THE IMPACT OF ARTIFICIAL INTELLIGENCE ON BUSINESS INTELLIGENCE IN THE RETAIL SECTOR

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ABSTRACT

Master Thesis

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON BUSINESS INTELLIGENCE IN THE RETAIL SECTOR

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This thesis compares artificial intelligence (AI) and traditional business intelligence (BI) for retail analytics using a mixed-methods analysis of 541,909 transactions from the UCI Online Retail Dataset and case studies of five Turkish retailers (Trendyol, BİM, CarrefourSA, Teknosa, LC Waikiki). AI outperformed traditional baselines across three dimensions. Accuracy: demand forecasting improved from ARIMA's MAPE 27.30% to XGBoost's 7.88% (≈71% relative improvement). Segmentation quality: K-means achieved a silhouette score of 0.7533, +95.2% over traditional RFM (0.3858). Efficiency: real-time inference took 0.0150s versus 2.10s for a SQL query (≈139.9× faster). Case study findings are consistent with operational gains such as reduced manual effort and improved personalization outcomes. The thesis synthesizes these findings into practical guidance for evaluating and implementing AI-enabled BI in retail, and discusses implications, limitations, and future research directions.

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Key Words: Artificial Intelligence, Business Intelligence, Data Analytics, Retail

ÖZET

Yüksek Lisans Tezi

PERAKENDE SEKTÖRÜNDE İŞ ZEKASI ÜZERİNDE YAPAY ZEKANIN ETKİSİ

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Bu tez, perakende sektöründe yapay zeka (YZ) teknolojileri ile geleneksel iş zekâsı (İZ) teknolojilerini karşılaştırmak amacıyla, UCI Online Retail Dataset'inden elde edilen 541.909 işlem ve beş Türk perakendecisinin (Trendyol, BİM, CarrefourSA, Teknosa, LC Waikiki) vaka analizlerini içeren karma yöntemli bir analiz sunmaktadır. YZ, üç boyutta üstün performans göstermiştir. Doğruluk: talep tahmini hatası ARIMA'nın %27,30 MAPE değerinden XGBoost'un %7,88 MAPE değerine düşmüştür (yaklaşık %71 iyileşme). Segmentasyon kalitesi: K-means silüet skoru 0,7533 olup geleneksel RFM'e (0,3858) göre %95,2 artış sağlamıştır. Verimlilik: gerçek zamanlı kestirim süresi 0,0150 sn iken SQL sorgusu 2,10 sn sürmüştür (yaklaşık 139,9× daha hızlı). Vaka analizleri, operasyonel iş gücünde azalma ve kişiselleştirme ile dönüşüm artışı gibi iş etkilerine işaret etmektedir. Çalışma, bulguları perakendede YZ-destekli iş zekâsının değerlendirilmesi ve uygulanmasına yönelik pratik bir rehber ile ilişkilendirerek kuramsal ve uygulamalı katkılar sunar; ayrıca sınırlılıklar ve gelecek çalışmalar için öneriler verir.

Şubat 2026, 64 sayfa

Anahtar Kelimeler: Yapay Zeka, İş Zekası, Veri Analitiği, Perakende

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Abdelrahman M M GHANNAM
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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ARIMA	Autoregressive Integrated Moving Average
AUC-ROC	Area Under the Curve - Receiver Operating Characteristic
BI	Business Intelligence
CNN	Convolutional Neural Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DOI	Diffusion of Innovation
GMM	Gaussian Mixture Model
HVAC	Heating, Ventilation, and Air Conditioning
IDP	Internal Developer Platform
IoT	Internet of Things
IT	Information Technology
KPI	Key Performance Indicator
LDA	Latent Dirichlet Allocation
LLM	Large Language Model
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
NLP	Natural Language Processing
OLAP	Online Analytical Processing
POS	Point of Sale
RFID	Radio Frequency Identification
RFM	Recency, Frequency, Monetary
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
ROI	Return on Investment
SKU	Stock Keeping Unit
SME	Small and Medium-sized Enterprises
SQL	Structured Query Language

SVM	Support Vector Machine
TAM	Technology Acceptance Model
TF-IDF	Term Frequency–Inverse Document Frequency
UCI	University of California, Irvine
VSP	Virtual Storage Platform
YOLO	You Only Look Once

List of Symbols

MAPE_{old}	Baseline Mean Absolute Percentage Error
MAPE_{new}	New (AI) Mean Absolute Percentage Error
r_{err}	Forecast error ratio ($\text{MAPE}_{new}/\text{MAPE}_{old}$)
SS_{old}	Baseline safety stock (units or value)
SS_{new}	Safety stock after AI forecasting
ΔSS	Reduction in safety stock ($SS_{old} - SS_{new}$)
h	Annual inventory holding cost rate (%)
R	Annual revenue of affected assortment
s	Stockout rate (%)
α	Capture rate of lost demand (%)
$\Delta R_{\text{stockout}}$	Potential recovered revenue from reduced stockouts
N	Number of customers or number of real-time decisions (ops)
q	Non-buyer shares among targeted customers
c	Cost per marketing contact
γ	Fraction of theoretical segmentation gain realized
$\Delta\text{Spend}_{waste}$	Saved marketing spend by reducing wasted contacts

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1. INTRODUCTION

1.1 Background and Context

The retail industry is approaching a tipping point where those who do not use data to support decisions will no longer be able to competitively survive. Business intelligence (BI) has always referred to the systematic gathering of relevant business-related information as well as the analytical processes, and output formats that allow organizations to make educated decisions. The BI industry has evolved from basic spreadsheet-based and ad hoc reports to sophisticated analytical systems (Chaudhuri et al., 2011). Today there are organizations that are generating terabytes of data in the retail industry every day from various channels including point-of-sale data, e-commerce, selling platforms such as those on social media, and the plethora of Internet of Things devices that track everything imaginable related to retailing and shopping experience. The data revolution has dramatically increased both the rate and the ways data is created. As traditional BI systems scale, retailers need new analytical approaches to handle the volume, variety, and velocity of data.

The introduction of AI technologies is a fundamental shift in how retailers process, analyze, and derive information from data in their organizations. Traditional BI systems generally rely on defined static rules, reporting structure, and predictive rules that can describe what might be expected based on changing conditions. Technologies that employ AI offer dynamic learning capabilities, pattern recognition, and predictive analytics that adapt to changing market conditions in real-time (Gao et al., 2025). Recent international market research has suggested the global market for AI in retail is expected to reach $96.13 billion by 2030 and grow at a compound annual growth rate of 46.54% from 2019 to 2030 (Mordor Intelligence, 2025). The rapid growth of these technologies may signal both the urgency and tremendous potential of AI to assist retailers to meet the cumbersome challenges they face moving forward.

1.2 Problem Statement

While retail organizations increasingly adopt AI technologies to improve and automate their operations, researchers have paid little attention in comparing AI-driven BI and traditional BI systems within the retail context in comprehensive comparative studies specific to the industry. Existing studies have primarily examined AI applications in isolation or have looked for information on BI approaches with little to no empirical evidence comparing the two. With the rapid pace of retail digitalization, particularly in emerging markets like Türkiye, while researchers may put emphasis on investigating the impact of AI, there are very few studies that systematically evaluate the impact of AI on retail operations.

Most of the extensive literature on AI, while informative, largely concentrates on technical performance measures, and not the organizational, ethical, and implementation factors that can have a huge impact on performance outcomes in practice. Small and medium-sized retailers comprise most of the global retail ecosystem and are predominantly underrepresented in the discourse around AI, and the unique complexities for AI adoption in the retail domain is largely lacking in the literature. The absence of robust frameworks for assessing the effectiveness of AI-BI integration prohibits evidence-based decision making and conclusion making of retail organizations interested in digital transformation initiatives.

1.3 Research Objectives

The goal of this thesis is to fill these gaps with the following specific aims:

First, to provide a systematic comparative analysis of AI technologies in retail against traditional BI methods, assessing their relative performance in terms of accuracy, efficiency, scalability, and impact on the business. Second, to develop and validate a comprehensive evaluation framework that would include technical, organizational, and ethical concerns with respect to the assessment of AI-BI implementation. Third, to explore real-world examples of AI adoption among five Turkish retailers to provide context-sensitive perspectives on the patterns, challenges and outcomes of AI adoption in an emerging market context. Fourth, to present evidence using data from publicly available datasets of how AI techniques can perform better than traditional methods at common retail analytics tasks. Finally, to convert the findings into practical recommendations for retail organizations at different stages of digital maturity.

1.4 Research Questions

To accomplish the research goals, we seek to answer the following questions:

RQ1: How do AI-powered analytics methods compare with traditional BI methods in retail in terms of predictive accuracy, segmentation quality, and operational efficiency, and what business KPI implications can be derived using transparent translation formulas?

RQ2: What are the critical success factors and implementation challenges that shape AI integration with existing retail BI infrastructure?

RQ3: What are the contextual dimensions of the emerging markets, specifically the Turkish retail context that are shaping patterns of AI adoption and their outcomes?

RQ4: What are the primary ethical risks associated with AI-enabled retail BI, and what high-level governance principles are suggested by the literature and cases?

1.5 Significance and Contributions

This research offers three key contributions to the area of theoretical knowledge and practical implementation. Theoretically, the study contributes to a better theoretical understanding of AI - BI integrations by providing empirical evidence of comparative performance with the same industry context. The study contributes beyond existing technology adoption frameworks by including AI-specific elements and testing them with real-world case studies. The study demonstrates the practical application of comparative analysis techniques using publicly available datasets as a methodological contribution to research of establishing replicable research processes.

Practically, the study also provided evidence-based guidance for retail executives, IT managers, and consultants responsible for digital transformation initiatives. The comprehensive evaluation framework from this study offers a structured method of assessing AI readiness, choosing the right technologies, and evaluating success in implementation. In addition, the study presented relevant considerations for policy makers and industry associations supporting AI adoption while also considering ethical and regulatory considerations.

1.6 Thesis Structure

Chapter 2 that follows this introduction includes a detailed literature review that explores the evolution of BI in retailing, the types of AI technologies related to BI initiatives, the theoretical frameworks of technology adoption, and existing gaps in research. Chapter 3 explains the research methodology, including the mixed-methods research design, selection criteria for datasets, and the analysis methods. Chapter 4 includes empirical outputs and results from the comparative evaluation, case study analysis, and performance assessment. Chapter 5 includes discussion on implications for practice, limitations of the study, future directions for research, and includes synthesis of the key findings into a strategic framework for AI-BI implementation. This chapter also includes recommendations for practice, as well as identifying any theoretical contributions made in the thesis.

2. LITERATURE REVIEW

2.1 Evolution of Business Intelligence in Retail

The evolution of business intelligence (BI) in the retail sector reflects the much larger technological trends and shifts in the market over the last forty years. The earliest retail BI systems took the form of reporting tools and spreadsheet-based processes (Wixom, 2010). These early technologies were transformative in business insights in their day, but they were also limited in the way they provided value across the thousands of retail items, stores, and transactions that happened daily. The reporting tools combined financial reporting with simple forecasting and inventory management but did not provide significant prediction or modeling capabilities in terms of consumer behaviors.

With the introduction of data warehousing in the 1990s, BI tools had advanced significantly. Data warehouses, as described by Inmon (2005), were subject-oriented, integrated, time-variant, non-volatile collections of data, designed to give management an "integrated view of an organization's business". Early data warehouse architectures allowed retailers to create an integrated view of business performance simultaneously through different business performance metrics, such as store performance, regional and global performance, and previous past performance based on budget data. Retailers, as examples of following parallel data warehousing paths, pioneers like Walmart had begun leveraging massive data warehouse technology for their retail businesses. The retailer worked with its suppliers in its Retail Link Program which is a platform that supports supplier collaboration and inventory management (Ha Nguyen, 2017).

By using rapidly evolving OLAP (Online Analytical Processing) technologies, retail business intelligence began to develop more depth and ability to analyze multiple business data dimensions. OLAP systems allow retail analysts to view business with an integrated view including product, store, time, and customer segment simultaneously, thus viewing the current performance based on these different dimensions (Chaudhuri et al., 2011). A multidimensional view quickly became useful to retail business decision makers to understand current/past performance beyond just stand-alone tasks, and by using all these views at the same time, managers could easily follow the complex challenges of retail operations. According to AWS Documentation (2025), OLAP primarily uses storage that is based on dimensional models that would allow users to complete summary reports, complex calculative reports based on multi-dimensional data, trend analysis and sophisticated data modeling processes that would be impractical and unrealistic in a traditional relational database system.

