Theme Prevalence and Co-Occurrence in Managerial Perceptions of AI Integration in Physical Retail: A Descriptive Qualitative Content Analysis

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The integration of artificial intelligence (AI) is increasingly shaping the transformation of physical retail, yet managerial perceptions of this process remain underexplored. This study investigates these perceptions through six semi-structured interviews across diverse retail sectors. Utilizing the MAXQDA software for qualitative content analysis, the research identifies key themes: implementation challenges, strategic benefits, required competencies, and human–technology interaction. Co-occurrence analysis reveals a critical tension between technological efficiency and human empathy. Findings indicate that while AI offers operational gains, its success is hindered by technological inadequacies and demographic hesitation. Results suggest that effective adoption depends on balancing automation with "hybrid intelligence" and proactive upskilling to maintain the relational value of physical stores. This research provides localized, practitioner-based insights into the socio-technical complexities of the evolving "phygital" retail landscape.

Keywords:
artificial intelligence,
physical retail,
managerial perceptions,
qualitative content analysis,
AI implementation,
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interaction

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1 Introduction

The global retail landscape is undergoing a profound transformation driven by the rapid evolution and integration of artificial intelligence (AI). Artificial intelligence refers to computational systems capable of simulating human cognitive functions such as learning, reasoning, and decision-making (Negnevitsky, 2005; Poole & Mackworth, 2017). In the retail context, AI technologies, including machine learning, predictive analytics, robotics, and computer vision, are increasingly reshaping traditional operations and enabling the transition from purely physical stores toward integrated digital–physical environments (Grewal et al., 2020; Verhoef et al., 2015). Historically, physical retail has struggled to maintain competitiveness in the face of rapidly expanding e-commerce. However, the emergence of AI has enabled retailers to bridge the gap between offline and online channels, contributing to the development of so-called "phygital" retail environments (Belghiti et al., 2018; Iannilli & Spagnoli, 2021). The concept of "phygital" retail refers to the integration of physical and digital touchpoints to create an integrated customer experience. Within such environments, AI supports both operational efficiency and enhanced customer interaction, fundamentally transforming the retail value chain.

Despite the growing body of research on artificial intelligence (AI) in retail, existing studies have predominantly focused on technological capabilities, operational efficiency, and consumer-facing applications, such as personalization, recommendation systems, and demand forecasting (Grewal et al., 2020; Haque et al., 2024; Wilson et al., 2024). While these studies provide valuable insights into the performance and strategic potential of AI, they place comparatively less emphasis on how retail managers interpret and make sense of AI in everyday physical store environments. More specifically, prior research has largely addressed managerial challenges–such as change management, employee resistance, and decision-making complexity–indirectly, treating them as organizational outcomes rather than explicitly examining managerial perceptions (Haque et al., 2024; Woudberg, 2022). Although emerging studies have begun to explore managerial attitudes towards AI adoption (Cao, 2021; Ukwuoma, 2025; Zerine et al., 2025), there remains a limited understanding of how managers perceive and evaluate concrete, practically relevant AI applications in physical retail contexts.

This gap is particularly important in physical retail settings, where AI is implemented through specific operational and customer-facing tools, such as inventory management systems, sales analytics, and in-store decision-support technologies, rather than abstract technological constructs. As a result, existing literature provides substantial knowledge about what AI can do in retail, but offers less insight into how managers understand its relevance, usefulness, and limitations in practice. This study addresses this gap by examining managerial perceptions of AI integration in physical retail, with a specific focus on how managers interpret the strategic benefits, implementation challenges, human–technology interaction, and competency requirements associated with practically relevant AI applications. In doing so, the study contributes to the literature by shifting the analytical focus from technological potential to managerial interpretation and socio-technical meaning in real-world retail environments.

The importance of managerial perception is especially pronounced in physical retail contexts, where direct human interaction remains central to value creation. Unlike purely digital environments, physical stores require managers to balance technological efficiency with relational and experiential aspects of customer service (Grewal et al., 2017). This creates a complex socio-technical setting in which AI implementation is not solely a technological challenge, but also an organizational and behavioral one (Wigand, 2017; Smith et al., 1992). Furthermore, in markets characterized by strong traditional retail practices and specific demographic structures, such as Slovenia, these dynamics may be particularly pronounced.

Against this backdrop, the purpose of this study is to explore and analyze managerial perceptions of AI integration in physical retail environments across different sectors. Specifically, the study examines how managers perceive the strategic benefits of AI, what implementation challenges they encounter, and how human–technology interaction influences required competencies and organizational adaptation. By adopting a qualitative exploratory approach based on semi-structured interviews and thematic content analysis using MAXQDA, the research seeks to provide empirically grounded insights into the socio-technical complexities of AI adoption.

This study contributes to the existing literature by addressing the identified gap between technological potential and managerial interpretation of AI in physical retail. It provides localized, practitioner-based insights into how AI is understood and implemented in real-world retail settings, highlighting the interplay between efficiency-driven automation and the preservation of human-centric service. The findings support the conceptualization of AI adoption as a process of developing “hybrid intelligence,” where human and technological capabilities are integrated rather than substituted.

The paper is organized into five sections. Section 2 reviews the relevant literature on AI in physical retail, including organizational challenges, strategic benefits, and human–technology interaction. Section 3 outlines the research methodology, including data collection and analytical procedures. Section 4 presents the empirical findings, focusing on theme prevalence and co-occurrence patterns. Section 5 discusses the results in relation to existing theoretical frameworks and highlights managerial implications, limitations, and directions for future research.

