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The role of information systems and technologies in monitoring and optimizing delivered product value in the age of artificial intelligence

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Abstract

Artificial intelligence (AI) is applied in almost all areas of business today, from process automation to personalization of product/service offers. As it is of great importance for any organization to understand the delivered value of its products and services, this paper aims to explore how information systems and technologies, enhanced with AI components, are used in this field. A systematic literature review highlights AI tools used for tracking key metrics, the most important metrics and AI's role in optimizing product offerings through predictive models and dynamic pricing. The study discusses how AI contributes to value creation by enabling personalized experiences and adaptive systems. Furthermore, the study proposes a framework for the level of adoption of AI in the context of value delivery. The findings suggest that while AI is widely applied in monitoring and optimization, its role in value creation remains underexplored, offering opportunities for further research.
Keywords: *AI, artificial intelligence, product value, delivered product value*

1. Introduction

Every few years, a new technology emerges that dominates the discourse, both in industry and academia. Just a few years ago, discussions were centered around blockchain, and before that, the Internet of Things (IoT), as well as technologies like virtual reality (VR) and big data. However, as explained by the Gartner Hype Cycle (Dedehayir & Steinert, 2016), interest in these technologies eventually declines after a period of intense enthusiasm. In contrast, over the past few years, since large language models (LLMs) became accessible to the wider public, interest in artificial intelligence (AI) has shown no signs of diminishing (Liang et al., 2025). Moreover, AI has become a part of the everyday lives of many people, something that the previously mentioned technologies did not fully achieve (Storey et al., 2025).

Artificial intelligence had already been applied across many fields, from medicine (Xie et al., 2023) and manufacturing (Kinkel et al., 2022) to services (Giebelhausen & Poehlman, 2024). However, in earlier stages, it was primarily the domain of AI specialists, while professionals from other industries rarely had the opportunity to directly interact with it (Costa et al., 2024). Considering the recent boom and the emergence of numerous user-friendly applications that simplify its use, it becomes particularly interesting to investigate, from an academic standpoint, how AI is being applied.

Information systems and technologies have long played a pivotal role in supporting business processes, enabling companies to collect, store, and analyze vast amounts of data (Chuma, 2020). With the advent of artificial intelligence, these systems have been further enhanced, offering unprecedented opportunities for monitoring product performance, predicting customer behavior, and improving overall value delivery. AI-driven tools enable real-time insights, intelligent automation, and advanced optimization techniques that surpass the capabilities of traditional information systems (Sarker, 2021). Mimmo et al. (2025) state that if businesses want to remain competitive, they need to think about the proactive integration of AI.

Therefore, this paper aims to explore how AI is applied in the context of monitoring and optimizing delivered product value. To the best of the author's knowledge, there is no existing study in the literature that directly addresses this issue. The paper is structured as follows: first, a theoretical background on delivered product value and its management will be

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provided; second, the methodological framework used in the study will be explained; a presentation of the results will follow this; and finally, the findings will be discussed.

2. Theoretical background

Product value represents the perceived worth that customers derive from a product or service relative to the costs they incur to obtain it (Blut et al., 2024). This concept extends beyond simple monetary calculations to encompass a multifaceted evaluation of benefits versus sacrifices (Yrjölä et al., 2025). Value encompasses multiple dimensions (Frank et al., 2021; Yrjölä et al., 2025):

- Utilitarian value - Rational, task-related benefits that help customers accomplish specific goals efficiently;
- Hedonic value - Emotional, experiential, and sensory benefits that provide intrinsic satisfaction;
- Symbolic value - Social meaning and identity-related benefits that enhance self-concept and status.

Modern conceptualizations recognize that product value is not merely about functional performance but encompasses the entire customer experience (Hoyer et al., 2020). As noted, "value propositions are competitive statements of the value offered to a specific group of customers" (Yrjölä et al., 2025), highlighting the strategic importance of clearly articulating and delivering intended value. Delivered product value represents the actual value that customers experience and perceive from a product in real-world usage contexts, which often differs significantly from the intended design value (Yrjölä et al., 2025). This distinction is critical because "customers might perceive the value of a firm's offering very differently from the firm's stated value proposition, especially when the value proposition is novel" (Yrjölä et al., 2025).

„Consumers often use objective as well as subjective criteria to evaluate a product.“ (Luo et al., 2008). Monitoring product value, therefore, requires comprehensive approaches that capture both. Traditional monitoring often focused on internal operational metrics, but contemporary approaches emphasize customer-centric measurements (Ledro et al., 2025). Key monitoring dimensions include:

- Performance Metrics - Technical specifications, quality indicators, and functional outcomes (More & Unnikrishnan, 2024; Wu & Monfort, 2023);
- Customer Experience Indicators - Satisfaction scores, engagement levels, and behavioral patterns (Hoyer et al., 2020; Roy et al., 2025);
- Usage Analytics - How customers actually interact with and utilize products (Kumar et al., 2019; Roy et al., 2025);
- Value Perception Measures - Customer assessments of benefits received relative to costs incurred (Frank et al., 2021).