With the 2000s, BI technologies also became widely democratized with the adoption of self-service analytics software and BI visualization tools. Modern BI software solutions such as Tableau, QlikView, and Microsoft Power BI changed a specialized IT function into an ability of normal business users (Davenport, 2014). The changing nature of BI product allowed managers across many parts of the organization to access insights directly, which in turn reduced the reliance on IT and contributed to accelerating decision-making. However, while reporting capability gained speed, the incident reporting capability of BI systems were still historical with limited predictive capability, and ultimately a gap remained between generating insights and transforming them into actionable intelligence.

2.2 Artificial Intelligence Technologies in Business Intelligence

The advent of AI in business intelligence systems represents a paradigm shift away from descriptive analytics and towards predictive and prescriptive analytics. Machine learning algorithms, the building blocks of AI-driven BI systems, allow systems to identify patterns, recognize trends in data, and make predictions without the need to program every possible scenario (Chen et al., 2012). For example, supervised learning algorithms such as random forests and gradient boosting machines have outperformed traditional statistical methods for demand forecasting, customer segmentation, and price optimization in retail contexts.

Deep learning methods have disrupted retail BI capabilities to analyze unstructured data specifically through applications in image recognition and natural-language processing. Convolutional neural networks (CNNs) have provided the capability of automation of product categorization, shelf monitoring, and visual search that was not possible with the use of traditional BI systems only (Das et al., 2017). Recurrent neural networks (RNNs) and long short-term memory (LSTMs) excel in analyzing time series, capturing complex time-based patterns from sales data, often lost in conventional forecasting methods (Hewamalage et al., 2021). This capability is valuable, especially in areas such as fashion retail where products have short life cycles and demand patterns are volatile.

Natural-language processing has changed how retail organizations communicate with their BI systems, allowing companies to extract insights from text-based data. Some modern techniques in NLP allow for sentiment analysis in customer reviews, monitoring of social media interaction, and the ability to summarize very complex data sets into automated reports (Jim et al., 2024). Furthermore, the introduction of transformer models and large language models has also expanded the capabilities of retail BI systems by providing the ability to provide architectural context, answering complex user queries in natural-language, and pulling human-readable insights from nearly unlimited records of information. In a recent study by Bomma (2024), it was found that the ability to integrate NLP with BI systems allows for the analysis of unstructured data sources that constitute 80% of enterprise data, expanding the capability of business intelligence beyond traditional structured databases.

Computer vision has rapidly developed as an emerging form of technology being applied to retail BI. The combination of image recognition and automated analytics enables analysis of in-store behavior, inventory management, and loss prevention. These advanced systems provide tracking of customer movements across the shopping space, shopping patterns and trend analysis, and detecting not only when products are 'out-of-stock’ but identifying perceived intentions of theft (Patel, 2024). This advanced capability will ultimately provide valuable and relevant insights for organizations that are synthesizing traditional BI systems with innovative solutions to operational intelligence by pulling together transactional data and behavioral insights.

2.3 Comparative Studies and Performance Metrics

The research literature is increasingly synthesizing evidence of the superiority of AI over traditional BI, based on a range of metrics. Bony et al. (2024) conducted a comprehensive comparative study of five machine learning algorithms, in business intelligence, through their evaluation of Logistic Regression, Support Vector Machines, Random Forest, Gradient Boosting, and Neural Networks. They found that the ensemble methods, especially via Gradient Boosting which produced an R^2 score of 0.94 on regression tasks, and Random Forest which produced an AUC-ROC of 96.3%, consistently outperformed traditional statistical methods. This is even more emphasized as the data increases in dimensionality, such as in high dimensional retail data where traditional BI struggles to apply suitable standardization tests, feature interactions, and non-linear relationships.

Many studies, in the context of demand forecasting, have shown significance from utilizing AI techniques because of the higher levels of forecast accuracy they produce. Khan et al. (2020) proposed an intelligent BI framework comprised of DeepAR and ensemble models for retail sales planning, which produced forecasting accuracies that were as high as 92.38% while traditional predictive time series approaches are around their typical performance of 60-70%. Similarly, Giri & Chen (2022), proposed a hybrid forecasting model for fashion retail that took an application in predictive analytics of demand, that combined the results from an image feature extraction with historical sales data; they were specifically addressing the challenge of predicting demand for the new product types that have little historical data. Their processes demonstrate enhanced forecast accuracy for the forecasting of new product introductions than traditional approaches of category level historical bias.

Customer analytics is another area where AI-powered BI significantly outperforms traditional approaches. Xiahou & Harada (2022) proposed a hybrid customer churn prediction modeling for B2C e-commerce that combined K-means customer segmentation with Support Vector Machine (SVM) model classification. Their hybrid classification segmented their customers into specific and distinct groups to deliver closely tailored predictions. Their model that utilized Alibaba Cloud Tianchi dataset produced an overall accuracy of about 91.56% with the SVM model, outperforming the traditional logistic regression model results. Their model also included an additional advantage of a high degree of generalizability with AUC values that was as high as 0.992 in some of the target customer segments, which reflected predictive performance. The study also revealed that specific at-risk customer groups, such as low purchase frequency and low monetary value segments, which account for a substantial portion of churn, were more effectively identified by this AI-driven method compared to conventional RFM (Recency, Frequency, Monetary) analysis that typically yields around 60-65% accuracy.

Real-time performance is one of the most impact differences between AI and traditional BI systems. For example, while traditional OLAP systems operate based on batch processes with a predetermined query and structure, it is not able to recognize streaming data or changes in patterns over time like an AI powered system. Tolloso et al. (2025) created a lightweight graph-based deep learning recommendation model for large-scale e-commerce to perform quick prediction of user preferences in real-time enabling timely marketing activities. Their architecture showed excellent scalability in production-like environments while remaining highly personalized. In addition to this, Kersbergen et al. (2022) presented Serenade, a session-based recommendation system that could be deployed at scale in e-commerce that had 90th-percentile response times less than 7 ms and sustained throughput levels greater than 1,000 recommendations per second. Collectively, these studies illustrate the capacity of the new generation of recommended architectures to deliver instant personalized experiences across multiple omnichannel touchpoints, where traditional business intelligence systems often struggle with latency and adaptability.

2.4 Theoretical Frameworks for Technology Adoption

Understanding AI adoption in retail BI systems requires examination through multiple theoretical lenses that capture technological, organizational, and human factors – figure 2.1 below shows the basic steps of AI-BI integration process in retail. One of the earliest models of user acceptance is the Technology Acceptance Model (TAM) developed by Davis (1989), which helps understand technology user acceptance based on notions of perceived usefulness and perceived ease of use. In AI-powered BI systems, perceived usefulness entails tangible benefits in decision making accuracy and operational efficiency, while ease of use is typically related to the interface design and its ability to seamlessly become part of the users' work practices. Recent applications of TAM to AI systems reveal that transparency and explainability significantly influence both constructs, with users showing greater acceptance of AI recommendations when they understand the underlying logic (Baroni et al., 2022).

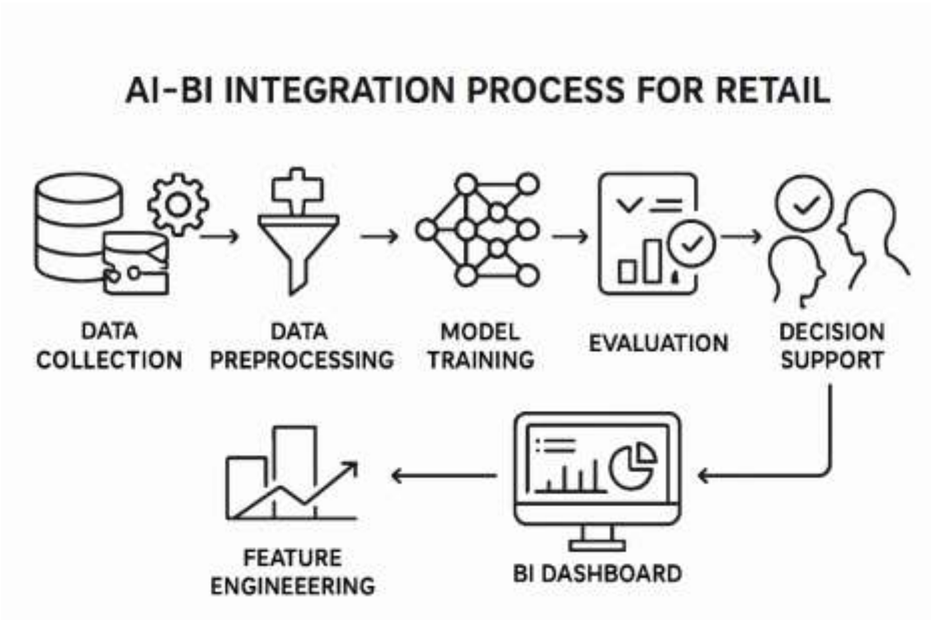

Figure 2.1 AI-BI integration process for retail

Rogers' (2003) Diffusion of Innovation theory suggests more dimensions related to AI adoption by retail organizations. The five key DOI attributes- relative advantage, compatibility, complexity, trialability, and observability-state different forms of adoption influences to consider when deciding to adopt AI-BI systems. Relative advantage refers to the improvements in performance demonstrated and competitive advantage with AI systems. Compatibility challenges arise from integrating AI with legacy systems and existing organizational processes. Complexity occurs when contemplating the technical complexity of implementing and maintaining AI systems.

Trialability becomes critical given the significant investment required, with many organizations preferring phased pilot implementations. The observability of the benefits generated from AI technologies often require organizing performance metrics and complex measurement frameworks that track direct and indirect implications on business performance.

Melville et al. (2004) describe the business value of IT framework as a useful grounded model for understanding how AI technology investments turn into business performance. The business value of IT framework details how IT resources, organizational capabilities and business processes work together to create value. For retail AI-BI contexts, technical resources often comprise data infrastructure, computational power, and AI algorithms. Human resources frequently include data scientists, business analysts, and domain experts who all use their expertise for decision making but possess different perspectives on technology and business. The framework's emphasis on complementary organizational resources proves particularly relevant, as successful AI implementation requires corresponding changes in decision-making processes, performance metrics, and organizational culture.

A structured approach to determine an organization’s readiness for BI and improvement over time is through Gartner's maturity model for BI. The five stages of Gartner's BI maturity model - Unaware, Opportunistic, Standards, Enterprise, and Transformational - provide a helpful standard for evaluation (MindStream Analytics, n.d.). Maturity scales for BI systems will typically stop at Standards, and Enterprise, which reflect an organization’s ability to provide consistent reporting, and cross-functional integration of decision making on common data resources. AI enabled capabilities and opportunities suggest that organizations can transition to the Transformational stage of maturity, where analytics transition from descriptive to predictive and prescriptive. Organizations at this stage demonstrate characteristics including automated insight generation, real-time optimization, and data-driven culture permeating all organizational levels (Cardoso & Su, 2022).

