A Systematic Review on Machine Learning and Optimization Theories for Smart Retail Management System: Applications, Methods, Challenges, and Future Research Directions

Abstract

To evaluate the effectiveness and integration of cutting-edge technologies in smart retail management systems, we conducted a Systematic Literature Review (SLR) in this study. We concentrated on improving customer experience, increasing operational efficiency, and enhancing security. Our study aimed to compile the technical tools used by the retail industry, including smart transaction systems, blockchain for safe transactions, customer interaction bots, demand forecasts, and IoT-based queue management systems. 271 relevant papers were found through our search across many electronic databases; of these, 67 were carefully chosen for further examination in accordance with predetermined inclusion and exclusion criteria. We carefully examined the chosen examples, drawing necessary conclusions about applying blockchain technology and machine learning algorithms in retail. The investigation showed that Artificial Neural Networks (ANNs) were widely utilized for machine learning tasks and that studies focusing on deep learning were increasingly using Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM) networks. Furthermore, it was mentioned that integrating blockchain technology would improve loyalty programs and transaction security and that IoT solutions would help with inventory tracking and queue management. Blockchain technology and intelligent transaction systems were shown to be essential for guaranteeing safe and adequate payment procedures. Our research highlights how these technologies can completely change retail operations, improving consumer satisfaction, loyalty, and management effectiveness. The study will help recommend areas for future research and highlight the necessity of looking into cutting-edge technical solutions for the problems that smart retail management constantly faces.

Keywords: Systematic literature review, Smart transaction system, Blockchain, Customer interaction bots, IoT-based queue management, Smart retail management.

1. Introduction

Modern retailing is undergoing a transformative wave of innovation, introducing a variety of technologies ripe for effective adoption. Smart retailing enhances this by integrating not only modern technological applications into the retail process but also an additional layer of intelligence in the use of these technologies (Pantano & Timmermans, 2014)[1]. Besides, a smart customer experience not only directly boosts satisfaction and lowers perceived risks towards smart retail technologies but also elevates customer satisfaction, which in turn amplifies behavioral intentions, word-of-mouth referrals, loyalty to the retailer, shopping efficiency, and overall customer well-being (Roy et al., 2017)[2]. Making consumers feel important to the retail company will help the companies to win consumer support and will make the consumers feel like they are a part of the company(Serravalle et al., 2023)[3]. The drive to transform retail stores into "intelligent" entities is significantly propelled by the impact of Artificial Intelligence (AI). AI solutions can execute multiple roles simultaneously, creating a network of interconnectivity among various activities within the retail value chain (Oosthuizen et al., 2020)[4]. The employment of advanced technological solutions in the contemporary retail landscape encompasses a broad spectrum, including demand forecasting and waste prevention (Falatouri et al., 2022; Sengupta, S. et al.,2023)[5][6], the deployment of intelligent bots to enhance customer interactions (Tran et al., 2021)[7],(Wang ey al., 2022)[8], blockchain for ensuring the safety of user data (Liu et al.,2019)[9] and restoring institution-based trust(Utz et al.,2023)[10], IoT-based queue management systems (Karjol et al., 2018)[11], and the assurance of secure transactions (Sun et al., 2021)[12]. We conducted a Systematic Literature Review (SLR) to synthesize existing knowledge on smart retail systems. An SLR identifies existing research gaps within a specific problem domain, offering a road map for both practitioners and scholars interested in undertaking new studies in this area. An SLR systematically aggregates and analyses pertinent studies from electronic databases, summarising findings to address predefined research questions. This approach not only fosters new insights but also equips emerging researchers with a comprehensive understanding of the current advancements in the field.

1.1. Motivation

The retail sector has undergone a huge transformation in recent years due to technological advancements. In this current scenario, it is important for shopkeepers and retail giants to evolve continuously to understand and capture the market successfully. For doing so, it is very important to know which are the technologies currently in use in the retail industry, and in this paper, we have tried to provide a comprehensive review of

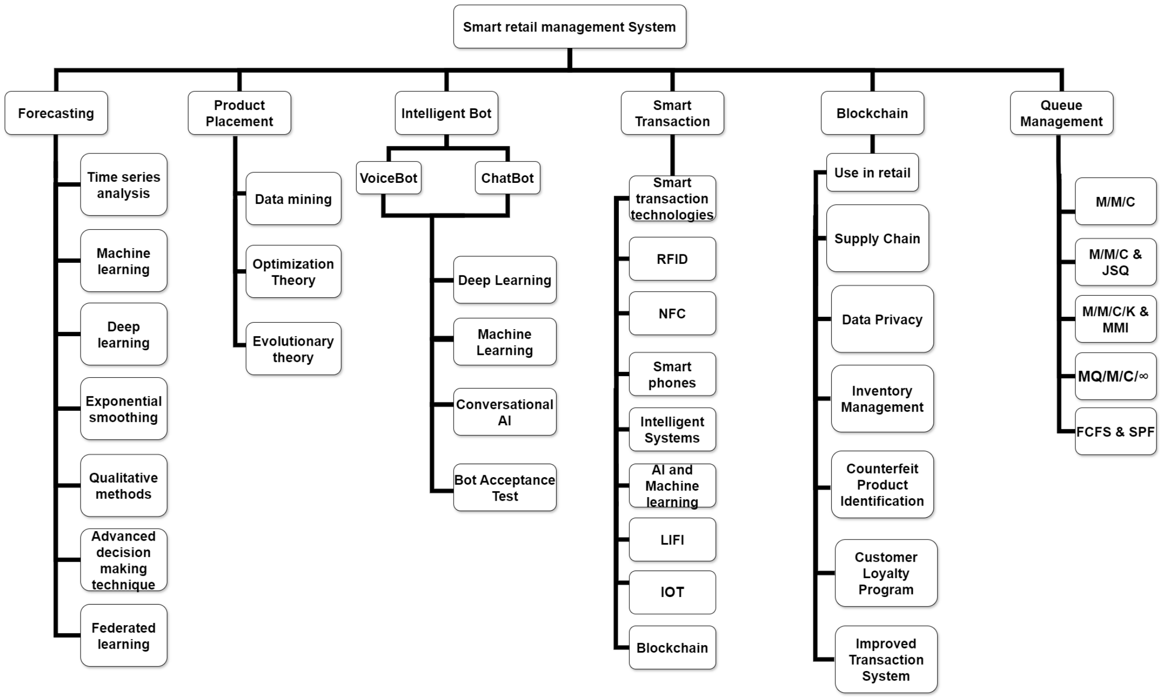

Figure 1: **Different sections of Smart management system and the methods used in these sections**

currently used technologies in the retail industry. With time, consumer preference also changes. Understanding consumer demand for the products and updating the inventory accordingly is important. Forecasting sales, understanding demand patterns, arranging loyalty programs, and product placement can be ways to understand customers. This paper focuses on sorting ideas that can help get customer attention. In the post-pandemic period, the retail sector is working to make up for the financial damage they have faced during the pandemic. The study focuses on ideas on how the retail industry can ensure a better customer experience, implement a smooth system, and ensure maximum profit by analyzing the existing studies. This can inform policymakers and researchers about the evolving retail technologies and their implementation in the industry in the upcoming days.

1.2. Related work

In their comprehensive review, Babai et al. emphasize the critical role of hierarchical approaches in demand forecasting for supply chain management, highlighting the utilization of data across various aggregation levels to enhance forecast accuracy. This study accentuates the advancements in hierarchical time series reconciliation, demonstrating its superiority over traditional methods, such as bottom-up and top-down approaches in specific scenarios. It also showcases the effectiveness of machine learning techniques in improving forecast accuracy across supply chain hierarchies, with significant empirical evidence from the M5 forecasting competition indicating that machine learning models, particularly when incorporating exogenous variables like promotions and price data, yield superior results in hierarchical retail sales forecasting. The review marks a pivotal shift towards integrating machine learning methods with comprehensive hierarchical approaches to achieve greater accuracy and efficiency in supply chain forecasting[13]. Paolanti, M et al., in their article, have reviewed the applications of pattern recognition in our day-to-day life. Extracting patterns from real-world data is a necessity to analyze real-world scenarios. The paper reviewed articles published between 2000 and 2020 from five different domains: retail, biomedical and biology, surveillance, social media intelligence, and digital cultural heritage. The paper compares and categorizes different pattern recognition methods like Machine Learning, Deep Learning, Statistical methods, etc. Comparing these methods' advantages and disadvantages, they have worked to picture the real-life applications of these pattern recognition methods in the mentioned domains. For instance, they have analyzed the applications of mining algorithms in retail and discussed how the pattern recognition methods are helping retailers to make retail strategies to develop and enhance business strategies[14]. Policarpo L. et al. discuss how machine learning has changed traditional service e-commerce systems. The article reviews the past five years' papers on machine learning applications in e-commerce, intending to understand how machine learning methods are helping this sector grow and offer customers a better user experience. Through the selection process, the author selected 70 articles from 15708 for review. The review shows that there is a change in retailers' approach to e-commerce, and they are more concerned about factors like fraud detection and understanding consumer behavior, which is leading them towards the use of Machine Learning methods and making it more popular in this sector. The study identifies 8 common applications of Ml methods in e-commerce. Moreover, they have focused on understanding what are the algorithms and frameworks commonly implemented in e-commerce. They have mentioned and reviewed various ML algorithms like naive bias, K-means, neural networks, SVM, etc. In the end, the authors have advised focusing on human behavior extraction techniques and improving customer relations through machine learning in future research [15]. Syntetos et al. focus on the practical application and robustness of aggregation approaches in supply chain forecasting, advocating for their use across time, customers, and products. The paper emphasizes the importance of integrating judgmental inputs, especially in relation to the length of the historical series. It suggests the optimal combination approach that encompasses the entire base forecast vector, allowing for the application of different forecasting techniques at various hierarchical nodes. By thoroughly reviewing and critiquing existing literature and identifying the gaps between theoretical advancements and practical applications, this study underscores the necessity of a better theoretical and practical understanding of aggregation and hierarchical forecasting methods within supply chains. The use of ARIMA and INARMA models to frame forecasting scenarios is highlighted, with the paper providing a forward-looking research agenda aimed at bridging the gap between theory and practice for more effective supply chain management strategies[16]. Shaw et al.[17] performed a review on the influence of product placement strategies on dietary-related behaviors of the customers of high-income countries. The paper's findings suggest that better positioning of healthy food or non-noticeable positioning of unhealthy foods can lead to better dietary behavior. The paper proposes a combination of both good placement and availability of products to have a better sales result for healthy dietary products. Eagle et al.[18] published a review on the development of product placement in traditional and new media platforms. In the article, the researchers have shown their concerns about the impacts of product placements on different age groups of people like children and adults in regard to narcotic products. Reviewing 68 papers, Jain, P. K. et al.[19] have focused on understanding customer sentiment, which can help to understand consumers' opinions about products and services. The article highlights customer sentiment analysis techniques, including data processing and feature selection techniques used in sentiment analysis. The review article shows the use of Machine Learning in sentiment analysis, predictive consumer recommendation, and fake review detection. Aich et al.[20] highlights the good sides of implementing IOT-integrated blockchain in different sections like the food industry and retail. Using conventional supply chain systems in these industries can be challenging in many ways. IOT-integrated blockchain can be the best way to improve supply chain efficiency by ensuring the transparency of the procedure. In another paper, Hader M. et al. (2020)[21] discusses blockchain integration in the retail industry, focusing on supply chain management and loyalty programs. By analyzing the existing works, the researchers presented their findings on blockchain technology in the retail industry. The paper explains the three major principles of blockchain technology: Transparency, Decentralization, and security. To use blockchain technology in the supply chain, it is advised that the network should be private and accessible to limited actors. Moreover, new entities are to be introduced to the traditional supply chain structure, which are registrars who ensure the uniqueness of user identity in the network, standard organizations that will help to define standard rules for supply chain policies, and certifiers who will provide certificates to the participants of the network. Products in the blockchain will have digital blockchain representation, allowing all the participants to access information about the products directly. In Addition that, smart contracts between both parties before any transactions will play a crucial role in the blockchain-based supply chain, and another key advantage is the technology helps to eliminate all the intermediaries like banks, which allows the transaction to be directly conducted between stakeholders and saves huge amounts of money. Blockchain technology can be used to conduct loyalty programs in the retail industry. The existing programs that are in use at this moment are not made with high safety measures, which can create problems for retailers if they are not implemented perfectly. A customer loyalty program is a bold move to maintain a strong customer base and secure brand loyalty, but the stats show that 96 percent of customers are not satisfied with the current loyalty programs. However, the loyal programs are improving with the touch of blockchain technology. With the help of a secure and time-stamped database of transactions, it is easy for customers to secure and track their loyalty programs. It can help us to prevent errors and fraud in loyalty programs. Pal et al. (2021)[22] review the studies related to blockchain technology in business, and their study shows how blockchain technology is being used to bring changes in the global business environment. The paper shows how technology is being used to transform the business world by adapting to securing business transactions, improving organizational functions, preventing fraud, and reducing costs. Highlighting the need to integrate blockchain technology in supply chain management, Queiroz et al.[23] have suggested a rethink of existing business models regarding including blockchain technology. The paper discusses the challenges and the benefits of integrating blockchain with SCM. Culot, G. et al.[24] reviews 123 articles to understand the real-life challenges of implementing supply chain management. The study found that the automotive industry is mostly focused in all these studies, and machine learning is the most commonly used AI approach. The result of this study describes how integrating artificial intelligence in SCM can help us enhance the data quality and save overall costs. Almansor et al.[25] provide a review of the chatbot's ability to generate appropriate responses to any queries. It presents the usage of these intelligent bots in both industry and academia and the importance of natural language understanding while building these systems. The research shows that by using chatbots, companies can improve response time and reduce operational costs. El Bakkouri et al.[26] conducted a systematic review to understand the role of chatbots in enhancing customer experience. The paper notices a rise in the number of chatbot users in the firms to deliver an improved customer experience. It highlighted the use of chatbots in marketing and customer service. In another research, Klaus et al.(2020)[27] have tried to understand how AI-based voice bots are used for marketing and influencing customer behaviour. The author approached the problem by searching in online databases and search engines using keywords like artificial intelligence, retail, consumer behavior, digital assistance, and voice by the system and reviewed 312 academic and managerial articles, conference papers, and industry reports between 2010 and 2018. Following the Macinnis three-step procedure of conceptual contributions, the findings from those papers were integrated and used to find out why people are shifting towards the use of voice assistants for shopping and what future trends can be related to AI Voice bots. Regarding the benefits of AI and machine learning in marketing, researchers [28] assessed the role of Chatbot as the most modern and advanced way to interact between humans and machines. While explaining the work of chatbots, the author talked about the use of natural language processing as a way to understand consumer queries. By understanding the purpose of the question, the system extracts the best result from its data server, and as the chatbot is built using pre-program scripts and machine learning applications, its response is both quick and accurate. Additionally, the research talks about digital personal assistants, which can provide different facilities to users. With the help of an acoustic model, which has a voice-recognizing system, it takes audio recording as input. Moreover, with the user's permission, it collects users' daily data from activities like Google searches, maps, and other applications. It is said that by using a personal assistant, marketing brands can earn up to 145 million per month, proving that AI and ML positively affect customer satisfaction and revenue growth.The paper examines methods for reducing long wait times in hospital emergency rooms, particularly emphasizing the use of medical informatics. The review[29] aims to evaluate research studies on long wait times, methods for reducing wait times, and informatics solutions to this problem. The keywords used included causes of ER wait times, effects of extended wait times, wait time solutions, and the impact of medical informatics on hospital wait times. Research studies from 1960 to 2012 were examined to understand better trends in methods for reducing wait times in emergency rooms. The review included studies on staff perceptions of causes of delay, violence against ER staff, the impact of electronic health records on documentation time, and Lean Thinking-based patient grouping. Data from studies on implementing an admission system based on telephone consultation between ED physicians and in-house hospitalists and the impact of waiting time information on customer reactions were also considered. The review investigated various approaches to reducing long wait times in hospital emergency rooms, including medical informatics. Causes of overcrowding and irrational behavior in emergency rooms due to long wait times have been determined. The study's results included the impact of electronic health records on documentation time for nurses and physicians, as well as the streaming of patients into groups using Lean Thinking. According to Hossain et al., [30], mobile commerce apps and associates with mobile point of sale (mPOS) capabilities can revolutionize the retail industry by facilitating transactional processes. IoT solutions improve business foundations and the shopping experience dramatically, making retail operations more sustainable and managing digital stores more effectively. However, IoT integration in retail is beset with several issues, such as network performance, wireless communication, device and traffic organization, data analysis and storage, and device identification and approval. Retailers use IoT for several functions, including hardware management, customer interaction, product and service tracking, inventory management, and hardware management. Advanced in-store technologies enable a premium shopping experience, such as virtual mirrors, AR, iPads, VR tables, automated displays, and 3D life-sized models. RFID tags, barcodes, and NFC readers provide real-time data interchange about products, enabling customers to purchase via mobile commerce applications or mPOS-enabled partners. In order to boost customer engagement and operational efficiency, Hossain et al. offer a model that shows how IoT improves retail by enabling smart transactions using sensors, personalized communication, and location-based technology. Moreover, Pantano et al.[31] argue that smart retailing includes the application of cutting-edge technologies to improve retail services and optimize transaction procedures. Incorporating these technologies makes self-service options possible, such as automated customer transaction systems and smart mirrors for virtual try-ons.The challenge lies in choosing transaction technologies that are both economically sustainable and meet the needs of retailers and customers. Retailers need to think about how technology advancements evolve and weigh the advantages and disadvantages that come with them. These breakthroughs must be financially sustainable, which calls for the creation of new capacities to oversee developing technology and market circumstances. In their theoretical study and evaluation of the literature, Pantano et al. highlight how smart technologies—like NFC and smart mirrors—can improve consumer transactions by offering a more efficient and personalized shopping experience. This integration improves perceived novelty and benefits while decreasing perceived risks and transaction complexity, which boosts service quality and retailer performance.

1.3. Study Selection

For the research article selection, we searched for papers using different keywords for different research sections. Here, we have tried to select all the relevant and high-quality papers related to our topic. To select the primary research articles for the paper, we searched through the significant databases available on the internet, such as Springer, Elsevier, Science Direct, IEEE Xplore, and Google Scholar, using different keywords. To find out Sales Forecasting base papers, we have searched with particular keywords like "Time series forecasting," "Forecasting in the super shop," "Sales Forecasting in the super shop", "Smart Super shop management and forecasting," "Use of ML in sales Forecasting," "The use of Forecasting in retail management," AI, ML, and Sales forecasting." These keywords are used to get all the forecasting-related papers, especially the research studies on supermarket management. While searching for papers, we focused on the contributions of Machine Learning(ML), Deep learning(DL), and Artificial Intelligence(AI) in the relevant sections of our study. We discussed the selection process of papers in detail before every section of our research. Figure 2 describes the selection criteria for the articles.

1.4. Inclusion Criteria

The Inclusion criteria for the selected papers are given below:

- IC1- The research papers utilize or propose AI, ML, DL, and optimized theories, methods, or algorithms to develop smart retail management.
- IC2- The paper is written in English
- IC3- The full paper is available on the internet

1.5. Exclusion Criteria

The studies were inspected based on some exclusion Criteria to exclude the unwanted and non-relevant papers. The Exclusion Criteria(EC) are given below:

- EC1- The study is not related to retail or super shop management
- EC2- Paper not written in English
- EC3- Publication is a review paper
- EC4- Duplicate publications that present the same data
- EC5- Full text of the study is not present online

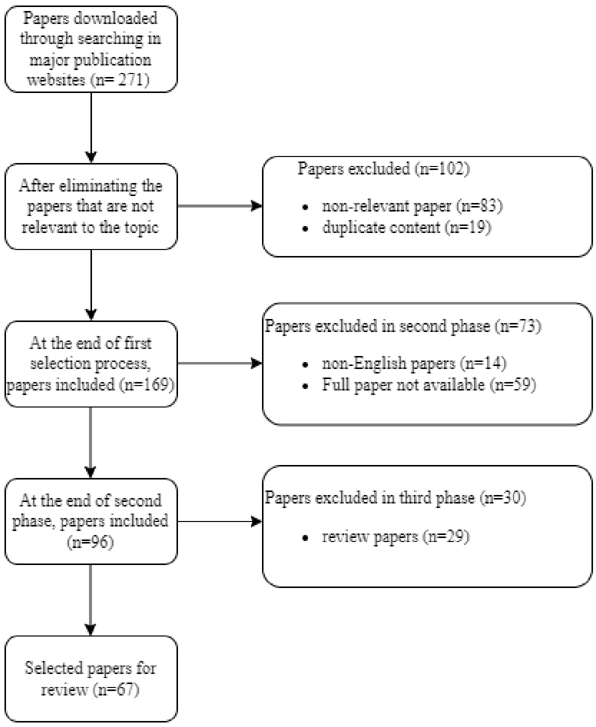

Figure 2: **Paper selection strategy flowchart including the reason for inclusion and exclusion**

By applying these exclusion criteria, the papers were selected for review.

1.6. Research Question

While reviewing the papers related to Sales Forecasting, Product Placement, Intelligent bots, Smart transactions, Blockchain, and Queue management within the context of a Smart Retail Management System, we aim to address the following research questions:

- Q1- What AI, ML, and DL theoretical algorithms have been utilized in the context of a Smart Retail Management System?
- Q2- Which methods have been used to address the existing challenges encountered in retail-based research, and what kind of solutions have been provided by the researcher to develop an effective Smart Retail Management System?
- Q3- What are the sources of data in this Smart Retail Management analysis, and if they have used any data preprocessing, then what data preprocessing techniques have been applied in the context of developing a Smart Retail Management System?
- Q4- What are the research challenges in smart retail management systems and their future research directions?

2. Methods used in Smart Retail management

To understand how to manage the existing retail industry smartly we have divided it into different categories like Sales Forecasting, Product Placement, Intelligent bot, Smart transaction, Blockchain, and Queue management. We will discuss about the existing works and their findings related to these sections one by one.