Modern monitoring systems increasingly leverage artificial intelligence to provide real-time insights. As demonstrated in recent research, "AI-powered loyalty programs meticulously track customers' behaviors and preferences and offer personalized rewards." (Roy et al., 2025), enabling continuous value assessment and adjustment.

Value optimization involves systematically improving the alignment between delivered value and customer expectations while maximizing organizational returns. This process requires dynamic capabilities that enable organizations to "sense, seize, and transform" in response to changing market conditions (Garg et al., 2025). It can include personalization and customization (More & Unnikrishnan, 2024; Roy et al., 2025), real-time adaptation (More & Unnikrishnan, 2024; Oteri et al., 2023) predictive enhancement: which means anticipating customer needs and proactively improving value propositions (Kumar et al., 2019; Roy et al., 2025), etc. The literature emphasizes that "AI enables businesses to make pricing decisions that are responsive to market dynamics, allowing them to stay ahead of the competition." (Oteri et al., 2023), illustrating how optimization extends beyond product features to encompass dynamic value delivery mechanisms. The importance of value management has intensified in the digital age, where "customer experience has become one of the most important concepts for understanding the interaction between businesses and their customers" (Skare, 2024).

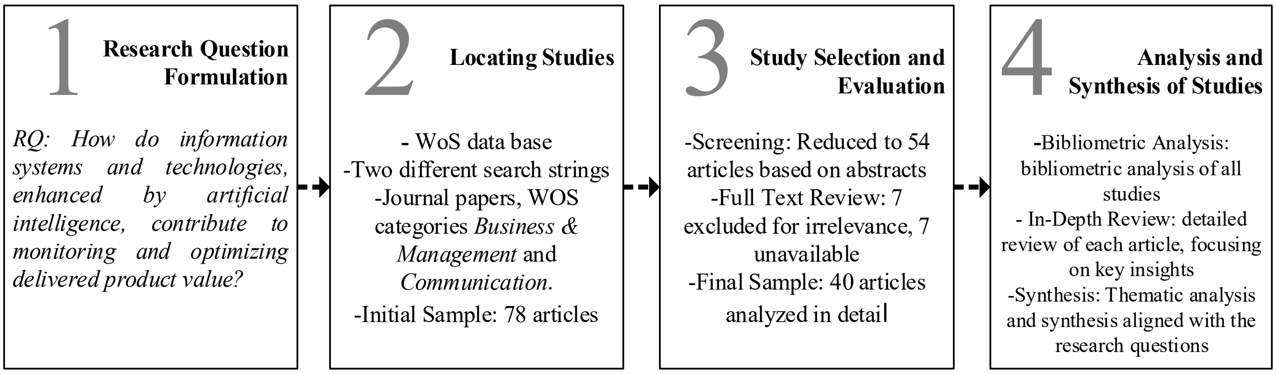
Designing value involves understanding the customer's world and their desired benefits. Companies aim to create a "value proposition," which is essentially a suggestion of the impact their offering can have on customers' practices. This process should be deeply rooted in customer insight. While companies design and deliver value, the actual "value-in-use" is actualized by the customer. This means that value emerges in the customer's everyday processes and is often invisible to the company (Ojasalo & Ojasalo, 2018).

Given the dynamic nature of customer perception and the co-creative aspect of value, continuous tracking and monitoring are essential. This helps companies bridge the gap between their designed value and the customer's perceived value.

3. Methodology

Designed (planned) value and delivered (perceived) value can be different. That is why monitoring and optimization are important; they enable timely adjustments. As already mentioned, the existing literature does not provide studies that directly address this specific topic in the context of AI. Therefore, a systematic literature review (SLR) was conducted to understand the landscape of the subject. The review was carried out in line with the framework of Denyer & Tranfield (2009), and the following illustrates how. Figure 1 depicts the steps of the SLR.

Figure 1. Literature review protocol based on denyer & tranfield (2009) framework



Source: Author´s analysis

First step of SLR is Research Question Formulation (Figure 1). Monitoring and optimization of the product value, especially delivered product value, are crucial for achieving business results. As technology has drastically evolved, and the use of AI is becoming more and more prevalent, the goal of this paper is to understand the role of artificial intelligence in monitoring and optimizing delivered product value. To achieve this research goal, the following overarching research question (RQ) was formulated:

RQ: How do information systems and technologies, enhanced by artificial intelligence, contribute to monitoring and optimizing delivered product value? To provide a more comprehensive answer to this question, several sub-questions were defined:

- RQ1: How is AI applied for monitoring and/or for optimization of delivered product value?
- RQ2: Which value-related metrics are most frequently monitored and optimized through information systems?
- RQ3: What types of information technologies and AI-driven tools are most utilized in this context?

The second step of SLR is Locating Studies (Figure 1). The Web of Science (WoS) database was used to source and collecting relevant studies. The initial search strategy relied on a complex combination of keywords directly aligned with the main research question: ("information systems" OR "information technologies" OR "digital technologies") AND ("monitoring" OR "tracking" OR "optimization" OR "performance evaluation") AND ("delivered value" OR "product value" OR "value-in-use" OR "customer value") AND ("artificial intelligence" OR "machine learning" OR "data analytics".

