High-Frequency Point-of-Sale Signal Processing and Inventory Trigger Intelligence: AI-Powered Demand Sensing Architectures for Retail Supply Chain Responsiveness

Dr. Tomohiro Naraoka, Associate Professor of Robotics, Osaka University, Japan

1. Introduction

Demand forecasting, or demand sensing, is one of the critical tasks in supply chain management that significantly contributes to its efficiency. However, consumer behavior volatility, driven by preference changes, external influencing factors such as media and social networks, or uncertainty, significantly impacts the forecasting practice of retail supply chains, which increasingly requires understanding consumer behavioral traits and mining respective data using adaptive retail demand sensing solutions. The business environment of modern retailers is complex, with dynamic adjustments in response to the changing landscape to adapt to consumer preferences. Furthermore, the globalization of retail, as well as the direct effects of market alterations, competitor response, and company strategy, have together led to the growth of a burgeoning industry of big data analytics, which is ever-expanding due to the quantity of newly created and mined big data from a variety of business domains.

In recent years, AI models have shown improvements in various tasks to achieve enhanced performance on different benchmarks, suggesting a pathway to drift away from traditional forecasting practices. As systems are trained on more and more data and validated and verified in different environments, there is a noticeable leap in using AI predictive models for understanding the dynamics of the retail industry as a whole. This commentary highlights the paradigm shift occurring in retail sales and profit forecasting due to market dynamics based on the fusion of AI and retail consumer behaviors. Developments in AI have facilitated the use of information about consumers' online and offline shopping behaviors to analyze and develop an association of customer purchase patterns, preferences, brand loyalty, and the driving factors influencing shifts in consumer purchase preferences as well as logics. The interconnectedness of emerging AI technologies, apart from being used to model retail consumer behaviors, models, and decisions, also considers scientific contributions in retail dynamic supply chain decisions. AI technologies will be deployed in retail domains, particularly to predict purchase behaviors in retail value chains, to maintain competitive superiority over other models.

1.1. Background and Significance

The main focus of retail supply chains has always been to efficiently match inventory with demand. In response to this, it has always been essential to forecast demand for an extended period into the future. Previously, traditional manual methods for forecasting matured and provided good results in various industrial segments, including retail. However, with the emergence of advanced technologies and globalized markets, the evolution of forecasting methods could not keep pace. These forecasting limitations posed further challenges due to uncertainties regarding promotions, the true causes of customer demand, delays in demand data throughout the supply process, globalization, and demand planning at local, regional, and global levels simultaneously. Retail trading has evolved from limited standard products to extensive stock-keeping units and customized products, such as unique items and bespoke flavors.

The advent of AI in retailing has been discussed mainly in the literature, aiming to introduce the benefits of integrated demand forecasting to address issues concerning supply chain management. Researchers have identified and advanced the use of AI to enhance demand management utilizing big data. In doing so, retailers can capture strategic and tactical opportunities to improve the customer experience. The potential application of big data through AI in retailing for logistics systems and processes is the next de facto focus. This paper introduces the system and historical perspective of AI technologies as a game changer in retailing. AI and deep learning in retailing present a strategic insight concerning demand sensing, demand shaping, and customer-based supply chain focus. The fundamental background of the integral approach of AI in retail supply chains, including the demand management area, is provided by considering the broad requirements for demand execution in the market, triggered by the current market situation and online price transparency.

1.2. Objectives and Scope

The purpose of the essay is to examine the impact of AI-powered demand sensing. In particular, we focus on how technological advancements and AI can forecast demand with accuracy in retail. Our objectives in the essay are partly as follows: (1) to study and examine potential methodologies, technologies, and AI models for fine-grained demand sensing; (2) to present the summary of the most recent AI models developed or implemented to forecast demand with greater accuracy; and (3) to identify potential areas where existing AI models can be extended or modified, depending on the supply chains' demand dynamics.