2.1. Sales Forecasting

Retail sales forecasting basically uses historical sales data and gives a basic overview of how future sales can be by analyzing the ongoing market. Many trending forecasting methods are already being used in this area and more new methods are coming which is improving and making the sales forecasting technology more accurate with time.

2.1.1. Research Article Selection

We have searched for papers in the major research paper databases using the keywords "Time series forecasting," "Forecasting in the super shop," "Sales Forecasting in the super shop," "Smart Super shop management and forecasting," "Use of ML in sales Forecasting," "The use of Forecasting in retail management," "AI, ML, and Sales forecasting", "Super shop sales prediction," "Time series forecasting in retail," "Sales prediction in Retail." We found a huge number of papers by searching with these keywords. From them, by applying our inclusion and exclusion criteria, we selected 19 papers that are connected with retail forecasting. Figure 3 describes the year-wise distribution of forecasting base papers.

2.1.2. Context of the Forecasting Research works

Forecasting has become indispensable to any effective retail management system, particularly with the rapid advancements in AI and statistical methodologies. The study by Falatouria et al. assesses the performance of SARIMA and LSTM models in retail supply chain management (SCM) demand forecasting, particularly highlighting SARIMAX's enhanced performance for products with stable demand patterns when factoring in promotions [32]. It advocates for a hybrid forecasting methodology to boost accuracy. Similarly, Ensafi et al. reveal that machine learning models, especially Stacked LSTM, surpass traditional forecasting techniques in predicting seasonal sales data accuracy [33]. Furthermore, Taghiyeh et al. introduce a novel multi-phase hierarchical (MPH) forecasting approach leveraging machine learning to notably enhance sales forecasting accuracy for hierarchical data structures within supply chains, significantly outperforming traditional methods by integrating multiple machine learning models at various supply chain levels to substantially decrease forecasting errors [34]. Albarune & Habib stress the importance of forecasting for decision-making and operational efficiency in supply chain management across sectors, underscoring the urgent need for enhanced practices and thorough research to boost accuracy and efficiency [35]. Ahmed & Karmaker demonstrate how the Delphi-based Analytic Hierarchy Process (AHP) method can optimize supply chain contract selection, particularly within a Bangladeshi retail setting, by methodically prioritizing criteria like flexibility and demand fluctuation to determine the most suitable contract type, with a preference for 'quantity flexibility contracts' for their effectiveness and cost-efficiency [36]. Ali et al. (2012) and Ali et al. (2017) discuss how aggregation strategies and the use of simple moving average methods in contexts lacking information sharing can lead to improved forecasting accuracy, inventory efficiency, and reduced costs, thereby boosting service levels[37][38]. Huang et al. introduce

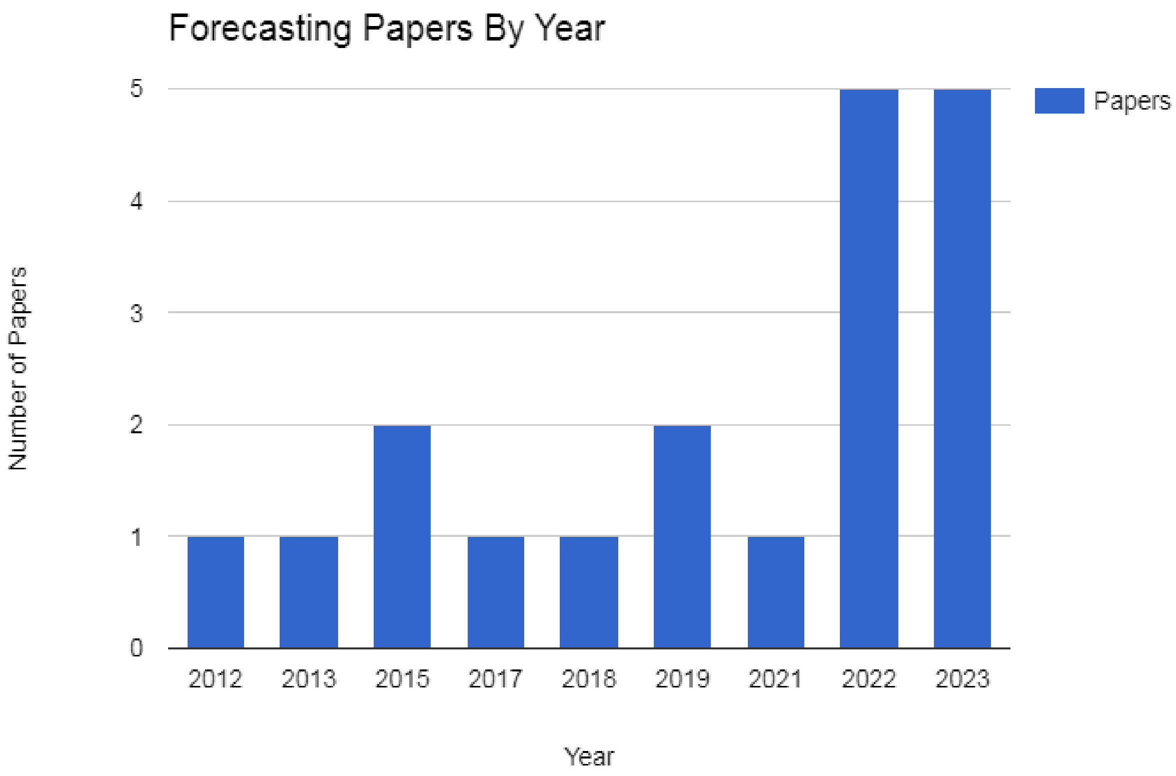

Figure 3: **Year-wise distribution of selected Forecasting base papers**

an automatic pricing and replenishment decision model employing XGBoost regression modeling for vegetable products, which, coupled with Particle Swarm Optimization (PSO), allows for predicting sales volume and attrition rates to optimize pricing and replenishment strategies for maximizing profits. This model's real-world application efficacy in vegetable sales management is underscored, demonstrating the significant role of machine learning and statistical tools in enhancing retail SCM forecasting accuracy and efficiency, from product demand prediction to optimizing inventory and supply chain management[39]. Babai et al. emphasized the importance of collaborative forecasting for supply chain efficiency by showing how information sharing between manufacturer and retailer in a two-stage supply chain, when confronting ARIMA(011) demand, dramatically reduces forecast errors and inventory costs [40]. In [41], the authors investigated machine learning techniques to forecast product demand for retail establishments, concentrating on elements such as store location, time of day, and event. They used algorithms like Gaussian Naive Bayes, K-Nearest Neighbor, and Decision Tree Classifier for demand forecasting. The study found that various factors substantially impact product demand, including the time of month, promotions, weekends, festivals, and weather. According to the survey, Gaussian Naive Bayes had the highest accuracy of all the algorithms examined, suggesting that it would be a valuable method for predicting retail demand. In addition, this study mentioned that machine learning methods can significantly improve retail demand prediction, which will help with supply chain and inventory management. Furthermore, The study shows that hybrid linear regression-XGBoost models, which achieve over 90% accuracy and provide considerable gains over individual algorithm-based forecasts, significantly improve product sales forecasting in supermarkets [42]. Besides, the research presents a Federated Learning (FL) based approach for demand forecasting inside the supply chain to improve accuracy and protect data privacy. This FL approach enhances supply chain visibility and forecasting performance over existing methods with restricted visibility by enabling collaborative, privacy-preserving data analysis across several supply chain stakeholders without disclosing raw data.[43]. The use of a Long Short-Term Memory (LSTM) machine learning model for demand forecasting in Thailand's agricultural supply chain is examined in the study by Kantasa-ard et al.. To improve prediction accuracy, a hybrid method that combines LSTM, a genetic algorithm, and scatter search is suggested for adjusting the model's hyperparameters. The study shows that when managing varying needs, the LSTM model outperforms more established techniques like ARIMAX, Support Vector Regression, and Multiple Linear Regression. For supply chain managers, especially in the context of the Physical Internet, this research is essential because it offers insights into increasing forecasting accuracy and, as a result, enhancing supply chain inventory and transportation management [44]. The paper by Wang et al. explores the best practices for vegetable pricing and restocking in supermarkets using ARIMA and BP neural networks to estimate demand

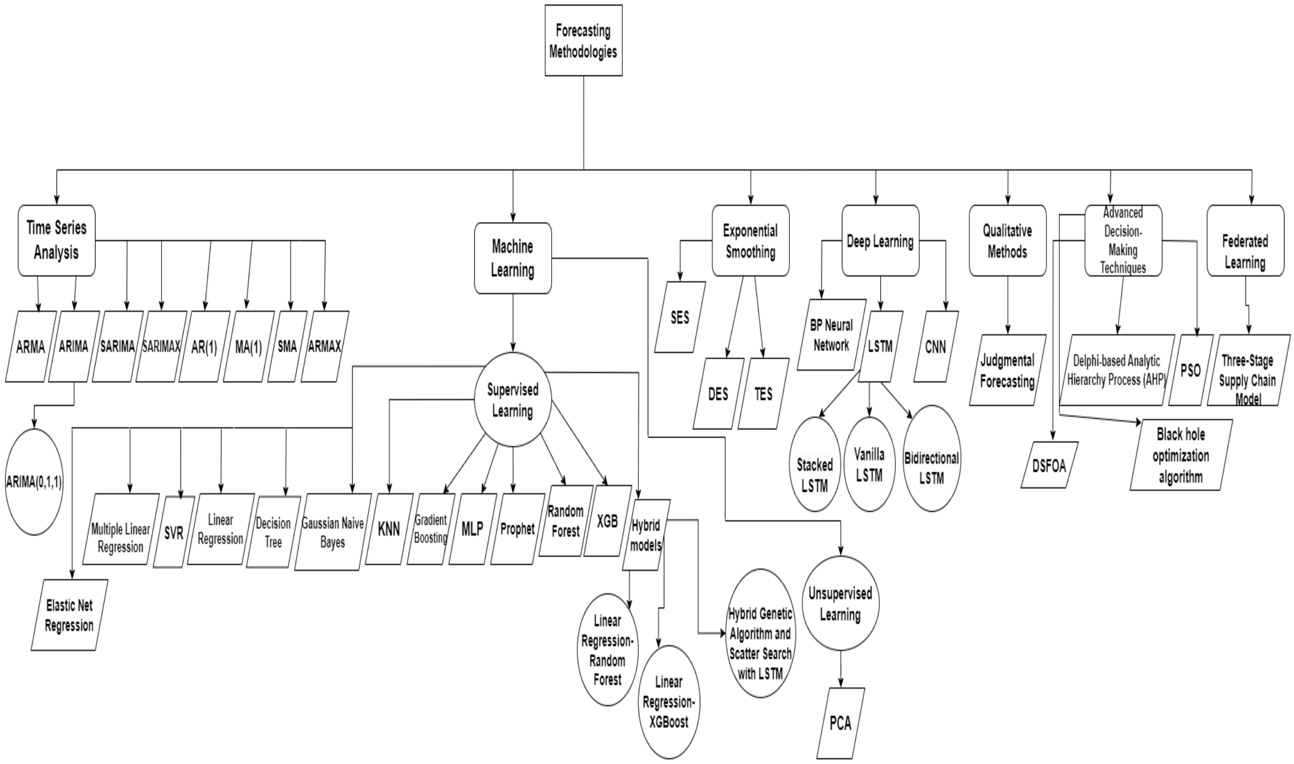

Figure 4: **Methods used in Forecasting**

and analyze historical data to increase sales efficiency and profit [45]. Another study predicts sales of online shopping using Linear Regression [46]. It shows how to compare projected sales for 2014 with actual sales to improve sales prediction accuracy to 84%. This approach helps with decision-making and strategy refinement for better business performance. Using particle swarm optimization, the study in [47] creates a replenishment and pricing decision model for vegetable commodities, improving decision-making in superstores by considering demand elasticity and market competitiveness. This strategy offers a more accurate and flexible way to manage vegetable stock and pricing strategies, showing a considerable improvement over existing models. According to Rostami-Tabar et al., it is more efficient to anticipate individual item needs first and then aggregate them in non-stationary demand scenarios instead of forecasting at the aggregate level first [48]. The study in [49] offers a novel method for product sales forecasting that uses search engine data, internet reviews, and historical sales data. Monthly sales for car models are forecasted with excellent accuracy using a back propagation neural network (BPNN) enhanced by a dynamic step length fruit fly optimization algorithm (DSFOA) after PCA is used to lower the dimensionality of the data. Regarding sales projections, this all-inclusive approach outperforms conventional models in forecasting, underscoring the significance of including various data sources and cutting-edge analytical methods. Moreover, In [50], the paper proposes using elastic net regression and BP neural networks to predict the sales of shops over time. In the table below, an overview of the findings can be seen.

Table 1: Brief Overview of the Methods Used in Different Research for Sales Forecasting (part-1)

Authors	Underlying Theory	Methods	Overview of Findings
Falatouri et al. (2022)[32]	Predictive Analytics in Supply Chain Management	The study used over 37 months of actual retail sales data from an Austrian retailer to compare the performance of SARIMA and LSTM models, with a focus on products with seasonal behavior and the inclusion of promotions as an external factor in the SARIMAX model.	The study found that SARIMAX performed significantly better for products with stable demand when promotions were considered. LSTM showed promising results, but SARIMA and SARIMAX were preferred for their accuracy in forecasting. The research suggests a hybrid approach by training SARIMA(X) and LSTM on similar preclustered store groups to improve forecasting quality.
Ensafi et al. (2022)[33]	Neural Networks, Classical and Advanced Time-Series Forecasting Techniques	Public dataset from a retail store covering sales from 2014 to the end of 2017, focusing on furniture. Methods: Seasonal Autoregressive Integrated Moving Average (SARIMA), Triple Exponential Smoothing, Prophet, Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN). Data was analyzed using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).	Stacked LSTM outperformed other methods in accuracy. Prophet and CNN models also performed well. The study highlighted the potential of neural networks for seasonal time-series forecasting.
Taghiyeh et al. (2023)[34]	Hierarchical forecasting, machine learning, time series forecasting, supply chain management, demand forecasting	The study uses sales data from a logistics solutions provider to compare multi-phase hierarchical (MPH) approach with traditional "bottom-up" and "top-down" methods. They employed machine learning techniques such as Multi-Layer Perceptron (MLP), Random Forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGB) to build forecasting models.	The MPH approach demonstrated an 82–90% improvement in forecast accuracy over traditional methods. The research highlights the potential of leveraging lower-level (SKU) and parent-level (brand) forecasts in a hierarchical supply chain model to improve forecast accuracy at the parent level.
Albarune and Habib (2015)[35]	Forecasting in Supply Chain Management, demand management, collaborative coordination	The study is based on secondary data including interviews with experts from life science, retail chain, and FMCG sectors. They analyzed forecasting practices and supply chain management's role, highlighting limitations and practical solutions.	The study demonstrates that forecasting is critical in SCM for various sectors in Bangladesh, focusing on life sciences, retail chains, and FMCG. It highlights the significance of collaborative planning and the sharing of forecasts to reduce the bullwhip effect and improve supply chain efficiency. The authors propose a forecasting management model to address current limitations and improve SCM practices.
Ahmed and Karmaker (2019)[36]	Delphi Method, Analytic Hierarchy Process (AHP), Multi-Criteria Decision Making (MCDM), Supply Chain Contract	Delphi method to identify evaluation criteria; AHP to determine the relative priorities of the selected criteria and to rank different types of supply chain contracts.	'Quantity flexibility contract' was found to be the best contract for the product line of powdered milk among various alternatives in a Bangladeshi super shop context.

Table 1: Brief Overview of the Methods Used in Different Research for Sales Forecasting (part-2)

Authors	Underlying Theory	Methods	Overview of Findings
Ali et al. (2012)[37]	Forecast accuracy and its distinction from forecast utility, particularly in inventory management where forecasting and stock control interactions are critical. The analysis focuses on ARIMA demand process representations.	Analytical and simulation approach to investigate the relationship between forecast performance (accuracy) and inventory implications under two scenarios: Forecast Information Sharing (FIS) and No Information Sharing (NIS) in a two-stage supply chain. Utilization of real sales dataset from a major European superstore for empirical validation.	The study demonstrates that forecast accuracy improvements through Forecast Information Sharing lead to inventory savings. However, these savings depend on the nature of the demand process. The improved inventory performance due to increased forecast accuracy does not always directly correlate with reduced inventory costs or enhanced service levels.
Ali et al. (2017)[38]	Supply Chain Management, Information Sharing, Simple Moving Average, ARIMA	Analytical expressions derived for different supply chain strategies using real sales data from a major European supermarket. Strategies evaluated: Downstream Demand Inference (DDI), No Information Sharing (NIS), and Forecast Information Sharing (FIS).	The DDI strategy, based on the SMA method, improves forecast accuracy and inventory costs compared to NIS, particularly when formal information sharing is not feasible. It demonstrates the value of mathematical demand inference under constraints like trust or system compatibility.
Huang et al. (2023)[39]	Fresh product replenishment and pricing strategies, machine learning, specifically XGboost regression	XGboost regression to forecast vegetable sales volume and attrition rates. Particle Swarm Optimization (PSO) for model optimization.	XGboost effectively forecasts sales volume for various vegetable products, aiding in making pricing and replenishment decisions. PSO algorithm assists in optimizing supermarket profit by adjusting pricing and replenishment strategies.
Babai et al. (2013)[40]	ARIMA(011) demand, forecasting, inventory performance, information sharing in supply chains	Analytical and empirical analysis of a two-stage supply chain (retailer and manufacturer) facing ARIMA(011) demand. They compared No Information Sharing (NIS) and Forecast Information Sharing (FIS) strategies using data from 329 SKUs from a major European superstore.	Forecast Information Sharing (FIS) significantly reduces forecast errors and inventory costs compared to No Information Sharing (NIS), demonstrating substantial benefits from sharing forecast information in the supply chain. The percentage reductions in inventory costs were generally less than the percentage gains in forecast accuracy, highlighting a discrepancy between forecasting accuracy and utility performance.

Table 1: Brief Overview of the Methods Used in Different Research for Sales Forecasting (part-3)

Authors	Underlying Theory	Methods	Overview of Findings
Arif et al. (2019)[41]	Machine learning for demand forecasting in retail.	Data collection from retail stores, statistical analysis, and application of K-Nearest Neighbor, Gaussian Naive Bayes, and Decision Tree Classifier algorithms. Performance evaluation using metrics such as MAPE, MPE, precision, F1 score, and Matthews Correlation Coefficient.	Gaussian Naive Bayes showed the highest accuracy among the algorithms tested (58.92%) for predicting product demand. Considering variables like month, occasion, and location, this strategy beats conventional approaches and offers a better retail demand forecasting solution. It implies that machine learning can greatly enhance demand prediction in retail settings.
Ahmed et al. (2023)[42]	Hyperautomation, Machine Learning, Time-series Analysis	Utilized hybrid machine learning frameworks (XGBoost, Linear Regression, Random Forest) for product demand forecasting.	Hybrid linear regression-XGBoost model outperformed other forecasting methods, enhancing stock management based on predicted demand.
Zhang et al. (2022)[43]	Federated Learning, Supply Chain Visibility, Privacy Preserving	Developed a discrete event simulation model of a three-stage supply chain and implemented a Federated Learning model for demand forecasting at the supplier level. The approach allows for privacy-preserving data aggregation from multiple supply chain entities without direct data exchange.	The proposed Federated Learning model outperformed traditional forecasting methods without supply chain visibility and achieved similar performance to methods with complete visibility. Demonstrated that supply chain visibility can be enhanced while preserving the privacy of individual entities' data
Kantasa-ard et al. (2021)[44]	Demand forecasting in the Physical Internet, machine learning techniques, supply chain management	Utilized Long Short-Term Memory (LSTM) networks for demand forecasting, incorporating a hybrid genetic algorithm and scatter search for LSTM hyperparameter tuning. A case study focusing on agricultural products in a supply chain in Thailand.	The LSTM method provided superior forecasting efficiency for fluctuating demand compared to traditional methods like ARIMAX, Support Vector Regression, and Multiple Linear Regression. The hybrid metaheuristic approach improved tuning efficiency over trial-and-error methods, enhancing prediction accuracy and reducing associated transportation and holding costs in the distribution process.

Table 1: **Brief Overview of the Methods Used in Different Research for Sales Forecasting (part-4)**

Authors	**Underlying Theory**	**Methods**	**Overview of Findings**
Wang et al. (2023)[45]	Merchandise pricing, replenishment decisions, time series analysis, regression models, neural networks.	To investigate item price and replenishment decisions, this study used data mining, cluster analysis, time series analysis, regression models, and neural networks. To be more precise, they employed the BP Neural Network for complicated time series prediction, the ARIMA for daily replenishment projection, the cluster analysis model for sales volume interrelationships, and the Pearson correlation coefficient for vegetable categories.	The paper demonstrates how to combine different analytical models and machine learning techniques to improve pricing and replenishment decisions for vegetable products in retail settings. The use of ARIMA and BP neural networks allowed for accurate demand forecasting, leading to more effective pricing strategies and inventory management.
Gopalakrishnan et al. (2018)[46]	Sales forecasting, Machine Learning, Linear Regression	Data from 2011-2013 were used to predict online shopping sales for 2014 using Linear Regression. The model was validated with real-time data from 2014 to compare predicted vs. actual sales.	The predictive model achieved an accuracy of approximately 84%. The study showcased the potential of linear regression in forecasting sales and aiding businesses like ZMart in strategizing for future sales based on past data.
Geng et al. (2023)[47]	Demand elasticity pricing model, ARIMA time-series forecasting, Particle Swarm Optimization	Utilized the ARIMA model to forecast sales for various vegetables and employed the particle swarm algorithm to optimize the replenishment and pricing decisions based on factors such as sales volume, cost-plus pricing, demand elasticity, and competitive market environment.	The particle swarm algorithm outperformed the black hole algorithm in optimizing the total amount of replenishment and pricing strategy, demonstrating its effectiveness in solving the replenishment and pricing decision problems faced by superstores. The study provides a basis for superstores to make more informed and profitable replenishment and pricing decisions.