This search resulted in only a small number of publications. Consequently, the search string was broadened to include more general keywords: "artificial intelligence" AND "customer value". Only articles published in peer-reviewed journals in the English language were considered. WoS also allows filtering by categories and research areas, so the search was further refined by selecting the categories: Business & Management and topic meso: Management and Communication. This process resulted in an initial sample of 78 articles.

The third step of SLR is Study Selection and Evaluation (Figure 1). All sample articles were screened by reading their abstracts, which reduced the pool to 54 articles. In the next step, the full texts were examined. Seven papers were excluded as they were not directly related to the research topic, while another seven were unavailable in full text. This resulted in a final sample of 40 articles, which were then analyzed in detail.

The fourth step of SLR includes Analysis and Synthesis of Studies (Figure 1). Firstly, a bibliometric analysis was performed to understand the studied body of literature as a whole, focusing on main themes. Then, each study was examined in detail to enable a thematic analysis and the synthesis of knowledge. The most significant insights were extracted for each article, along with bibliometric details, methodology, and other relevant information. Particular attention was given to how each study addressed the defined research question(s). Given the relatively small sample size, it was decided to conduct a narrative synthesis rather than a statistical meta-analysis. The final step (Reporting and use of the results) of the SLR (Denyer & Tranfield, 2009) is presented in the following chapter.

4. Results

4.1. Bibliometric analysis

The first step of this systematic literature review was Bibliometric analysis. Bibliometric analysis was conducted using the Bibliometrix (Aria & Cuccurullo, 2017) package in R. Although a small number of papers were included in this review, the Bibliometric analysis was useful for understanding the broader picture of this research context.

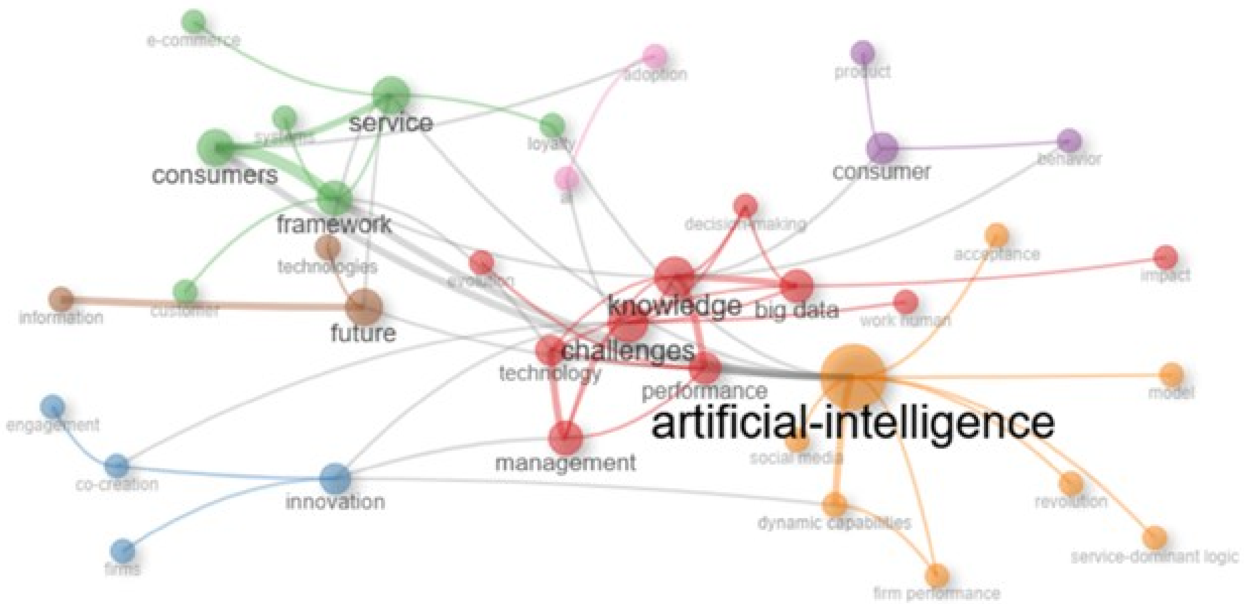
Figure 2. Bibliometric data at a glance – generated using Bibliometrix

Source: Author´s analysis

Figure 2, in the form of a dashboard, summarizes the bibliometric corpus of this research. It was generated using Bibliometrix. Data set covers articles published in the 2018–2025 timespan, and includes 40 documents from 27 different sources. There are 137 authors, with only 2 single-authored papers; the average is 3.55 co-authors per paper and 57.5% international co-authorship, indicating strong collaboration. Annual publication growth is 34.59%. The corpus contains 3,379 references and 188 author keywords (DE). Documents are on average 2 years old and receive 62.2 citations per paper.

Moving on to the thematic analysis, Figure 3 illustrates a co-occurrence network of key terms related to AI and its impact on consumer value. Each node represents a term, and the thickness of the lines between them indicates the frequency with which these terms co-occur in the analyzed literature. The central term, "artificial intelligence," is strongly linked to terms such as "knowledge," "big data," "performance," and "challenges," highlighting the core role of AI in shaping business and consumer outcomes. Other terms like "consumer," "framework," "service," and "loyalty" point to the influence of AI on consumer behavior and business models, emphasizing how AI contributes to the creation and optimization of consumer value. This network demonstrates the intricate relationships between technological, business, and consumer factors in the context of AI and value creation.