2 Artificial Intelligence in Physical Retail

Artificial intelligence (AI) refers to advanced computational systems and agents designed to simulate human cognitive functions, empowering machines to learn from data, reason, process natural language, and execute autonomous decisions (Negnevitsky, 2005; Poole & Mackworth, 2017). In the contemporary retail landscape, the rapid integration of AI represents a profound paradigm shift, transitioning traditional brick-and-mortar operations into highly automated, data-driven "phygital" ecosystems (Belghiti et al., 2018; Iannilli & Spagnoli, 2021). Historically, physical retail struggled to maintain its competitive advantage against the surge of digital commerce; however, AI technologies–ranging from machine learning and computer vision to robotics and predictive analytics–are now being leveraged to bridge the gap between offline and online environments (Grewal et al., 2020; Verhoef et al., 2015). Within physical stores, AI manifests in numerous consumer-facing and operational applications, such as autonomous shelf-scanning robots, checkout-free systems utilizing sensor fusion, interactive smart mirrors, and intelligent self-service kiosks (Inman & Nikolova, 2017; Polacco & Backes, 2018).

For retail managers, AI is no longer viewed merely as a supplementary technological tool but as an inescapable strategic imperative that fundamentally alters the retail value chain (Oosthuizen et al., 2020; Woudberg, 2022). Managers perceive AI as a transformative force capable of redressing the competitive balance by optimizing supply chains, enhancing in-store customer engagement, and minimizing operational costs (Balchandani et al., 2020; Daugherty & Wilson, 2018). Consequently, managerial perceptions and interpretations of AI's utility are central to understanding its successful deployment, as retail leaders are tasked with rethinking traditional business models and steering their organizations through this complex digital evolution (Hensellek, 2020; Tigre et al., 2023). Because physical retail involves direct, localized human interaction, managers must carefully orchestrate the integration of these intelligent systems to ensure they complement rather than disrupt the traditional in-store experience (Grewal et al., 2017).

Taken together, the reviewed literature indicates that research on AI in retail has predominantly focused on consumer behavior, technological performance, and operational efficiency. In particular, prior studies extensively examine personalization, recommendation systems, chatbots, and augmented reality applications, as well as operational benefits such as supply chain optimization, demand forecasting, dynamic pricing, and inventory management (Haque et al., 2024; Wilson et al., 2024; Khandelwal & Singh, 2025).

Beyond these general observations, the literature further emphasizes that, when successfully integrated, AI delivers profound strategic benefits, fundamentally optimizing the retail value chain and providing the core motivation for managerial investment (Oosthuizen et al., 2020; Woudberg, 2022). Managers often perceive the strategic benefits of AI through frameworks that emphasize three distinct pillars of value creation: cost reduction, revenue increase, and the enhancement of the customer experience (Anica-Popa et al., 2021; Grewal et al., 2017).

Operationally, AI serves as a powerful catalyst for cost reduction and workflow efficiency. Machine learning algorithms and predictive analytics revolutionize inventory management by analyzing historical sales data, weather forecasts, and localized market trends to execute highly accurate demand forecasting (Oosthuizen et al., 2020; Petropoulos et al., 2018). Managers perceive this predictive capability as crucial for optimizing stock levels, minimizing waste, and drastically reducing costly overstock and stockout scenarios, thereby ensuring operational leanness (Bughin et al., 2017; Wenzel et al., 2019). Additionally, AI-driven automation streamlines back-end supply chain logistics and in-store operations–such as utilizing autonomous robots for shelf scanning or facility cleaning–allowing human employees to focus on higher-value tasks (Culot et al., 2024; Daugherty & Wilson, 2018).

Strategically, AI empowers retail managers to transition from intuition-based choices to highly accurate, data-driven decision-making (Brynjolfsson & McAfee, 2014). By processing vast volumes of structured and unstructured market data, AI facilitates dynamic pricing strategies, allowing retailers to adjust product prices in real-time based on competitor actions, inventory levels, and immediate consumer demand to maximize profitability (Cebi & Bayraktar, 2021; Grewal et al., 2020). Most importantly, AI serves as a powerful tool for customer retention and revenue growth by enabling hyper-personalization at scale (Arora et al., 2021; Scholdra et al., 2023). By synthesizing browsing habits, in-store movements, and past purchases, AI systems can deliver precise product recommendations and tailored marketing campaigns (Chen et al., 2022; Grewal et al., 2017). Managers view this ability to create an engaging, individualized physical shopping experience as a critical competitive advantage, fostering immense customer loyalty and satisfaction that redresses the balance with e-commerce competitors (Oosthuizen et al., 2020; Poushneh & Vasquez-Parraga, 2017).

However, despite these strategic benefits, the actual integration of AI into physical retail remains a highly complex endeavor fraught with multifaceted organizational, technological, and ethical challenges (Anica-Popa et al., 2021; Worek & Aaltonen, 2024). Retail managers frequently perceive these challenges through a sociotechnical lens, recognizing that a change in technology inevitably disrupts an organization's existing structure, people, and daily tasks (Smith et al., 1992; Wigand, 2017). A primary barrier to adoption is the immense financial cost associated with AI implementation. Managers note that AI requires high initial capital investments for advanced hardware, software, and ongoing system upgrades, which can be particularly prohibitive for small and medium-sized enterprises (Davenport & Ronanki, 2018; Maresova et al., 2017). Furthermore, managerial narratives heavily emphasize technological inadequacies; AI's efficacy is strictly dependent on the availability, consistency, and quality of data (Grewal et al., 2020; Woudberg, 2022). Retail organizations frequently struggle with poor, fragmented data and an overreliance on outdated, disconnected legacy IT systems that lack the processing capacity necessary to run advanced AI applications, making seamless integration incredibly difficult (Balchandani et al., 2020).