Table 1: Brief Overview of the Methods Used in Different Research for Sales Forecasting (part-5)

Authors	Underlying Theory	Methods	Overview of Findings
Rostami-Tabar et al. (2015)[48]	Non-stationary Demand Forecasting, Cross-Sectional Aggregation	Theoretical analysis supported by extensive numerical investigation and empirical validation. The study compares the effectiveness of top-down (TD) versus bottom-up (BU) approaches for forecasting aggregate and sub-aggregate demand in non-stationary environments. The demand processes considered follow a non-stationary Integrated Moving Average (IMA) process. Single Exponential Smoothing (SES) was used to extrapolate future requirements.	The study demonstrates increased benefits from cross-sectional forecasting in non-stationary environments compared to stationary ones. It offers valuable insights for demand planners, suggesting that cross-sectional aggregation can lead to improved forecast accuracy in non-stationary demand scenarios. The results also advocate for further research into integrating cross-sectional and temporal aggregation methods.
Zhang et al. (2022)[49]	Sales forecasting using online reviews and search engine data	Developed a novel forecasting method using online reviews and search engine data, incorporating Principal Component Analysis (PCA), Back Propagation Neural Network (BPNN), and an improved Fruit Fly Optimization Algorithm (DSFOA). Employed sentiment analysis and time difference correlation analysis for data preprocessing.	The method significantly improves forecast accuracy with robustness for predicting monthly sales of 14 automobile models. It demonstrates the efficacy of integrating sentiment and search data into the forecasting model.
Lili (2022)[50]	Elastic Net Regression and BP Neural Networks, Machine Learning	Elastic Net Regression, and BP Neural Network models were applied for predicting superstore sales. One-hot encoding was used for categorical data preparation, and performance was measured using MAE, MPE, and RMSE.	The BP Neural Network model outperformed the Elastic Net Regression model in forecasting sales. The neural network model showed superior performance, especially in predicting peak sales periods, making it more suitable for practical applications in superstore sales forecasting.

Table 2: Some widely used Sales Forecasting Features in different research works and their Mathematical Expressions (part 1)

Feature name	**Mathematical Expressions**
Missing Data Imputation	$\hat{Y}_{ij} = \frac{1}{n}\sum Y_{ij}$
Mean Absolute Percentage Error (MAPE)	$\text{MAPE} = \frac{100\%}{n}\sum \left\lvert \frac{y_t - \hat{y}_t}{y_t} \right\rvert$
Root Mean Square Error (RMSE)	$\text{RMSE} = \sqrt{\frac{1}{n}\sum (y_t - \hat{y}_t)^2}$
SARIMA Model	$\text{SARIMA}(p,d,q)(P,D,Q)_m$
Mean Squared Error (MSE)	$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2$
Augmented Dickey Fuller (ADF) Test	$y(t) = \lambda y(t-1) + \mu + \beta t + \alpha \Delta y(t-1) + ... + \alpha \Delta y(t-k) + \epsilon$
Auto-Regressive Integrated Moving Average (ARIMA)	$y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - ... - \theta_q \epsilon_{t-q}$
Double Exponential Smoothing (DES)	$y_t = \alpha x_t + (1-\alpha)(y_{t-1} + b_{t-1})$
Triple Exponential Smoothing (TES)	$y_t = \alpha \frac{x_t}{c_{t-L}} + (1-\alpha)(y_{t-1} + b_{t-1})$
Mean Absolute Error (MAE)	$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert$
Mean Relative Absolute Error (MRAE)	$\text{MRAE} = \frac{1}{N}\sum_{i=1}^{n} \left\lvert \frac{y_i - \hat{y}_i}{y_i - \hat{y}_i^*} \right\rvert$
HyperOpt Loss Function	$\min_\omega \frac{1}{n}\sum_{i=1}^{n} l(\theta(x_i;\omega), y_i)$
Forecast Error	Error = Forecast − Actual
Mean Absolute Deviation (MAD)	$\text{MAD} = \frac{1}{n}\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert$
Tracking Signal	$\text{Tracking Signal} = \frac{\sum(\text{Forecast Error})}{\text{MAD}}$
Saaty's Pairwise Comparison	$a_{ij} = \frac{1}{a_{ji}} \quad \text{and} \quad a_{ii} = 1$
Normalized Decision Matrix	$c_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}$
Weighted Normalized Decision Matrix	$w_i = \sum_{j=1}^{n} c_{ij}$
Eigenvector Calculation	$E = \frac{\sum \text{Rowmatrix}}{n}$
Consistency Index (CI)	$CI = \frac{\lambda_{\max} - n}{n-1}$
Consistency Ratio (CR)	$CR = \frac{CI}{RI}$
Conditional Expectation of Lead Time Demand	$E\left(\sum_{i=1}^{L+1} D_{t+i} \mid D_t\right) = \frac{\tau}{1-\rho}\left((L+1) - \sum_{j=1}^{L+1}\rho^j\right) + \frac{\rho(1-\rho^{L+1})}{1-\rho} D_t$
Conditional Variance of Lead Time Demand	$\text{Var}\left(\sum_{i=1}^{L+1} D_{t+i} \mid D_t\right) = \frac{\sigma^2}{(1-\rho)^2}\sum_{j=1}^{L+1}(1-\rho^j)^2$
Lead Time Demand for AR(1) Process	$\sum_{i=1}^{L+1} D_{t+i} = \frac{1}{1-\rho}\left(\tau \sum_i (1-\rho^i) + \rho(1-\rho^{L+1})D_t\right) + \epsilon_{t+L+1} + (1+\rho)\epsilon_{t+L} + \ldots + (1+\rho+\rho^2+\ldots+\rho^j)\epsilon_{t+1}$
Minimum Mean Squared Error (MMSE)	$\text{MMSE} = \text{Var}\left(\sum_{i=1}^{L+1} D_{t+i} \mid D_t\right)$
Mean Squared Error (MSE) under DDI	$\text{MSE}_{\text{DDI}} = \frac{\sigma^2}{1-\rho^2}\left((L+1) + \frac{2L\rho}{1-\rho} - \frac{2\rho^2(1-\rho^L)}{(1-\rho)^2}\right) + \frac{(L+1)^2\sigma^2}{N(1-\rho^2)}\left(1 - \frac{2\rho(1-\rho^N)(1-\rho^{L+1})}{(1-\rho)^2}\right) + \frac{2(L+1)^2\rho\sigma^2}{N^2(1-\rho)}\left(N - 1 - \frac{\rho(1-\rho^{N-1})}{1-\rho}\right)$
MMSE Forecasting Method	$f_{t+L+1} = \frac{\tau}{1-\rho}\left((L+1) - \sum_{j=1}^{L+1}\rho^j\right) + \frac{\rho(1-\rho^{L+1})}{1-\rho} d_t$
Forecast Error	Error = Forecast − Actual
Order-Up-To (OUT) Policy	$I_t = I_{t-1} + Q_t - d_t$
Sales as Function of Price	$n_j = f_j(P_j)$
Total Profit	$\text{Max Total Profit} = \sum_{j=1}^{6} n_j a_j$
Total Sales Function	$SF = \sum_{j=1}^{6} n_j a_j = \sum_{j=1}^{6} f_j(P_j) a_j$
Replenishment > Sales Condition	$SSF_j = \sum \left(\frac{p_i s_i - p_i}{b_i c_i}\right)_j$
Individual Item Profit	$a_j = \frac{\sum(p_i s_i - p_i)}{b_i c_i} \frac{n_j}{SSF_j}$
Final Total Profit Expression	$SF = \sum_{j=1}^{6} n_j a_j = \sum_{j=1}^{6} f_j(P_j) \sum \left(\frac{p_s - p_i}{b_i c_i}\right)_j n_j$
XGBoost Loss Function	$J(\theta)$
ARIMA(0,1,1) Demand Model	$D_t = D_{t-1} - (1-\alpha)e_{t-1} + e_t$
Conditional Expectation of Demand	$E\left(\sum_{i=1}^{L+1} D_{t+i} \mid D_t\right) = (L+1)[D_t - (1-\alpha)e_t]$

Table 2: Some widely used Sales Forecasting Features in different research works and their Mathematical Expressions (part 2)

Feature name	Mathematical Expressions
Conditional Variance of Demand	$\mathrm{Var}\left(\sum_{i=1}^{L+1} D_{t+i} \mid D_t\right) = \sum_{i=0}^{L}(1+\alpha i)^2\sigma_e^2$
Mean Squared Error (MSE) for Retailer	$\mathrm{MSE}_R = 1 + L + L(L+1)\alpha + \frac{L(L+1)(2L+1)}{6}\alpha^2 \cdot \sigma_e^2$
Optimal Order-Up-To Level for Retailer	$S_t = (L+1)\left[D_t - (1-\alpha)e_t\right] + F^{-1}\left(\frac{b}{b+h}\right) \cdot \sigma_e\sqrt{1 + L + L(L+1)\alpha + \frac{L(L+1)(2L+1)}{6}\alpha^2}$
Manufacturer's Demand Process	$Y_t = Y_{t-1} - (1-\beta)x_{t-1} + x_t$
Optimal Order-Up-To Level for Manufacturer	$S_t = (L+1)[Y_t - (1-\beta)x_t] + F^{-1}\left(\frac{b}{b+h}\right) \cdot \sigma_x\sqrt{1 + L + L(L+1)\beta + \frac{L(L+1)(2L+1)}{6}\beta^2}$
Accuracy Formula	$\mathrm{accuracy}(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\mathbf{1}(y_i = \hat{y}_i)$
Mean Percentage Error (MPE)	$\mathrm{MPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{A_t - F_t}{A_t} \times 100$
Precision	$\mathrm{precision} = \frac{\text{true positives}}{\text{true positives+false positives}}$
F1 Score	$F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision+recall}}$
Matthews Correlation Coefficient (MCC)	$MCC = \frac{c \cdot s - p \cdot t}{\sqrt{(s-p)(s-t)(s-c)(s-t)}}$
K-Nearest Neighbor (KNN) Distance	$d(\mathbf{q}, \mathbf{p}) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}$
Gaussian Naive Bayes	$P(x_i \vert y) = \frac{1}{\sqrt{2\pi\sigma_y^2}}\exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$
Decision Tree Entropy	$H(X) = -\sum_{x \in \mathcal{X}} p(x)\log p(x)$
Support	$\mathrm{Support}(A \to B) = \frac{\mathrm{Support}(A \cup B)}{n}$
Confidence	$\mathrm{Confidence}(A \to B) = \frac{\mathrm{Support}(A \cup B)}{\mathrm{Support}(A)}$
Lift	$\mathrm{Lift}(A \to B) = \frac{\mathrm{Support}(A \cup B)}{\mathrm{Support}(A) \times \mathrm{Support}(B)}$
Linear Regression	$y = (\text{weights} \cdot \text{features}) + \text{bias}$
Gini Index	$\text{Gini Index} = 1 - \sum_{i=1}^{n}(P_i)^2$
Weighted Gini Index	$\text{Weighted Gini Index} = \sum_{\text{branches}} \text{Gini Index} \times \text{Weight}$
XGBoost Loss Function	$\sum_{i=1}^{n} l(y_i + \hat{y}_i f_t(x_i)) + \Omega(f_t)$
R-Squared	$R^2 = 1 - \frac{\mathrm{RSS}}{\mathrm{TSS}}$
Customer Demand	$DR_t = N\left(\frac{1}{t-1}\sum_{\tau=1}^{t-1} DR_\tau + U(-c, c), d\right)$
Demand for Upstream Entity	$D_{i+1}^{t+1} = \lvert LI_i^t - \hat{D}_i^t \rvert$
Min-Max Normalization	$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}$
LSTM Output	$o_t^l = \sigma(W_o^l X_t^l + U_o^l h_{t-1}^l + b_o^l)$
Mean Absolute Scaled Error (MASE)	$\mathrm{MASE} = \frac{\mathrm{MAE}}{Q}$
Genetic Algorithm	$F_{\mathrm{GA}} = \text{minimize } f(x), x \in \mathbb{R}^n$
Scatter Search	$F_{\mathrm{SS}} = \text{improve the performance of solutions based on integration of reference solutions}$

Table 2: Some widely used Sales Forecasting Features in different research works and their Mathematical Expressions (part 3)

Feature name	**Mathematical Expressions**
ARIMA Model	$(1-\phi_p(L))(1-L)^d Y_t = (1+\theta_q(L))\epsilon_t$
BP Neural Network	$y = f(Wx+b)$
Pearson Correlation Coefficient	$r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2 \sum_{i=1}^{n}(Y_i-\bar{Y})^2}}$
K-Means Clustering	$J = \min \sum_{i=1}^{k} \sum_{x \in S_i} \lVert x-\mu_i \rVert^2$
Cost Function	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
Gradient Descent Update	$a_1 := a_1 - \alpha \frac{\partial}{\partial a_1} J(a_1, a_0)$
Percentage Error	$\text{Percentage Error} = \frac{\lvert\text{Actual}-\text{Predicted}\rvert}{\text{Actual}} \times 100$
AR Model	$y_t = u + \sum r_i y_{t-i} + \delta_t$
MA Model	$y_t = u + \sum \theta_i \delta_t + \delta_t$
Price Elasticity of Demand	$E_t = \frac{\Delta P}{\Delta Q} = \frac{P_t - P_{t-1}}{Q_t - Q_{t-1}}$
Black Hole Attraction	$x_i(t+1) = x_i(t) + \text{rand}(x_{\partial H} - x_i(t)), i = 1, 2, \ldots, N$
Black Hole Radius	$R = \frac{f_{\mathrm{BH}}}{\sum f_i}$
PSO Velocity Update	$v_i = v_i + c_1 \times \text{rand}(\theta) \times (p_{\text{best}i} - x_i) + c_2 \times \text{rand}(\theta) \times (g_{\text{best}i} - x_i)$
PSO Position Update	$x_i = x_i + v_i$
Linear Decreasing Weight	$\omega(t) = (\omega_{\text{ini}} - \omega_{\text{end}})(G_k - g)/G_k + \omega_{\text{end}}$
Planning Model	$\max W = I - XP$
Top-Down Forecasting Error Variance (TD)	$V_{TD} = \sum_{i=1}^{N} \sigma_i^2 + \sum_{i \neq j} \rho_{ij}\sigma_i\sigma_j$
Bottom-Up Forecasting Error Variance (BU)	$V_{BU} = \sum_{i=1}^{N} \sigma_i^2 + \sum_{i \neq j} \rho_{ij}\sigma_i\sigma_j$
Forecasting Accuracy (MSE)	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$
Demand Aggregation (TD)	$D_t = \sum_{i=1}^{N} D_{i,t}$
Single Exponential Smoothing (SES)	$\hat{D}_{t+1} = \alpha D_t + (1-\alpha)\hat{D}_t$
Integrated Moving Average (IMA)	$D_t = \theta_1 D_{t-1} + \epsilon_t$
Sentiment Score of Individual Review	$S_{tikq} = \theta_{tikq} O_{tikq}$
Word-of-Mouth Effect	$R_{tk} = \frac{B_{tk}(1+A_{tk})}{1+\sum_{j=1}^{n_t} B_{tj}} \cdot P_{tk} + \left(V_{tk} - \frac{V_{\max}}{2}\right)$
Sentiment Index	$R_t = \sum_{k=1}^{n_t} R_{tk}$
Principal Component Analysis	$z_i = l_{i1}U_1 + l_{i2}U_2 + \cdots + l_{ip}U_p$

Table 2: Some widely used Sales Forecasting Features in different research works and their Mathematical Expressions (part 4)

Feature name	**Mathematical Expressions**
Activation Function	$f_h(x) = \text{relu}(x) = \max(0, x)$
Weighted Absolute Percentage Error (WAPE)	$\text{WAPE} = \frac{\sum_{t=1}^{n} \lvert y_t - \hat{y}_t \rvert}{\sum_{t=1}^{n} y_t}$
Cost Function (Elastic Net Regression)	$\text{Cost}(w) = \sum_{i=1}^{N} (y_i - w^T x_i)^2 + \lambda\rho \lVert w \rVert_1 + \frac{\lambda(1-\rho)}{2} \lVert w \rVert_2^2$
Weight Minimization	$w = \text{argmin}_w \left(\sum_{i=1}^{N} (y_i - w^T x_i)^2 + \lambda\rho \lVert w \rVert_1 \right)$
Neural Network Forward Propagation (Hidden Layer)	$\text{net1} = w^T x + b1, h = g1(\text{net1})$
Neural Network Forward Propagation (Output Layer)	$\text{net2} = v^T h + b2, \hat{y} = g2(\text{net2})$
Loss Function	$E(\theta) = \frac{1}{2} \sum_{i=1}^{2} (y_i - \hat{y}_i)^2$
Gradient Descent (Weights Update)	$v(k) = v(k-1) - \eta \nabla(k) v, b2(k) = b2(k-1) - \eta \frac{\partial E}{\partial b2}$
Gradient Descent (Weights Update for Hidden Units)	$w(k) = w(k-1) - \eta \nabla(k) w, b1(k) = b1(k-1) - \eta \frac{\partial E}{\partial b1}$
Data Normalization	$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$
Inventory Holdings under FIS	$I_{\text{FIS}} = \frac{\tau}{2(1-\rho)} + K\sigma\sqrt{V_{\text{FIS}}}$
Inventory Holdings under NIS	$I_{\text{NIS}} = \frac{\tau}{2(1-\rho)} + K\sigma\sqrt{V_{\text{NIS}}}$
Reduction in Inventory	$I_{\text{NIS}} - I_{\text{FIS}} = K\sigma \left(\sqrt{V_{\text{NIS}}} - \sqrt{V_{\text{FIS}}} \right)$
Simple Moving Average (SMA) Forecast	$f_{t+1} = \frac{1}{N} \sum_{k=0}^{N-1} d_{t-k}$
Local Inventory	$LI_i^t = LI_i^{t-1} + S_{i+1}^t - S_{i-1}^t$
Shipment Requirement	$SR_i^t = BO_i^t + D_i^t$
Required Shipment	$S_i^t = \min(SR_i^t, LI_i^t)$
Back Order	$BO_i^{t+1} = BO_i^t + D_i^t - S_i^t$
Expected Demand	$\hat{D}_i^t = LT_i \cdot \frac{1}{T} \sum_{\tau=1}^{T} D_i^{t-\tau}$

2.2. Product Placement

Product placement is a very crucial section in retail management. Improving product placement can improve store sales and can also save time for customers.

2.2.1. Research Article Selection

We have searched for papers in the major research paper databases using the keywords "Product placement algorithm," "Product placement methodologies," Product Placement Strategies," "Product placement using machine learning," "Data mining and product placement," and "product placement in retail," "Shelf space optimization in super shops," "Shelf Space arrangement in Supermarkets," "Shelf arrangement in retail stores," "The use of AI and ML in supermarket product placement." We selected 12 papers connected with retail product placement after the screening process. Figure 5 describes the year-wise distribution of product placement base papers.

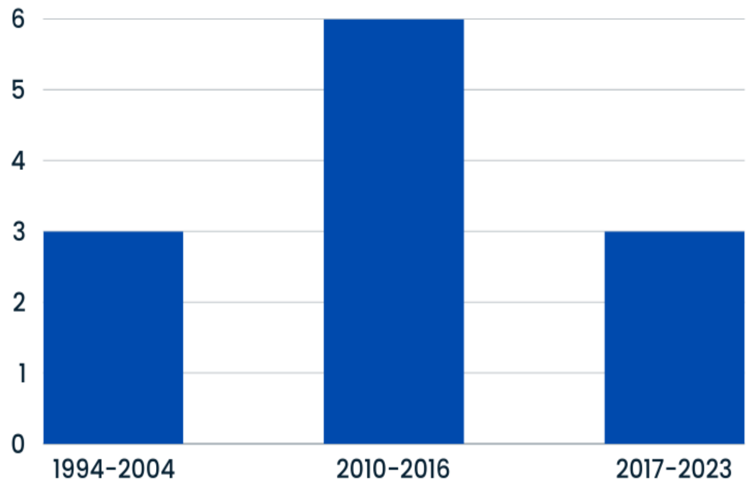

Figure 5: **Year-wise distribution of selected product placement base papers**

2.2.2. Context of the Product placement Research works

Agarwal et al.[51] proposed an Apriori hybrid model in their work that will help the vendor to create a market-based program and plan. Through this, they can deal with very large amounts of data as it will mine for association rules very quickly. In their other work, Agarwal et al.[52] had performed with 3 models to deal with the problem of mining sequential models. Working with large amounts of customer transaction retail data, they faced the need for models to extract meaningful rules from this data. The paper presents the concept of a sequential model. In another paper, Ito et al.[53] have discussed a dynamic product placement model that will help us find the correlation between products and can lead to significant efficiency and productivity by placing the right product in the right place. To solve the puzzle of customer needs and make the shopping experience hassle-free, a paper[42] has worked with three market basket algorithms and suggested the best algorithm to help the super-shop owners understand the customer needs and make the business more profitable. Another paper[54] proposed to solve the product placement problem, keeping in mind that shelf space allocation and product display have a significant role in customers' buying behavior. They used a market basket algorithm using data mining techniques to find frequent item sets and sequences of products often bought together. Working with 225 different products collected from the sales data of a supermarket on the Vancouver Island

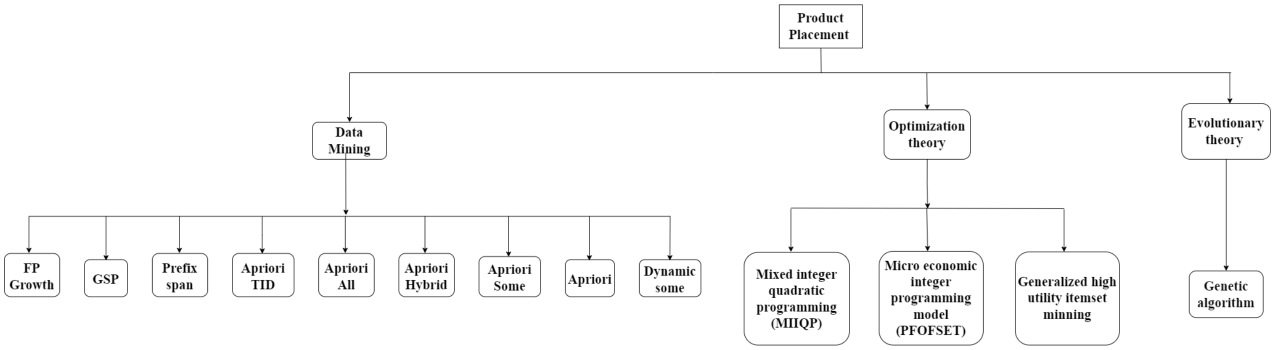

Figure 6: **All the used methods in retail management for managing Product placement**

University website, the author[55] of the paper applied market basket analysis algorithms like Apriori and Fp growth algorithm to find out the rules to understand customer demand precisely.