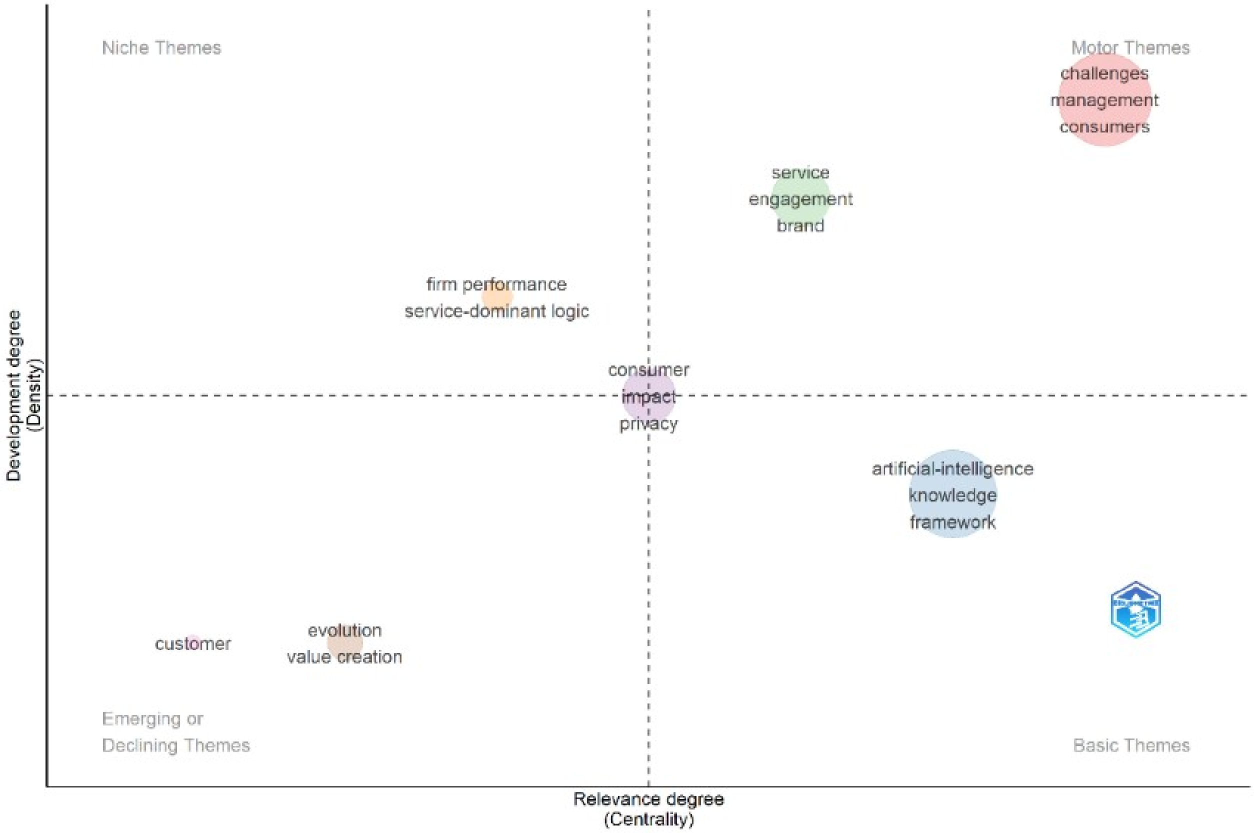
Figure 3. Key themes - co-occurrence network – generated using Bibliometrix



Source: Author´s analysis

Figure 4. illustrates the positioning of various themes related to AI and customer value based on their development degree (density) and relevance degree (centrality). Themes such as consumer, impact and privacy occupy central and high-development areas, reflecting their growing importance in the evolving landscape of AI and customer value. Conversely, themes like firm performance and service-dominant logic are placed in more peripheral areas, signifying their declining relevance or emerging status. The chart emphasizes the dynamic nature of the field, highlighting key areas like AI frameworks and consumer engagement that are driving current discussions and innovations.

Figure 4. Themes - relevance and development – generated using Bibliometrix



Source: Author´s analysis

Both graphs were based on article keywords, using the keywords plus option in Bibliometrix.

4.2. Optimization and monitoring value

None of the papers in the sample deal directly with the optimization and monitoring of product value alone. The sample can be divided into two categories: papers that characterize optimization and monitoring as important elements of technology application but do not go beyond that, and those that engage with these topics more directly. The split is approximately 2/3 to 1/3. Regarding the first category, these are mostly papers that mention relevant aspects related to this topic in their literature reviews or theoretical backgrounds, but such aspects are absent from the core of the work. On the other hand, the second group of papers explores the topic in greater depth, most often focusing on product customization achieved through the use of AI.