Ethical concerns and data privacy also dominate managerial perceptions and serve as significant barriers to AI adoption (Martin, 2019; Mazurek & Małagocka, 2019). AI systems necessitate the mass collection of consumer data, sparking severe data privacy risks under strict regulatory frameworks like the General Data Protection Regulation (GDPR) (Mäihäniemi, 2022; Torre et al., 2021). Managers must grapple with the "black box" dilemma inherent to complex AI models; when internal decision-making processes lack transparency and explainability, it severely erodes organizational trust and accountability (Ajunwa, 2020; Miller, 2019). Coupled with this is the persistent risk of algorithmic bias, where AI trained on flawed historical data can produce discriminatory outcomes in dynamic pricing or personalized marketing, directly threatening brand reputation and consumer trust (Danks & London, 2017; Mayson, 2018).

On an organizational level, the introduction of AI routinely triggers profound workforce resistance (Bodea et al., 2024; Golgeci et al., 2025). Managers face the daunting challenge of alleviating employee anxieties regarding job displacement and mitigating resistance to unfamiliar, automated workflows (Bankins et al., 2024; Frey & Osborne, 2017). This resistance is compounded by a severe industry-wide shortage of skilled personnel capable of operating, maintaining, and developing AI systems, making organizational readiness and change management critical hurdles for retail leaders to overcome (Carutasu, 2023; Worek & Aaltonen, 2024).

Despite these insights, several important dimensions remain underexplored. Existing research often addresses managerial challenges–such as change management, employee resistance, and decision-making complexity–only indirectly, treating them as organizational outcomes rather than explicitly examining the perceptions of managers themselves (Haque et al., 2024; Woudberg, 2022). Although more recent studies begin to directly investigate managerial attitudes and decision-making in relation to AI (Ukwuoma, 2025; Zerine et al., 2025; Cao, 2021), the understanding of how managers interpret and balance technological capabilities with human judgment in everyday retail operations remains limited.

This suggests that AI adoption in physical retail is not solely a technological or operational issue, but a socio-technical process in which managerial interpretation plays a central role (Wigand, 2017; Dellermann et al., 2019). While AI offers clear strategic benefits, its implementation remains complex and context-dependent, making managerial judgment a critical factor in translating technological potential into organizational outcomes. As decision-makers responsible for aligning technological solutions with organizational goals, retail managers influence how AI is evaluated, implemented, and integrated into daily practice (Hensellek, 2020; Tigre et al., 2023). Therefore, examining managerial perceptions provides a relevant and necessary lens for understanding how the strategic potential of AI is translated into practice and how implementation challenges are navigated in physical retail environments.

2.1 Human–Technology Interaction and Managerial Competencies

The proliferation of AI in the retail environment necessitates a paradigm shift in how human–technology interaction is conceptualized and managed (Bankins et al., 2024; Dellermann et al., 2019). Managerial narratives increasingly reflect an understanding that AI should not be viewed merely as a tool for outright human replacement, but rather as an enabler of human-AI symbiosis or hybrid intelligence (Dellermann et al., 2019; Wilson & Daugherty, 2018). In this collaborative dynamic, AI systems serve to augment human intelligence by automating heavy data processing and routine analytical tasks, thereby freeing human employees to focus on complex, high-level functions that require emotional nuance (Daugherty & Wilson, 2018; Sowa et al., 2021).

This transition demands a profound evolution in required managerial and employee competencies. As AI takes over routine decision-making, managers perceive a critical need for their workforce to pivot toward uniquely human capabilities that machines cannot replicate (Frey & Osborne, 2017; Morandini et al., 2023). Consequently, managerial competencies must now heavily index on "soft skills," such as critical thinking, complex problem-solving, empathy, emotional intelligence, and ethical judgment (Morandini et al., 2023). Digital leadership becomes paramount; managers must possess the technological literacy to interpret AI outputs and strategically align AI initiatives with overarching business goals while navigating the complexities of algorithmic management (Hensellek, 2020; Tigre et al., 2023).

Crucially, to overcome the pervasive skills gap and employee anxiety highlighted in implementation challenges, managers must implement robust change management practices (Hayes, 2022; Sibanda et al., 2023). This involves transparently communicating the purpose and benefits of AI to their staff, alleviating fears of job displacement, and actively investing in extensive upskilling and reskilling initiatives (Bodea et al., 2024; Istenič et al., 2022). Retail leaders are tasked with cultivating technological literacy among their workforce, ensuring that employees are equipped with the competencies needed to operate, interpret, and effectively collaborate with AI systems (Malathi et al., 2024). Ultimately, the successful deployment of AI is contingent upon the manager's ability to foster a trusting, collaborative environment where human judgment remains an essential, authoritative factor in all strategic choices, seamlessly balancing efficiency gains with organizational stability (Glikson & Woolley, 2020; Rossi, 2019).

While the term artificial intelligence (AI) is often used broadly in retail literature, it encompasses a wide range of technologies and applications with varying levels of complexity. In general, AI refers to systems capable of performing tasks that typically require human intelligence, such as learning from data, recognizing patterns, and supporting decision-making processes (Huang & Rust, 2018; Davenport et al., 2020).

In the retail context, AI capabilities are reflected in a variety of applications, including demand forecasting, inventory management, sales analytics, and customer-facing tools such as recommendation systems and digital interfaces (Grewal et al., 2020; Haque et al., 2024). These examples illustrate that AI in retail is not a single technology, but rather a set of data-driven tools embedded across different parts of the retail value chain.

Prior research further indicates that these applications differ in their function and level of technological complexity, ranging from decision-support and analytics systems to more advanced forms of automation, such as robotics, computer vision, and checkout-free technologies (Inman & Nikolova, 2017; Polacco & Backes, 2018; Woudberg, 2022). Taken together, this body of literature suggests that AI in retail should be understood as a multi-dimensional construct, rather than a clearly bounded or homogeneous technology. In the context of this study, the focus is on those AI applications that are practically relevant and currently implementable in physical retail environments. These include systems such as inventory management tools, data analytics solutions, and decision-support technologies used in store operations. More advanced forms of AI, such as fully autonomous stores or robotics-based systems, are acknowledged but are not the primary focus of the empirical analysis.