A website called Weka, developed by the University of Waikato and purely developed for machine learning purposes, is used in this research. This website can do both mining and data preprocessing, but there was a problem related to the dataset. The dataset collected was a binary type dataset with two possible values, 0 and 1, which in this case was used to determine whether a product is purchased. However, Weka was only compatible with numeric data, so the author rearranged the dataset using the Numeric to Nominal Function. It converts the numeric data into a nominal one and was also set to have no class option. Because of this, the researchers could not use the Apriori algorithm, as the algorithm does not perform well with numeric datasets. Depending on the conviction values, the fp growth algorithm generated the top 10 association rules. Russel et al. [56], with their partner utilizing data from liquor stores, have researched where to locate products in a retail shop. They proposed a mixed integer, quadratic program with a quadratic objective function and a linear set for shelf space allocation. The discrete model has been optimized to partition the shelf spaces and locate items into them.The reason for using the discrete model is that it can solve a huge problem in an optimal or near-optimal way. At first, they processed the solution with MIQP to overcome the shelf management problem, but it was terminated after the 1000N branch and bound nodes to overcome the problem of the process being extensive and time costly.To solve this problem, the CPLEX MIP emphasis value was set to a higher value, and a polishing heuristic was applied for N minutes to solve this issue. Doing this solved the problem within 1.5 hours of CPU time.Focusing on the market basket analysis, another paper[57] has worked to analyze sports store equipment data. In this research, business intelligence has tried to help sports retailers increase their sales through product placement and recommendations by using data mining tools. Using market basket algorithms, they have determined which items are frequently purchased together by the customers, which can help the sellers improve their market and sales strategies. Collecting data from sports stores in India, the researchers have found that some common items were purchased frequently. To find the relationship between these items, they have used the fp growth algorithm. The findings can be useful and applied to optimize the display of the sports stores to maximize sales. The researchers recommended that the layout of a sports store should contain items like tumblers, towels, running shoes, socks, and backpacks with sports equipment to attract more customers to the store. All the rules in this paper were generated with minimum support and minimum confidence of 1. Moreover, they have focused on other indicators like product recommendation and promotion for better results. To solve the problem of product placement on product listing pages of retail websites, a mathematical model using genetic algorithms was proposed by Chen and his team[58]. The study amalgamates visual attention literature and the theory of shelf space allocation to develop the model. The main features of the genetic algorithm are fitness function, encoding, crossover mechanism, and mutation mechanism. Keeping this in mind, while applying a genetic algorithm, the author used a decimal encoding for individuals. Managing each individual as a decimal string, a possible solution was proposed where each individual's fitness was evaluated by total profit. The model addresses the problem of how to allocate the display locations considering the effects of visual stimuli such as color, shape, and size. It gives more importance to the first page as it gets more attention from the users to maximize the profit of online stores. Working with real-life data collected from convenience store brjis and other authors of the paper[60] proposed a microeconomic integer programming model for product selection (profset) based on the use of frequent itemsets collected rule mining. The minimum support threshold for 10 frequent item sets was mined from the dataset, which was integrated into the integer programming model, considering the retailers' microeconomic parameters for product placement.This integration of frequent item sets into the microeconomic model for product selection (PROFSET) will allow the retailers to make product assortment decisions based on qualitative criteria as the model uses sensitivity analysis, it will allow the retailers to evaluate the profit of different product placement decisions. Research suggests using a generalized utility itemsets (GUI) index to collect generalized high utility itemsets from two real-life datasets and place the products in retail stores. A Revenue-based Generalized item placement (RGIP) model was proposed. The RGIP model determines the high revenue generalized itemsets depending on item size and places them on the leaf-level category in the product placement taxonomy. At first, the generalized profset model was used to allocate the premium slots, which is named GPF. Later, the RGIP scheme was applied to place the high-revenue itemsets in premium slots from the kUI index and GUI indexes, which were named KUIP and GUIP, respectively. Highlighting the increasing trend of online shopping and the importance of website interface, the other paper [61] talks about the design of product listing pages on commercial websites. The paper discusses a visual-attention-dependent demand (VADD) inventory model to determine optimal product placement and replenishment decisions. The VADD model, combined with a genetic algorithms-based search method, will mimic the process of natural selection and provide the best way to balance price and popularity. This will help retailers achieve an increase in sales. The proposed model suggests that visual stimuli like the size and location of product images greatly impact product demand.

Table 3. Some widely used Product Placement Features in different research works and their corresponding Mathematical Expressions

Feature name	Mathematical expression
Support	(A→B) = P(A∪ B)/n
Confidence	(A→B) =P(B| A)/Support(A)
Leverage	Confidence(A→B)/Support(B)=Support(A→B)/*Support*(A)+Support(B)
Conviction	(A→B)= 1- Support(B)/1-Confidence(A,B)
Lift	(A→B)=SUP(A∩ B)/SUP(A)*SUP(B)
Quadratic function to maximize profit	$\xi_i = \beta_{0i} + \beta_{1i}X_i + \beta_{2i}X_i^2 + \sum_k[\beta_{3i}(h_kY_ik) + \beta_{4i}(h_kY_{ik})^2 + \beta_{5i}(h_kY_{ik})^3 + \beta_{6i}Z_{ik} + \beta_{7i}Z_{ik}^2]$
Maximize total profit	$\prod = \sum_i \varnothing_i \xi_i$
Defining constraints and variables in shelf space allocation	$A_{fk} \leq X_{i(f)}$-$d_{i(f)}$ / $2 \cdot Z_{i(f),k}$+l_k(1-Y_{ik})$, \forall i(f), k$
	$B_{fk} \geq X_{i(f)}$+$d_{i(f)}$ / $2 \cdot Z_{i(f),k}$-l_k(1-Y_{ik})$, \forall i(f), k$
	B_{fk}-$A_{fk} = \sum_{i(f)} d_{i(f)}Z_{i(f),k,}\forall f, k$
	$W_{fk} \leq \sum_{i(f)} Y_{i(f),k}, \forall f, k$
	$W_{fk} \geq Y_{i(f),k}, \forall i(f), k$
	$R_f \geq kW_{fk}, \forall f, k$ [12]
	$S_f \leq M$-$(M$-$k)W_{fk}, \forall f, k$
Demand rate	$d_i(x_i, y_i) = \alpha_i \sum_{s=1}^{S} \sum_{t=1}^{T}(x_i st.A)^{\beta ist} + \sum_{n=1}^{N} \sum_{w=1}^{W}(y_i nw.A')^{\beta_i' nw} fori = 1, 2....I$
price cross elasticity	$d_i(x_i, y_i) = \alpha_i \sum_{s=1}^{S} \sum_{t=1}^{T}(x_i st.A)^{\beta ist} + \sum_{n=1}^{N} \sum_{w=1}^{W}(y_i nw.A')^{\beta_i' nw}$
Profited sequential pattern value	$PSP(x) = Sup(x) * Profit(X)/l(X)$
Interest	S(A→B)/s(A)*S(B)
Positive Correlation	$p(A \cap B)/P(A) - P(B) \geq 0$

Table 4. The data description of the papers related to Product Placement

Data List			
Author	Total records	Description	Availability
Agarwal et al. (1995)[51]	46873 and 213972	transaction	N/A
Agarwal et al. (1994)[52]	transaction data was used in the problem, which consists of the following fields: customer-id, transaction-time, and the items purchased in the transaction.	synthetic data	N/A
ITO et al.(2016)[53]	N/A	N/A	N/A
Shuvro et al. (2023)[42]	158,293	Daily sales of supermarket	N/A
Aloysius et al.[54] (2013)	large dataset consists of 50000 transactions of 50 items, Small dataset consists of 40000 transactions	Rule Synthetic dataset for experimentation and two datasets for evaluation	N/A
Unvan et al. (2021)[55]	225 different items, 1361 transactions	Data of any supermarket collected from Vancouver Island University website	Vancouver Island University website
Russel et al. (2010)[56]	Flavored vodka dataset(34 items, 9 families) Unflavored vodka dataset(103 items, 36 families)	-	N/A
Kaur et al. (2013)[57]	N/A	Collected from various sports markets of India	N/A
Chen et al.(2014)[58]	N/A	N/A	N/A
Brijs et al.(2004)[59]	27148 sales transaction	data collected from a fully-automated convenience (FAC) store over a period of 5.5 months in 1998.	N/A
Bapna et al.(2020)[60]	DSET1 no. of item 49688, transaction 3214874; DSET2 no. of items 169, transaction 9835	1.instacart retail dataset (DSET1) 2.Classical R "groceries" market basket analysis dataset (DSET2)	DSET1 avaialable online
Chen et al.(2016)[61]	N/A	Two datasets were randomly generated. First dataset for high involvement product, Second dataset for low involvement product	N/A

Table 5. Brief Overview of the Methods used in different research for Product Placement

Reference	Description	Models used	Year
Agarwal et al.[51]	The proposed data can be helpful to extract patterns from huge meaningless databases like sales data. It identifies patterns from customer transactions which are used for product recommendation and inventory management	AprioriSome, Apriori-All, DynamicSome	1995
Agarwal et al.[52]	The paper works with two different algorithms, Apriori and Apriori TID. By using the best features of these algorithms, it creates a new algorithm, Apriori hybrid, which performs better than Apriori in almost all cases	Apriori, Apriori TID, Apriori Hybrid	1994
ITO et al.[53]	The paper proposes a dynamic model that will help to reduce the order picking time in the wear house by using the correlation method to decide where to place the products	Apriori	2016
Shuvro et al.[42]	The paper works with three different algorithms to find out which one performs better in extracting rules from customer transaction data	Fp growth, Apriori, GSP	2023
Aloysius et al.[54]	The paper performs an experiment on synthetic and supermarket datasets by applying prefixSpan to at first mine the sequence of product categories and, later on, mine the patterns for each category to arrange the products based on sales	Prefix span	2013
Unvan et al.[55]	The study uses software developed at the University of Waikato. It has modules that can perform data mining using the apriori and FP Growth algorithm was used in the dataset	Weka program for data analysis, Apriori and Fp growth for Association rule analysis	2021
Russel et al.[56]	The paper proposes to keep the products of the same category together, which will help the customers to find the products comfortably. Moreover, they have considered putting the highly demanding products in prominent positions to improve sales	Quadratic objective function and Mixed integer quadratic program(MIQP)	2010
Kaur et al.[57]	The paper works with the FP Growth algorithm to analyze sports equipment market basket to find the pattern. The FP Growth algorithm was chosen to avoid the need to produce candidate sets	FP Growth	2013
Chen et al.[58]	The study works to use the visual attention literature and theory of shelf space allocation along with a genetic algorithm to develop a product placement model for the product listing page	Optimal model using Genetic algorithm for online product listing, reviews visual attention and shelf space allocation theory	2014
Brijs et al.[59]	Suggested implementing frequent itemsets in the microeconomic model, which will allow the identification of the cross-sales potential of products. It also works with a sensitivity analysis that helps the retailers to decide which product to offer	Proposes a Microeconomic (PROFSET) model	2004
Bapna et al.[60]	Analyzing the knowledge acquired from generalized high utility itemsets to understand the consumer buying behavior and for making product placement strategies. The proposed model offers an approach to allocating premium slots to high-revenue products.	Generalized high utility itemset mining	2020
Chen et al.[61]	The model shows how a product's representation helps create its demand and how the absence of a popular product can create room for another product.	Visual attention dependent demand inventory model where genetic algorithm was used for maximizing total profit	2016

2.3. Intelligent bot for retail management:

The introduction of intelligent bots in retail can ameliorate the customer service experience.

2.3.1. Research Article selection

To identify the relevant papers basic search was done in Google Scholars, IEEE Xplore, Elsevier, and Science Direct, which includes keywords "Intelligent bot for super shop management system," "Voice bot for super shop management system," "Chatbot for super shop management," "Voice bot for retail," "chatbot for retail," "Intelligent bot for super shop management," "AI bots for supermarket management," Virtual assistant for retail," "Smart retail management using AI bots." After executing the search and choosing procedure, we selected a total of 11 papers for review. Figure. 7 describes the year-wise distribution of Intelligent bot base papers.

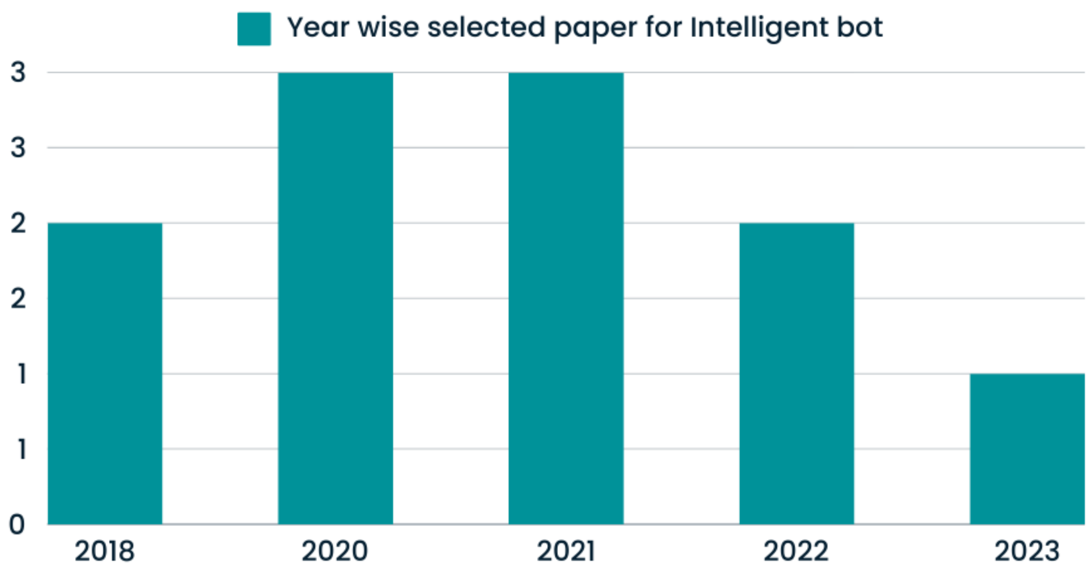

Figure 7: **Year-wise distribution of Selected Intelligent bot base papers**

2.3.2. Context of the Intelligent Bot Research works

We have distributed the intelligent bot section into two parts

1. Voicebot 2. Chatbot.

1. Chatbot:
   An intelligent bot is one of the ways to communicate with customers for any small or big business model. It is profitable for vendors and makes the shopping experience hassle-free for the consumer. Trying to decode the small and medium-sized enterprise customer behavior towards shopping Selamat. et al.(2021) and team found out that a chatbot that contains a combination of four attributes: responsive, humanized conversation, personalized recommendation, and small steps to trigger customer actions can influence the way of acting of customers, perceived usefulness and perceived enjoyment compared to regular chatbots[62]. To conduct the research, they used quantitative data collected through online surveys of 315 sme customers and quantitative data gathered through interviewing sme business owners and customers. Data was collected using a chatbot prototype from the sme customers aged 15 to 40, which was necessary to understand the feature demand of chatbots and their influence on human behavior. By conducting the first survey, they identified the influence of chatbots' features on sme consumers, and the second survey

found out the influence of chatbots on anthropomorphism and its impact on customers' intentions. The paper mainly aims to provide a chatbot that includes all the necessary features from the perspective of sme owners and customers. Please see Figure 8.

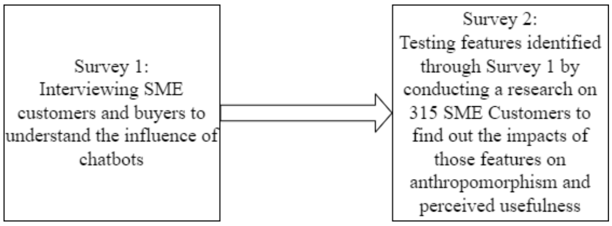

Figure 8: **Top level overview of the conducted research[62]**

Another study[63] proposes an intelligent chatbot system based on artificial intelligence markup language for e-commerce, where they have worked to build a bot that is both accurate and provides fast responses. They designed the bot to answer basic customer queries, which were classified into three sections: general questions, calculations, and stock checks. The bot is also used for the Telegram application. The chatbot system was built using 15,129 data records collected from Indonesian e-commerce restaurants, of which 35% data was independent research results, and the rest of 65% was gathered from books. Feeding the user input into the system, they used parsing, pattern matching, and data crawling to process the input and generate the response. In the parsing stage, it was checked if the user input was structured correctly according to the syntax rules defined in the bot knowledge base, and to do so, it breaks down the query. It extracts the necessary information to understand the question. In the pattern matching stage, the system eliminates the unnecessary parts from the question and classifies the customer queries into three sections: general questions, stock checks while taking orders, and calculation of payment. When pattern matching is done, the system uses the result to create a context vector in the third stage and collects the relevant information from the database to generate a response to the query. Ultimately, the chatbot was tested using 300 user questions that measured the chatbot response time. The result shows that the chatbot created using AIML responses is faster than other bots. In 300 trials, the system responds to all the questions without any errors, with an average response time of 3.4 seconds. Please see Figure 9.

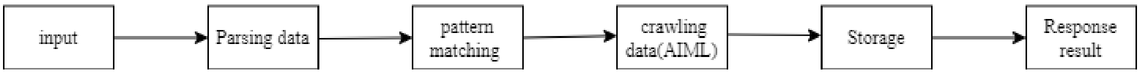

Figure 9: **Top level overview of the conducted research [63]**

In a different vein, R Angeline (2018) [64] have worked to develop a system using IOT and AI to automate supermarkets. While working on automating the super shop, they suggested using a chatbot made with the chatterbot library on Python to handle the information and advertising section. The main system consists of five parts, and the chatbot will work as an assistant for the customer who is in a rush and wants to know the exact location of the products.They have made a whole system from the exit to automate the shopping experience, and for doing so, they have made an application in which a chatbot is an important part, along with the use of QR entry /exit, smart aisle, and virtual cart. The paper mentions collecting data using QR scanning, PIR sensor, and infrared sensor, and the data is always monitored and shared between devices to make the user experience smooth. In their research, Dey. D et al.(2022) [65] have dug into the topic of user acceptance of chatbots in retail, and for doing so, they have presented a model and research framework for understanding the acceptance. To understand the individual acceptance of the technology, the authors have used the theory of reasoned action (TRA) and technology acceptance model (TAM), where TRA focuses on attitude towards subjective norms and TAM focuses on the usefulness of the technology. Additionally, other theories like the motivational model(MM) focus on understanding user behavior based on intrinsic and extrinsic innovation, and the innovation diffusion theory (IDT) focuses on ease of use and compatibility. To explain relationship marketing, they have focused on antecedents and relationship outcomes. Here, antecedents are the factors that influence the acceptance of the chatbot in the retail sector, and relationship outcomes are the result of participant and chatbot interaction. There are three types of relationship outcomes: customer-focused outcome, which is used to measure customer loyalty; seller-focused outcome, which examines sales growth and profit performance; and dyadic antecedents, which examine the joint actions between customer and chatbot. By going through all these models and frameworks, the authors assimilated the constructs from different models to propose a meta-analytic framework for relationship marketing, including all relationship outcomes. To explore the customer experience of AI-based chatbots in e-retailing, Chen, J.S. et al. (2021)[66] used a research model-based approach in their study. The research findings offer valuable insights about the acceptance of this technology. During their research, they found that the bot's usability and responsiveness significantly impact customer satisfaction. To conduct the study, they did an online survey using Amazon Mechanical

Turk (Mturk), and from the questionnaires, 425 valid responses were registered. On the collected data, Statistical product and service solutions (spss) and smarts were applied to understand the measurement model and test the proposed hypothesis. Exploratory factor analysis(EFA) and confirmatory factor analysis(CFA) were done in Spss and Smarts to test the bot's reliability. Moreover, a few more constructs like average variance extracted(ave), composite reliability, and Cronbach's alpha were measured to assess the reliability and validity of chatbots in e-retailing. Overall, the study found that the chatbot has a positive impact on online customer service, where the bot's personality, usability, and responsiveness have the most significant impact. Two studies [67] were done on young university students to understand the role of chatbots on customer purchase intention. The sample size of the collected data was N=184; on 104 students, a hedonic product study was done. On 80 students, a utilitarian product experiment was done. The study was conducted in Italy, and participants' demographic data, including their age and gender, was collected. A monofactorial experimental design was employed in the study where two conditions of online interactions, website and chatbot, were used. Here, the website worked as a control condition, and the chatbot condition invited the participants to discuss the hedonic and utilitarian products. Participants in the experiment were asked some questions related to brand familiarity and their experience. Later on, they were asked to browse the official website. At the end of the experiment, the participants were instructed to fill out a survey, and two control questions were asked, which were used to evaluate the contributions of chatbots. The experiment shows that websites can shift the value perception of products and play a big role in influencing the customer's intentions. On the other hand, chatbots can contribute to building brand awareness and shift the perception of the value of hedonic and utilitarian goods towards utilitarian and hedonic values. The result of the study shows that digital assistants can enhance the online shopping experience by increasing hedonic value and reducing the time for decision-making by reinforcing the utilitarian value perception of the product. Please see Figure 10.

