant in terms of both financial losses and reputation damage.

In contrast, features like Auto Customer Support Chatbot and Demand Forecasting performed well in terms of implementation cost. These features are relatively low-cost to implement, particularly with the advancement of existing chatbot frameworks and predictive analytics tools. Although they are not as high in customer value as some other features, they represent quick wins—easy-to-deploy solutions that can enhance customer support and operational efficiency with a relatively low investment. This reflects a broader trend in AI product development where businesses look for features that can quickly improve user satisfaction without requiring significant upfront investment. These features also contribute to operational agility and can provide foundational systems that lead to more complex AI features in the future.

The Importance of Data Readiness in AI Product Development

The importance of data readiness cannot be overstated. The results highlight that features with high data readiness, such as Personalized Recommendations and Fraud/Risk Detection, are more likely to be prioritized and successfully implemented. This is consistent with the literature on AI adoption, which emphasizes that the availability of quality, clean, and structured data is a critical factor in the success of AI initiatives (Dalal, 2018; Hegde, 2021). In contrast, AI features with low data readiness, like Predictive Maintenance, face significant barriers to implementation, underscoring the need for strong data management systems and processes that can ensure data availability and quality from the outset.

For organizations looking to implement AI features, this result emphasizes the need to invest in data infrastructure and data governance. AI is only as effective as the data it is trained on, and without the right data infrastructure, even the most innovative AI features may fall short of their potential. Therefore, ensuring that data is accessible, clean, and structured is as critical as the development of the AI model itself.

Using Prioritization to Align Stakeholders and Resources

Another key takeaway is the importance of prioritization frameworks in aligning various stakeholders within the organization. AI product teams often consist of product managers, data scientists, engineers, and other stakeholders, all of whom may have different views on what constitutes the most important features. The prioritization tool presented in this study helps align these stakeholders by providing a clear, structured approach to feature evaluation. By using the tool, teams can make data-driven decisions and avoid conflicts over which features to prioritize.

The grouped bar chart (Figure 2) and heatmap (Figure 4) visually demonstrate how these features compare across the three dimensions, allowing teams to easily communicate trade-offs and justify prioritization decisions. This transparency in decision-making is essential for fostering collaboration across teams, ensuring that everyone is on the same page about the resource allocation and development timeline for each AI feature.

Trade-Offs Between Features: Short-Term Wins vs. Long-Term Impact

The study also illustrates the trade-offs between short-term wins and long-term impact in AI product development. Features like Auto Customer Support Chatbot and Demand Forecasting represent quick wins—they are cost-effective, easy to deploy, and improve user experience or operational efficiency relatively quickly. While their customer value scores are lower than features like Personalized Recommendations, they provide immediate benefits and can serve as foundational components that allow for more sophisticated AI features down the road.

On the other hand, features like Fraud/Risk Detection and Personalized Recommendations, while higher in customer value and data readiness, require a more significant investment in terms of both time and resources. These features represent long-term investments that can drive substantial returns, especially in high-risk or high-value business domains such as fraud detection or customer engagement. The prioritization tool enables teams to evaluate whether they should focus on immediate, cost-effective improvements or invest in more complex, high-value features that will take longer to develop but provide substantial business benefits in the long run.

Implications for AI Product Teams

The findings from this study offer several practical implications for AI product teams. First, data readiness should be a foundational consideration when prioritizing AI features. Teams should assess whether the necessary data infrastructure is in place before pursuing features that require substantial data inputs. Second, while implementation cost is a critical factor, features with high customer value should be prioritized even if they come with higher implementation costs, provided the long-term benefits justify the investment. Finally, using a structured framework like the one presented in this study can help teams make informed decisions, align stakeholder interests, and allocate resources more effectively.

Limitations and Future Research

While this study provides valuable insights into AI feature prioritization, several limitations should be acknowledged. First, the tool was tested using an illustrative set of AI features and may require customization for different industries or types of AI applications. Future research could extend this tool by testing it across different domains (e.g., healthcare, finance, e-commerce) to explore its applicability in various contexts. Additionally, the tool could be enhanced by incorporating real-time performance metrics to further refine the prioritization process and improve its predictive accuracy.

Conclusion

This study addressed a practical and increasingly urgent challenge in AI product management: how to prioritise AI features in a way that is customer-focused, data-aware, and resource-realistic. While traditional prioritisation models often emphasise user demand and engineering effort, AI products introduce additional complexity because outcomes are heavily shaped by data quality, accessibility, and model feasibility. To respond to this gap, this research proposed a simple, structured prioritisation tool that balances three key dimensions—customer value, data readiness, and implementation cost—and translates them into an interpretable scoring and visual decision system.

The results suggest that the tool can serve as an effective early-stage decision aid for AI roadmapping. Features that scored high on customer value and data readiness while maintaining manageable implementation cost emerged as clear priority candidates. Conversely, features with strong potential value but weak data readiness or higher cost were positioned as later-stage opportunities requiring foundational investment in data pipelines, governance, or infrastructure. This pattern reinforces an important insight: AI feature success is not determined by desirability alone, but by the intersection of value, data feasibility, and delivery constraints. The tool helps make this intersection visible and actionable.

A key contribution of this study is its emphasis on alignment across cross-functional teams. AI prioritisation typically involves competing perspectives: product teams advocate for user impact, data teams emphasise data quality and availability, and engineering teams focus on complexity, integration, and delivery timelines. The proposed framework offers a shared language and structured criteria that reduce subjective debate and create a more transparent rationale for resource allocation. In this sense, the tool is not only a ranking mechanism but also a collaboration and governance aid that improves planning discipline and reduces the risk of prioritising AI work that is structurally unready.

From a managerial perspective, the findings imply that organisations can improve AI outcomes by adopting a two-speed prioritisation logic. First, prioritise "ready-to-win" features that combine high customer value with strong data readiness and reasonable cost. Second, build a parallel track for "high-value but not-yet-ready" features by investing in data strategy, instrumentation, and scalable architecture. This approach enables firms to generate short-term wins while building the foundations for more advanced AI capabilities. The tool therefore supports both immediate product effectiveness and long-term AI maturity.

Despite its practical strengths, the study has limitations. The prioritisation logic is intentionally lightweight and may not capture complex interdependencies such as regulatory risk, model drift exposure, real-time infrastructure constraints, ethical impact, or strategic differentiation in highly competitive markets. In addition, the scoring process still relies partly on expert judgment. Therefore, the tool is best viewed as a structured decision support framework, not a fully automated truth engine.

Future research could extend this work in several ways. First, the model could be enhanced by adding optional modules for risk, ethics, compliance, and sustainability. Second, empirical testing across multiple industries could validate whether the weighting of value, data readiness, and cost differs between sectors such as healthcare, finance, telecom, and e-commerce. Third, longitudinal studies could assess whether features prioritised by this tool deliver stronger real-world performance, adoption, or ROI over time. Finally, integrating the framework with live product analytics and data observability systems could enable dynamic reprioritisation as data maturity and business needs evolve.

In summary, this study demonstrates that a simple, well-structured tool can meaningfully improve AI feature prioritisation by making trade-offs explicit and comparable. By balancing customer value, data readiness, and implementation cost, the proposed method helps teams invest in AI features that are not only attractive but also achievable. As AI becomes a standard layer of modern products, such pragmatic prioritisation frameworks will be essential for turning ambitious ideas into deliverable, measurable outcomes.

Conflicts of Interest: "The authors declare no conflict of interest."

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