Authors approach optimization and monitoring from different perspectives. Huang & Rust (2021) divide AI into three parts: mechanical, thinking, and feeling, each of which is intended to meet different needs and serve different purposes. Mechanical AI is used for repetitive, simple tasks that are straightforward and standardized. Thinking AI is applied to more complex, systematic, and well-defined tasks, while social AI is directed towards emotional, communicative, and interactive tasks. Although the authors do not state this explicitly, all three types of AI can be used for optimization and monitoring of delivered value. In this context, they particularly emphasize Thinking AI, presented as a tool for predictive analytics, market prospecting, and service creation, enabling firms to monitor customer preferences and continuously adapt offerings. Nevertheless, for all of this to be possible, mechanical AI is also necessary.

The literature presents cases where the focus is solely on monitoring. In Libai et al. (2020) work on AI and customer management, AI is presented as a tool to monitor customer behavior (IoT sensors, Alexa/voice assistants), but it is also noted that AI plays a role in optimizing value through habit formation and automatic personalization.

However, authors are often more focused on parallel monitoring, evaluation, and consequently optimization through the use of AI. Yrjölä et al. (2025) show how AI-enabled inventory tracking, dynamic pricing, demand forecasting, drone/driverless deliveries, and real-time product availability updates illustrate how AI monitors and optimizes offerings. Similarly, Mimmo et al. (2025) highlight AI-based inventory control, real-time stock level monitoring, and "manufacturing on request" strategies, which reduced overproduction by nearly 30% and enhanced supply chain transparency via blockchain-enabled garment QR codes in the fashion industry. The same is noticeable in Kumar et al. (2019) study, which highlights AI's role in automating data collection, storage, and real-time curation; enabling dynamic pricing (Jet example), delivery time optimization (Uber Eats example); The paper discusses adaptive recommendation engines as a key application of machine learning algorithms for personalizing customer experiences.

On the other hand, part of the literature also focuses on optimization of offerings, but more through customer behavior analysis. AI-powered analytics are important for immediate measurement and understanding of customer behavior and responses to product features or campaigns, allowing for quick insights into performance (More & Unnikrishnan, 2024). More & Unnikrishnan (2024) discusses how real-time AI analytics monitor customer responses and adjust campaigns or product offerings instantly, improving conversion rates. Liu-Thompkins et al. (2022) examines AI capabilities for preference construction, personality assessment, and goal inference that support personalization and recommendation, although it does not explicitly focus on monitoring aspects. Skare (2024) claims that AI is used for predictive analytics, pattern recognition, and real-time personalization that help forecast demand, optimize inventory, and streamline the entire customer journey. Post-deployment AI models are designed to continually update and learn (e.g., reinforcement learning, periodic recalibration) (Grewal et al., 2024, Overgoor et al., 2019); the model drift and regular performance checks are also stressed as important (Ledro et al., 2025). AI relies on IoT sensors, wearables, and AI-enabled data capture to track usage and tailor services (e.g., smart home bots), as well as chatbots that monitor post-purchase interactions (Gao & Liu, 2023).

AI-powered analytics enable a shift from merely reacting to problems to proactively predicting customer needs and market trends. This allows for the optimization of customer experiences and overall business outcomes by seamlessly integrating new technologies (Hoyer et al., 2020; More & Unnikrishnan, 2024).

Authors also emphasize the importance of AI for the bottom line. This involves using data-driven decision-making, predictive analytics, and dynamic pricing models that adjust in real time based on market conditions, demand fluctuations, and customer behavior to maximize profitability (Oteri et al., 2023). Studies highlight AI-enabled real-time data, automated pricing, and back-end support that improve service efficiency and product optimization (Chen & Prentice, 2025; Khoshtaria et al., 2025; Oteri et al., 2023; Roy et al., 2025). AI can also monitor competitor prices, demand fluctuations, inventory levels, and external factors (weather, events) to adjust prices in real time (Oteri et al., 2023).

4.3. Metrics and key performance indicators

This part of the paper will explore metrics and key performance indicators (KPIs) influenced by AI use as well as ways of measuring AI success. Although the sub-research question primarily focuses on delivered product value metrics, it is also important to consider the success of AI technology adoption, since effective implementation is a prerequisite for monitoring, optimizing, and delivering product value.

When measuring the success of AI use, financial performance is often the first category to look at. Revenue impact and return on investment (ROI) stand out as key indicators. Research shows that AI marketing strategies have significant positive effects on organizational performance, leading to improvements in profits, sales growth, and customer satisfaction (Wu & Monfort, 2023). AI-driven pricing and revenue optimization can maximize profitability while at the same time helping with customer satisfaction (Oteri et al., 2023).

Model performance and quality metrics are also very important. Predictive accuracy of the model and model reliability can be recognized as the most relevant. High accuracy rates have been achieved across different AI tools, with customer behavior prediction models generally ranging between 83% and 88.2% (More & Unnikrishnan, 2024). Continuous monitoring and retraining are crucial to ensure the sustained performance of AI over time. For example, customer behavior models may require updates every few months, but technical systems might need it on a daily basis (Ledro et al., 2025). Aspects such as response times also matter, with studies showing that AI customer service can handle up to 88% of interactions and significantly reduce waiting times, while also demonstrating better problem-solving ability for low-complexity tasks compared to human agents (Xu et al., 2020).