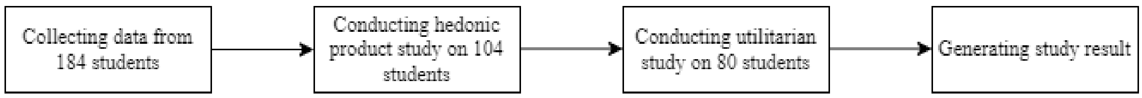

Figure 10: **Top level overview of the conducted research [67]**

Highlighting the drawbacks of existing systems, Aarthi et al.(2020)[68] proposed a chatbot system developed with Python as front-end and My SQL as a back-end language. The author mentioned having a large and comprehensive library as a reason for choosing Python as front end language and data safety for using My SQL in the back end. The system takes data from the user and processes it using a sequence-to-sequence RNN model to generate the output. The model has two components, encoder RNN and decoder RNN, where encoder RNN uses bidirectional LSTM to build the encoder and concatenate it with the input of the decoder, which is made of RNN where Gated Recurrent Unit (GRU) helps to overcome the vanishing gradient problem. The research points out the necessity of a secure window application to handle the furniture retail shops.

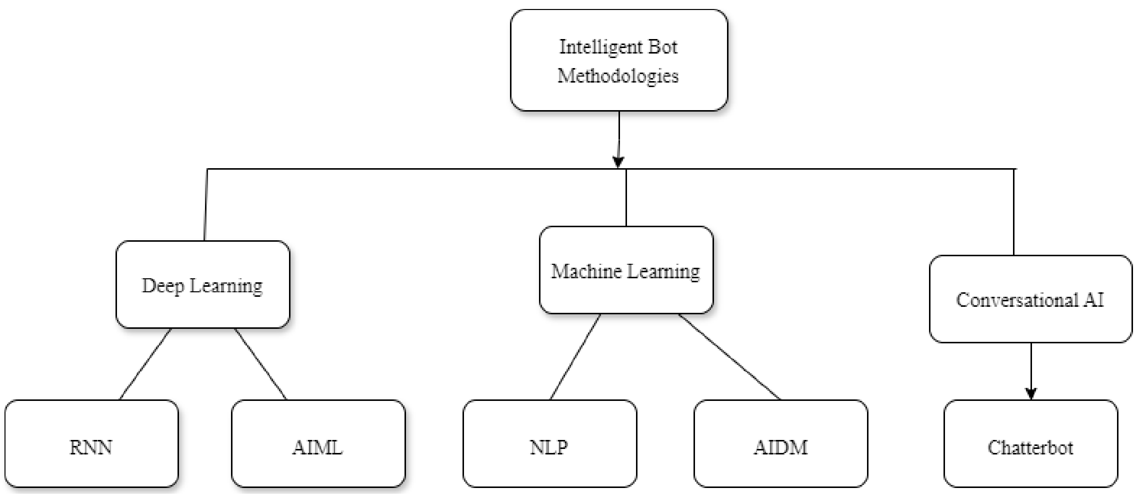

Figure 11: **AI & ML methods used in Intelligent bot**

2. Voicebot

Applying the Macinnis framework for conceptual contributions of summarization, integration, and delineation, Klaus et al.(2022)[69] proposed a new AI influence decision-making model (AIDM) focusing on the customer's increasing dependency on AI to make regular buying decisions. To propose the model, the author used MacInnis's three-step procedure of conceptual contributions and chose 389 articles from 2010 to 2020 as the first AI Voicebot introduced by Apple in 2011. They summarized and integrated the findings from 53 academic and 65 managerial articles that fulfilled their requirements to understand the influence of shopping bots on a person's choice and retail service. After summarizing and integrating, the delineation process demonstrates how the voice bot influences the customer's and managers' insight into the retail environment. To get a deep understanding of proposed heterogeneity in terms of low-involvement purchases vs high-involvement purchases, they suggested an empirical testing of the AIDM model. The research focuses on gathering data to understand the impact of AI on consumer decision-making processes and tries to investigate how and when voice bots can take over customer-brand interaction. Please see Figure 12.

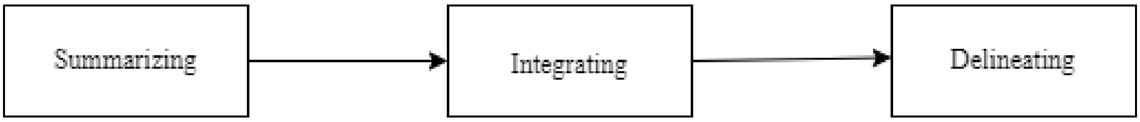

Figure 12: **Top level overview of the conducted research [69]**

In a recent study done by Ahmed. et al. (2023)[42] focused on automating the super shops using innovative ideas like intelligent bots, product placement, and product demand prediction models. This research aimed to automate the supermarket sector to generate high profits and enhance operational efficiency. The research says that the voicebot has two major functions: one is to participate in conversations with customers, and the second one is to answer their queries. To develop the voice bot, they first installed software libraries like PyAudio, Speech Recognition, and Pandas to complete the data management and audio processing tasks. Subsequently, They worked with Spacy beats NLTK library to split the text into individual tokens; after that, parts of speech tagging were used for assigning grammatical tags to the texts. After applying POS to tag the input text words, the words and their grammatical tags were placed in variables. Later, they were compared with the data library using NLTK's bleu function, and similarity scores were calculated. Lastly, pyttsx3 local speech engine was used to convert the text output into speech even without any internet connection, ensuring that the consumers can use the voicebot without any internet connection. Zierau. N et al.(2022)[70] in their research have said that voicebots nowadays provide us with a positive user experience, helping us build improved consumer service. The study aims to clarify how fundamental theories of human communication can be linked with voice-based interfaces to create a more experienced voice service for consumers. The research comprises four studies, each of which works to explore different aspects of voice bots. At first, they worked to find the best nature of voice modality by examining different types of boundary conditions, underlying psychological mechanisms of the effects, and whether the outcome focuses more on perception than behavioral consequences. In the first study, they compared voice-based interfaces with chat-based interfaces, which shows that the voice-based system provides a more flow-like user experience. Randomly, 184 persons were selected and assigned either text-based or voice-based interfaces related to an insurance claiming filling task. The result of the study shows that the voice-based interface provides a higher perception of intercept flow. In the second study, the effect of semantic fluency on the user's perception of interface flow was tested in voice-based interfaces. Moreover, they have focused on exploring whether the voice-based interface affects both perceptual and behavioral outcomes. For this experiment, they randomly chose 612 participants and assigned them to different interface modalities and semantic fluency conditions. Objective readability scores showed the manipulation of semantic fluency and contributed to understanding the role of semantic fluency in voice-based interfaces. In experiment 3, a total of 610 participants were selected to understand the impact of voice-based interfaces on perceptions of interface flow and alternative explanations. The final study was divided into two parts. In the first part, it was investigated whether the observations of previous studies regarding customer experience of interface flow were accurate. The second part tested the impact of voice bots on behavioral outcomes. For this task, 811 were randomly given a voice-based or text-based interface for the first part of the study. The task that was assigned was the same as the first three tasks. For the second part, an additional advertisement was presented at the end of the experiment, and users were asked to sign up, but a few students got the advertisement in the voice interface, and some got it in the text interface. In the end, the result of the study was extracted from the count of people who had signed up divided by the number of unique pages visited. Research [71] was conducted to elucidate how luxury brands can adopt the chatbot virtual assistance as a part of e-service to increase customer satisfaction. For this research, the author collected 29 items from previous studies, which were used to measure marketing efforts based on different measurements like entertainment, trendiness, and problem-solving. These items were previously used to understand how brands affect customer relationships using virtual environments where customer satisfaction is measured using a five-point Likert scale. The study focuses on the young customers of South Korea because European luxury brands have gained popularity among young shoppers by 60% in recent years. For the research, a survey was conducted on 161 students aged 20 to 30, and the incomplete surveys were eliminated. The data was used to test a five-dimensional model to measure the customer perception of chatbot e-service. The survey scale reliability composite reliability (CR) coefficient and average variance extracted (AVE) were used. The AVE value exceeded 0.5, which confirms the validity of all cases except communication competence, which was tested in CR, and the value was 0.76. Overall, the result shows that chatbot e-service can effectively increase customer satisfaction and brand-consumer relationships in the luxury fashion industry. This study shows that online communication history can be used in the future to introduce customized products, and marketers have to ensure the accuracy and credibility of one-to-one interactions. Research was conducted to understand the acceptance of text-based chatbot Emma in online fashion stores. The research shows that factors like authenticity of conversations and perceived enjoyment can positively impact consumers. Still, there are also factors like privacy and immaturity of technology, which can negatively impact people. A study was conducted on 205 German millennial participants to test the acceptance rate of Emma chatbot. To measure the acceptance of the chatbot, the Technology acceptance model(TAM) and uses and gratification(U&G) acceptance models were used by the authors Rese A. et al.(2020).[72] The Technology acceptance model(TAM) is a classic method of evaluating the acceptance of new technologies. Still, on the other side, U&G is not a classic acceptance model. To determine if the study provides accurate results, utilitarian and hedonic factors were examined. The study revealed that both factors positively influence the acceptance of the chatbot. Later On, TAM and U&G factors were juxtaposed, which shows that the TAM factors, like authenticity of conversations and perceived usefulness, are more impactful and completely overshadow hedonic factors like perceived enjoyment. Overall, the study underscores the complex relationship between utilitarian and hedonic factors influencing customer perception of emerging technologies such as chatbots in online fashion retail.

Table 6.Acronyms found in the papers related to Intelligent bot

Acronym	Description
SME	Small and medium-sized enterprises
AIML	Artificial intelligence markup language
AI	Artificial intelligence
AIDM	AI influence decision making model
SQL	Structured query language
RNN	Recurrent neural network
GRU	Gated recurrent unit
LSTM	Long short-term memory networks
ML	Machine learning
IoT	Internet of things
QR	Quick response
NLTK	Natural language toolkit
POS Tag	Part-of-speech tag
TAM	Technology acceptance model
U&G	Uses and gratification
TRA	Theory of reasoned action
MM	Motivational model
IDT	Innovation diffusion theory
SPSS	Statistical product and service solution
Mturk	Mechanical turk
EFA	Exploratory factor analysis
CFA	Confirmatory factor analysis
AVE	Average variance extracted

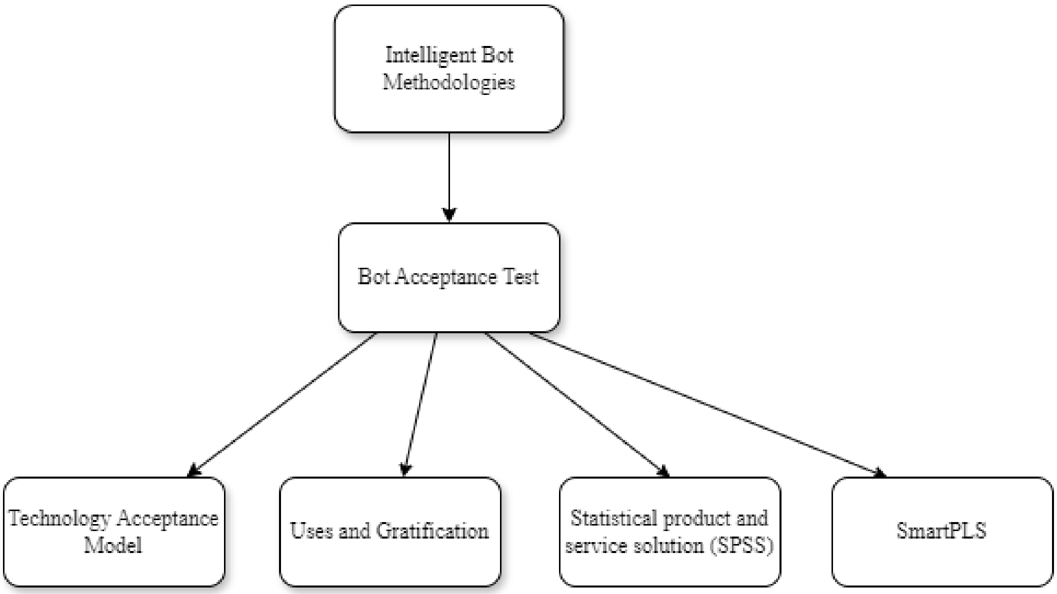

Figure 13: **Acceptance tests executed to measure the Intelligent bot performance**

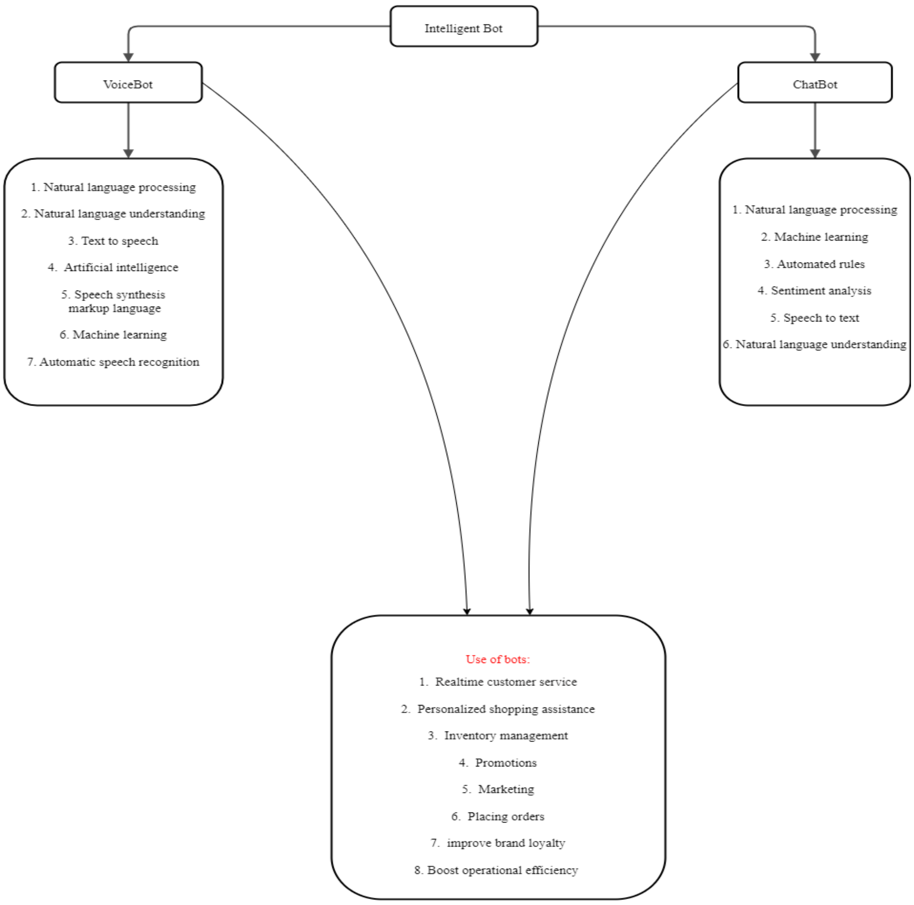

Figure 14: **Methods used in two sections of Intelligent bot and their use in retail industry**

Table 7.Information about the Data used in the papers related to Intelligent bot

Data List		
paper	Data Description	Bot type
M.A.Selamat et al. (2021)[62]	Study 1 contains data collected through interviewing SME consumers and buyers; Study 2 consists data collected from 315 SME customers	CHATBOT
Nursetyo A. et al.(2018)[63]	15129 data collected from Indonesian e-commerce restaurants	CHATBOT
Klaus P. et al.(2021)[69]	Gathering data by reviewing 53 academic and 65 managerial articles	Voicebot
Angeline R. et al.(2018)[64]	Used IOT and AI to collect data by sensing activities	CHATBOT
Ahmed S. et al. (2023)[42]	Collected daily sales data from a superstore	Voicebot
Zierau. N et al.(2022)[70]	Study 1: data collected from 184 participants Study 2: data collected from 612 participants Study 3: data collected from 610 participants Study 4: data collected from 811 participants	Voicebot
Rese A. et al.(2020)[72]	conducting a survey on 205 German millennials	Chatbot
Chen, J. S. et al.(2021)[66]	online survey using Amazon Mechanical Turk (Mturk)	Chatbot
Lo Presti L. et al(2021)[67]	Study on 184 Italian university students	Chatbot
Chung M. et al. (2020)[71]	Survey conducted on 161 Korean students from which 157 were complete and accepted in the end	Voicebot

Table 8. Brief Overview of the Methods used in different research for Intelligent Bot

Reference	Description	Models used	Year
Selamat et al.[62]	The study conducted two surveys. The first one is to decide the use features that should be included in the bot. The second survey identifies the influence of those features of chatbots on anthropomorphism and their impact on customer intention.	Conducting two surveys to find out the chatbot functions and the effects of those functions on customers	2021
Nursetyo et al.[63]	The research suggests an AIML-based e-commerce smart chatbot. The bot will receive the user input and process it in three stages: parsing, pattern recognition, and data crawling. The bot was tested on 300 users, where it showed 100% accuracy with a response rate of 3.4 seconds.	AIML	2018
Klaus et al.[69]	The paper used the MacInnis framework for making conceptual contributions of summarization, integration, and delineation. Later on, they submitted a new AIDM base model to update the traditional decision-making models in the market	AI influence decision-making model (AIDM) based on the MacInnis framework	2022
Aarthi et al.[68]	The paper used Python as the front-end language to develop the GUI and MySQL to develop the system's back-end. The processing of the user input takes place in the server using Recurrent Neural Networking and the output is generated	RNN	2020
Angeline et al.[64]	The customers will make an entry by scanning the QR code. Every aisle of the shop is monitored by cameras, which will help to recognize the products picked by the customer by capturing the unique key of the product and the customer's face. Chatbot will be there to help the customers with product details and their location in the shop	Chatbot using the chatterbot library on python	2018
Ahmed et al.[42]	The paper addresses the issue of communication in retail and proposes using a voicebot using NLP. The voicebot mainly participates in conversations with consumers and answers their questions.	Using NLP libraries like NLTK and POS tagging pyttsx3 local speech engine to convert text output into voice	2023
Zierau et al.[70]	The research organized four studies to understand the impacts of voice-based interfaces on customers. By computing different metrics values like FRE, ARI, and DCR, they calculated the impact on customer experience. & boost service outcomes	Four studies were conducted to test the impacts of voice bot on customers and firms	2022
Rese et al.[72]	The study measured the acceptance of text-based chatbot "Emma" by using TAM and U&G model to analyze the acceptance of voice base interfaces	Comparing TAM and u&g acceptance test results	2020
Dey et al.[65]	By assimilating different models used in various research, the researchers merged the overlapping constructs and dropped the constructs with limited relevance. They proposed 11 constructs as antecedents for their proposed framework.	Proposed an analytic framework and model for understanding the chatbot acceptance	2022
Chen et al.[66]	The research explores the usability and responsiveness of AI base chatbots through testing the reliability and validity using SPSS and SmartPLS	Analyzing the acceptance of AI Chatbots using Statistical product and service solutions (spss) and smartPls model	2021
Lo Presti et al.[67]	The paper investigated the role of chatbots on the perception of hedonic and utilitarian goods. It notices the hardness and the functionality of the products perceived by the customers before and after the experiment	Hedonic and utilitarian product experiments were conducted	2021
Chung et al.[71]	The study measures the customer satisfaction of Chatbot services in luxury brands by testing the reliability using the Composite reliability coefficient and AVE.	Five-dimensional model for measuring the customer perception of chatbot e-service	2020

2.4. Smart Transaction

The use of a smart transaction system in retail management can enhance security and make transactions hassle-free.

2.4.1. Research Article selection

To identify the relevant papers, a basic search was done on Google Scholars, which included the keywords "Smart Transactions for retail management," "Intelligent Transaction in the super shop," Smart transaction in the super shop," "Automated transaction system in retail," "Smart transaction using Artificial Intelligence, Machine Learning, and Deep Learning," "Digital payment system for retail." After executing the exclusion criteria, we selected ten papers for review. Figure. 15 describes the year-wise distribution of Smart transaction base papers.