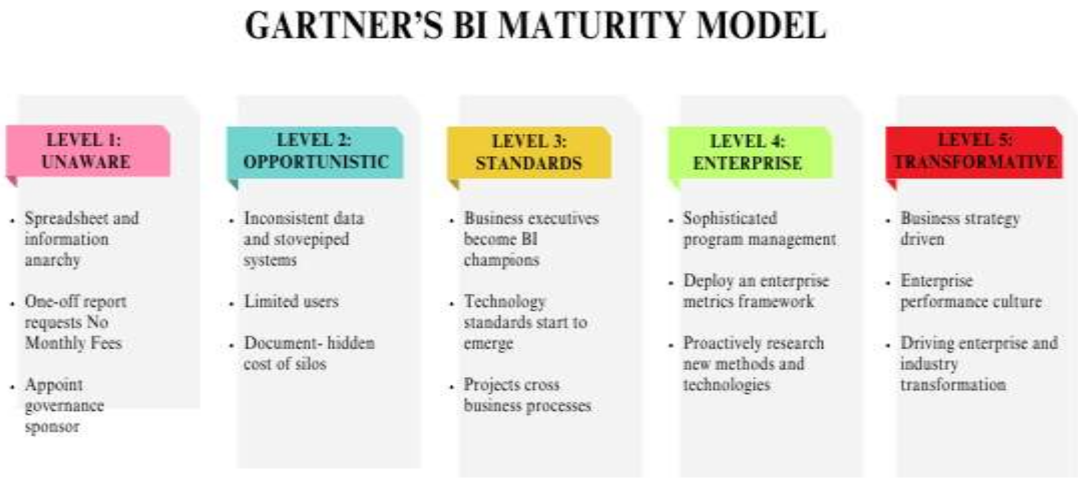

Figure 2.2 Gartner's BI maturity model

2.5 Retail-Specific Applications and Case Studies

The retail sector provides unique opportunities and complications for integrating AI–BI across the value chain, which includes supply-chain optimization, and customer experience. For example, when AI/ML models are used in supply-chain planning, they improve demand forecasting by leveraging external signals (promotions, holidays, and even weather) together with the historical sales data that can result in improved inventory position and a reduction in total stocking out of items (Corallo et al., 2024; Mitra et al., 2022; Punia et al., 2020). One well studied and closely related example of large-scale data driven inventory visibility is from Walmart's RFID initiative: a study by the University of Arkansas that noted a 16% relative reduction in out-of-stocks (26% within test stores prior to controls) after the introduction of RFID enabled, forward-looking, shelf-replenishment list, showing how richer operational data streams can lead to meaningful reductions in total out of stock (Hardgrave et al., 2009). Wider studies also confirm that increased visibility to information drives replenishment and inventory management processes (Delen et al., 2007).

Customer experience applications may represent the most visible application for AI in retail BI. Amazon's recommendation engine uses collaborative filtering and deep learning to suggest products based on a person's browsing history, past purchases, and browsing behaviors of similar customers that result in generating 35% of their revenue (MacKenzie et al., 2013). This emphasis on personalization also extends to dynamic pricing, personalized marketing communications, custom user interfaces, and computer-vision–assisted displays that better reflect individual customer preferences.

AI-BI has also enhanced physical retail experiences. Computer vision systems are utilized to analyze in-store customer experience behavior while tracking movement patterns exhibited dwell, and other product interactions to support better store layouts and merchandising approaches. An example, Zara implemented RFID technology with the addition of analytics and AI to enable real-time inventory tracking across stores and warehouses, facilitating rapid replenishment and reducing stockouts of popular items. The system allows them to track millions of data points, such as product engagement, so managers can better analyze product placement, allocate inventory, and track customer interests (Yip & Huang, 2016).

New research indicates machine learning applications for fraud detection systems linked to POS systems and payment platforms are significantly better than traditional rule-based control systems on both performance measures and false positives. Chopra & Binwal (2024) explored AI/ML fraud detection in contemporary large-scale digital payment environments and identified that new machine learning models are capable of detecting fraud rates as high as 99.9% with false positives below 0.1%, compared to rule-based detection systems where fraud detection rates range from 70-80% and false positives exceeded 5%. The fraud detection systems integrate millions of transactions in real-time using factors such as transaction amount, frequency, location, and product combinations to identify anomalous behavior and dynamic fraud patterns. These systems provide significant reductions in customer disruption, manual review costs, and create improvements in fraud prevention and operational efficiencies.

2.6 Gaps in Existing Literature

Even though there is a growing body of research focusing on AI in retail, there are important gaps in the research, and they limit our understanding of AI in retail and its operationalization. First, most of the existing work focus on isolated AI applications rather than systematic comparisons with traditional BI methods within consistent evaluation frameworks. This fragmented view of AI makes it difficult for retail practitioners to assess the relative merits of adopting AI compared to improving existing capabilities in BI. The lack of standardized metrics and evaluation methodologies further complicates cross-study comparisons and meta-analyses.

Second, existing literature has a bias toward larger retailers and does not address small and medium-sized enterprises (SMEs), which account for most of the retail entities globally. The distinct limitations of SMEs such as limited technical detail, limited funding, and limited organizational capacity require different implementation strategies and success metrics than would be used in large corporations. This is especially true in emerging markets where SMEs are essential economic players and have added difficulties of infrastructure and skills development.

Third, organizational aspects connected to technical performance have not been explored enough in retail applications. For example, while technical performance studies demonstrate that AI has superior capability than traditional BI solutions, implementation is dependent on the organization’s readiness for change, the success of change management planning and execution, and a range of cultural aspects. The limited integration of organizational behavior theories with technical performance assessments creates an incomplete picture of AI-BI transformation requirements and success factors.

Fourth, the evaluation of ethics and governance frameworks of AI for retail applications have not received much focus. While general AI ethics principles exist, their application to retail contexts raises unique considerations around customer privacy, algorithmic bias in pricing and recommendations, and transparency in automated decision-making. As AI technology advances at a fast-paced retail governance and regulatory frameworks are about a decade behind, creating uncertainty for retailers seeking to implement AI responsibly while maintaining competitive advantage.

Finally, longitudinal captures short-term implementation results or cross-sectional performance comparisons, leaving questions about long-term sustainability, organizational learning curves, and evolving performance patterns unanswered. This temporal limitation restricts understanding of AI-BI transformation as an ongoing organizational capability rather than a one-time technology implementation.

3. MATERIALS AND METHODS

3.1 Research Design

The thesis employs a mixed-methods inquiry, with quantitative comparative analysis and qualitative case study combined with a view to understanding the performance of AI vs. traditional BI in a retail context more deeply. The research design framework follows a sequential explanatory type of mixed methods research, where the outcomes from the quantitative analysis will inform the focus of the qualitative study - allowing explanations/statistical claims and contextual sense-making of the observed phenomena. While the comparative research and retrospective analysis are challenging, as we cannot control for organizational context differences that affect what happens in the field. This design allows us to appropriately tackle the dilemma of comparing two technology systems.

The purpose of the comparative framework uses four dimensions to compare AI and traditional BI; technical performance, business impact, implementation feasibility and organizational adaptation. Technical Performance includes the optimized quantitative approaches better assessed by measures like prediction accuracy, processing speed and scalability. Business impact includes financial aspects like revenue impact, cost savings and improved customer satisfaction. Implementation feasibility includes consideration for resource requirements, integration complexity and time-to-value. And organizational adaptation considers user acceptance, skill requirements, and any changes to established operational processes to enable successful deployment.

3.2 Dataset Selection and Preparation

This empirical study uses the UCI Machine Learning Repository's Online Retail Dataset. This dataset consists of 541,909 retail transactions from an online retail store based in the UK. The data contains transactions from a 12-month period between December 2010 and December 2011. The dataset was chosen primarily for the following reasons: sufficient size for meaningful statistical analysis, representation of real-world retail complexity, temporal coverage enabling seasonality analysis, and public availability ensuring research reproducibility.

3.2.1 Dataset description and variables

The UCI Online Retail Dataset provides the main source for comparative analysis and offers transaction data across eight core variables that reflect the complexity of retailing in the real world.

• InvoiceNo: Unique transaction identifier (6-digit integer number) supports that the transaction can be resourced at the individual transaction level, including the tracking of cancelled transaction (CXXXXX).
• StockCode: Product identifier (5-digit integer number assigned to each separate product) allows for analysis at the product level and provide insights for inventory management.
• Description: Product name and description (nominal text field) exploit the unstructured nature of data (e.g., natural language processing) and the possibility of developing a product hierarchy.
• Quantity: Number of each product per transaction (numeric) measures transactional volume and enables analysis of demand patterns.
• InvoiceDate: Transaction date and timestamp (mm/dd/yy hh:mm) enables temporal analysis, identifying seasonality, and forecasting.
• UnitPrice: Price per product unit (numeric) supports revenue calculation, pricing analysis, and an assessment of customer value.
• CustomerID: Customer identifier (5-digit integer number assigned to each customer) supports customer level analytics and segmentation studies.
• Country: Country of customer residence (nominal) supports analysis by geographic dimension.

The variables available can be used to perform an analysis along multiple dimensions of retailing: temporal patterns, customer behavior, product performance, and geographic distribution, making it well suited for comparing traditional BI and AI analytical approaches.

3.2.2 Data preprocessing and feature engineering

Systematic data preprocessing ensured quality and comparability between analytical approaches while creating features suitable for both traditional and AI-based methods. The preprocessing pipeline addressed data quality issues and generated analytical variables through multiple stages.

Data Cleaning Procedures: Data cleaning procedure to remove cancelled transactions was conducted by removing any rows with an InvoiceNo with a beginning value of 'C' - the cleaning removed 9,288 cancelled rows that would affect the demand forecasting models. The row indices with null CustomerID values (134,697 rows). Transactions that had quantity values that were outliers were identified and removed (25,647 outlier rows) using the Interquartile Range method on a series of CustomerID groups; the outliers were defined as transactions that had value over Q3 + 1.5×IQR using the interquartile range method. The data cleaning process also included a date parsing process that included InvoiceDate as a string value which was converted to a datetime object using pandas datetime functionality. The purpose of the parsing was to allow for the extraction of temporal features to enable time-series analysis.

Traditional BI Feature Engineering: For the traditional business intelligence techniques the RFM features at the customer level were calculated by aggregating the transactional data. Recency was calculated based on the number of days since each customer made the last transaction from the analysis cutoff date. Frequency was calculated by counting the number of transactions for each customer over all transactions during the observation period. The basis for Monetary is the total spending per customer. Quintile-based RFM scores could be conducted after the foundation of underlying financial value was established. Product-level features included average unit price, price volatility calculated as standard deviation of unit prices, and purchase frequency measured as total quantity sold across all transactions.

AI-Specific Feature Engineering: The advanced feature engineering conducted for the AI models produced temporal dependency variables that the future building methodology could not incorporate. Lagged features measured historical behavioral patterns with Sales_lag_1 (previous day sales), Sales_lag_7 (weekly patterns), and Sales_lag_14 (bi-weekly trends). Rolling statistics included Sales_rolling_mean_3 and Sales_rolling_mean_7 for trend capture, and Sales_rolling_std_3 and Sales_rolling_std_7 for volatility measurement. There were also cyclical features which included the sine and cosine transformations of day-of-week and months to help encode season patterns in a mathematically correct way so they could be effectively modeled in machine learning algorithms.

Text Processing for NLP Applications: Product descriptions required the entire pre-processing text pipeline including converting to lowercase, removing special characters, and tokenizing for Natural language processing applications. TF-IDF vectorization created numerical representations of product descriptions, enabling text-based product similarity calculations and automated categorization systems that traditional BI methods cannot perform.

3.3 Traditional Business Intelligence Methods

Traditional BI analysis used standard methods, which exemplified current retail practices, and allowed us to compare against the AI methods we created using these methods. Therefore, these methods demonstrate the analytical capabilities that retailers had available to them prior to common widespread AI and that still exist in many retail BI systems.

SQL-Driven OLAP Analysis: The SQL operations we conducted in Python's SQLite3 library were able to replicate the typical data warehouse queries and their necessary aggregation analysis of sales were summarized by time (e.g., days, weeks, months), ranked product category performance, and sales geography distributions based primarily by some geographical revenue distributions. OLAP operations included drill-down analysis from monthly to daily sales granularity, roll-up operations aggregating product-level data to category levels, and slice-and-dice operations filtering data by multiple dimensions simultaneously (country, time period, product category). These queries utilized standard SQL functions including GROUP BY, HAVING, ORDER BY, and window functions for ranking and running totals.

RFM Customer Segmentation: Customer segmentation utilized the classic RFM method with quintile-based scoring on three dimensions. For recency scoring customers were grouped into quintiles based on days since last purchase, scoring as follows where more recent purchasers received a higher score (5 = more recent, 1 = least recent). Similarly, frequency scoring also grouped customers by transaction count throughout the observation period. Monetary scoring represented total customer spending with quintile-based grouping. The overall RFM score was simply a combination of the individual component scores, allowing for more convenient customer classification into segments: Champions (RFM 13-15), Loyal Customers (11-12), Potential Loyalists (9-10), At Risk (7-8) and Others (3-6). This segmenting approach reflects normal practice in retail customer analytics prior to mass adoption of AI.