Another important perspective is the examination of key success factors for AI implementation. Research emphasizes that AI initiatives must align with organizational goals and be integrated across hierarchies and functions (Kumar et al., 2019). Success depends on establishing clear KPIs at the project's outset, as companies that set overly ambitious or vague goals often fail to deliver results (Ledro et al., 2025). The availability of high-quality, representative data is fundamental (Oteri et al., 2023), and organizations must also ensure robust data governance, transparency and address potential biases

(Ledro et al., 2025). Human oversight remains indispensable (Ledro et al., 2025), as the most effective approaches combine AI capabilities with human judgment and skills to work alongside AI systems (Ferraro et al., 2024). Successful implementation further requires ongoing performance assessment, retraining of models, and adjustments to shifting market conditions (Ledro et al., 2025; Oteri et al., 2023).

Finally, the customer experience and engagement dimension is also central when evaluating AI success. AI-driven personalization has been shown to significantly increase customer satisfaction, with tools achieving scores of 87.6 out of 100 (More & Unnikrishnan, 2024). Predictive segmentation has reached engagement rates as high as 83.2%, confirming the effectiveness of AI in customer targeting (More & Unnikrishnan, 2024). There is also a strong positive correlation between real-time AI campaign adjustments and conversion rates, while predictive retention strategies have demonstrated the highest improvements in customer retention (More & Unnikrishnan, 2024).
When it comes to value optimization, the literature reveals a very diverse picture that cannot be easily generalized. Depending on the specific case, different parameters were observed, as each situation aimed to achieve a different outcome. This heterogeneity highlights that optimization through AI is highly context-dependent, with metrics and approaches varying across industries, goals, and implementation settings.

It is noticeable that there is no direct metric focused solely on value itself, which is completely expected given the difficulty of measuring this value. However, there are numerous metrics that indirectly indicate whether value is being delivered or not. Often, these metrics are related to engagement, such as click-through rate (Overgoor et al., 2019) and engagement rate (Hoyer et al., 2020; More & Unnikrishnan, 2024). Another important metric here is customer lifetime value (Raji et al., 2024). Furthermore, metrics such as conversion rates, customer satisfaction (Raji et al., 2024), and post-purchase satisfaction (Hoyer et al., 2020) also play an essential role. Retention rates are another key indicator to be considered (More & Unnikrishnan, 2024).

4.4. Technologies

The last sub-research question is aimed at exploring the types of information technologies and AI-driven tools are most utilized in this context. More & Unnikrishnan (2024) provide an overview of tools that can be used for customer analytics and segmentation. These tools use deep learning and machine learning algorithms to predict customer behavior and recommend personalized products (More & Unnikrishnan, 2024). They can analyze customer data to generate insights and predictions, helping prioritize leads and automate follow-up in sales teams (Roy et al., 2025). Some tools offer robust natural language processing (NLP) and sentiment analysis capabilities. Studies show these tools analyze customer opinions and preferences based on reviews, social media and feedback in order to understand emotional insights for customer segmentation (More & Unnikrishnan, 2024). These tools also provide AI-powered analytics to audit behavioral trends, customer journeys and website traffic (More & Unnikrishnan, 2024). Machine learning algorithms enable real-time customer interaction assessment and AI-driven segmentation effectiveness evaluation.

Dynamic pricing and revenue optimization are common ways of utilizing AI to optimize offerings and therefore delivered product value. Most notably, Uber and Lyft use AI-powered dynamic pricing systems that adjust prices in real-time based on demand, traffic, and location data (Hoyer et al., 2020). These systems provide transparent, supply-and-demand-based pricing for transactions. Similarly, hotels and airlines extensively use AI algorithms to alter prices based on market conditions, booking patterns as well as customer demand (Oteri et al., 2023). For example, AI algorithms can forecast demand rises and adjust prices dynamically during peak periods.

When it comes to predictive analytics tools and machine learning (ML), these can be found in many companies. In retail, there are recommendation systems that use ML algorithms to analyze customer browsing history, purchase patterns, and the behavior of similar users to suggest products (Raji et al., 2024; Yrjölä et al., 2025). This system continuously learns from customer data to optimize product recommendations and has contributed to Amazon's success in cross-selling. Similarly, recommendation systems are used for content personalization. Netflix leverages AI to personalize content recommendations by analyzing user ratings, viewing history, and genre preferences. This approach has played a role in good retention rates and keeping users engaged on the platform (Raji et al., 2024). Similarly, Spotify uses AI to create personalized playlists like "Discover Weekly" based on users' listening history and favorite genres among other criteria, and (Kumar et al., 2019; Raji et al., 2024).

Literature also shows AI is used for customer service, often based on NLP. Chatbots and virtual assistants like Alexa, Siri, and Cortana are used for customer service optimization. (Huang & Rust, 2021; Kumar et al., 2019). These systems use NLP to understand and respond to queries in real-time. Some other notable examples are 1-800-Flowers' Gwyn Chatbot that acts as a personal gifting concierge, asking customers 5-6 questions about gift recipients to recommend perfect products based on shopping needs (Liu-Thompkins et al., 2022). Similarly, there are AI-enabled Call Center that quickly analyzes customer call nuances using NLP, processing heterogeneous voices and inquiries to provide real-time answers (Liu-Thompkins et al., 2022).