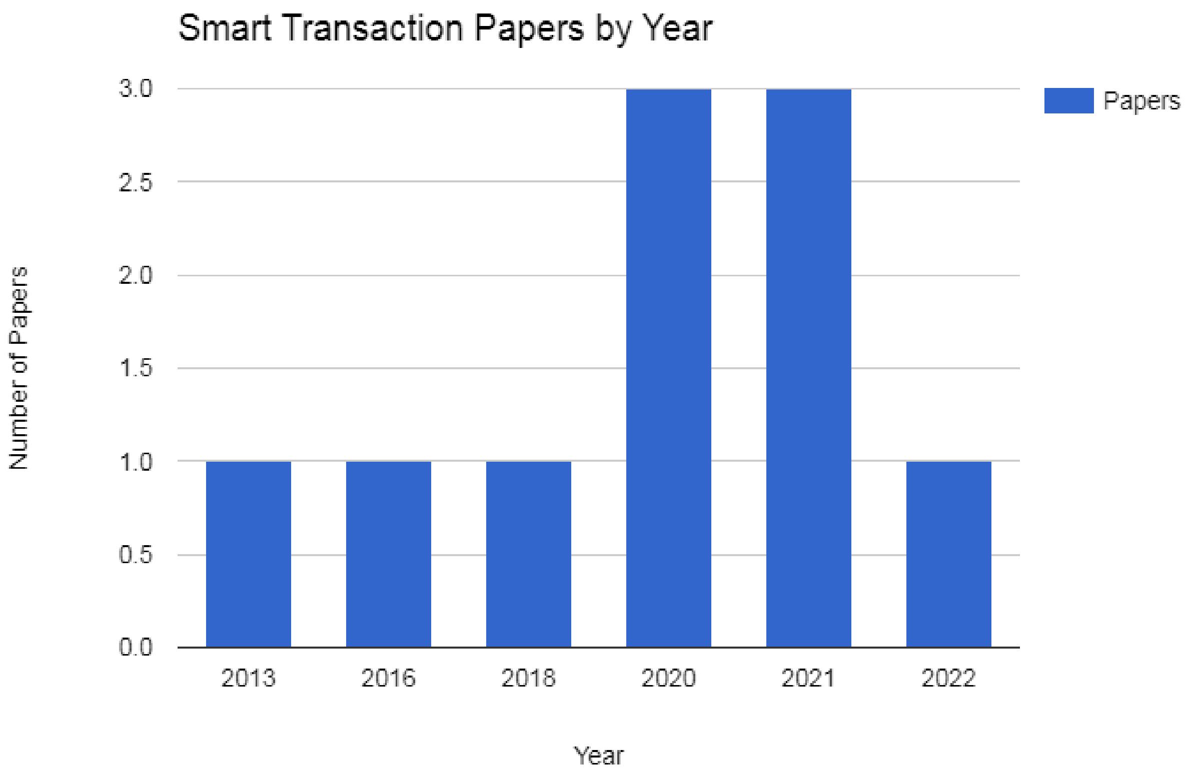

Figure 15: **Year-wise distribution of Selected Smart Transaction-based papers**

2.4.2. Context of the Smart Transaction system Research works

Smart transactions have become crucial to guarantee a safe and smooth transaction procedure and to maximize the client experience. According to Adapa et al., [73], lowering the perceived risk and complexity of smart retail technology can enhance customer experiences and raise the possibility of repeat business because of increased perceived value and store loyalty. The study presented in paper [74] highlights the significance of efficient technology integration by showing how intelligent interactions and systems in smart retail significantly impact customer engagement in transactional and non-transactional contexts. Kabir and Han offer a thorough usability evaluation model for point-of-sale (POS) systems in developing nations to improve transaction efficiency and overcome the shortcomings of existing assessment models. This model considers the multifunctionality and intricate interfaces of these systems [75]. Maitra et al. emphasize using comprehensive customer data and cutting-edge neural network applications to improve retail marketing strategies by using sophisticated soft computing techniques to assess an extensive retail dataset for customer lifetime value prediction. The study emphasizes the importance of isolating the variables that impact CLV and shows how soft computing may be used to create customized business solutions using easily accessible transaction data [76]. To improve customer convenience and shorten shopping times, the study in [77] suggests an IoT and Li-Fi-based application to optimize item positioning and supermarket payment options. To increase consumer traffic and sales volume, Paper [78] presents an AI and IoT-enhanced unstaffed retail shop system that uses an upgraded SSD algorithm for accurate goods detection. According to research [79], combining smart mirror fashion technology (SMFT) with conventional in-store procedures enhances customer happiness and service quality in the retail clothes industry. It offers a fresh foundation for improving in-store interactions. The research aids in creating a fresh framework that improves SMFT's integration with conventional in-store transaction procedures. Customer lifetime value positively influences the relationship between socio-technical stimuli and customer experiences. The study in [12] examines how WeChat mobile-payment technologies improve interactions and communication, enhancing the retail customer experience. An intelligent self-service vending system with extensive data management and settlement features that uses image recognition for non-barcode items is described in paper [80], emphasizing the system's high accuracy and efficiency in optimizing retail operations. The framework proposed in [81] utilizes NFC-enabled smartphones for seamless retail transactions, emphasizing the benefits of integrating advanced cryptographic technologies to enhance the security and efficiency of mobile payment systems.

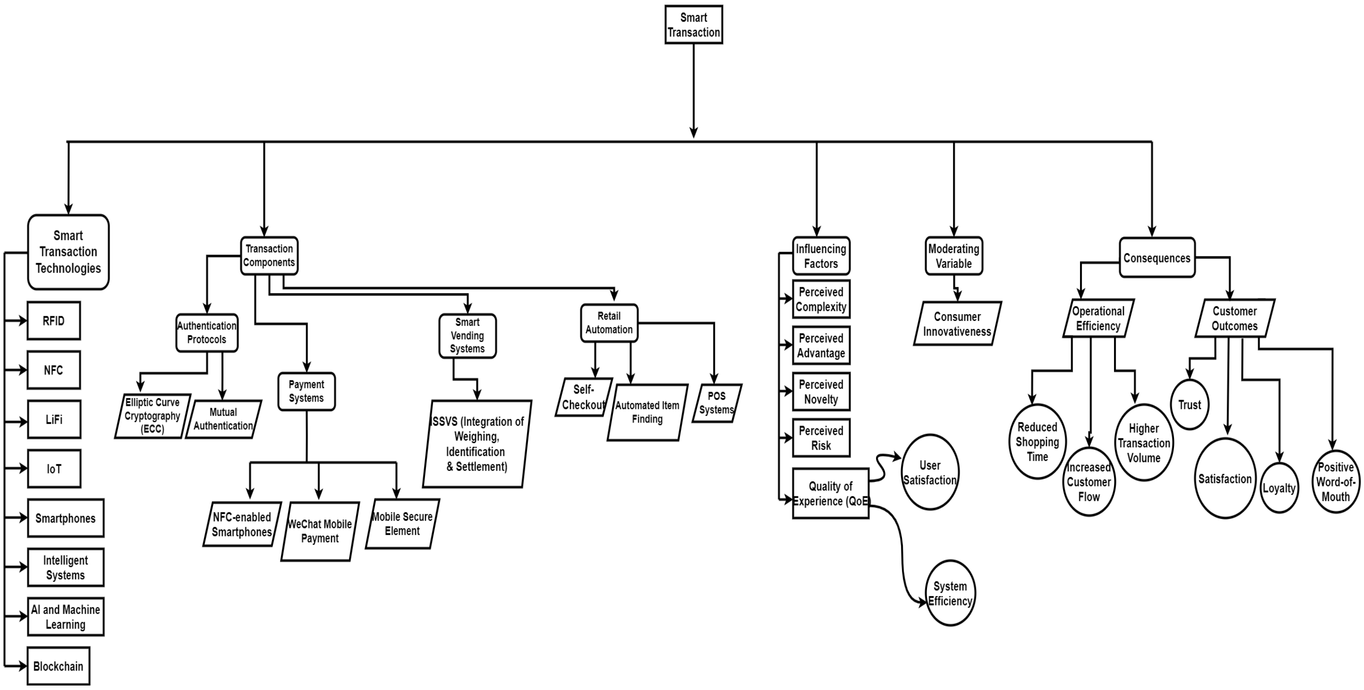

Figure 16: **Methods used in Smart Transaction**

Table 9: Some widely used Smart Transaction Features in different research works and their corresponding Mathematical Expressions

Feature name	**Mathematical Expressions**
i^{th} model M_i with p usability factors	$M_i = < f_{i1}, f_{i2}, ..., f_{ip} >$
Aggregate duplicated or similar factors from 10 models	$UF = RS((RD(M_1,M_2,.....,M_{10})))$
Customer Lifetime Value (CLV)	$CLV = \frac{\text{Margin}\times\text{Retention Rate}}{1+\text{Discount Rate}-\text{Retention Rate}}$
Min/Max Normalization	$x_{\text{new}} = \frac{x-x_{\text{min}}}{x_{\text{max}}-x_{\text{min}}}$
Variance of Weights (W)	$\text{Var}(W) = \frac{1}{n_{\text{in}}}$
Gradient Descent Update Rule	$\theta_j := \theta_j + \alpha \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right) x_j^{(i)} \quad \text{(for every } j\text{)}$
Mean Within Each Group	$\overline{Y}_i = \frac{1}{n} \sum_j Y_{ji}$
Grand Mean	$\overline{Y} = \frac{\sum_i \overline{Y}_i}{a}$
Sum of Squares Between Groups (SB)	$SB = \sum_{i=1}^{n} \left(\overline{Y}_i - \overline{Y}\right)^2$
Chi-Squared Test Statistic	$\chi^2 = \sum \frac{(\text{Observed}-\text{Expected})^2}{\text{Expected}}$
Two-Sample t-Test Statistic	$t = \frac{\overline{x}_1-\overline{x}_2}{\sqrt{\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}}}$
Detecting Nearest Coordinate	$(3959 \times \arccos\left(\cos(37) \times \cos(\text{lat}) \times \cos(\text{lng} - (-122)) + \sin(37) \times \sin(\text{lat})\right))$
Output voltage	$U_{OUT} = \left(\frac{R_1}{R_1+R_2} - \frac{R_4}{R_3+R_4}\right) U_{IN}$
Output voltage with resistance	$U_{OUT} = \left(\frac{R+\Delta R_1}{2R+\Delta R_1+\Delta R_2} - \frac{R+\Delta R_4}{2R+\Delta R_3+\Delta R_4}\right) U_{IN}$
Loss function	$L(x, c, a, b) = \frac{1}{N} \left(L_{conf}(x, c) + \gamma L_{loc}(x, a, b)\right)$
Readability	$d = \frac{Y}{2^{24}}$
Linearity	$\delta = \frac{\Delta Y_{max}}{Y} \times 100\%$
Elliptic Curve Point Multiplication	$P = sQ$
Authentication Step	$a_T = s_T Q_T Q_S + r_T s_T Q_S$
Authentication Step	$a_S = s_S Q_S Q_T + r_S s_S Q_T$
Sign-in Verification	$a_S s_T - r_S s_S P_T = P_S P_T$
Check-out Verification	$a_T s_S - r_T s_T P_S = P_T P_S$

Table 10: Brief Overview of the Methods Used in Different Research for Smart Transaction (Part-1)

Authors	Underlying Theory	Methods	Overview of Findings
Adapa et al. (2020)[73]	Consumer Behavior, Information Systems, and Relationship Marketing	Survey with 338 actual shoppers, Structural Equation Modeling	Smart Retail Technology enhances customer shopping value by reducing perceived transaction complexity and perceived risks while enhancing perceived novelty and advantages
Fan et al. (2020)[74]	Stimulus-Organism-Response framework	Two surveys with 201 and 321 respondents, analyzed using structural equation modeling.	The study finds that intelligent systems, human-machine interaction, and product content from the quality intelligent experience significantly impact customer engagement in smart retail. This engagement is mediated by the cognitive and emotional responses of customers, which in turn influences their loyalty and word-of-mouth behavior. However, the findings did not support the impact of self-service quality on customer engagement.
Kabir and Han (2016)[75]	Usability Models and Evaluation, Software Engineering	Integration of factors from ten well-known quality models; Design of usability scenarios and corresponding questionnaires; Survey with customers in Bangladesh	Developed an improved usability evaluation model for POS systems containing 12 comprehensive usability factors; Demonstrated effectiveness and comprehensive evaluation of POS system's usability from multiple aspects
Maitra et al. (2021)[76]	Customer Lifetime Value (CLV) Metrics, Neural Networks, Soft Computing	Exploratory Data Analysis, PostgreSQL, TensorFlow-coded Neural Networks, Statistical Inference	A classifier was developed to predict customers' CLV in digital retail based on their purchasing tendencies. This involved mining customer data to create input features for a TensorFlow-coded neural network that predicted profitability ranges. Statistical inference was used to validate features. The research provides methods for both predicting and amplifying CLV through data mining and soft computing
Akter et al. (2018)[77]	LiFi and IoT in Retail, Smart Shopping Assistance	Internet of Things (IoT), Li-Fi technology, mobile and web application development, database design, location-based services, barcode scanning, octree algorithm for cashier interface	Proposed a Li-Fi and IoT based application enhancing the shopping experience by assisting in item finding, price checking, and expedited checkout to save customer's time.
Xu et al. (2020)[78]	IoT, Artificial Intelligence	Enhanced SSD (Single Shot Multibox Detector) model for product detection in unstaffed retail shops, training with a dataset of 18,000 images from different scenarios	The enhanced SSD model showed a mean average precision of 96.1% for product detection, demonstrating the feasibility and efficiency of AI and IoT in improving unstaffed retail shop operations.
Ogunjimi et al. (2021)[79]	The transformative effect of technology on the retail industry and service quality improvement using innovative technology like smart mirror fashion technology (SMFT)	Qualitative approach with Soft System Methodology (SSM) based on interviews, observations, and field notes, focusing on the top five UK clothing retail chains	The use of SMFT in retail settings enhances service quality and influences customer satisfaction, offering a positive relationship between service quality and the use of SMFT. This results in better managerial practices and improvements in service delivery in offline clothing retail service providers

Table 10: Brief Overview of the Methods Used in Different Research for Smart Transaction (Part-2)

Authors	Underlying Theory	Methods	Overview of Findings
Sun et al. (2022)[12]	Stimulus-Organism-Response (SOR) Paradigm, Socio-technical Systems	Survey and data analysis based on 462 WeChat mobile-payment retail customers.	WeChat mobile-payment-based smart retail technology enhances the customer experience by improving perceived relationship orientation, employee-customer interaction, and communication effectiveness. Customer Lifetime Value (CLV) positively moderates the relationship between socio-technical stimuli and customer experience.
Xia et al. (2021)[80]	Smart Retail; IoT; Deep Learning	Integrated self-service vending system with real-time object detection and weight data acquisition; use of MobileNet-SSD for product detection; application of TIDL on TI devices for efficient processing.	The system demonstrated high accuracy in identifying non-barcode items with a deep learning model. Real-time integration of weight identification and online settlement was achieved, enhancing the efficiency and convenience of retail transactions.
Urien and Piramuthu (2013)[81]	NFC, RFID, Public Key Infrastructure	Proposes a transaction system using NFC-enabled smartphones and mutual authentication protocols between customer and store system.	Designed protocols to enable secure and efficient automated checkout in retail environments through mutual authentication between smartphones and retail systems, using elliptic curve cryptography for improved security and efficiency in resource-constrained devices like RFID tags and smartphones.

2.5. Use of Blockchain in retail

Blockchain technology is getting widely adopted. Including it in retail will make the system more transparent and help it gain more acceptance.

2.5.1. Research Article selection

To identify the relevant papers, a basic search was done in major data banks using the following keywords: “Blockchain for retail management,” "Blockchain in supply chain management," "Blockchain and supermarket management," "Blockchain in retail," and “Blockchain for supermarket management.” After executing the evaluation method, we selected a total of 8 papers for review. Figure. 17 describes the year-wise distribution of Blockchain base papers.

2.5.2. Context of the Blockchain base Research works

Blockchain in the retail sector has opened the gate of revolution, which can help us introduce a modern system that benefits all the parties involved in this sector. The retail industry has a huge scope for improvement, and blockchain can improve multiple sectors of this industry. Keeping all the challenges and market trends in mind, Chakrabarti A. et al.(2017)[82] have discussed the potential use of this technology in retail sectors. The paper explains the working process of blockchain technology, its existing use in retail, and the challenges that can be faced while implementing it. The paper mentions its use in storing different sorts of data like personal and package or shipment information and how storing data in this technology ensures transparency, which is a key part that ensures both customers and retailers get to know the key information of a package. Talking about the safety measures of blockchain technology, they highlight how the data is stored in different blocks and connected in a chain system. Still, to ensure safety measures, it is stored on different computers, which ensures that anybody can access the main copy, and the technology also ensures that nobody can temper the data. All the old data is preserved forever with new transaction data. Improve the existing business blockchain can provide different business growth processes like 1. improving the supply chain process by keeping track of shipments in real-time and identifying damaged items 2. building a data warehouse that can store customer information and use those to identify customers product buying and payment patterns, which can help the retailers to forecast area wise demand and enhance inventory management 3. Using blockchain technology in the payment system can help us to handle fraudulent monetary transactions 4. Transparency in data collection helps retailers and

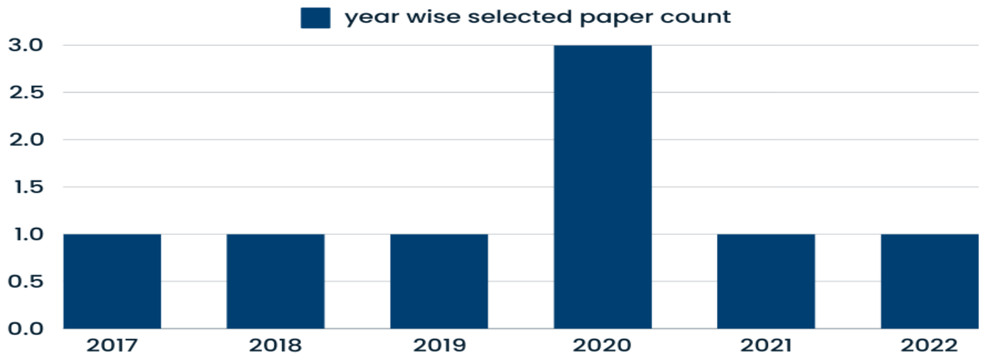

Figure 17: **Year-wise distribution of Selected Blockchain base papers**

consumers know every detail about the product and identify unethical practices 5. The technology can validate product authenticity and gain customer confidence by ensuring product quality. In 2016, blockchain technology was revealed as a more disruptive technology to the retail industry than any other industry, which clearly shows the impact and potential of this technology in the retail sector. Medida R.S.S. (2020)[83] have also highlighted the potential benefits of using blockchain technology from the perspective of both customers and retailers. The technology is a great way to manage customer data, security, and sharing. Discussing blockchain technology and its purpose, the author mentions how it provides a decentralized digital database, a distributed ledger. The paper talks about the six steps of asset exchange using blockchain: 1. Proposal for a hashed transaction, which includes basic information such as date, time of transaction, and sender and receiver 2.Transmission to a network of distributed processing and authentication computers 3. Machines process and authenticate the transaction 4. The transaction was added to the ledger 5. Authentication and completion of credit transfer between two parties 6. Creation of a complete, permanent, and verifiable history of all transfers. Two types of blockchains were discussed in the paper based on access type 1. Private blockchain, which allows governing individuals to access the ledger 2. Public blockchain. which allows everyone to communicate with another party involved in the transaction. In the application section, the writer talks about points like 1. Stopping retail fraud and counterfeiters 2. Governing the products across the supply chain to find out the product's origins will help to stop counterfeiters 3. Using cryptocurrency payment methods to switch the revenue source and attract more customers worldwide 4. Designing new loyalty programs using Blockchain technology. Though technology is a massive inclusion in the retail sector, there are still many steps that have to be taken as it continues to grow. There is a need for blockchain developers who can fasten the implementation of this technology.Bhatkar et al. (2018) [84] have emphasized the need for data monetization in different industries using blockchain. Through collecting customer transaction data, the authors have worked to categorize the data using blockchain based on different criteria. They have worked on a blockchain system that can handle season-wise sales data by ensuring transparency and immutability. Moreover, they have used predictive analysis to understand customer behavior and to set the price of products, which keeps fluctuating by keeping all the possible factors in mind. The reason for using predictive analysis is that it works more accurately in forecasting brand-new customers' buying habits. The paper explores potential benefits, such as improved customer profiling and improved inventory management through blockchain in the retail industry. As a benefit of using blockchain in the retail sector, they have highlighted points like minimizing managerial and security risks, identifying detailed customer usage data, and uncovering new opportunities for monetization in this part of the industry. The use of blockchain in storing transaction data is a very transparent technique; every time a customer processes a transaction, it is stored in the blockchain as a new block, which contains all the important information about the collected data like the sender, amount of data exchanged, etc. Every block created with the transactions has a unique hash ID, which not only helps us differentiate one block from another but is also a big security part of the blockchain that helps prevent unauthorized changes to the data. As the data is sorted sequentially, it creates a chain of blocks representing the entire transaction history, ensuring us a way to verify and audit the data easily. Please see Figure 18.

Miraz M.H. et al. (2020)[85] have analyzed the implementation of blockchain in the Malaysian retail market to improve the customer experience. The authors have focused on improving the transaction policy, management, adaption, and implication and proposed a theoretical framework related to blockchain. To conduct the study, the researchers collected data from individual customers and retail persons, where the population was

Figure 18: **Top level overview of the conducted research[84]**

around 4335. Through systematic sampling, approximately 512 responses were selected. The study includes data analytical tools like SPSS V23 for pilot testing and smart PLS 2.0 for predicting the complex structural model. The research includes a 5-point Likert scale to access the variables related to blockchain implementation, and the study used UTAUT2 combined with Transaction cost theory to analyze the blockchain factors and their impact on the retail market. The result was displayed in three tables: fornell-larker criterion of discriminant validity, HTMT ratio of discriminant validity, and VIF. The study acknowledges a need for more awareness and knowledge about blockchain technology to maximize its use in the retail industry. Latif R.M.A et al.(2020)[86] in their research have worked to address the product traceability problem of the supply chain using a community traceability network built with blockchain. They have suggested storing all the commodity details history in a global database through smart contacts and building a chain system that will help trace back the goods' source. To do this, they have collected all the data about the stock-keeping unit and added them to the blockchain to represent the products. Incorporating these data with user login forms, transaction logs, and QR scan codes made the product information accessible to the customers. Every participant in the system business, as well as customer and supply chain regulators, has an Ethereum account, which serves as their identity in the system and allows them to execute the smart contact system. Blockchain technology ensures a secure and transparent way to record and verify transactions, which increases trust and eliminates the third party to validate the transactions. Using blockchain in retail will give us the advantage in supply chain authenticity, anti-counterfeiting, consumer profiling, loyalty programs, and tracking product manufacturing history. Truffle, a smart contract creation platform specially designed for Ethereum, is used to build the commodity traceability network proposed in the paper. Comparing the blockchain-based traceability method with the existing method shows that the blockchain-based system proposed by the authors outperforms the other schemes. Kurdi, B. et al. (2022)[87] collected data from 700 participants through a survey. Of them, 303 participants' data was selected using the cluster sampling technique to understand the impact of blockchain and smart inventory systems on supply chain performance. The survey was conducted on employees working in retail companies in the UAE, and a quantitative technique with cluster sampling was used to collect and analyze the data. The online questionnaire contained a total of 27 items, out of which nine were used to measure blockchain impact, ten were used for smart inventory analysis, and 8 were used for supply chain analysis. The participants rated the items with a five-point Likert scale. The collected data was used for reliability analysis to measure the validity of data, regression & hypothesis testing was done using ANOVA, and Cronbach's alpha was used for analyzing the reliability of constructs. The study suggests that the retail sector can use blockchain to make a position in the market but to do so, they need to focus on the quality of their products, services, and supply chain. Li, M. et al.(2020)[88] in their paper proposed a blockchain-enabled logistic execution platform to execute logistic financing for E-commerce retail. Discussing all the challenges small and medium enterprises face in acquiring capital from logistic finances, the paper proposed the model using a cross-layered architecture, hybrid finite state machine-based smart contract (HFSM-SC), and blockchain-enabled multi-agent system. The HFSM-SC model was used to associate and coordinate with agents involved in Logistic finance (LF) operations. They integrated blockchain technology with agent technology to execute smart contracts more effectively and created a blockchain-enabled multi-agent system (BcMAS). A case study was done to verify the proposed BcLFEP model and demonstrate its application. The model comprises 13 key steps classified into three phases: LF application, assessment, and inspection. In the first step, the e-commerce retailers raised the LF application with financial institutions in BcLFEP. Financial institutions assess these applications using their rules in the second step. In the final step, LF inspection includes the retailers paying the deposits, the supplier preparing the goods, the 3PL performing receiving and warehousing operations, and the financial institution issuing loan capital. The case study demonstrates the effectiveness of BcLFEP-enabled dynamic pledged management in retail. Liu et al.(2019)[9] proposed an anonymous reputation system for IIoT-enabled retail marketing to preserve customer identity and encourage the customer to write more feedback. The system uses cryptographic primitives and a Proof-of-Stake consensus protocol to ensure privacy. The blockchain-based ARS-PS system guarantees system transparency, and the system's feasibility is proved through a proof of concept implementation based on parity Ethereum.