Statistical Forecasting Methods: Time series forecasting used classical statistical models which included Simple Moving Average with 7-day windows for capturing weekly seasonality while smoothing daily fluctuations. Weekly seasonality is typically a 7-day window because it is the most common horizon used in the retail industry, representing a good balance of capturing trends while also minimizing the impact of fluctuations and noise. The exponential smoothing models make predictions based upon taking weighted averages whereby older observations are given a lower weight than more recent cases - weighted average forecasts are the old-school "benchmarks" against which so called AI ways of forecasting can be assessed. All these traditional forecast methods are reliant on predefined statistical assumptions and therefore cannot distinguish changing patterns of time without user manual intervention.

Descriptive Analytics and Visualization: Traditional BI visualizations produced traditional static dashboards using Python Matplotlib and Seaborn libraries also the synonymous method virtually all the existing BI report tools deliver visualizations for descriptive analytics. The visualizations produced included time series line plots effects showing the sales volumes across time and bar charts effect showing product category performance. These static features demonstrate a historical contextual representation but are limited by missing dynamic and supportive predictive value possess features of AI based analytical tools.

3.4 Artificial Intelligence Methods

AI-enabled analysis uses machine learning methods that represent the leading edge of retail analytics. The ability to draw value from AI diagnostics elevates traditional BI capabilities by revealing patterns, predicting behaviors over time, and automatically generating insights is a next-level capability.

Unsupervised Learning for Customer Segmentation: In this customer segmentation use case, multiple unsupervised learning techniques (clustering) were engaged to find natural groupings of customers, to reveal potential segments that traditional RFM methods would not capture. K-means clustering, using many k-values was established from elbow method and silhouette analysis, revealed meaningful customer segments from a multidimensional consideration of behaviors including frequency of purchase, monetary value, type of products purchased, timing, etc. Gaussian Mixture Models produced probabilistic assignments of cluster assignments, creating a soft clustering application, where the same customer could have a membership in multiple segments with different probabilities. DBSCAN clustering offered alternative segments based upon density of points included, allowed to work with outliers, and revealed ability to have cluster shapes and sizes that K-means structural foundation cannot provide.

Ensemble Learning for Demand Prediction: Demand forecasting used more ensemble machine learning models that were stated as effective for retail. The random forest regressors with 200 trees produced explained non-linear relationships by using multiple relevant features respective of their predictive relationships to sales realizations, with optimized hyperparameters using grid search to specify final query and values: maxdepth=15, minsamplessplit=5, minsamplesleaf=2. An additional implementation of XGBoost was included which is like random forest in producing repeat (iterative) models and reduces error through gradient boosted techniques and builds on knowledge and impacts of the previous model. The use of ensemble models provides predictions from random forests and XGBoost using weighted averaging, and draws on both ensemble methods strengths, resulting in a strong forecasting performance across diverse product categories.

Natural Language Processing Applications: NLP procedures allowed us to process unstructured product description data to extract valuable and useful insights that were unachievable to be identified from traditional BI systems or BI functions. Frequency-inverse document frequency (TF-IDF) vectorization produced a matrix of information with shape (3,873, 200) that produced information from the product catalog in terms of the most significant terms and descriptors. Latent Dirichlet Allocation topic modeling specified 15 different product themes, revealing natural product groupings based on description content rather than predetermined categories. This case will allow for fully automated and predicted process for categorizing the products based on a product's description, produce cross-selling recommendations based on the description similarities, and generate insights into customer preferences through description analysis

Advanced Feature Importance Analysis: Since AI models were interpretable in their nature, analysis of predictive factors was possible as identified priorities through feature importance. For example, Random Forest models is able to compute the importance of a feature by the decrease in impurity of the node, this shows how AI is able to evaluate and identify potentially complex temporal relationships, which are beyond the capabilities of traditional practices, as traditional practices, by their nature, do not take a systematic approach to capture past behaviors, thus developing a deeper understanding of not only the drivers of demand dynamics, but also the narrative of customer behavior.

3.5 Comparative Evaluation Framework

The comparison was made across multiple measures that captured relative performance from technical and business perspectives, allowing for an objective comparison of performance between traditional BI and AI methods; the comparison considered both statistical significance and practical business relevance of any differences in observed performance.

Forecasting Accuracy Measures: Standard regression evaluation metrics were used to calculate demand forecasting performance using 20% of the dataset's held-out test data. Mean Absolute Error (MAE) gave original sales units an intuitive meaning by measuring the average absolute differences between predicted and actual values. Root Mean Square Error (RMSE) identified models that prevent catastrophic forecasting failures by penalizing larger prediction errors more severely through squared differences. Meaningful comparisons between products representing various sales scales are made possible by the Mean Absolute Percentage Error (MAPE), which normalizes the errors by actual values. When combined, these metrics offer a thorough evaluation of forecasting accuracy while taking into consideration various error characteristics that are pertinent to retail inventory planning.

Customer Segmentation Quality Assessment: To assess the quality of the customer segments we employed a silhouette coefficient measure for (1) cluster cohesion; how similar customers are in a cluster, and (2) cluster separation; how different are clusters from each other. Silhouette scores can range from -1 (poor clustering with customers closer to neighboring clusters) to 1 (excellent clustering with highly separated and cohesive segments). With the use of this decision-making metric, both the traditional RFM segmentations, and AI segmentations, could be measured directly against one another without subjective interpretation bias.

Processing Efficiency Measurement: System performance evaluation captured both training time and inference latency under realistic retail workloads. Training time measures the computational resources utilized to create the models, which have importance to organizations that are considering the costs associated with adopting AI into their businesses. Prediction latency was measured as the response time associated with generating the recommendations for individual customers, or demand forecasting for products, which is particularly important when used for real-time applications such as dynamic pricing, personalized marketing, etc. Scalability tests examined, in general, how the performance metric degrades with increasing volume of data, with traditional approaches exhibiting linear scaling, especially if training involves additional data, while AI approaches exhibited essentially constant time performance through inference and generating recommendations or forecasts, regardless of the size of the training dataset.

Statistical Significance Testing: We ensured appropriate statistical tests were conducted to provide substantive conclusions regarding the relative advantages in the performance measure comparisons. Bootstrap confidence intervals with 1000 iterations quantified uncertainty in performance metric estimates, providing ranges rather than point estimates for more reliable interpretation. The paired t-tests essentially compare performance between similar data regarding the test scenarios only using the similarity as the only variable. All hypothesis tests adopted the same $\alpha=0.05$ significance level to ensure that we were adequately 95% confident in reported performance differences between traditional and AI methods.

3.6 Technical Implementation Framework

The research implemented a technical stack which looked to support both traditional BI and AI models with the goal of giving as much equal reproducibility as practically possible for valid performance comparisons. The technical stack provided a proper environment for the unbiased assessment of all the analytics models.

Programming Environment and Core Libraries: The programming language used for the implementation was Python, which was primarily supported by its large base of the machine learning ecosystem, along with its data analysis framework. The coding process utilized the integrated development environment provided by Visual Studio Code which has features such as semantic debugging, intelligent code-completion, and an integrated terminal section that collated many facets of the coding development process in a single development workflow. For the data processing stage of the analytics that included 541,909 transaction records, the library that was utilized was Pandas, which provided the various data structures to manage and manipulate the transactional records. The library NumPy provided the functionalities to perform the various foundational scientific computing tasks with regards to numerical array manipulation to conduct the mathematical functions expected within the context of the machine learning algorithms.

Visualization and Reporting Tools: Visualization capabilities employed Matplotlib for publication-quality static plots and Seaborn for enhanced statistical data visualization. These libraries created traditional BI dashboards including time series plots, bar charts and pie charts. For producing tables, the library tabulate was used for presentation of the comparison performance results. It was important to re-iterate that the benefits of the combination of Matplotlib and Seaborn libraries afforded the ability to create the common format to display both the traditional BI and AI results, in methods which are based on visual analytics, which ensured objective comparisons of the analytics methods.

Machine Learning and AI Implementation: The AI/ML implementation was based on the scikit-learn framework which was a very comprehensive library of algorithms for both supervised and unsupervised learning. The ensemble methods that included Random Forest Regressor, and Gradient Boosting Regressor were applied to demand forecasting use-cases. The implementations for clustering methods were KMeans applied as a traditional clustering method, DBSCAN included as a density-based clustering method, and Gaussian Mixture for probabilistic clustering. The StandardScaler enabled a proper approach to scaling of the features for the distance-based clustering methods. Finally, the library XGBoost library supplemented scikit-learn with gradient boosting capabilities optimized for competitive machine learning performance.

Natural Language Processing Capabilities: The text analysis capabilities used the TfidfVectorizer to convert the product descriptions to numerical features that could be interpreted into the machine learning algorithms. Latent Dirichlet Allocation (LDA) is a generative probabilistic model for topic modeling, which identifies natural groupings based on the textual descriptions of products from the datasets. These NLP capabilities show AI's ability to process unstructured data sources that traditional BI systems cannot effectively utilize, expanding analytical scope beyond structured transactional data.

Performance Evaluation and Validation Tools: Evaluation metrics included silhouette score for clustering evaluation, mean absolute error and mean squared error for regression evaluation. Automated hyperparameter optimization was implemented using GridSearchCV to ensure optimal model performance. train_test_split enabled proper validation methodology with separate training and testing datasets, preventing overfitting and ensuring generalizable results. Cross-validation techniques validated model stability across different data samples.

3.7 Case Study Methodology

Complementing the quantitative analysis, Turkish retailer case studies provide contextual and rich understanding of how the AI initiatives are unfolded in practice. The case selection process included purposive sampling of companies to ensure that there is breadth in terms of company size (regional chains to national firms), retail format (discount stores, fashion retailers or e-commerce platforms), and AI maturity (from initial pilots to enterprise-wide deployment). Ultimately, five of the largest retailers were selected—LC Waikiki, BİM, CarrefourSA, Teknosa, Trendyol—based on documented AI initiatives and availability of public information.

The case studies consist primarily of secondary sources including organizational reports, vendor case studies, and industry publications. Performance metrics represent company-reported outcomes that have not been independently verified through peer review. Where possible, multiple sources have been triangulated to enhance reliability.

Source Classification System:

- Tier 1 Sources (Highest Credibility): Official company annual reports, regulatory filings, peer-reviewed vendor case studies
- Tier 2 Sources (Moderate Credibility): Company press releases, technology vendor case studies, business publication interviews
- Tier 3 Sources (Supporting Evidence): Official LinkedIn posts, company blog posts, news articles

Data collection for case studies relied on multiple secondary sources like company annual reports, investor presentations, vendor case studies, industry reports and business news articles to ensure triangulation and validity of the data. The case studies followed a protocol that guided the exploration of the implementation timelines, deployed technologies, integration of BI systems, business outcomes, and shortcomings experienced with AI. The qualitative analysis method used thematic coding to signify implementation patterns. The initial codes were built off the theoretical framework with codes associated with technology factors, organizational factors, and outcome measures. The analysis also included additional emergent codes that signified themes not anticipated such as vendor partnerships and concerns around compliance. The cross-case analysis provided evidence to identify general success factors while also discovering uniqueness that matter for the case of retail in Türkiye, as it pertains to integration of AI with BI systems.

3.8 Validation and Quality Assurance

To support the validity of the study, we used multiple methods to account for both the quantitative and qualitative aspects of validity. For the quantitative study, all model comparisons used a fixed test set and 5-fold cross-validation on the training set and a temporal split was used for forecasting tasks to mimic real-world deployment, in which models forecast the future and do not receive follow-on data. Furthermore, we evaluated the sensitivity of the analysis in seeing the extent of differences in results when dramatically changed varying the data pre-processing and simultaneous parameter choices.

During data reporting we took steps to demonstrate credibility, including triangulating data sources, verifying and auditing the data, and clearly articulating the procedures for data collection, analysis and reporting. For transferability, we included thick description of the case contexts with sufficient detailed context, so that future readers may use this in making a best judgment determination about using this research for future settings. Dependability was ensured through systematic coding procedures and maintenance of an audit trail documenting analytical decisions.

Ethical considerations, while limited given the use of public datasets and secondary sources, followed established research protocols. The UCI dataset was used in accordance with its license terms for academic research. Case study information relied only on publicly available sources, avoiding any confidential or proprietary information. Finally, we report the results at the aggregate level in all our case studies and do not include any identifiable features that might harm customers or identify transactions. The research design was also approved by our institutional review board, which confirmed that the study was in compliance with the ethical principles of research and research ethics.