Kumar and colleagues (2018) give interesting examples from the automotive industry where cloud technologies have been used to power AI. Tesla stores cloud data from all running cars and uses AI tools to customize driving suggestions and improve subsequent models. In one instance, Tesla used AI to identify and fix overheating problems across all running cars through cloud-enabled solutions. Mercedes MBUX enhances the driving experience through AI-enabled voice assistants and safety features based on data collected while driving.

5. Discussion

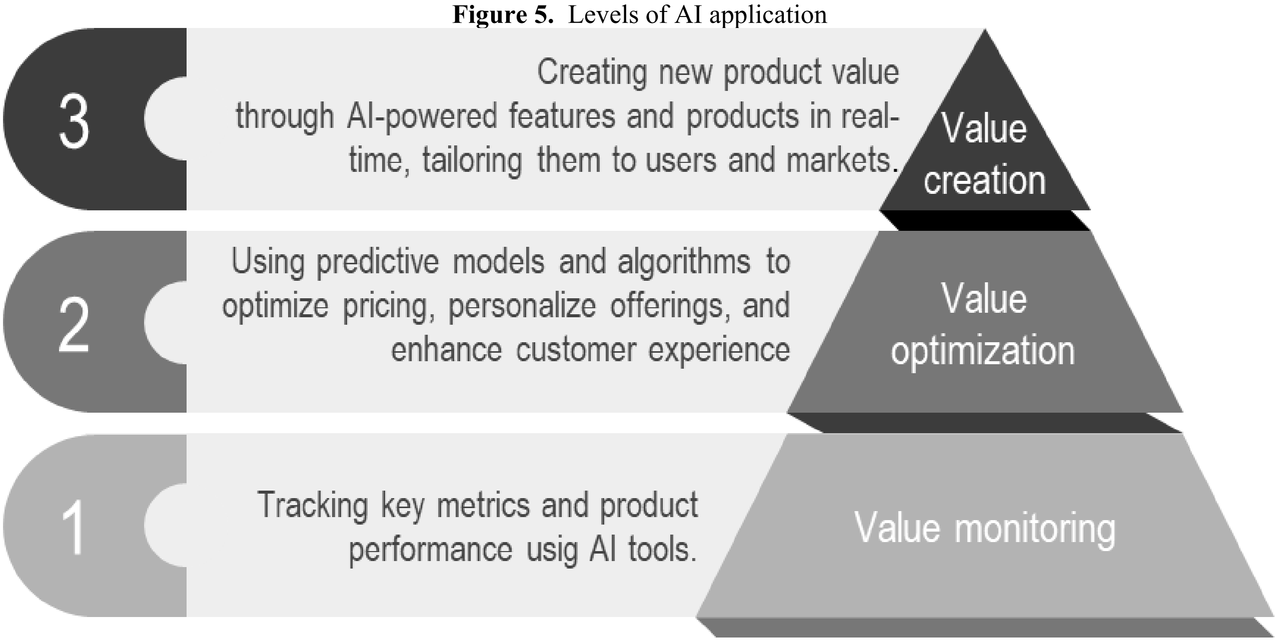
The first research question concerned the monitoring and optimization of delivered product value. Based on the literature review, it is clear that the application of AI for monitoring and optimization is substantial. While this is evident, the literature is generally sparse, with only a few studies available, reflected in the sample size. The studies examined in this research do not discuss the application of AI in the context of delivered value; this must be inferred indirectly. A smaller portion of the studies reviewed focused solely on monitoring value. AI applied in this context mainly involves tracking metrics such as customer satisfaction, churn prediction, sentiment analysis, and anomaly detection in product performance. These models appear simpler, and they do not directly impact the delivered value; instead, they track it (either directly or indirectly). When it comes to AI applications for optimization, AI tools such as predictive models, dynamic pricing algorithms, and product personalization systems enable organizations to improve customer experience or enhance products. In this way, direct influence is exerted on the product offering, which, if done correctly and aligned with user needs, should also impact the delivered value.

The second research question concerned the metrics and KPIs that are monitored and optimized. This review showed that many different metrics can be tracked and optimized. The question is whether it is necessary to use AI for monitoring some of them. When dealing with a complex metric that is hard to track using other systems, AI is needed. For instance, when we have IoT or advanced technologies that operate based on AI. However, monitoring simple metrics does not necessarily require AI. On the other hand, if these metrics are also optimized in parallel, this starts to make sense. Here, we can also distinguish whether optimization occurs in real-time or if data collection and optimization are completely separate.

Regarding the third research question, AI-based information technologies and tools used, the paper provides an overview of their applications, as well as existing solutions described in the literature. Various business intelligence (BI) systems, enterprise resource planning (ERP) systems, customer relationship management (CRM) systems, and analytics platforms are used for performance optimization and monitoring, but they were not the focus of this paper, as they are not necessarily based on AI technologies. When it comes to AI tools and technologies, the most common are: predictive analytics, machine learning models, NLP, deep learning for pattern recognition, and generative models for personalization.