This distinction is crucial for interpreting the findings, as it clarifies that the managerial perceptions captured in this study relate to concrete, practically relevant AI applications rather than highly advanced or experimental technologies. Furthermore, this conceptual breadth is important, as it reflects the diversity of AI applications discussed in the literature, while the empirical part of this study focuses specifically on those applications that are currently accessible and relevant in everyday retail practice.

3 Methodology

3.1 Research Design

This study adopts a qualitative exploratory and descriptive research design to investigate managerial perceptions of artificial intelligence (AI) integration in physical retail settings. Given that AI adoption in retail is a relatively recent phenomenon and that managerial interpretations of technological change remain underexplored, a qualitative approach is particularly suitable for capturing nuanced perceptions and experiences (Creswell & Creswell, 2018). Qualitative research enables researchers to examine complex organizational phenomena through the perspectives of individuals directly involved in decision-making processes.

The study employs a hybrid approach to qualitative content analysis, combining deductive category application with inductive category development (Hsieh & Shannon, 2005; Mayring, 2014). Following the data collection phase, an initial familiarization with the interview transcripts was conducted to identify recurring topics and patterns in managerial narratives. Based on this preliminary review, and guided by the theoretical framework outlined in Section 2, a set of core thematic categories was defined prior to the formal coding process in MAXQDA, including strategic benefits, implementation challenges, human–technology interaction, and required competencies. During the coding process, an inductive approach was applied to capture additional nuances emerging from the empirical data. As new themes, relationships, or contextual variations appeared, the coding scheme was reviewed and, where necessary, refined through the introduction of subcategories and minor adjustments to existing codes. This ensured that the analysis remained grounded in the data while preserving alignment with the theoretical constructs. This combination of theory-informed category development and data-driven refinement enabled a structured yet flexible interpretation of managerial perceptions of AI integration in physical retail.

3.2 Data Collection

The empirical data were collected through six semi-structured interviews with managers working in physical retail stores in Slovenia. The participating organizations represented a diverse range of retail sectors, including fashion retail, sports and nutrition products, home goods, and gift retail. The managers interviewed were directly responsible for store operations and managerial oversight, and therefore had firsthand experience with technological developments and operational decision-making within their organizations. Participants were recruited using a purposive approach aimed at capturing variation across retail sectors, complemented by convenience-based access in the field. Managers were approached directly in retail environments and invited to participate based on their managerial roles. This approach enabled access to practitioners actively involved in day-to-day retail operations, ensuring that the data reflect practical managerial perspectives.

The sample size of six interviews is consistent with an exploratory qualitative research design, where the objective is to generate exploratory qualitative insights rather than achieve statistical generalization (Creswell & Creswell, 2018). During data collection, recurring patterns in responses were observed across interviews, indicating sufficient thematic consistency for addressing the research objectives.

A semi-structured interview guide was developed based on the theoretical framework outlined in Section 2, particularly drawing on themes related to AI benefits, implementation challenges, human–technology interaction, and managerial competencies. The questions were organized into thematic areas while remaining sufficiently open-ended to allow participants to elaborate on their experiences and viewpoints. Prior to data collection, the interview guide was informally reviewed to ensure clarity and comprehensibility. The interviews followed a conversational format, allowing flexibility in the order and phrasing of questions and enabling the use of follow-up prompts where appropriate (Kvale & Brinkmann, 2009). This approach ensured both consistency across interviews and the ability to capture context-specific insights. The interviews were conducted primarily in person at the participants' workplaces, while one interview was conducted online via Zoom. Each interview lasted between approximately 20 and 45 minutes. Although some interviews were relatively short, the semi-structured format enabled participants to focus directly on the most relevant aspects of AI integration in their retail context. Therefore, the analysis should be understood as exploratory and descriptive rather than as an exhaustive in-depth reconstruction of managerial experience. With the informed consent of the participants, the interviews were audio recorded to ensure accuracy and completeness of the collected data. All recordings were subsequently transcribed verbatim for systematic analysis.

To ensure conceptual clarity, it is important to specify how artificial intelligence (AI) was understood in the empirical context of this study. The analysis of interview data indicates that managers referred to a heterogeneous set of AI-related technologies, which can be broadly categorized into three types.

First, participants discussed AI tools that are already in practical use, such as data analytics, automated reporting, and generative AI applications (e.g., ChatGPT), primarily supporting information processing and decision-making tasks. Second, managers referred to operational AI systems relevant to retail practice, including inventory management, automated ordering, and customer analytics. Third, some responses included more advanced and largely hypothetical applications, such as robots, smart shelves, or customer-facing chatbots, which are not yet widely implemented in their immediate work environment. This variation indicates that managerial perceptions of AI are not tied to a single, clearly defined technological category, but rather reflect a spectrum of applications with different levels of maturity and implementation. As a result, the findings should be interpreted in light of this conceptual heterogeneity, as managers simultaneously evaluate both existing tools and anticipated future technologies when discussing AI in retail.

3.3 Data Analysis

The transcribed data were analyzed using MAXQDA software, following the principles of thematic qualitative content analysis (Mayring, 2014). The analysis proceeded through several structured phases to ensure a systematic and transparent interpretation of the data.

In the first phase, all interview transcripts were carefully read to achieve familiarization with the data and to gain an overall understanding of the managerial narratives. This initial reading enabled the identification of recurring topics and patterns relevant to AI integration in physical retail.

In the second phase, a coding procedure was conducted using a predefined set of thematic categories, including strategic benefits, implementation challenges, human–technology interaction, and required competencies. These categories, developed prior to coding as described in Section 3.1, served as the primary analytical framework. Relevant segments of text were systematically assigned to these categories using MAXQDA. During the coding process, minor refinements were made through the introduction of subcategories and adjustments to code application where necessary, allowing the analysis to capture nuances emerging from the data while maintaining consistency with the initial coding structure.