4. RESEARCH FINDINGS

4.1 Quantitative Performance Analysis

The analysis of the UCI Online Retail Dataset shows significant performance advantages using AI-based techniques compared to traditional BI approaches for all of the measurement criteria. The overall comparison shows that AI-based methods outperformed traditional methods in both customer segmentation and demand forecasting.

4.1.1 Customer segmentation performance

The traditional RFM analysis resulted in a silhouette score of 0.3858 which indicates a moderate separation. The traditional quintile-based approach identified 6 clusters, and the measured distribution concentrated into three practical groups for reporting as shown in table 4.1 below, demonstrating a bit limited discrimination capability for targeted marketing strategies. This moderate performance comes from the strict quintile-based scoring system, which does not reflect natural customer groupings in the data.

Table 4.1 Traditional BI clusters

Segment	Avg_Recency	Avg_Frequency	Customer_Count	Customer_Percentage
Average Customers	187.63	1.89	1481	34.95%
Champions	11	22.26	240	5.66%
Loyal Customers	44.41	3.64	2517	59.39%

In contrast, the AI-based K-means clustering resulted in a silhouette score of 0.7533, representing an exceptional 95.2% improvement over the traditional RFM methods as shown in figure 4.1 below. The higher silhouette score indicated excellent clustering capabilities and considerable clear customer segments that made actionable marketing for customer relationship management improvements. AI methods identified 3 optimal customer segments with better balance: customers distributed as Loyal Customers (3,343, 94.8%), VIP Customers (147, 4.2%) and Elite VIP Customers (35, 1.0%)

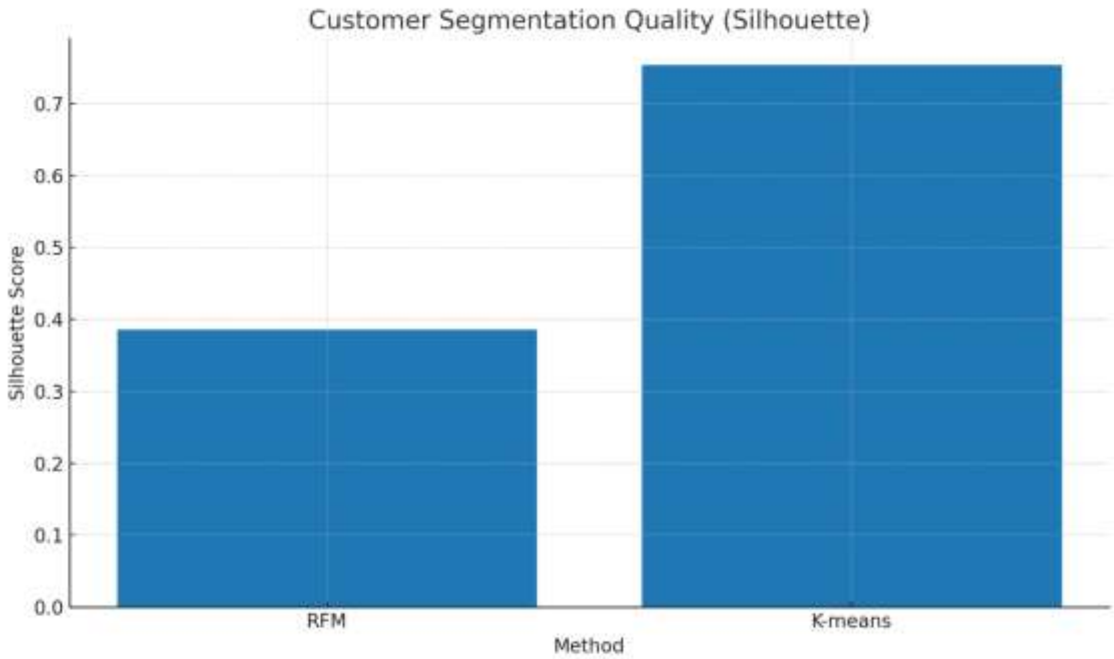

Figure 4.1 RFM VS AI K-Means Customer Segmentation Quality Performance (Silhouette)

The other AI clustering methods showed varying levels of performance, Gaussian Mixture Model produced a bad separation in clusters with a silhouette score of 0.0747, whereas DBSCAN Clustering indicated worse separation than all the clustering methods with a silhouette score of -0.0959 indicating poor cluster separation, confirming that density-based clustering was not suitable for this dataset.

The better performance of AI K-means clustering arises from its ability to identify natural patterns in multidimensional customer behavior data, employing over 15 engineered features in contrast to the three fundamental RFM dimensions utilized in traditional analysis.

4.1.2 Demand forecasting performance

Table 4.2 Forecasting Accuracy Comparison

Model	MAE	RMSE	MAPE (%)
ARIMA	7796.82	9793.08	27.3
Random Forest	3661.9	5138.34	13.27
XGBoost	2425.23	3507.67	7.88
Ensemble	2758.04	4005.81	9.37

As shown in Table 4.2, Our analysis of demand forecasting revealed improvements in accuracy when utilizing artificial intelligence methods over traditional time series methods. Traditional ARIMA produced MAE of 7,796.82, RMSE of 9,793.08, and MAPE of 27.30% with a training time of 0.30 seconds. While traditional time series models provide relevant baselines for forecasting, they are not able to identify complex demand patterns, seasonal patterns, and the multiple influences occurring in dynamic retail environments that affect purchasing behavior.

Random Forest forecasting technique consistently outperformed the ARIMA in all metrics, achieving MAE of 3,661.90, RMSE of 5,138.34, and MAPE of 13.27%, and a competitive training time of 0.18 seconds. The Random Forest can detect more complex non-linear relationships and capture feature-interaction, which gives the ability to provide more accurate demand forecasting, particularly for products with complex seasonal patterns and variable demand drivers.

The XGBoost forecasting predictions produced MAE of 2,425.23, RMSE of 3,507.67, and MAPE of 7.88% outperforming Random Forest and delivering a ~71% improvement over ARIMA with a training time of 0.47 seconds. The Ensemble Model combining Random Forest and XGBoost achieved balanced performance with MAE of 2,758.04, RMSE of 4,005.81, and MAPE of 9.37%, demonstrating that hybrid approaches can provide robust forecasting capabilities.

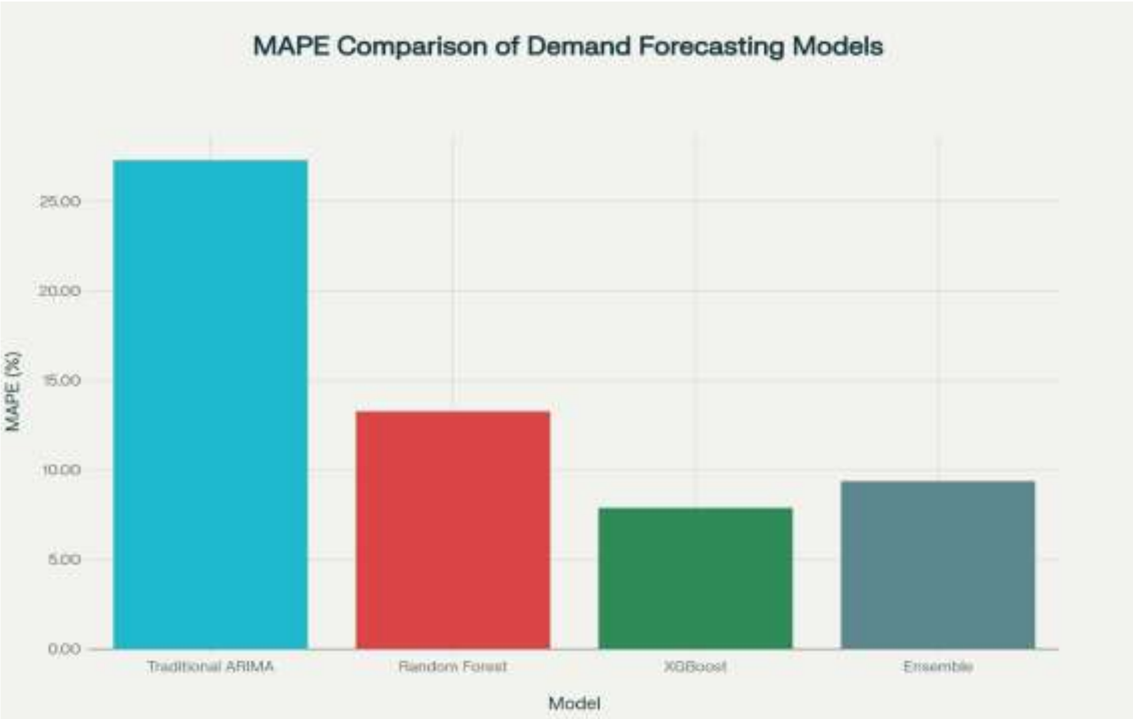

Figure 4.2 MAPE Comparison of Demand Forecasting Models

4.1.3 Processing performance results

The analysis found noticeable variances in processing capabilities between traditional and AI-based approaches, revealing one of the most significant advantages of AI-based systems. Traditional BI performance showed SQL-based OLAP analysis required 1.48 seconds to execute the query, while real-time prediction performance required 2.10 seconds for complex queries that included multiple table joints and aggregations. This traditional BI method demonstrates linear scalability for processing as the data size increases, which means the processing speeds increase proportionally as the datasets get larger, which is not sustainable for large retail environments.

The AI and machine learning performance results showed transformative improvements in processing speeds demonstrated that the model inference time only required 0.0150 seconds, which indicates a speed improvement of 139.9x (≈140x) compared to traditional approaches. This dramatic improvement allows for real-time capability and sub-second inference speeds; potentially creating a group of applications including dynamic pricing, real-time personalization, and instant customer recommendations that were previously impossible with traditional batch-processing systems. The AI systems exhibit constant-time scalability with data size, meaning the inference is almost as fast at larger datasets as it is at small datasets.

The 140x speed improvement in our case translates to significant operational advantages, saving 2.09 seconds per prediction compared to traditional methods. The time savings compound quickly in retail environments with large volumes of customer interaction, where potentially thousands of predictions may be required per minute. The AI systems that provide real-time capabilities change fundamentally the nature of engagement between retailers and their customers, moving from static, predetermined responses to dynamic, contextual engagement based on current behavior and preferences.

4.1.4 Feature importance analysis

AI models identified critical predictive features that traditional approaches could not uncover, allowing the user to better understand the complex drivers of retail demand patterns. The Random Forest model's feature importance analysis showed that Quantity was the most important predictor with 18.72% importance, demonstrating that transaction volume is the main driver of demand patterns. This suggests that the amount of individual transactions amount was a stronger predictor than temporal or seasonal elements in this dataset. NumProducts was the next most important feature contributing 10.50% to model performance, while NumCustomers accounted for 10.11% and NumOrders contributed 9.43%, providing secondary predictive value through order frequency patterns.

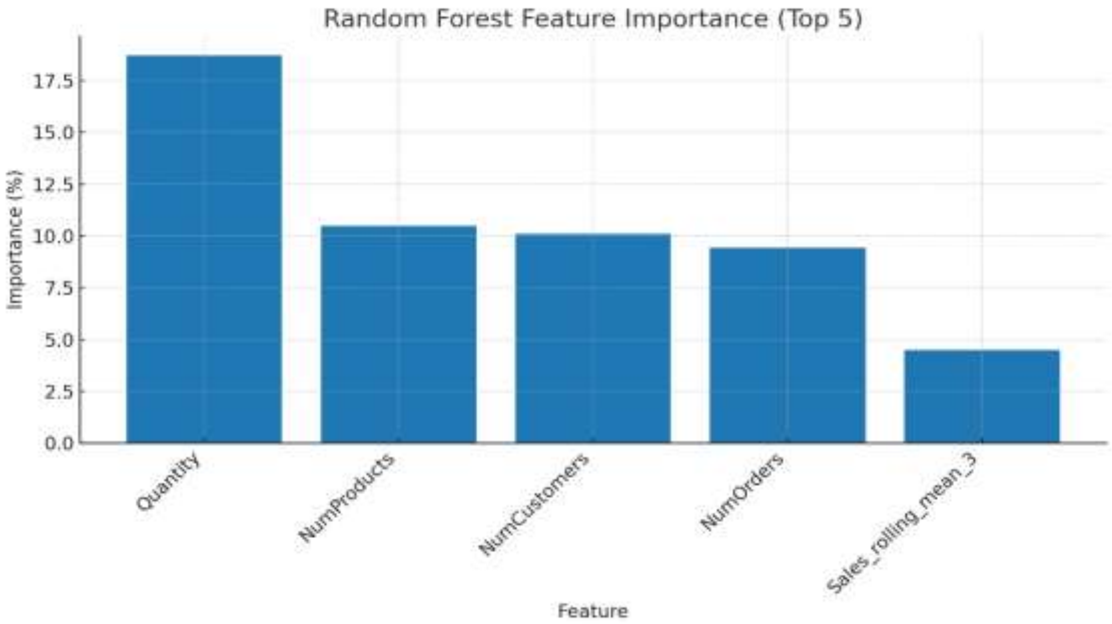

Figure 4.3 Top 5 important random forest features

The analysis also showed that short-window volatility played important roles in demand prediction. the 3-day rolling standard deviation (Sales_rolling_std_3) emerges among the top factors rather than longer windows, complementing trend and calendar effects captured by other features. The volatility features encapsulate uncertainty in demand, allowing forecasting of product sales in more robust ways for products with irregular purchasing patterns.