With all this in mind, AI can be used for monitoring or optimization alone, and there are also situations where it is used for both. However, there is one additional step that is not as clearly represented in the literature, which is when AI is used for monitoring, optimization, and creating delivered value. Figure 1 depicts the levels of AI application in the context of delivered value. This is a conceptual model based on the presented literature review.

Figure 5. Levels of AI application



Source: Author´s analysis

As already mentioned, the first level in the proposed model is using AI only for monitoring. For example, this level relates to using computer vision technologies to monitor defects in products on a production line. In this case, AI only detects errors, while humans make decisions about corrections. In the context of delivered value, this has an impact because it is directly related to the quality level of the product itself. Similarly, if we consider customer satisfaction, it could be measured using sentiment analysis of online reviews. Based on the analysis results, managers would make decisions about what needs to be done with the product/service to impact the delivered value. In the same way, we can observe metrics such as click-through rates and engagement on social media.

The next level in the model is direct optimization. Looking back at the first example, this would mean that AI not only detects errors but also recommends corrections in the manufacturing process. Based on data analysis, the system can suggest optimal production parameters, reduce errors, or even automatically adjust machine settings to improve product quality. If we consider sales and sentiment analysis, the second example, based on reviews and tracking, based on customer satisfaction data, AI can personalize offers or suggest specific actions (e.g., sending coupons, personalized promotions) to customers who have shown signs of dissatisfaction. It can also automate communication with customers and predict which products or services they are likely to want in the future, increasing their satisfaction. When it comes to marketing campaigns, based on collected data, AI can automate the creation of campaigns in real-time, suggesting changes to the target audience, campaign timeframes, or even ad types. It can also test A/B variants and immediately apply the most effective option, increasing ROI.

Finally, the last level is the creation of value for the customer through monitoring and optimization. A good example of this is streaming platforms and services, such as Spotify and Netflix. Spotify and Netflix use AI to create personalized recommendations for users based on their previous activities (listening to music, watching movies/TV shows). AI analyzes user data (how they listen to music, which movies/TV shows they watch) and suggests new content in real-time. Based on user preferences, AI creates new playlists or recommends new movies/TV shows that the user might not have discovered on their own, thus creating new content specific to each user, which not only complements a good content library but also represents the value delivered to users. In this way, AI models not only optimize the content available to users but also create new value through completely personalized experiences that enhance user satisfaction. This is, however, just a conceptual model and further studies should be conducted to better understand the value creation aspect as well as its impact on business.

4. Conclusion

The aim of this paper was to examine the use of AI technologies in monitoring and delivering value. This research was conducted as a systematic literature review following the recommendations of Denyer & Tranfield (2009). The review covered 40 papers, which were thoroughly analyzed. This paper illustrates both a short bibliometric analysis of the literature as well as an in-depth thematic analysis. To illustrate the scope and recency of the evidence base, the paper includes a compact bibliometric snapshot (Figure 2) of the corpus. A literature review protocol flow (Figure 1), as well as source search strings, is provided to enable replication.

The conducted study provides a comprehensive perspective on the literature that deals with the application of AI for the purpose of monitoring and optimizing value. This area of literature is not extensively developed, meaning that AI usage is often not contextualized in terms of product value or delivered product value. This paper synthesized how value is monitored and optimized, which KPIs are tracked, and how AI, supports these practices. Building on the evidence, this research proposes a three-level conceptual model of AI adoption for delivered value (monitoring → optimization → value creation – Figure 5).

The research is not without limitations. First of all, the sample size of the papers is relatively small, including only 40 papers. The search was limited to the Web of Science, and access to certain databases (Taylor and Francis, ScienceDirect) was not available. Given the rapid progress in fields such as artificial intelligence and optimization, many studies quickly become outdated, which may hinder the application of their conclusions in the current context. On the other hand, academic papers often lag behind real-world applications in the industry. These limitations have led to the following directions for future research. It would be beneficial to expand the number of papers and, in addition to those in the business management AI field, include other disciplines, and perform the search in additional indexing databases. The research should be repeated with a combination of other keywords that would provide a broader view of the literature, and it is possible to conduct a bibliometric review of the literature to better cluster the emerging themes. Furthermore, the proposed model is simple and can be expanded, especially in terms of the use of the technologies themselves - that is, types of AI technologies.

While this review highlights the significant potential of AI in monitoring, optimization, and value creation, several gaps remain. Future research should aim to develop comprehensive frameworks that explicitly connect AI applications with delivered product value, as the current literature is fragmented and often limited to technical performance rather than business outcomes. In addition, more empirical studies are needed to validate how AI-driven monitoring and optimization translate into measurable improvements in delivered value across different industries. Another important avenue concerns the challenges and risks of AI adoption. Issues such as data availability and quality, algorithmic bias, explainability, and user trust must be addressed to ensure that AI-driven systems truly enhance value rather than compromise it. Future studies should investigate not only the benefits but also the limitations and ethical implications of applying AI in this context. Finally, it would be beneficial to integrate AI maturity frameworks with product value perspectives, in order to assess organizational readiness for leveraging AI at different levels—from monitoring to optimization to value creation. Comparative studies across industries (e.g., healthcare, manufacturing, marketing) could further enrich understanding by identifying domain-specific pathways through which AI contributes to delivered value.

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