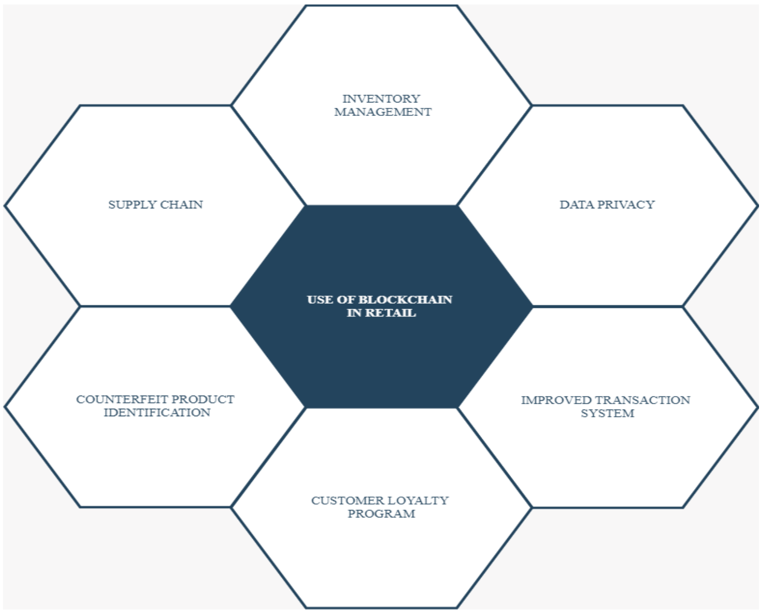

Figure 19: **The potential uses of blockchain technology in retail management**

Table 11. Brief Overview of the Methods and Data used in different research for Blockchain

paper	Data description	Method
Bhatkar et al.(2018)[84]	Customer transaction data	used predictive analysis to understand the customer behavior and for setting the price of products which keep fluctuating
Miraz M.H. et al. (2020)[85]	Conducting a study on 512 individual customers and retailers in malaysia	Used Statistical Package for Social Science (SPSS v23) for pilot testing and the smart Partial Least Squares 2.0 for predicting the complex structural model
Chakrabarti A. et al.(2017)[82]	Not specified	Analyses the potential use of blockchain technology in retail
Medida R. S. S. et al.[83] (2020)	Not specified	The paper talks about the six steps of asset exchange using blockchain
Latif R. M. A. et al.(2021)[86]	Not specified	Uses the truffle development platform to build a commodity traceability network using blockchain technology. It works to create a smart contract system and uses distributed ledger technology to store the transactions.
Kurdi, B. et al. (2022)[87]	Collected data through a survey from 303 employees working in retail companies in UAE	The research used quantitative data analysis and collection techniques. Reliability analysis to measure the validity of data, regression & hypothesis testing was done using ANOVA, and Cronbach's alpha was used for analyzing the reliability of constructs
Li, M. et al.(2020)[88]	Not specified	Proposed a blockchain-enabled logistics finance execution platform(BcLFEP) to execute logistic financing for E-commerce retail
Liu et al.(2019)[9]	Not specified	Designed a blockchain-based reputation Anonymous reputation system using cryptographic primitives and proof of stake consensus protocol which can help customers to write product reviews without disclosing their identity

2.6. Queue management in retail

Queue management technology in retail can be a revolutionary inclusion as it will help retailers manage big crowds smartly using modern technology.

2.6.1. Research Article selection

For the selection articles, we searched the internet for papers related to queue management. Relevant keywords like "Queue management in the super shop," "Retail queue management," "Queue management strategies in retail," "Improvement of queue management in the super shop," "Improving queue management strategies in retail," "Customer waiting time management in retail" are used to look for papers. After executing the selection mechanism, we selected nine papers for review. Figure.20 describes the year-wise distribution of Queue management base papers.

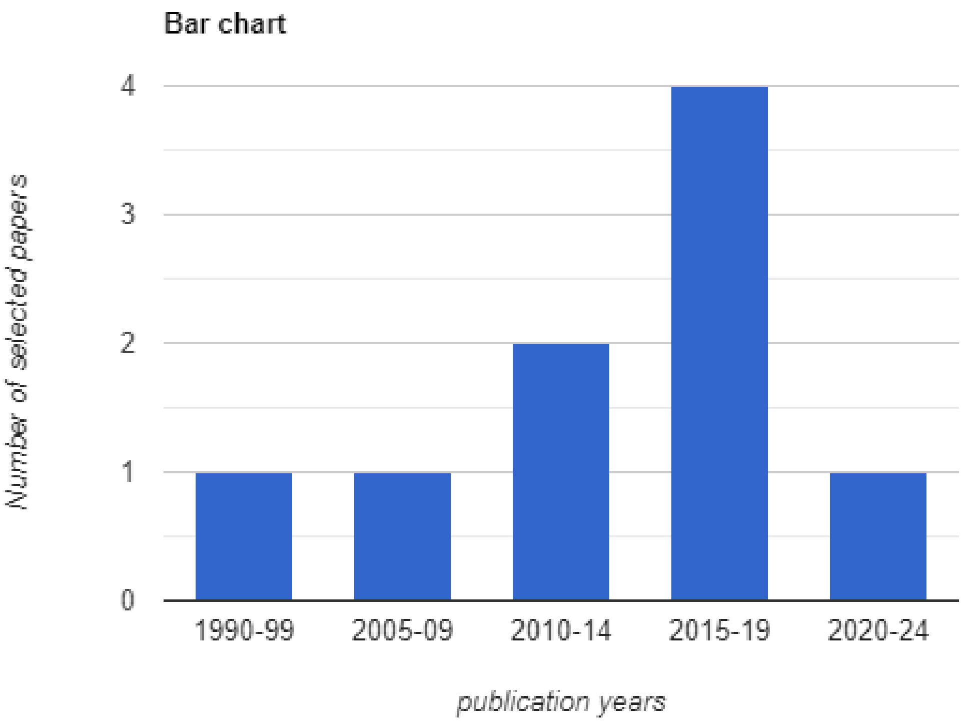

Figure 20: **Year-wise distribution of Selected Queue management papers**

2.6.2. Context of the Queue management Research works

This study[89] uses queuing theory to examine the sales checkout service unit at Alankulama Supermarket using empirical data. The primary goal is to create a mathematical model to analyze the performance of the checkout service unit, taking into account parameters such as service rate and time between customer arrivals. The study uses data from the supermarket, such as customer arrival times and service duration, to develop a queuing model with five servers and queues. The efficiency of queueing models in terms of application and waiting length. The study aims to improve client service by expanding the number of queues while lowering waiting times during peak server loads. The primary goal is to estimate waiting times and queue lengths in the supermarket checkout operation. Empirical data, such as arrival time in the queue, departure time, and service time, is gathered using a specially designed questionnaire soliciting customer feedback. In their investigation, they compared the average of the queueing model. There are three methods for estimating queue length: single-queue multi-server, single-queue single-server, and multiple-queue multi-server. All results are determined on a First Come, First Served (FCFS) basis. The supermarket may have multiple units that perform the same checkout procedure, each with a single employee. They developed this model using the Markovian exponential distribution of inter-arrival times and the Markovian exponential distribution of service times. There are no predefined formulas for networked queues, that is, multiple queues. The complexity of the model is the primary reason for this. So, they adopted notations and formulas for a single queue with parallel servers. To estimate performance for multiple queues and servers, WinQSB simulation software is used to generate sample results. They used a Monte Carlo simulation for the estimation. Regarding performance analysis, queuing model 2 (multi-queue multi-server) outperforms model 1(single-queue multi-server). A queuing model with a single queue and multiple parallel servers does not provide precise performance evaluations for each server. The utilization factor for both servers varies across assessments. Model 1 is 89%, while Model 2 is 99%.In server 2, each customer must wait 15.67 minutes if there are 40 customers in a queue, whereas in server 1, each customer must wait 21.87 minutes if there are 31 customers in a queue to be served. The study [90] examines how waiting in line at a

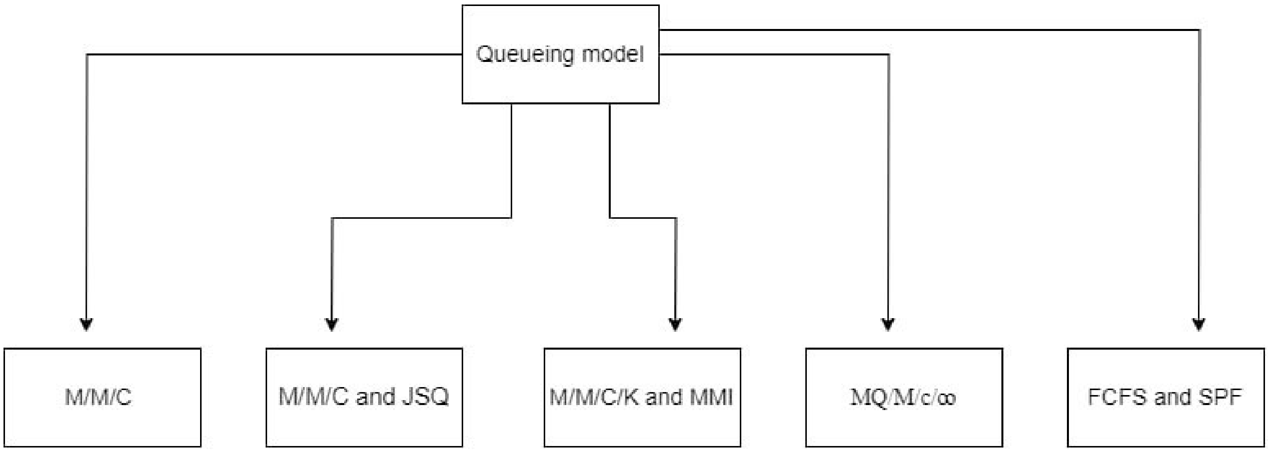

Figure 21: **Queueing methods used in retail queue management**

retail store affects customer purchasing behaviour using a novel dataset combining video recognition technology and point-of-sale information. The findings show that waiting in line nonlinearly affects purchase decisions, with customers prioritizing queue length over speed. Consolidating queues may result in longer perceived waiting times and lower revenue. Additionally, customer sensitivity to waiting varies, which influences pricing strategies. The paper examines the significance of capacity management in service operations and attempts to quantify the impact of service levels on customer purchases. Unlike previous research, this study employs objective measures of actual service to provide insights for managing service facilities and addressing issues such as reverse causality and missing data. Empirical analysis shows that queue length significantly impacts purchase incidence, with customer sensitivity to waiting being inversely correlated with price sensitivity, influencing pricing decisions in congested environments. Over the course of seven months, the researchers conducted a pilot study in the deli section of a supercenter in a significant Latin American metropolitan area, tracking queuing dynamics and point-of-sale data using digital snapshots analyzed by image recognition technology. They observed peak traffic hours on weekdays and weekends, with congestion resulting in a positive correlation between aggregate sales and queue length. To address this, we used detailed customer transaction data, including a loyalty program that matches 60% of transactions with customer identification numbers. The analysis focused on grocery purchases made by loyalty card customers who visited the store at least once a month, totaling 284,709 transactions from 13,103 customers. The methodology used in this study is a logit regression model estimated using maximum likelihood methods to examine the impact of queue state on customer purchase incidence. In addition, Bayesian methods are used to estimate parameters. The methodology also includes better-estimating transition probability matrices to better understand customer behavior dynamics in the queue. Data collection entails taking digital snapshots with image recognition technology and tracking the number of people waiting in a supercenter's deli section. A rigorous approach is developed to address the challenges posed by missing data in periodic snapshot information. This approach allows for the inference of missing data, emphasizing addressing issues of reverse causality and missing data, thereby ensuring the analysis's robustness. The study addresses the difficulty of gathering objective data on waiting times and customer service measures by creating an econometric technique based on queuing theory. The study found that queue duration had a more significant impact on consumer decisions than server count, which has implications for queue management and service design. It also investigates consumer segmentation based on waiting and price sensitivity, emphasizing the importance of considering customer heterogeneity when making pricing decisions in the face of congestion effects. As a result, it discovered that waiting in a queue has a nonlinear impact on consumer purchase incidence, with customers prioritizing the length of the queue over the speed at which the line advances. The paper identifies that merging different lines into a single queue might increase the observed queue length, resulting in lower profits. The study also found that customers' sensitivity to waiting varies and is adversely connected with price sensitivity, which has ramifications for pricing strategies in congested multi-product categories. Limitations and potential extensions for future study are highlighted, focusing on integrating approaches from operations management and marketing better to understand the relationship between queues and customer behavior.

This paper [91] explores the frequency of waiting for lines or queues in various organizations, notably those focused on profit, such as petrol stations, supermarkets, clinics, hospitals, and manufacturing enterprises. It emphasizes the significance of measuring system performance using average service rate, system utilization, and expenses. The study examines efficient queue management in Nigeria, specifically in Makurdi, using the "M/M/I" model since it is simple and relevant to the researched firms. The investigation uncovers deficiencies in queue management in Makurdi, leading to recommendations for addressing these difficulties, which may be applied to comparable challenges in other developing countries. The research uses the "M/M/I" queuing model to examine queue management in Makurdi. The paper draws on data from a case study conducted in Makurdi, Nigeria, concentrating on waiting activities in supermarkets in the area. It also examines queue management in selected enterprises, including the City Company, Nobis Ltd, Dobbiac, and Eke Ltd. The analysis includes system performance metrics such as average service rate, system utilization, and the expenses associated with a specific capacity level. The paper also addresses the costs associated with the queuing process, the primary actors involved in waiting lines, and the queuing framework in general. The queue simulation technique generates approximated solutions and analyses the queuing system. The paper discusses the "M/M/I" model, which illustrates a queuing system with a Markovian exponential distribution of inter-arrival times, service times, and a specified number of servers. The paper employs several queuing models, including the MMcK model, which reflects a Markovian exponential distribution of inter-arrival times, service times, and a defined number of servers. The first M represents the Markovian exponential distribution of inter-arrival times, the second M represents the Markovian exponential distribution of service times, c is the number of servers, and K denotes the number of consumers in the queuing system. The paper also goes over the fundamental queuing process, which includes the formation of consumers by an input source, providing the needed service by the service mechanism, and exiting customers from the queuing system. The investigation finds that queue management in Makurdi, Nigeria, is generally poor, inefficient, and ineffective. The data gathered from direct observations in four supermarkets in Makurdi town demonstrate that the mean arrival and mean service rates vary between the stores. Last but not least, The City Company Ltd had the highest mean arrival and mean service rates, possibly due to its strategic location. Nobis Ltd and Dobbiac Ltd had lower mean arrival and service rates. Eke Ltd, which is relatively hidden from the railway, had the lowest mean arrival and service rates scores. The paper[92] explores retrial queues of the $|MQ/M/c/\infty|$ type, where the number of repeated calls determines the input flow rate, and each call is granted just one retry attempt. If a call's retry attempt fails, it quits the system without providing service. The research investigates the prerequisites for a stationary regime and provides a vector matrix of stationary probability for the service process. It uses an approximation method and a limited transition to the model. It also provides a threshold approach for controlling the input flow rate and solves a multi-criterion optimization problem to identify the optimal control strategy, using quality functionals based on stationary probability. The research focuses on analyzing and optimizing multi-channel queuing systems with a single retail attempt, utilizing mathematical models and algorithms. The work is mainly based on mathematical modeling and analysis rather than empirical data. The work formulates a multi-criterion optimization problem to identify the optimal control strategy, with quality functionals represented by stationary probabilities. As a result, the method of linear convolution is used as the primary way to solve the multi-criteria problem. The writers consider economic aspects and seek to identify the best control method that maximizes earnings while minimizing costs. The methods employed in this work primarily involve mathematical modeling, analysis, optimization, and the linear convolution approach to determine the optimal control strategy for the examined queuing systems. The paper's findings provide light on optimizing multi-channel queuing systems with a single retail effort, thereby adding to the field of decision sciences. Finally, the research emphasizes optimizing the control strategy in retrial queues and presents a mathematical framework for analyzing and solving such systems. This paper [93] outlines constructing a computer simulation model to improve the queue

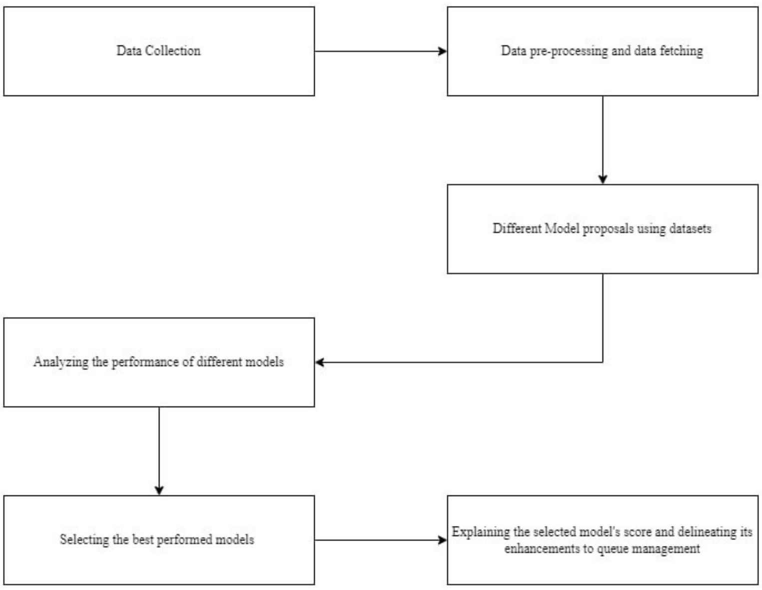

Figure 22: **Top level overview of all the queue management base reviewed publications**

system at a hypermarket using Discrete Event Simulation (DES). Data from Hypermarket A were collected via time studies, and Arena Simulation Software was used to generate a model of the actual system. Three scenarios were examined, and the most efficient queuing system was established using scenario analysis, resulting in a potential 26% improvement in customer waiting time (equal to 5.24 minutes). This study contributes to a better understanding of queuing system performance and suggests improvements to overall efficiency. The data obtained included information on the number of customers queuing and the time it took for each consumer to finish purchasing at the checkout system. Data was gathered from Hypermarket A through time study, observation, and interviews. The correctness of the data was critical in ensuring the legitimacy of the conclusions. The obtained data was utilized to create a computer simulation model utilizing Arena simulation software that replicated the hypermarket's actual queue system. The simulation model enabled scenario analysis and system performance evaluation, resulting in the selection of the most efficient queuing system. In terms of methodology, the study used a computer simulation model constructed with Discrete Event Simulation (DES) and Arena simulation software to reproduce the hypermarket's actual queue system. The simulation model enabled scenario analysis and evaluation of the system's performance. Three scenarios were examined, and the alternatives were graded according to the efficiency of the system performance. The proposed enhancements to the queuing system reduced client wait times by up to 26%, or 5.24 minutes. The simulation model was validated by comparing its behavior to the actual system using metrics like Mean Absolute Percentage Error (MAPE). The study attempted to increase customer happiness by improving service performance, which was assessed using a simulation model. The paper [94] explores the relevance of queue management in shaping consumers' perception of service quality at a multinational industrial gas and welding company's retail outlets. While earlier studies on queuing theory have been focused on fast-moving consumer goods (FMCG) retailing, this study investigates customers' views of inefficient queue management and service delivery in an industrial retail scenario. Based on empirical data, the notion that customers encountered service inefficiencies due to system limits was refuted, but other issues with service efficiency and customer relationship management were highlighted. The paper proposes a model for tackling these difficulties in an industrial retail setting. The study is based on internal and external empirical findings to analyze consumer perceptions of queue management and service delivery in an industrial, retail environment. It also used an open-ended questionnaire circulated internally to firm personnel to collect qualitative data on the proposed problem areas in customer service. The study centered on customer impressions of service quality and queue management in an industrial company, specifically the South African division of a global industrial gases and welding company. The researchers also examined external studies to identify potential problem areas and managerial implications for service efficiency and client retention. The researchers use the Customer Value Management (CVM) methodology, which has been customized to match the South African environment based on feedback from internal interviews at Company X. The CVM approach analyzed various constructs, including customers' total value assessments. The researchers used an open-ended questionnaire disseminated internally among firm personnel to collect qualitative data on the indicated customer service problem areas. Internal and external empirical findings were used to study consumer views of queue management and service performance in an industrial retail scenario. The idea that customers suffered service inefficiencies due to system limits was rejected based on internal and external empirical findings. Several other issues with service efficiency and customer relationship management in industrial retail were found. In addition, the researchers proposed a paradigm for addressing these issues. The study [95] attempts to build an Automated Queue Management System to manage client flow in diverse service environments, focusing on banks. It investigates several queueing techniques used by banks to lower average waiting times. The system uses an Intel Galileo Microcontroller to control processes and has been tested to determine its performance under various scenarios. The study analyses multiple queuing algorithm approaches banks use to serve clients and determines the average waiting time. It also implements a queuing architecture model capable of switching between alternative scheduling algorithms based on average waiting time testing results. The Intel Galileo Microcontroller, which is software-compatible with the Arduino software development environment, is also utilized to control the queue system. They also analyze the system's performance under various scenarios to determine its effectiveness. The technology seeks to increase service providers' efficiency and productivity by automating the queue management process and making intelligent selections about which customers to serve first. The system's performance was assessed under various scenarios to determine its effectiveness. This study [96] explores the impact of queues on customers' experiences in retail contexts, specifically how customers are affected when others queue behind them. According to Social Impact Theory, customers feel pressured by individuals waiting behind them, resulting in bad experiences, less engagement in co-creation settings, and lower service quality evaluations. Field and experimental investigations validate these expectations, demonstrating that queue length and client waiting time influence their experience. Strategies for mitigating negative effects include comforting consumers and removing waiting customers from their line of sight. The study contains five fields and controlled experimental investigations to evaluate the predictions and investigate the influence of lineups on customers utilizing a retail service. The investigations entail observing customers standing in line at a checkout in a crowded supermarket in a major German city, with queue lengths ranging from zero to fourteen persons. The information gathered includes measurements of client experiences, perceptions of social pressure, emotive experiences, and perceptions of service quality. Using seven-point measures, the researchers adapt questions from prior studies to assess the negative effects reported by clients. Manipulation checks are performed to ensure that participants accurately record the number of individuals waiting in line behind them.