In the final phase, the coded data were examined using MAXQDA's visual and analytical tools to identify patterns and relationships across cases. A Word Cloud was generated to explore the lexical focus of the interviews, the Code Matrix Browser was used to assess the distribution and intensity of themes across participants, and the Code Relations Browser supported the analysis of thematic co-occurrence. This structured analytical procedure ensured that the findings were systematically derived from the data while remaining aligned with the study's theoretical framework.

4 Results

4.1 Descriptive Overview

The dataset comprises six semi-structured interviews with managers from diverse retail sectors in Slovenia. To maintain ethical standards and participant anonymity, the organizations and individuals are referred to by coded IDs (P1–P6), as detailed in Table 1.

Table 1: Profile of Research Participants and Retail Sectors

	Retail Sector	Managerial Level
P1	Sports & Nutrition	Franchise Owner
P2	Cosmetics & Perfumery	Store Manager
P3	Fashion & Apparel	Head of Retail
P4	Home Goods	Store Manager
P5	Lingerie & Fashion	Store Manager
P6	Gift & Specialty Retail	Store Manager

Source: own.

To provide an overview of the distribution of themes across participants, the study utilized the Code Matrix Browser to visualize the distribution of the four primary thematic pillars across all participants. The resulting intensity matrix (see Figure 1) suggests that the discourse was not dominated by a single participant; rather, all six managers consistently addressed the key research dimensions. The inclusion of different retail sectors was intended to capture variation in retail contexts rather than to enable systematic comparison between sectors.

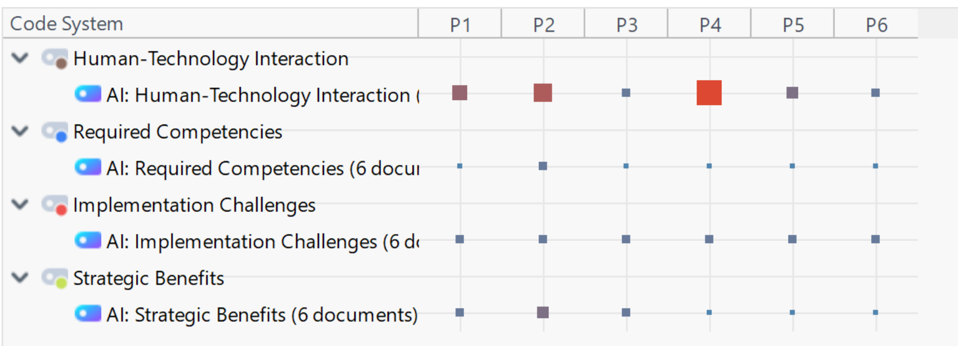

Figure 1: Cross-Case Thematic Intensity Matrix

Source: own research using MAXQDA software.

The matrix reveals that Human–Technology Interaction was the most intensely discussed topic across the entire sample, particularly in the narratives of P1 and P4. Implementation challenges were also present across participants, with a notable focus from P5 and P6. The strategic benefits of AI, while present in all cases, were most frequently highlighted by P2 and P3. This cross-case consistency ensures that the subsequent thematic results reflect a consistent pattern within the studied sample.

As a supplementary descriptive step, a word frequency analysis was performed to provide an initial overview of the most frequently used terms in the interviews (see Figure 2). The word cloud is not used as a standalone analytical result, but as an illustrative complement to the thematic coding and co-occurrence analysis. After manually refining the dataset by excluding non-content functional words (e.g., conjunctions and particles) and merging inflectional forms, the analysis reveals a clear focus on the relational and operational dimensions of retail management. Notably, the core research terms "AI" (as well as the Slovenian equivalent "umetna inteligenca") were intentionally excluded from the final visualization. This methodological decision was made because these terms represent the overarching subject of all interviews; their inclusion would disproportionately dominate the visual space without providing incremental insights into the specific themes discussed by managers. By removing these "contextual anchors," the analysis allowed more nuanced and descriptive terms to emerge.

Figure 2: Supplementary Word Frequency Cloud of Managerial Discourse
Source: own research using MAXQDA software.

The frequent appearance of the term "stranke" (customers) suggests that customer-related issues were prominent in the managerial discourse on AI integration. This is accompanied by the prominence of "zaposleni" (employees) and "ljudje" (people), indicating that human-related aspects were also frequently present in the interviews.

Furthermore, operational terms such as "trgovine" (stores), "čas" (time), and "lažje" (easier) point to the practical and operational vocabulary used by participants when discussing AI. These observations should be interpreted as preliminary and descriptive, while the main analytical interpretation is based on thematic coding and co-occurrence analysis.

4.2 Theme Prevalence and Managerial Focus

The initial phase of the empirical analysis focused on determining the prevalence of key thematic categories within the collected managerial narratives. Utilizing the AI Assist Premium feature in MAXQDA, the researcher conducted a comprehensive coding process across all six interview transcripts to identify the frequency of coded segments associated with the four primary research pillars. The analysis yielded a total of 426 coded segments, providing a structured descriptive overview for the subsequent qualitative interpretation.

The distribution of these themes, as summarized in Table 2, reveals a significant disparity in the focus of retail managers regarding AI integration.

Table 2: Frequency Distribution of Identified Thematic Categories

	Coded Segments (n)	Relative Frequency (%)
Human–Technology Interaction	208	48.8
Implementation Challenges	99	23.2
Strategic Benefits	72	16.9
Required Competencies	47	11.0
Total	**426**	**100.0**

Source: own.

The data indicate that Human–Technology Interaction is the dominant theme in managerial discourse, appearing in nearly half of all coded segments (n = 208). This high prevalence suggests that managers perceive the success of AI adoption primarily through the lens of relational dynamics, specifically, how employees perceive, trust, and collaborate with automated systems in a high-touch service environment. As one manager emphasized, "people really value personal interaction… it is difficult to imagine a robot replacing that kind of communication" (P1), and, "for personal contact, there will always need to be a human factor" (P2).