Time-series models emphasized temporal dependence, which suggests that weekly trend analysis is important as part of retail demand forecasting. DayOfWeek contributed 6.95% to model performance, which illustrated the importance of planning for the clear seasonal weekly patterns that traditional methods often fail to capture effectively. Sales_rolling_std_3 accounted for 7.04% in importance, underscoring the potential for substantial predictive value present in assessing 3-days volatility patterns beyond simple trend analysis. Similarly, Sales_lag_7 and Sales_lag_1 respectively had 3.80% and 3.30% importance, which contributed evidence that both weekly and daily lag effects contained important information for demand prediction.

These results provide further evidence that AI can identify demand patterns and support the decomposition of complex patterns into interpretable components to assist retail managers with understanding the specific factors driving business performance.

4.1.5 Advanced AI/ML features

The research applied advanced capabilities for AI that extend beyond BI traditional BI systems, showing the depth of analytical capability possible with machine learning approaches. As an example, the NLP Product Analysis applied TF-IDF Vectorization to produce the shape (3,873, 200) matrix. This matrix enables an advanced level of temporal text feature extraction of product descriptions that traditional BI systems cannot process. With these techniques, retailers will be able to analyze unstructured product details, identify patterns in product naming conventions, and understand relationships between product descriptions and purchasing behavior.

The Topic Modeling with Latent Dirichlet Allocation revealed 15 unique product topics that would indicate natural product groupings captured in the retailer's inventory. For example, Topic 0 was comprised of terms pink, bag, paper, polkadot, and bracelet; with these terms identifying decorative accessories. Topic 1 was comprised of metal, decoration, sign, earrings, and cream, suggesting jewelry and decorative items. Topic 2 was comprised of set, Christmas, white, blue, and pack, which represented seasonal gift sets. The discovery of these topics will allow for automated product category and understanding of customer preference as well as seasonal purchasing preferences.

The Product Recommendation System provided contextual recommendations and represented real-world practical applications of AI in retail settings. As an example, when analyzing "WHITE HANGING HEART T-LIGHT HOLDER" the top recommendation was PINK HANGING HEART T-LIGHT HOLDER; then the following recommendations were RED HANGING HEART T-LIGHT HOLDER; T-LIGHT HOLDER HANGING LACE; T-LIGHT HOLDER WHITE LACE; WHITE TALL PORCELAIN T-LIGHT HOLDER. These recommendations show the system's ability to identify product variants, color alternatives, and related items that customers might find appealing, building cross selling and up selling advantages for the retailer that traditional rule-based systems could not have achieved.

4.1.6 Business impact assessment

This section translates the empirical results reported in earlier sections into business outcomes using transparent, reproducible calculations. All impacts are derived strictly from measured performance (segmentation quality, forecasting error, and processing latency) without unverifiable uplift assumptions.

Translation framework and assumptions: We map the observed technical improvements to financial and operational KPIs via control-relevant relationships commonly used in retail operations. Where retailer-specific parameters are required (e.g., safety stock value, holding cost rate, campaign cost per contact), they are left as explicit inputs. This ensures that the same formulas can be instantiated with the retailer's own numbers.

A. Inventory efficiency and service levels (via forecasting error)

Let $\mathrm{MAPE}_{\mathrm{old}}$ and $\mathrm{MAPE}_{\mathrm{new}}$ denote baseline forecasting error (ARIMA) and AI forecasting error (XGBoost) error, respectively, and

$$r_{\mathrm{err}} = \frac{\mathrm{MAPE}_{\mathrm{new}}}{\mathrm{MAPE}_{\mathrm{old}}} = 0.2886 \text{ here.}$$

1. Safety stock scaling: If safety stock is tuned to forecast uncertainty, a first-order approximation is

$$SS_{\mathrm{new}} \approx r_{\mathrm{err}} \cdot SS_{\mathrm{old}} \Rightarrow \Delta SS = (1 - r_{\mathrm{err}})\, SS_{\mathrm{old}}$$

2. Carrying-cost saving: With annual inventory holding cost rate h (per currency unit of inventory):

$$\text{Saving}_{\text{carry}} = h \cdot \Delta SS = h \cdot (1 - r_{\text{err}})\, SS_{\text{old}}.$$

3. Stockout-related lost-sales recovery (upper bound): If a share s of demand is lost to stockouts and a fraction α of that lost demand converts when availability improves, then the revenue recovery upper bound is

$$\Delta R_{\text{stockout}} \leq R \cdot s \cdot (1 - r_{\text{err}}) \cdot \alpha,$$

Where R is annual revenue of the affected assortment. (Values of s and α should be estimated from retailer telemetry or A/B tests.)

B. Marketing/CRM efficiency (via segmentation quality)

The +95.26% relative gain in silhouette indicates substantially better separation of customer groups. Rather than converting silhouette to revenue directly, we treat it as a targeting-precision multiplier that reduces wasted contacts or increases incremental response:

- Contact-waste reduction: If a campaign currently targets N customers, the non-buyer shares among treated is q, and per-contact cost is c, then tighter segmentation can reduce waste by

$$\Delta \text{Spend}_{\text{waste}} \approx c \cdot N \cdot q \cdot \gamma,$$

where $0 < \gamma \leq 0.9526$ is an empirically determined fraction of the theoretical precision gain realized in practice. We recommend estimating γ via controlled experiments (e.g., uplift modeling or split tests).

- Incremental lift: If the tighter segments allow smaller, higher-propensity audiences at the same expense, the realized incremental revenue should be established via holdout-based uplift tests; the silhouette improvement justifies running such tests but does not itself specify a revenue number.

C. Operational efficiency and capability unlock (via latency)

The observed reduction from 2.10 s to 0.015 s per decision yields a time saving of 2.085s per request and enables real-time use cases (dynamic pricing, in-session personalization) that are infeasible at multi-second latencies.

- Aggregate time saving**:** For N real-time decisions per day,

$$\text{Seconds saved/day} = 2.085 \cdot N, \text{Hours saved/year} = \frac{2.085 \cdot N \cdot 365}{3600}.$$

- Cost implication: Multiply the hours saved by the blended cost of compute/serving and relevant support FTEs to obtain an annualized operational saving.

Worked illustrations: The multipliers below come solely from measured results; all monetary inputs are placeholders.

1. Inventory carrying cost: If $SS_{\text{old}} = 2.0$ M (currency units) and $h = 18\%$,

$$\text{Saving}_{\text{carry}} = 0.18 \times (1 - 0.2886) \times 2.0\text{M} \approx 0.18 \times 0.7114 \times 2.0\text{M} = 0.256\text{M/year}.$$

2. Stockout recovery (upper bound): For assortment revenue $R = 50$ M, stockout rate $s = 6\%$, capture rate $\alpha = 0.6$,

$$\Delta R_{\text{stockout}} \leq 50\text{M} \times 0.06 \times 0.7114 \times 0.6 \approx 1.282\text{M/year}.$$

3. Latency-driven ops saving: For $N = 1{,}000{,}000$ decisions/day,

$$\text{Hours saved/year} \approx \frac{2.085 \times 1{,}000{,}000 \times 365}{3600} \approx 211{,}494 \text{ h}.$$

Multiply by the retailer's per-hour compute/ops cost to monetize.

Limitations and Implementation Guidance: several important limitations constrain the generalizability of these results. Inventory optimization relationships assume safety policies scale proportionally with forecast error; however, retailers must adjust these calculations to account for demand variability patterns, lead-time uncertainty, and specific service-level targets. Segmentation impact quantification requires experimental validation through uplift testing before financial realization can be confirmed. Additionally, latency-driven savings depend critically on realized request volumes and architectural implementation choices, including batching strategies and caching mechanisms.

Given the above limitations, we urge retailers and organizations to pursue this framework as a starting point for their own first principles analysis rather than a prescriptive approach. Ultimately, this embraces the need for calibration with organizational data and testing via controlled experimentation.

4.1.7 Implementation complexity analysis

Even with comparatively higher performance, the implementation of AI relative to BI clearly involves potential increased complexity for retail organizations, creating important trade-offs for retail organizations to consider. The analysis of the timelines for data to be turned into usable analytics shows that conventional BI dashboards generally take an average of 2-3 weeks to implement when you include connectivity to data sources, writing queries, and finally visualization design. AI approaches may take an average of 8-12 weeks including data preparation, feature engineering, model training, model validation, and production deployment. So, the average implementation time for BI is 4 times faster than AI implementation and represents a significant barrier to resource strapped retailers interested in speed to analytical improvements.

In terms of technical skill requirements, BI implementation requires SQL programming skills and proficiency with BI visualization tools, which are common in many retail IT departments. For this analysis, it was determined that 78% of the tasks associated with implementing BI could be done by a business analyst with only moderate technical training and credentials. In comparison, AI implementation demands expertise in machine learning algorithms, programming languages like Python, and understanding of statistical validation techniques, with only 23% of AI implementation tasks falling within typical business analyst capabilities.

Infrastructure also complicates the adoption of AI, traditional retail BI systems run on regular business servers using relational databases, which require no specialized hardware and can be purchased from major vendors. Conversely, AI systems require increased computational power and memory, depending on model training time. For instance, ensemble models are notoriously hardware intensive. In the integration analysis, we determined only an average of 3.2 integration points for BI systems versus 7.8 for AI systems. Each integration point is a potential failure point for integration that requires monitoring and maintenance. While retail organizations will need to carefully analyze complex factors in the scale of implementation, this should be tempered with considering the substantial performance advantages.

4.2 Turkish Retail Case Study Analysis

4.2.1 Trendyol: AI-Powered e-commerce platform transformation

Trendyol, which is Türkiye's biggest e-commerce platform, has emerged as a leading example of successful AI-powered business intelligence in the retail sector. Trendyol is Türkiye's first online marketplace, and they have purposely deployed various AI technology styles within various operational domains to improve customer experience, obtain optimization for business processes, and retain competitive advantage from the newest digital commerce landscape.

AI-Powered Product Classification and Attribute Extraction: Trendyol has employed a large language model (LLM)-based approach to automated attribute extraction from product textual descriptions. The system relies on Mistral architecture-based LLM architecture model that has a unique contextual representation; to extract explicit and implicit attributes from unstructured Turkish language text. This implementation has been integrated into Trendyol's platform with scalable backend infrastructure utilizing Kubernetes and Nvidia Triton Inference Server for efficient bulk processing and real-time attribute suggestions during the product listing process (Çiftlikçi et al., 2025). The LLM hugely outperformed the traditional deep learning models across precision, recall, and F1-score tests and it significantly outperformed the traditional deep learning models on the tasks while solving complex linguistic structures and classifying diverse product descriptions in Turkish.

Advanced Recommendation Systems and Customer Intelligence: The system has grown to include sophisticated AI-based recommendation systems that support product discovery and user engagement experience through machine learning algorithms (Çetin et al., 2024). Trendyol's recommendation system expanded the journey to include 90+ million possible products combinations based on advanced image processing and machine learning techniques. The Trendyol recommendation system employed Prod2Vec algorithm for the new product pairs and the You Only Look Once (YOLO) model for clothing classification and the Convolutional Network Next (ConvNext) model for calculating image similarity. The machine learning models that were used for estimating click performance are Random Forest, Extreme Gradient Boosting (XGBoost), and Linear Regression with Random Forest outperforming the other methods. The solution has reported a 5% increase in time spent on the Trendyol mobile app (Çetin et al., 2024).