The researchers investigate techniques for mitigating the negative consequences of waiting lines, such as verbally reassuring the focal client and shifting waiting customers out of the line of sight. According to the research findings, the customer's experience deteriorates when line length increases, resulting in more unpleasant affective experiences, decreased engagement in co-creation settings, and reduced service quality evaluations. Perceptions of social pressure influence this effect. The impact of delays on clients is mitigated by their own waiting time. When customers' waiting times decrease, lineups forming behind them have a more significant impact. The study also suggests two ways for mitigating the adverse effects of waiting lines: directly reassuring the focal customer that they are not under any pressure to be efficient and removing waiting consumers from the focal customer's line of vision. Manipulation tests demonstrate that participants accurately identified the number of individuals waiting in line behind them. This supports the validity of the experimental setting.

This paper [97] explores the universal difficulty of lines in consumer interactions across many industries, such as hospitals, contact centers, and retail outlets. It emphasizes that customers dislike waiting and refers to past queue management research. The essay seeks to improve this understanding by introducing a taxonomy of how service managers can influence customers' perceptions of waiting. It categorizes queue factors as totally controllable, moderately controllable, or beyond the firm's control and then provides queue management solutions based on these classifications. It also emphasizes the queue's impact on the customer's overall satisfaction with the service experience and future behavior toward return visits. The report also emphasizes the importance of contact personnel training and good service recovery behaviors in controlling customer perceptions and decreasing employee stress. The study discusses conceptual frameworks, empirical findings, and recommendations based on prior research and literature. The authors examine the relationship between customer satisfaction, waiting time, and perception, employing a qualitative and subjective method to uncover elements influencing customer satisfaction while waiting. The report proposes that contact people be appropriately trained to handle angry customers and reduce employee stress successfully. It implies that improving actual service performance and managing customer expectations are critical to managing lines and increasing customer satisfaction. It emphasizes how the queuing experience can affect total customer satisfaction with the entire service experience and future customer behavior.

TABLE 12. Some widely used Queue Management Features in different research works and their Mathematical Expressions

Authors	Expressions
Priyangika et al. [89]	$L_s = L_q + \frac{\lambda}{\mu}$, $W_q = \frac{L_q}{\lambda}$,$W_s = \frac{L_s}{\lambda}$
Y Lu et al. [90]	$$E(Y_t \mid \{X_r\}_{r \leq t}) = \sum_{s=0}^{6} X_{t-s}\theta_s$$, $$Y_t = \sum_{s=0}^{6} X_{t-s}\theta_s + u_t$$
Igwe et al. [91]	$L_q = \frac{\lambda_2}{\mu(\mu-\lambda)}$, $L = \frac{\lambda_2}{\mu-\lambda}$, $W_q = \frac{\lambda}{\mu(\mu-\lambda)}$, $W = \frac{1}{\mu-\lambda}$, $P = \frac{\lambda}{\mu}$, $P_n = (1-\frac{\mu}{\lambda})\left(\frac{\mu}{\lambda}\right)^n$
Pryshchepa et al. [92]	$$L_{k+1}(H) = h_1 \sum_{j=0}^{H_1} \pi_{cj}(H) + h_2 \sum_{j=H_1+1}^{H_1} \pi_{cj}(H) + \ldots + h_k \sum_{j=h_{k-1}+1}^{\infty} \pi_{cj}(H)$$
Mohamad et al. [93]	$$\text{MAPE} = \sum \frac{\lvert X_m - X_d \rvert}{X_d} \times 100\%$$
Garnett et al. [94]	N/A
Uddin et al.[95]	$$CWT_{\rceil} = \text{SSTC}\, AWT = \frac{\sum CWT_i}{TN}$$
Dahm et al. [96]	N/A
Davis et al.[97]	N/A

Table 13: **Brief Overview of the Methods used in different research for Queue management (Part-1)**

Authors	**Theory**	**Datasets**	**Method used**	**Results**
Priyangika et al. [89]	queuing theory,single-queue multi-server, single-queue single-server, and multiple queue multi-server (M/M/C)	empirical data including variables as arrival time, departure time, and service time, number of customers in a queue based data	queueing models, Monte Carlo simulation, Markovian exponential distribution, WinQSB simulation	The study compares the average queue length estimated from raw data with that of queuing models to assess the efficiency of the system. Model 1, Lq(Queue Length)= 6.856 , Wq(Waiting Time in Queue)=4.2 min, percentage =89, Model 2, Lq= 67.581 , Wq=25.0821 min, percentage =99
Y Lu et al. [90]	queuing theory (M/M/C and JSQ)	novel dataset, experimental and observational data from the fields of operations management, marketing, and economics, the dataset that included customer fixed effects, daily dummies, and hour-of-day dummies interacted with weekend/holiday dummies, the dataset that included information on the length of the queue and the expected waiting time	Bayesian methods and Markov chain Monte Carlo (MCMC) methods	Waiting in a queue has a nonlinear impact on purchase incidence, with customers being more sensitive to the length of the queue rather than the speed at which the line moves.Pooling multiple queues into a single queue may increase the length of the queue observed by customers and lead to lower revenues.Customers' sensitivity to waiting is heterogeneous and negatively correlated with price sensitivity, which has implications for pricing in a multiproduct category subject to congestion effects
Igwe et al. [91]	Basic queuing theory (M/M/C/K and MMI)	Four supermarkets in Makurdi town, Nigeria to collect data on mean arrival and mean service rates.Queuing parameters, including the average number of customers in the queue, the average number of customers in the system, and the average time spent waiting for service, using equations and computed values. System performance such as average service rate,system utilization and costs	MMI (Memoryless Markovian exponential distribution) queuing system, which represents the most basic queuing system with Poisson arrival and exponential service times.The queuing models used in the paper include the MMcK model, which represents a Markovian exponential distribution of inter-arrival times, service times, and a specified number of servers.	Queue management in Makurdi town, Nigeria, is grossly inadequate, inefficient, and ineffective for the most part. The mean service rate in the studied supermarkets was poor, and the average time customers spent waiting for service was too long. The input utilization, which represents the proportion of time each server is busy, was generally very high, indicating that servers were being over-stressed. The City Company Ltd had the highest mean arrival and service rates, possibly due to its strategic location. Nobis Ltd and Dobbiac Ltd had lower mean arrival and service rates. Eke Ltd, which is relatively hidden from the railway, had the lowest scores in terms of mean arrival and mean service rates
Pryshchepa et al. [92]	Queuing theory, optimization theory ($\vert MQ/M/c/\infty\vert$)	This study relies on mathematical modeling and analysis rather than empirical data.	A mathematical modeling approach was used to analyze retrial queues of the $\vert MQ/M/c/\infty\vert$-type; a multi-criterion optimization problem was considered to find the optimal strategy of control—two-dimensional Markov chain model. The method of linear convolution is employed as the primary approach to solving the multi-criterion problem. The use of a truncated model for analysis	The findings include the study of retrial queues, establishment of existence conditions, representation of stationary probabilities, optimization of control strategies, and insights into the system's effective functioning. The paper highlights the importance of optimizing the control strategy in retrial queues and provides a mathematical framework for analyzing and solving such systems.
Mohamad et al. [93]	queuing theory	Data for the study was collected from Hypermarket A using observation, interviews, and time study methods. The data collected included information on the volume of customer queuing and the time each customer took to complete the buying process at the checkout system	The study utilized a computer simulation model developed using Discrete Event Simulation (DES) and Arena simulation software.	Three scenarios were tested, and the alternatives were ranked based on the efficiency of the system performance. The most efficient queuing system was identified based on scenario analysis, and it resulted in an improvement of up to 26 percent in the waiting time for each customer, equivalent to 5.24 minutes. The simulation model was validated by comparing its behaviour with the actual system, using measures such as Mean Absolute Percentage Error (MAPE).

Table 13 Brief Overview of the Methods Used in Different Research for Queue Management (Part-2)

Authors	Theory	Datasets	Method used	Results
Garnett et al. [94]	Queuing Theory, Perception Theory	The researchers utilized an open-ended questionnaire distributed internally among company employees to gather qualitative data on the proposed problem areas in customer service. The sampling was based on various criteria such as region, product category, product use in industry, gender, population group, age, and business income. Internal and external empirical findings were used to investigate the perceptions of customers regarding queue management	The researchers utilized the Customer Value Management (CVM) methodology, which was customized to reflect the South African environment.	The hypothesis that customers were experiencing service inefficiencies due to system constraints was rejected based on internal and external empirical findings. Several other problems were identified regarding service efficiency and customer relationship management in the industrial retail environment. It also suggests a model for mitigating these problem areas, which may be useful for other industrial retailers.
Uddin et al. [95]	Queuing Theory, Ruled based theory (FCFS and SPF)	Not specified	Automated queue management system, Utilization of Intel Galileo Microcontroller, which is software-compatible with the Arduino software development environment, to control the queue management system. An automated queue control system is used to analyze the queue status	The system aims to enhance the efficiency and productivity of service providers by automating the queue management process and making informed decisions on which customer to serve first. The performance of the system was evaluated under different conditions to assess its effectiveness
Dahm et al.[96]	Queuing Theory	The research includes five fields and controlled experimental studies to test the predictions. It involves observing customers standing in line at a checkout in a busy supermarket in a large German city, with queue lengths ranging from zero to fourteen people. The data collected includes measurements of customer experiences, perceptions of social pressure, affective experiences, and perceptions of service quality. It also adapts items from previous studies using seven-point scales.	Bootstrapping analysis	The research findings indicate that as queue length increases, the customer's experience deteriorates, leading to more negative affective experiences, poorer participation in co-creation settings, and lower perceptions of service quality. Perceptions of social pressure mediate this effect.The impact of queues on customers is moderated by their own waiting time. Customers are more affected by queues forming at their backs when their own waiting time decreases.It also identifies two strategies to attenuate the negative effects of waiting lines: explicitly reassuring the focal customer that they need not feel pressured to be efficient and removing waiting for customers from the line of vision of the focal customer
Davis et al. [97]	Queuing management Theory	Not specified	The paper discusses conceptual frameworks, empirical insights, and recommendations based on previous research and literature.	The paper emphasizes the need to consider firm- and customer-controlled factors that influence customer perception of queues. It suggests that improving actual service performance and managing customer expectations are key elements in managing queues and enhancing customer satisfaction. The paper recommends proper training of contact personnel to handle dissatisfied customers effectively and reduce stress for staff.

3. Challenges and Future Research Directions

The future of the retail sector is dependent on continuous innovations and digitization. Technology is having a huge impact on the retail sector environment, helping the sector boom. The use of artificial intelligence and machine learning can be seen in the Amazon Super Shop, known as the world's most advanced Super Shop, because of the hassle-free shopping experience it offers customers. E-commerce is expected to grow at a rapid pace as people become more comfortable with the use of mobile phones and other day-to-day devices. Many factors peep into our minds when we think about the development of the retail industry. One such factor is customer satisfaction, which is discussed in [98][99][100] papers. Yeoman, I. et al.[98] in their research have discussed the pricing in retail and advised to keep factors such as the international financial situation and customer satisfaction which can be the best way to do economic modeling for the future. Rodríguez, M. et al.(2016) [99] in their paper highlight the role of technology in customer satisfaction. To do so, it is important to analyze the market and gather internal and external data to develop a better customer shopping experience. To upgrade the customer experience in India JayashreeRamanan, C. M. A. et al.(2014)[100] have said that the Indian retail industry has the opportunity to embrace the technology by evolving from brick and mortar to digital platforms. Von Briel, F.et al.(2018)[101] have focused on using omnichannel retail strategies to improve the operational productivity of the shops. For that, physical stores will be the key ingredient that can help to adjust the organizational mindset towards omnichannel retail. Retailers must adapt quickly to the changing market and new technologies like blockchain, artificial intelligence, and robotics [102]. The future of the retail sector depends highly on data security. The retail sector needs to earn the customer's trust by ensuring data security using technologies like IoT, which can handle all the challenges related to this sector. Moreover, using iPads as interactive options in the shops can be helpful in many ways, like providing all the product information to the customers and making inventory management easy for the shopkeepers [103]. Fernie, J. et al. (1997)[104] in his article discusses the changes in the United Kingdom retail environment and its impact on the logical support of shops. The author talks about the possibility of developing a dual strategy combining mail-order and electronic shopping soon, which will be needed if electronic retailing becomes successful and presents an opportunity for mail-order companies and logistical service providers to grab a position in the market. A research[105] conducted on the G8 countries talks about the importance of gathering knowledge about the retail sector of other countries. By doing so, retailers will have all the retail insights and be able to identify the gaps in their retail sector. Evaluating the international retail formats will provide the retailers with adequate knowledge to anticipate and adapt to the upcoming changes in the market. Dawson, J. (2009)[106] in his paper has provided insights about the future changes in the European retail industry. According to the author, retailers will be the major elements of Europe's economy in the coming days, with the application of the latest technologies like RFID. Santalova, M. S. et al.(2019)[107] in their paper have discussed different digital technologies like big data, predictive analysis, and omnichannel, and according to them, modern technology is important for the sector. Still, the main focus should be consumer satisfaction. Though digitalizing retail is important, customer behavior will determine future changes in the retail sector. Krafft, M. et al.(2006)[108] identified the importance of understanding evolution in technology, the emergence of multi-channel retailing strategies, customers giving more importance to the shopping experience, and personal selling assistants as the key trends that will be impactful in the future of the retail industry. Augmented and virtual reality can be game-changing technologies in retail as they will provide consumers with virtual showroom experiences, try-ons, and many more facilities. Many researchers have considered omnichannel integration as a key element for the future. It works to break the barriers between the online and physical channels and give consumers a seamless shopping experience. Moreover, cashless or contactless payment technologies will be the future payment methods and technologies like RFID will be introduced in retail.
Now, we will briefly discuss the future trends and challenges of all the sections of smart retail management discussed in this research.

1. Sales Forecasting: The demand for forecasting sales has grown in the retail industry with the introduction of machine learning methods[109]. The retailers have understood that effective demand prediction in supermarkets can enhance organizational competitiveness and improve their decision-making process[110]. Because of this understanding, sales forecasting will see further changes in the future with the integration of AI and machine learning, which will make real-time data analysis faster and easier. Moreover, the use of Big data and cloud computing will improve forecasting accuracy. Improving sales forecasting will help the retailers to offer clearance sales smartly, predicting demand accurately and helping to avoid redundant products [111]. In sales forecasting, we have to deal with multi-seasonal sales data, and many times, multiple events happen simultaneously, which is a challenging act to perform and difficult to make predictions [112]. Sales forecasting can be affected by weather variables like rain or snow, etc. Forecasting sales for a new product is tough as little or no data is available. The same challenges can arise while trying to improve sales forecasting as it needs constant exploration and improvement in forecasting strategies [113]. Moreover, the existing Forecasting methods contain insufficient information[114] and cannot handle noise and external uncertainties[115]. It is necessary to tackle these challenges to make the forecasting models more acceptable in the retail industry.
2. Product Placement: The future of product placement depends on introducing all new technologies to

understand customer behavior and their thinking. People should think beyond the existing works of product placement and focus on product placement in different social media sites like Facebook, youtube which will help to generate word of mouth among the people[18]. By considering the ongoing trends, brands can amplify their engagement and gain success. According to Balasubramanian et al., researchers must study how product placement affects people's behavior in the long run rather than looking for short-term effects[116]. The main challenge in product placement strategies is finding a global solution for product placement, as people in different countries have different choices of products. And because of having other options, product placement strategies may influence the people of various countries differently [117]. Though product placement is essential in many aspects, it is also a concern that it can be used to market products that are harmful to our health. So, it is crucial to be careful to prevent the negative consequences [118].

3. Intelligent Bot: Intelligent bots can significantly impact the future of the retail industry. With the use of bots in retail, the industry can provide shopping assistance to customers, and retailers can run marketing campaigns. Moreover, we will see a shift from the traditional sales approach, which depends on phone calls now and will be replaced by AI-based bots in the upcoming future[119]. Research shows that competence and warmth perception can contribute to determining users' continuance intentions while using Intelligent personal assistant[120]. More research must be done on this topic to understand how it affects users' intentions. Intelligent bots should be able to generate suitable responses naturally at a human-like level. To make this a reality, it is vital to identify the current issues in intelligent bots and involve technologies that can push the limits of AI in improving bots' interaction with users[25]. However, working with intelligent bots can be costly due to expensive technologies. Moreover, there are security concerns, as using bots in retail heavily relies on consumer data to work perfectly. Hence, it is vital to ensure data safety for getting customer trust[121]. Though most of the Current research has worked to understand and build a bot system that talks about how we can understand the perception of customers, limited research is done on the broader perspective of what can happen when we switch from human customer service to AI bot base service[122]. There are many issues with the existing bots. The existing bots lack emotional dimension[123], the capability to identify the user requirements accurately, and it face issues while understanding the in long conversations[124]. Investigations also show that the sensory language of bots can lead to a decrement in consumers' purchase intention[125]. These errors can reduce the confidentiality of product and marketing information, which can cause economic threat for any business [126]. Moreover, these errors cause consumer trust issues and affect consumer intention to shift to human agent[127]. Privacy can be a concern for the customers while using AI-based bots, which can create trust issues about the use of bots and can have negative word of mouth about chatbots in service[128].
4. Blockchain: As retailers try to change this industry, Blockchain can transform this sector by ensuring transparency and data security and improving product traceability. We will see the use of trends like blockchain-based product provenance platforms and decentralized supply chain finance systems in the upcoming future[129]. The introduction of blockchain will significantly impact the future use of big data in the retail sector as it will allow more secure data processing. Blockchain technology can be an alternative to lessen the vulnerabilities in the IIOT domain for smart manufacturing[130]. However, scalability and privacy leakage can be a problem while using this technology as there is a limitation in block size, and the user information can be tracked with public-private keys[131]. Comparing the existing solutions with the blockchain will be a challenging task, and replacing the existing system with blockchain will need careful evaluation as the existing data systems often have redundant and incomplete data, which will impact the performance of blockchain [132]. Though, in general, the use of blockchain is increasing, there is a lack of research about its use and industry adaptation to the financial sector[133].
5. Smart Transaction: The introduction of an intelligent transaction system will make the payment method hassle-free. We are heading towards a cashless timeline where all the payments will be made through smart systems with the combination of complex technologies like QR codes, RFID, and Smartphone transactions[134]. Though these technologies will help us achieve the future, there are uses like breaking off and getting lost with QR codes and RFID [135].
6. Queue management: In future work, it is critical to incorporate green environmental factors into the design of customer queue management systems. This includes using energy-efficient technology like low-power devices and renewable energy sources to cut overall energy consumption. Transitioning to paperless alternatives like digital tickets and e-ink displays can drastically reduce paper waste. Furthermore, using sustainable materials and developing recyclable components can assist in reducing the environmental impact of physical infrastructure. Conducting life-cycle assessments and implementing recycling programs will ensure the systems are ecologically benign throughout their lifecycle. In one study, the QueueAdmin system was tested in a new store with various customers and barbers to determine its impact on wait times and customer satisfaction. Future studies will be conducted by selecting other test barbershops to sample a diverse range of system users and gain more information. Replicating the problem-solving approach employed in QueueAdmin's development to create similar solutions for domains other than barbershops, using the findings of this study [136]. In another work, Future research should look at the indirect link between automated queue management systems (EQMS) and service delivery to determine

the viability of the findings [137]. Furthermore, AI-powered chatbots are being developed for initial client engagement and query resolution before entering the queue. We can also investigate customer behavior patterns and their impact on queue dynamics to build better predictive models and queue management tactics. However, traditional SR technology lacks automation, resulting in consumers needing a lot of help from shopkeepers/staff while shopping. Besides, from the perspective of the service providers, it is always challenging to manage long queues manually. Therefore, e-ticketing can be a solution. On top of that, it requires many human resources to provide perspective service and meet and interact with the customers' needs. To solve this issue, AI-integrated chatbots can be used, which will help to reduce the human interaction for the basic information of the customers [138].

4. Conclusion

This study has worked to explore the impacts of modern technology in the retail sector. By reviewing different papers related to technologies and strategies used in supermarkets, it is clear that technologies used smartly can change the dimension of this industry. From all the papers, we have seen that through intelligent retail management, we can improve customer service, optimize operations, reduce extra costs, and make the shopping experience hassle-free for consumers. The use of IoT, AI, and other technologies is widespread in today's society, and to cope with the modern world and meet consumer expectations, retailers need to get used to these technologies as early as possible. However, every innovation has some faults, and the technologies used in retail are not different in this scenario. To address problems like data security, it is crucial to do more research in this section, which can improve the technologies in use day by day. Overall, we can conclude that creating a bond between technology and retail retailers can position them for the long run.

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