Implementation Challenges followed as the second most frequent category (n = 99), representing 23.2% of the discourse. This reflects a pragmatic managerial awareness of the organizational and technical barriers that accompany digital transformation. Concerns about employee reactions were also evident, as one participant noted a "fear of the unknown" when introducing new technologies (P3). This concern is also reflected in managerial views on cost, as one participant noted that "the question is how high the costs of implementing such technology would actually be" (P1). Interestingly, while the Strategic Benefits of AI were frequently acknowledged (n = 72), they were discussed significantly less often than the human and operational challenges. Nevertheless, some managers still highlighted efficiency gains, noting that "it would make everything easier, since a robot does not make mistakes or delays tasks" (P1), and other improvements, with one stating that AI enables "faster processing and more accurate information" (P5).

The least prevalent theme was Required Competencies, which accounted for only 11.0% of the identified segments (n = 47). This relatively low frequency may indicate a critical gap in managerial awareness; while retail leaders are deeply concerned with how AI will be received by the workforce, they appear less certain about the specific skill sets and educational frameworks necessary to sustain such a transformation.

This uncertainty is reflected in managerial statements, as one participant noted that "managers would probably need some additional skills, but nothing too specific" (P6). At the same time, others emphasized the need for continuous adaptation, highlighting that "you have to keep up with the pace of AI development, otherwise you fall behind" (P2).

This distribution of themes underscores a socio-technical orientation where the human element remains at the forefront of the retail AI narrative.

4.3 Strategic Benefits and Implementation Challenges

The second phase of the findings focuses on the duality of AI integration, specifically the tension between anticipated strategic advantages and the practical hurdles identified by retail managers. This "dual-edged" perception is evident in the frequency of coded segments, where the promise of operational efficiency is frequently tempered by concerns regarding organizational readiness and resource constraints. As one manager noted, AI can make processes “much easier and faster,” but at the same time “there are still many errors and uncertainties in how reliable these systems are” (P2).

Strategic benefits accounted for 16.9% of the managerial discourse (n = 72), with a primary focus on operational leanness and the automation of routine tasks. Managers identified process automation and inventory management as critical areas for high-value returns, frequently highlighting "smart orders" (pametna naročila) and "automated stock detection" (zaznavanje izpraznjenih polic) as essential tools for reducing human error and minimizing stockouts. As one participant explained, AI could significantly support inventory processes, particularly in complex supply chains where “it is difficult to manage stock levels due to the large number of products and suppliers” (P1). Beyond inventory, respondents emphasized the role of AI in resource optimization and operational ease, noting that technology significantly "eases the workload". This is reflected in everyday use, as one manager explained, “it helps us a lot… especially when processing large amounts of data” (P2). Similarly, another participant highlighted that AI improves efficiency by making processes “faster and more accurate” (P5).

Finally, AI is perceived as a catalyst for customer experience enhancement through hyper-personalization. Managers envision smart systems, such as interactive kiosks or digital mirrors, providing customers with expert product information during peak hours, thereby maintaining service quality when staff availability is limited. This is illustrated by one manager’s observation that AI can provide customers with “more information in situations where staff are unable to assist everyone at the same time” (P1).

Implementation challenges were discussed more frequently than benefits (n = 99, 23.2%), indicating a cautious and pragmatic approach to technology adoption among retail leaders. These hurdles are categorized into distinct economic, technical, and psychological dimensions. Economic and technical constraints, particularly high initial capital investment, remain a significant deterrent, as managers expressed concerns regarding the "payback period" and whether efficiency gains would ultimately justify the substantial costs of hardware and software upgrades. This concern is reflected in managerial perspectives, as one participant noted that “the investment is quite high, and it is difficult to estimate when it would actually pay off”

(P4). This is compounded by technological skepticism, where several segments highlighted the "black box" nature of AI. Managers articulated a need for more transparent and explainable outputs, often citing a lingering concern regarding the accuracy of AI suggestions and noting that systems are still in a learning phase prone to errors. As one manager explained, “we still do not fully understand how the system makes decisions, which creates a lack of trust” (P3).

However, the most critical challenge identified was the human resistance factor, characterized by employee anxiety regarding job displacement. As one participant explained, “people are still not advanced enough to fully understand and trust these technologies” (P1). This concern is reinforced by broader fears about workforce impact, as another participant noted that “robots could replace jobs, which affects people’s livelihoods” (P5). Managers emphasized that the "fear of the unknown" often leads to a lack of commitment during the initial rollout, which necessitates a robust focus on change management and transparent communication.

The interplay between these two themes suggests that while the strategic motivation for AI–driven by speed, precision, and cost-reduction–is clear, the path to implementation is heavily obstructed by human and financial considerations. This conceptual tension explains the frequent co-occurrence of these themes in managerial narratives, necessitating a deeper exploration of their structural relationship in the following analysis.

4.4 Co-occurrence Analysis and Mapping the Interplay Between Themes

While the prevalence of individual themes provides a baseline for understanding managerial focus, the co-occurrence analysis reveals the underlying structural logic of how retail leaders conceptualize AI integration. By employing the Code Relations Browser in MAXQDA, the researcher mapped the intersections of thematic categories within the same coded segments. The resulting matrix, visualized in Figure 3, identifies several critical "gravity centers" in the managerial narrative.

The most prominent intersection (indicated by the largest intersection square in the matrix) occurs between Human–Technology Interaction and Implementation Challenges. This co-occurrence is analytically relevant; it indicates that when retail managers discuss the difficulties of adopting AI, they frequently link these hurdles to the human factor. The challenges of cost or technical integration are rarely discussed in isolation; instead, they are framed within the context of employee trust, workplace adaptation, and the potential disruption of established social dynamics within the store. This suggests that for managers, the "problem" of AI is inherently a socio-technical one.