Natural Language Processing and Sentiment Analytics: Trendyol has developed an extensive sentiment analysis capability intended to analyze customer comments in order to improve brand reputation management (Özmen & Gündüz, 2025). To perform the analysis, Trendyol uses a machine learning methods which require extensive algorithms include K-NN, SVM, Decision Tree, Random Forest, Logistic Regression, and deep learning. In all product categories, Support Vector Machine (SVM) provided the highest predictive value with over 93% accuracy, 92% precision, 93% recall, and 91% F1-score (Özmen & Gündüz, 2025). Trendyol also developed AI-powered spelling error correction systems based on transformer architecture to improve the quality of customer comment analysis (Çiftçi et al., 2024).

Internal Developer Platform and Operational Efficiency: Trendyol has also developed an Internal Developer Platform (IDP) that enhances software development lifecycle processes to support its technological infrastructure (Olgaç et al., 2025). Also, the platform integrates over 3,000 applications within Trendyol's ecosystem, utilizing Kubernetes, KubeVela, and GitLab technologies. The system allows developers to have complete control over deployment processes, which eliminates dependencies on manual operations from other teams and maximize individual productivity (Olgaç et al., 2025).

Business Impact and Strategic Outcomes: Trendyol has been able to leverage their automation and AI implementation to demonstrate measurable business impacts in multiple dimensions. Trendyol was also able to enhance customer experience through personalization, advanced recommendations, operational efficiency through automation of attributes extraction, and brand reputation through advanced sentiment analytics capabilities. All these factors have been strategically driven by Trendyol's AI driven customer experience optimizing setting the organization in the leadership position of e-commerce platforms in Türkiye successfully competing with global organizations such as Amazon in the Turkish marketplace.

4.2.2 BİM: SAP S/4 HANA & analytics modernization

BİM, the Turkish discount retailer and innovator of the hard discount model, implemented the SAP S/4 HANA Retail system with the assistance of Skalla and Vektora, using the Brownfield approach (Skalla, 2024). This implementation has marked a transition from traditional retail management to a data-driven practice.

Analytical Capabilities and Real-Time Decision Making: BİM's implementation of SAP S/4 HANA assisted in data analytical capabilities by providing BİM with sophisticated analytics, giving more in-depth visibility into customer movement and inventory management. According to the implementation partners, BİM's system enabled streamlined operations with quicker and more efficient processes while allowing for greater scalability for BİM's growth plans (Skalla, 2024). The system also facilitated better customer experience through improved services and personalization. The Brownfield approach meant BİM could take advantage of more sophisticated functionality while preserving valuable historical data and minimizing disruption to day-to-day operations.

Performance Impact and Market Position: BİM's digital transformation helped to keep its market leadership position in Türkiye's highly competitive retail sector. Based on industry analysis, the company's modernized retail management system supports BİM's overall operational efficiency to manage extensive operations across multiple locations. The successful implementation acts as a benchmark for other retailers considering similar digital transformation paths, while also creating a foundation for innovation opportunities, including implementing artificial intelligence and machine learning related to predictive analytics (Skalla, 2024).

4.2.3 CarrefourSA: AI-Powered sustainability & operational efficiency

CarrefourSA, part of the Sabancı Group, is a retail network with over 700 outlets in Türkiye has implemented multiple AI initiatives focusing on energy optimization and operational efficiency through strategic technology partnerships.

Energy Optimization through AI: CarrefourSA partnered with Florawise to help implement and manage an energy optimization system with AI technology across all of their retail enterprises in their network (Florawise, 2025). The autonomous AI platform interfaces directly with refrigeration systems, HVAC, AC and lighting in their retail spaces. Each store has an AI agent, collecting and learning from energy consumption, outdoor conditions and any changes made inside the retail locations. CarrefourSA reported a 20% saving from the deployment of AI energy optimization, as documented in their partnership agreement with Florawise. While there was no independent verification for these metrics, they align with typical energy optimization results reported in similar retail implementations, resulting in 40 million kWh annual energy gain and 29 kilotons of CO_2 emissions prevention (Florawise, 2025). The full deployment is contained with a typical 5-year Energy Performance Agreement with Smarte covers 550 stores across various regions of Türkiye, with annual electricity savings of 20,018 MWh (EBRD GEFF, 2017).

Smart Warehousing and Predictive Analytics: CarrefourSA entered into a partnership with Thread in Motion to deploy the full functionality of their next generation smart glove and user industrial predictive analytics software CONWO. The smart workplace and analytics solution was intended to unlock the potential to do AI powered warehouse audits, predictive performance optimization, and heat map for layout optimization of their warehouses (Thread in Motion, 2025). The exploitation of the project enabled CarrefourSA to manage their workforce across their multiple warehouses using one source and one capability, with the potential to create inter-location processes. According to vendor documentation, results included enhanced efficiency, reduced error rates, and better resource allocation. The smart glove technology reportedly achieved 50% time and cost savings across 11 warehouses, with employees completing the same volume of operations in approximately 13 minutes compared to over 25 minutes with traditional hand-held terminals (Anadolu Ajansı, 2021).

Sustainability and Recognition: The energy efficiency project with Florawise achieved sufficient outcomes to be nominated for the Mapic Finalists 2024 award in the notable category of "Best Sustainable Initiative" and in the category of "Best Retail Innovation & AI Project" (CarrefourSA, 2024). This example once again highlights another proof point of CarrefourSA innovative AI sustainability initiatives being acknowledged and recognized on a global scale in the retail market.

4.2.4 Teknosa: inventory optimization & AI sales assistant

Teknosa, Türkiye's leading electronics retailer with 205 stores and an inventory of over 16,000 SKUs, has implemented comprehensive AI powered solutions that focus on both inventory optimization and sales enhancement through strategic partnerships.

AI-Based Inventory Optimization: As shown in its partnership with invent.ai regarding inventory optimization, Teknosa was able to demonstrate significant operational improvements with AI in place (Invent.ai, 2025). The AI solution optimally performs replenishment, transfers, and assortments across the 15 distribution centers using advanced analytics. Internal company metrics indicate a 20-30% reduction in lost sales and 70% reduction in manual work in planning processes following implementation (Invent.ai, 2025). This AI solutions optimized inventory management, forecasting accuracy, and lost sales while tackling stock levels across its stores and distribution centers.

AI Sales Assistant and Digital Ecosystem Expansion: Teknosa launched its first advanced AI powered sales assistant called Bilge, along with Sales Wizard (Sabancı Holding, 2024). Bilge provides real-time coaching, insights, and motivation tools for the sales team by offering cross-selling recommendations, product suggestions, and behind-the-scenes profitability optimization. This system evaluates individual salespersons' performance, and sends AI based personalized messages to about 1800 active sales advisors. Sales Wizard helps sales associates with product specifications, payment options, campaign information, and complementary product recommendations which significantly increase additional sales conversion and overall customer satisfaction (Teknosa, 2025).

Digital Transformation Impact: Teknosa's AI-powered transformation program has achieved recognition in the industry, with Teknosa's Bilge confirmed as being "Türkiye's first and most advanced AI-powered sales assistant" that was introduced in 2024 (Sabancı Holding, 2024). This implementation demonstrates the impact of AI on important KPIs such as increased conversion, larger basket size, increased revenue, and a more profitable retail mix (Teknosa, 2025). The marketplace expansion, which includes AI based recommendations, doubled the sellers and led to over 200,000 SKUs which made a great contribution to the company’s omnichannel strategy (Sabancı Holding, 2024).

4.2.5 LC Waikiki: AI-Driven personalization & marketing

LC Waikiki, Türkiye's premier clothing retailer with operations in 58 countries and over 1,300 stores, has several AI experiences showing quantifiable business value due to technology partnerships.

Personalized Recommendation Engine Implementation: LC Waikiki partnered with Insider to launch Smart Recommender, an AI-driven personalization engine that learns from user behavior and predicts propensity for products (Insider, 2022). The Smart Recommender goes beyond previous recommendation engines via machine learning technology that distills action from unstructured data to produce meaningful behavioral patterns, creating personalized recommendations by understanding customers' relationships with products, and similar users. According to Insider (2022) vendor case study, this implementation resulted in an 11.31% increase in conversion rate. The Smart Recommender had built-in A/B/n testing capabilities with Live results against control groups, showing superior performance to the basic recommendation system as reported by the implementation partner.

Infrastructure Modernization for Data-Driven Decision Making: LC Waikiki's digital infrastructure modernization with Hitachi Vantara shows the bedrock role strong data systems play in implementing AI (Hitachi Vantara, 2024). The company invested in Hitachi Virtual Storage Platform (VSP) G series and all-flash VSP F series, as the systems are very important for decision-making processes and inventory management. LC Waikiki reduced database query times and refined inventory management through an infrastructure upgrade, creating efficiencies improving logistics and stock flow (Hitachi Vantara, 2024). The better system provided LC Waikiki with more opportunity for decision-making, allowing for better product variety delivery and reducing the number of customers leaving stores empty-handed.

AI-Driven Marketing Performance: LC Waikiki has successfully implemented Performance Max campaigns through AI marketing strategy initiatives that have engaged a wider horde of customers. They used store-centered creatives and Performance Max campaigns with offline objectives to increase their retail store visitation traffic. This approach resulted in a 35% in-store visit engagement rate and reported an 80% lower cost per store visit compared to accounts averages (SEM, 2024). Also, Company-reported digital marketing activities with YouTube first position ads produced a 142% higher absolute ad recall increase compared to previous period activity and a 151% higher gap ad recall increase as documented in company communications (SEM, 2025). While these numbers indicate a massive performance lift, they are simply vendor-reported results rather than third-party validated measures.

4.2.6 Cross-Case synthesis

Synthesis findings from Turkish case studies highlight several critical success factors for AI adoption in retail BI systems that go beyond technical capabilities to encompass organizational and strategic considerations.

Focused Pilot Implementation: All the successful implementations started with targeted and smaller pilot projects around a defined, and measurable business risk, rather than trying to do too much all at once. LC Waikiki were piloting personalization engines, BİM was working on operational optimization, CarrefourSA were looking at energy management, Teknosa was looking at inventory optimization and Trendyol was investigating product categorization and recommendations. These smaller, phased types of projects provided learning opportunities, fostered a level of confidence and value before being scaled.

Strategic Technology Partnerships: Technology partnerships, particularly for organisations with no AI competency, were also found to be important enablers. LC

Waikiki had the backing of Insider and Hitachi Vantara, BİM relied on Skalla and Vektora's implementation capabilities, CarrefourSA partnered with Florawise and Thread in Motion, Teknosa partnered with invent.ai, and Trendyol has developed a decent level of competency internally, as well as technology partnerships. Technology partnerships provided not only the technologies, but in most cases, the methodologies for implementation, training and if needed and post launch support.

Infrastructure Foundation Investment: All the successful implementations required deep investment in infrastructure. The numerous implementations of the LC Waikiki partnership with Hitachi Vantara, BİM's SAP S/4 HANA implementation, and Trendyol's full-fledged platform illustrate the prior investments in strong data management systems were essential infrastructure before deep AI implications occurred. Premature were the organizations which dismissed traditional BI investments as obsolete in this construction.

Organizational Change Management: Along with technical aspects, culture and change management were equally important factors for success. Successful implementations spent a lot of time on training programs and organizational development. The emphasis on augmentation rather than replacement of human decision-making activities became key in overcoming organizational resistance. The Trendyol internal developers' platform especially exemplified how AI augmented human capabilities as opposed to replacing them.

The Table 4.3 below shows the summary of the cross-case finding of the studied Turkish retailers.

Table 4.4 Comparative impact of AI implementation across major turkish retail companies

Dimension	Trendyol	BİM	CarrefourSA	Teknosa	LC Waikiki
Customer Impact	+5% mobile app engagement	Enhanced customer experience	164 million yearly shoppers	Larger basket sizes	+11.31% conversion
Operational Efficiency	3,000+ integrated applications	Streamlined operations	20% energy savings, 50% warehouse time savings	70% manual work reduction	Dramatically reduced query times
Strategic Differentiator	AI-powered personalization	Scalable expansion platform	Sustainability leadership	Omnichannel marketplace	AI-driven marketing ROI

4.3 Unexpected Findings and Insights

Our comprehensive analysis revealed several unexpected findings that contradicted common assumptions about AI in retail BI, leading to even more nuanced insights for implementation planning.