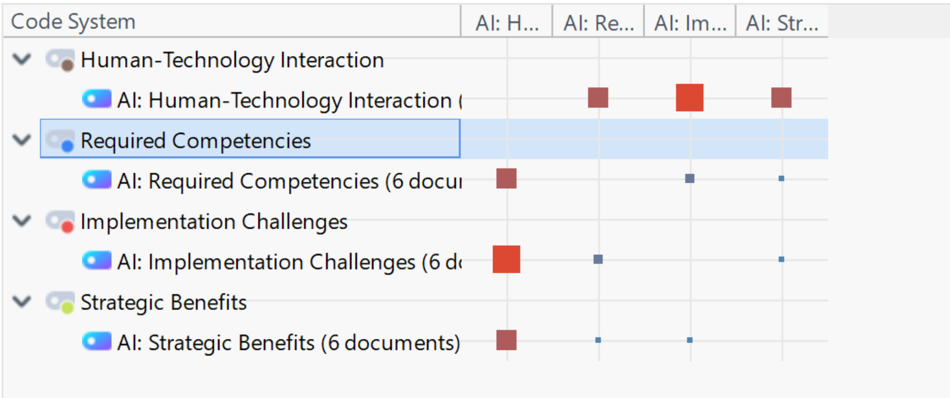

Figure 3: Code Relations Matrix Visualizing Thematic Intersections
Source: own.

A second significant pattern is the co-occurrence of Strategic Benefits and Human–Technology Interaction. This link demonstrates that managers perceive the value of AI–such as efficiency gains and automated inventory management–as being strictly contingent upon how employees interact with the technology. In managerial narratives, the "benefit" only materializes if the human-AI collaboration is well-coordinated. For example, the benefit of a "smart shelf" system is only realized if the staff trusts the automated alert and acts upon it efficiently.

Conversely, the matrix reveals a relatively weak link between Strategic Benefits and Required Competencies. This is a critical finding, as it suggests a conceptual disconnect: while managers recognize the strategic value of AI, they do not yet strongly associate these gains with the necessity of a specific upskilling or reskilling agenda.

Mapping these interplays suggests that the retail manager’s perspective is fundamentally human-centric. The successful transition to a "phygital" retail environment is not seen as a triumph of software over manual labor, but as a complex renegotiation of the relationship between the staff, the technology, and the operational goals of the organization.

5 Discussion

The findings of this study provide a nuanced understanding of how retail managers in Slovenia perceive AI, effectively bridging the theoretical concepts of "phygital" ecosystems (Belghiti et al., 2018) with operational reality. A central tension identified in the results is the balance between technological efficiency and the preservation of "human warmth." While Grewal et al. (2017) emphasize that AI should complement rather than disrupt the store experience, participants in this study (particularly P4 and P5) expressed a more protective stance over human interaction. This suggests that in some retail contexts characterized by a stronger emphasis on personal interaction, the "human-AI symbiosis" proposed by Wilson and Daugherty (2018) may be perceived not as a balanced distribution, but as a dynamic where human empathy remains the primary factor.

Regarding the strategic benefits, the managerial focus on inventory optimization and demand forecasting (P1, P3, P6) strongly supports the predictive analytics frameworks discussed by Oosthuizen et al. (2020) and Petropoulos et al. (2018). However, while Brynjolfsson and McAfee (2014) argue for a transition to purely data-driven choices, Slovenian managers still maintain a high degree of "intuition-based" decision-making, particularly when AI systems fail to account for local market nuances. The reported inefficiency of robotic systems (P5) and AI-generated errors in training (P4) provide empirical evidence for the "technological inadequacies" and "fragmented data" issues warned about by Balchandani et al. (2020) and Woudberg (2022).

The generational divide emerged as a critical factor that is often understated in broad strategic literature. While Arora et al. (2021) discuss hyper-personalization as a tool for revenue growth, our findings (P2, P5) indicate that for older demographics (60+), AI-driven personalization may trigger privacy anxieties rather than loyalty. This reflects the "black box" dilemma and privacy risks highlighted by Mazurek and Małagocka (2019). The resistance noted by managers aligns with the workforce anxieties described by Frey and Osborne (2017), yet our data suggests that "soft skills"–empathy and critical thinking–are not just future competencies but are currently being used as a strategic buffer to maintain consumer trust during the digital transition, as theorized by Morandini et al. (2023).

The thematic synthesis of this study, supported by visual co-occurrence mapping and code frequency analysis in MAXQDA, provides empirical confirmation of the theoretical frameworks regarding AI's strategic imperative in retail (Oosthuizen et al., 2020). Specifically, the high intensity of the "Human–Technology Interaction" category across all cases, especially in the narratives of P4 and P5, supports Grewal's (2017) assertion that AI must complement rather than disrupt the traditional in-store experience. Furthermore, the co-occurrence analysis suggests a link between "Implementation Challenges" and "Required Competencies," indicating that managers sometimes refer to technological limitations–such as those reported in automated logistics (P5) and AI training errors (P4)–in connection with the continued importance of human judgment and skills. These segments do not imply a direct causal relationship but rather highlight how such challenges are discussed alongside reflections on human capabilities. This can be interpreted as aligning with the broader shift toward uniquely human "soft skills" emphasized by Stefano Morandini et al. (2023). At the same time, the relatively weaker connection between strategic benefits and required competencies suggests a possible gap in managerial awareness regarding systematic upskilling and reskilling. This intersection suggests that while Wilson and Daugherty (2018) theorize a seamless human-AI symbiosis, the operational reality in the Slovenian retail market remains a "cautious integration," where managers act as essential mediators to mitigate the perceived coldness of automated systems and address the "black box" dilemma identified by Mazurek and Małagocka (2019).