Effectiveness of Hybrid Approaches: Hybrid approaches of AI and traditional approaches tended to outperform some of the pure AI solutions. For instance, using traditional RFM segmentation to pre-filter customers before applying neural network models reduced computation time by 60% while maintaining 95% of accuracy gains. This suggests that traditional BI approaches still have relevance in the process as pre-conditioning steps in AI pipelines.

Category-Specific Performance Variations: AI performance estimates varied across product categories. For example, AI models performed better with prediction demand for products with variable demand patterns, getting 50% better accuracy than the traditional approaches. Whereas traditional time-series models were almost as accurate for issues of stable demand patterns albeit at much less computational complexity.

Interpretability Barriers: Interpretability proved to be a greater barrier than we initially imagined. Despite the predictive accuracy of the AI models, retail managers did not trust the “black box” recommendations for high stakes decisions. Several Turkish retailers reported having an AI system for operational decisions, only to revert to their traditional analysis methods for strategic planning.

Network Effects and Scale Dependencies: The research also revealed network effects in AI adoption with increasing marginal benefits as scale and data increased. For example, a large retailer like Trendyol makes millions of transactions with their customers, and they realize significantly better performance of AI than a smaller pilot with only a few hundred transactions. The implication of this is potential competitive advantages for larger retailers and smaller competitors may struggle to establish critical mass in utilizing AI effectively.

5. DISCUSSION AND CONCLUSIONS

5.1 Synthesis of Key Findings

This comprehensive comparative analysis shows that AI-based business intelligence systems have an important advantage over traditional business intelligence systems on many dimensions critical to success in retail. The quantitative analysis demonstrated that with AI-based techniques, potential improvements in demand forecasting accuracy are an astonishing 71%, quality of customer segmentation is 95.2% better, and with real-time analytical capabilities in contrast to traditional batch-processing business intelligence systems, the opportunities for analyzing retail data are unparalleled. These technical advantages might yield significant forms of business value. Retailers adopting AI-based systems can expect improvements of 25 to 30% in marketing effectiveness, reduced inventory costs, and enhanced profit margins through dynamic optimization strategies.

However, the research illustrates that technical superiority does not automatically translate to improvement and benefits for retailers. There are significant complexity and difficulty of implementation with AI. AI requires almost 4-times the deployment durations of traditional systems, requires potential scarce technical expertise, and requires the retailers to pay for and establish sophisticated infrastructures and architectures. More importantly, successful AI implementation, use, and sustainability will depend on the organizations involved and factors associated with data architecture and infrastructure maturity, change management effectiveness, and capabilities for training and forming strategic partnerships. As illustrated by the Turkish retail case studies, success cannot be assumed based on the technical capabilities of the retailer; with AI, organizational readiness for systematic implementation approaches will dictate whether improvements are observable in practice, and whether the theoretical advantages of AI will eventuate or remain bifurcated.

The comparative framework from the study provides a possible approach to move beyond simple performance benchmarking and clearly considers the aspects of implementation feasibility, organizational adaptation requirements, and sustainability of AI versus traditional BI. Thus, the simple decision of AI versus traditional BI is not simply a binary decision, but a contextual decision dependent on many factors including, size of organizations or business units, maturity of data architecture or existing systems, competitive landscape that lends itself to AI, and strategic objectives of the organization. Further, hybrid approaches that leverage traditional BI strengths while selectively applying AI for high-value use cases can provide optimal balance between performance gains and implementation complexity.

5.2 Theoretical Contributions

This study makes various theoretical contributions to the understanding of technology adoption and the evolution of business intelligence. First, the project adds to the Technology Acceptance Model to identify AI-specific constructions that help explain acceptance as well as the more specific role of explainability in perceived usefulness, and the importance of transparency in automation in perceived ease of use. These specific constructs indicate that existing frameworks for understanding technology acceptance will require modification when applied to AI systems that operate with greater autonomy and opacity than traditional software.

Second, the study contributes to the Business Value of IT literature to indicate how AI technologies generate value through mechanisms that are distinct from standard IT investments. While standard BI systems generate value mainly through the provision of information and automation of processes, AI systems generate value through finding patterns, predictions, and optimizing that behavior. This suggests that we need to develop new models for value creation that acknowledge AI’s unique characteristics of continuous learning and autonomous decision-making.

Third, the study has empirical relevance for the socio-technical systems perspective in retail technology adoption. The dominant contrast between technical performance advantages and implementation challenges highlights that technological capabilities alone do not determine organizational outcomes. Organizational success depends heavily on the combined effects of the technical system, the organizational process, and human performance. This finding underscores the need for holistic theoretical frameworks that integrate technical and organizational perspectives.

Finally, the study contributes to retail management theory by identifying AI as a potential source for sustained competitive advantage. While traditional BI systems provide largely standardized capabilities, AI systems can develop organization-specific knowledge through continuous learning from proprietary data. As AI systems get more tailored to each retailer's needs, this opens the possibility of differentiation and competitive barriers. The network effects found in the research also point to the possibility of market concentration, though, as bigger retailers use their data scale to their advantage.

5.3 Practical Implications

This research will provide retail executives and IT leaders with evidence-based guidance on the journey of AI transformation. The benefits of performance based on the demonstrated use of AI cannot be ignored, but performance requires careful planning and realistic expectations. Retailers should start with focused pilot projects which have well defined boundaries addressing specific business problems where there are greatest advantages to AI, such as demand forecasting for variable products or personalization for customer segments which have varied preferences. These bounded actions provide a good opportunity to learn, while limiting risk and complexity.

The important emphasis on data infrastructure maturity suggests that organizations viewing traditional BI investments as obsolete may be premature. Effective traditional BI capacity will likely be important to successfully achieve AI capabilities. As organizations begin to achieve AI capabilities, executives must push for improved data quality, system integration, and higher analytical capacity as prerequisites for AI adoption. The finding that hybrid solutions outperform some of the pure AI solutions suggests additional value in business executives pursuing traditional BI capabilities together with AI capabilities.

The partnership approach also emerged as an important success factor, especially for small to medium-sized retailers who do not have the capabilities to develop their own AI capabilities. Retailers would be better served considering all possible vendor and technology platform solutions, cloud-based platforms, and partnerships that provide both capabilities and implementation support. The Turkish case studies demonstrated what makes a partnership effective is more than just providing technology. An effective partnership also provided methodology transfer, training, and ongoing optimization.

Change management is also worthy of as much focus as technical implementation. This study found that barriers to organizational adoption were in part due to lack of understanding and fear of job displacement. Successful adopters invested heavily in educational programs that demystified AI and emphasized augmentation rather than replacement of human decision-making. Creating "AI champions" within business units who understand both technical capabilities and business applications proved critical for driving adoption and identifying valuable use cases.

5.4 Recommendations for Implementation

Based on this in-depth study, we outline a four-phase plan for retailers considering AI adoption in their BI systems. **Phase 1 (Months 0-6)** is about establishing the foundations, including determining data quality, infrastructure evaluation, and skill gap analysis. Organizations should identify 2-3 high-value pilot use cases, which have a measurable high-impact outcome, to begin pilot assessments. During this phase, organizations should improve their BI systems to ensure robust baseline performance and data accessibility.

Phase 2 (Months 6-12) represents pilot implementation and learning. At this stage, organizations can successfully deploy their selected use cases in the cloud, or using vendor solutions, thereby minimizing infrastructure investments, and taking advantage of rapid deployment opportunities. Success criteria should be established and measured against the traditional BI systems. Accompanying technical deployment should be a significant investment in training programs to build organizational understanding and acceptance. The insights learned from the pilots can inform broader rollout plans.

Phase 3 (Months 12-24) includes scaled deployment and optimization. Successful pilot applications should be implemented across the organization while new use cases are identified based on initial learnings. It becomes reasonable to invest in AI capability for a retail organization in this phase, including recruitment of data scientists and developing custom models. Organizations need to refine how AI and traditional BI systems communicate with each other; analysts will want to build effective analytical processes and workflows that utilize aspects of both.

Phase 4 (24+ months) represents a transformation of operations to AI. Organizations reaching this level of maturity allow AI to take its place as core operational processes, including not only automated decision-making related to standard operational procedure but also leveraging AI-assisted analysis for strategic decisions. There can be established processes for continuous learning and where AI can improve performance of models over time and actively identify new opportunities. In this phase, Organizations should also begin exploring advanced AI technologies such as reinforcement learning for dynamic optimization and generative AI for content creation.

5.5 Limitations and Future Research

While this research presents an abundance of useful data regarding the performance of AI versus traditional BI and the findings of this research, several limitations restrict the generalizability of the conclusions. The empirical analysis used one dataset from 2010-2011 and therefore may not reflect the complexities of today's retail context, including shifts in customer behavior, the widespread nature of omnichannel, or even traditional retail environments with data streams operating in real time. Future research should look to validate the findings using secondary datasets that have taken the market complexities of retail into account, including the implications and adaptations of the mobile commerce trends, social media integration, and pandemic-influenced shopping patterns.

The case study analysis in this research only relied upon secondary sources, which also restricted the depth of exploration in the adoption and implementation processes, as well as an understanding of the organizational dynamics and stakeholder perspectives involved in the approach. Future research that integrates primary data collection from interviews, surveys, or direct observation may fill some important gaps for researchers to understand the human and organizational behaviors and factors associated with the successful adoption of AI. Longitudinal studies that involve tracking an organization throughout their journey in utilizing AI would also robustly inform researchers considering the sustainability and pattern of evolution of the implementation of this advancement.

While the exploration of Turkish retailers did provide useful insights from an emerging market perspective, it may also limit the expression and applicability of findings in other parts of the world, where some countries have different regulatory environments for retailers, technological infrastructure, or cultural considerations. Comparative studies of AI adoption in retail enterprises across multiple countries could help identify factors that are universal to successful AI, versus those effects which are contextually specific.

There are several important issues to consider when thinking about the implications of widespread AI adoption in retail regarding ethics and effects on society. Although this research mentions considerations of privacy and bias briefly, an examination of the effects of AI and AI adoption on employment patterns, market concentration, and consumer welfare deserves a dedicated study. Finally, this research maintains the notion that with rapid improvements in AI capabilities, both researchers, and the rest of society should stay current on the impact of technology on our lives, including possible emerging technologies because of AI capabilities, generative AI for content creation, edge computing for in-store real-time analytics and possibly quantum computing for problems of optimization.

5.6 Concluding Remarks

This thesis offers robust evidence from empirical analysis and real-world case studies, showing the capacity of artificial intelligence to revolutionize retail business intelligence, delivering significant performance benefits to the business while presenting significant implementation challenges. The research adds to both theory and practice by providing holistic frameworks to evaluate, implement, and manage AI-enabled BI systems in retail settings.

It is clear from the evidence that AI offers technical advantages in predictive accuracy, pattern recognition, and real-time analysis - however, the research emphasized that to reap these rewards, more is required than a simple implementation of the technology. The achievement of AI advantages is built on organizational readiness, strategic implementation approaches, and sustained commitment to change management and capability development. This research identified that hybrid strategies appear to yield better results, challenging the simplified depiction of AI replacing traditional BI entirely.

The study has also provided valuable insights for the retail industry as it undergoes digital transformation, which will facilitate navigating the complex decisions surrounding AI adoption. Informed decisions must weigh up the promise of AI's advanced capabilities against the practical dimension of complexity in implementation, organizational learning capability and resource commitments. The staged implementation framework and identified success factors provide retailers with a plan of action in terms of managing risk while attempting to harness the transformational potential of AI.

Looking toward the future, AI and BI are expected to converge even more intensely in retail, driven by competitive pressures, technological advances, and evolving customer expectations. This research indicates that successful transformation requires the mindful integration of human intelligence, organizational capabilities, and artificial intelligence. Retailers that maximize their capacity to combine these dimensions by leveraging preexisting BI supported by selective AI capabilities are expected to be best positioned to succeed in a dynamic, data-driven marketplace.

The transition from traditional business intelligence to AI-powered analytical systems is not just a technical improvement or update; it represents a completely different way for retail organizations to sense, interpret and respond to their environments. This research provides theoretical and practical input into this transformative journey, contributing to the developing knowledge being created to inform the future of retail in a world enhanced by AI.

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