The findings of this study contribute to the existing literature on AI in retail in several important ways. The results extend prior research that has predominantly focused on technological capabilities and operational efficiency (Grewal et al., 2020; Haque et al., 2024) by demonstrating that managerial perceptions are strongly shaped by socio-technical considerations. In particular, the dominance of human–technology interaction highlights that AI adoption in physical retail is not merely a technological implementation process, but a relational and organizational transformation. This study also provides empirical evidence that managerial discourse is characterized by a clear tension between perceived strategic benefits and implementation challenges. While existing literature often treats these dimensions separately, the findings show that managers experience them simultaneously, suggesting that AI adoption should be understood as a dynamic balancing process rather than a linear transition. Additionally, the relatively low emphasis on required competencies reveals a potential blind spot in managerial thinking, indicating that skill development and organizational learning may be underprioritized in early stages of AI adoption. This insight contributes to the growing discussion on the human capital implications of digital transformation (Woudberg, 2022; Ukwuoma, 2025).

Taken together, these findings reinforce the view that AI integration in physical retail is best understood as a socio-technical process in which technological, organizational, and human factors are deeply intertwined.

5.1 Managerial Implications

The findings of this study provide several important managerial implications for retail organizations implementing AI technologies. First, the dominance of human–technology interaction in managerial discourse highlights the critical importance of effectively managing employees during the AI adoption process. Managers should not treat AI implementation solely as a technological upgrade, but as a change management process that requires clear communication, employee involvement, and trust-building. Addressing employee concerns, particularly the fear of job displacement, emerges as a key priority for ensuring successful adoption.

Second, the observed tension between strategic benefits and implementation challenges suggests that AI integration should be approached incrementally rather than through large-scale, immediate transformation. A phased implementation strategy allows organizations to test solutions, reduce uncertainty, and gradually build internal acceptance. This is particularly important in environments such as physical retail, where operational disruptions and employee resistance can significantly affect customer experience.

Third, the relatively low emphasis on required competencies indicates that retail organizations may underestimate the importance of skill development in the context of AI adoption. Managers should therefore prioritize both technical and non-technical competencies. While digital literacy and data understanding are essential for interacting with AI systems, soft skills–such as adaptability, communication, and critical thinking–are equally important for navigating socio-technical change and collaborating with intelligent systems.

Finally, the findings suggest that AI should be implemented as a complementary tool that enhances, rather than replaces, human interaction in physical retail. Given the central role of personal contact in in-store environments, managers should focus on integrating AI in ways that support employees and improve customer experience without undermining the relational aspects of retail service.

5.2 Limitations and Future Research

Despite the depth of the qualitative insights, this study is subject to certain limitations. The sample size of six managers, while sufficient for exploratory qualitative research and providing sector diversity, does not allow for statistical generalization across the entire Slovenian retail market. This limitation is particularly relevant given the specific characteristics of the Slovenian retail context. Slovenia represents a relatively small, highly service-oriented economy, where retail activity is predominantly embedded in local markets and closely tied to small and medium-sized enterprises (SMEs) (OECD, 2024). The sector is characterized by a high share of smaller firms, including family-owned businesses, which often operate with limited financial and technological resources and may therefore adopt digital innovations more gradually (EY, 2015). Although the sample includes managers from different retail sectors, the study does not allow for systematic comparison between sectors due to the small number of participants. The sectoral diversity was intended to capture variation in retail contexts rather than to support sector-specific conclusions.

At the same time, the Slovenian retail environment is shaped by strong local customer relationships and a traditionally high emphasis on personal interaction in service delivery. These structural and cultural characteristics may influence how managers perceive and implement AI technologies, particularly in terms of employee interaction, trust, and customer experience. As such, the findings of this study should be interpreted within this specific context and may not be fully generalizable to larger or more technologically advanced retail markets. Furthermore, the findings are based on self-reported managerial perceptions, which may differ from the actual lived experiences of frontline employees or the direct reactions of customers.

Future research should address these gaps by employing longitudinal designs to examine how managerial perceptions evolve as AI systems become more embedded in daily retail operations. Future studies could explore differences across organizational scale, comparing small and medium-sized retailers with large multinational retail chains, to better understand how resource availability and organizational complexity influence AI adoption and implementation challenges. Additionally, further research should consider sector-specific dynamics within retail, as the relevance and application of AI may vary significantly between industries such as fashion, food retail, and specialized product segments. This would provide a more nuanced understanding of how contextual factors shape managerial perceptions and strategic priorities. Importantly, future studies should incorporate the perspective of front-line employees, who directly interact with both customers and AI systems in physical retail environments. A bottom-up approach would allow for a deeper understanding of workforce adaptation, resistance, and the practical implications of human–technology interaction in everyday operations. Finally, comparative cross-country studies would be valuable in identifying how institutional, cultural, and economic differences influence AI adoption in retail. Extending the analysis beyond managerial perspectives to include customer viewpoints would further enrich the understanding of how AI affects the retail experience in "phygital" environments.

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Summary

This research investigates managerial perceptions of artificial intelligence (AI) integration in physical retail environments, focusing on the Slovenian market. Through six semi-structured interviews with managers from diverse sectors, the study identifies a significant tension between the drive for technological efficiency and the fundamental need to preserve "human warmth" and empathy in-store. Utilizing MAXQDA for thematic and co-occurrence analysis, the findings reveal that while managers recognize the strategic benefits of AI, such as inventory optimization and data-driven decision-making,

they face substantial implementation hurdles, including technological inadequacies, high costs, and demographic resistance from older consumer segments. The results underscore the necessity for a "hybrid intelligence" approach, where AI augments rather than replaces human staff. Furthermore, the study highlights a critical gap in managerial focus regarding the specific upskilling and reskilling strategies required for a successful digital transition. Ultimately, the research suggests that the future of "phygital" retail depends on the orchestration of a seamless human-AI symbiosis that maintains the relational value of the physical shopping experience.

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