The main scope of the essay pertains to the retail supply chain. It covers several aspects of demand forecasting, the associated costs, and how AI facilitates the diminished rate of misprediction. Practically, this essay uses the following set of methodologies: speculate by evaluating existing AI models and identify their current applicability; be specific about where there may be gaps in the state-of-the-art techniques; consider areas where the existing demand-sensing AI models can potentially be extended; and critically analyze gaps or limitations in the existing research through speculative investigation. In approaching the topic, the ethical aspects of using AI in supply chains will bear importance in this essay. We will show how AI can assist in making smarter predictions in retail supply chains, which in turn can alleviate the bullwhip effect. We will also mention the challenges of using AI. Thus, AI is the analysis dimension used to guide our discussion in the essay.

The essay will be divided into different areas which, more or less, will discuss the questions of the structure. The core of the structure could be as follows: forecasts in retail supply chains, the bullwhip effect, demand sensing in supply chain – an AI approach.

2. Understanding Demand Sensing in Retail Supply Chains

Retail supply chains utilize modern techniques to sense customer demand patterns at fast-paced retail stores for getting a real-time bearing of consumer demand movements. E-commerce purchasing behaviors have not only increased the number of stock holding units at a retail store but also further necessitated a shift to just-in-time retailing with expeditious inventory replenishment signals. Retail stores with autonomous decisions of stock replenishment at the store level align the retail inventory management goals by ensuring product availability, enhanced service levels, and reduced stock-out rates. Demand sensing is a collection of techniques that leverage real-time data to anticipate the demand while minimizing latency in demand signals and data products. Demand sensing avoids reliance on aggregated shipment or order data and integrates downstream POS data consumption signals from a wide variety of disparate, structured, and unstructured information aggregated from point of sale data, social sentiment, weather, and location-based data. Thus, a dependable approach to realize autonomous demand sensing is a hybrid approach that integrates consumer, store, and distribution center analytics.

There is a large body of research on demand sensing that primarily focuses on data integration and hybridization. Applying multiple sources of information results in good forecasting performance, increasing the level of forecast accuracy. The advancement in technology has played a crucial role in creating efficient data mining tools for the retail industry that can simultaneously handle the vast amount of data that corporations house. With improvements in chip technology that have enabled extremely fast and powerful computing at a low cost, data mining has become an essential tool and technique for choice-based marketing decisions. Demand sensing initiatives present significant value for retailers, including enabling inventory optimization and more efficient capacity and resource planning, supported by higher levels of supply chain agility to meet consumer demand. The initiatives also play a non-trivial role in the circular economy, helping to reduce overproduction and facilitate top environmental indicators such as food waste reduction in the grocery vertical. Democratising demand sensing solutions can bring these and direct benefits to smaller, less mature organizations. However, several common misconceptions and implementation pitfalls remain. These include issues of data integration, requirement of detailed data, management support, top-level support, and the need for sophisticated forecasting systems, among others.

2.1. Definition and Concept

Demand sensing is important to understand as it increasingly plays a pivotal role in today's retail supply chain. It is not just another way to forecast demand, at least not traditional demand forecasting. While long-term and strategic demand forecasting is crucial to support sales and grow the business, demand sensing describes how to make a sales plan a reality in the time domain close to execution. Exploiting near-real-time information, demand sensing helps move merchandise using accurate, actionable insights and operational decision-making. This could be done by the retailer at the store and even from the shelf point of sale level, and by the supplier directly from the portal, and possibly from the shelf category level. The driving power behind demand sensing is retail agility.

However, it is not enough for retail agility to know how to sense demand; knowing how to fulfill the forecasted demand by creating a responsive and agile supply chain is crucial. This is where demand sensing, retail agility, and supply chain agility are closely interrelated. A supply chain can only be as agile as the ability for visualization, synchronization, collaboration, and decision-making through application integration and adapting to accommodate the changes that take place in demand and supply. Rapid detection and response, especially with significant variation or myriad data coming from multiple daily baskets of goods sold and other sources, demand high precision in sensing the demand to avoid stale inventory. Why does it matter for demand sensing to play a crucial role? Because the resulting sales forecast and demand-driven retail strategies will help in determining what will be happening in, and driving the rest of the supply chain.

3. Machine Learning in Retail Demand Sensing

Introduction Demand sensing in retail is the set of techniques and tools used to estimate sales behavior for short time intervals in supply chains. Even though modern forecasting tools are available, demand sensing is becoming increasingly important for retail companies because of the rapid changes in consumer demand. Demand sensing and unsupervised machine learning are intertwined disciplines. The former needs different machine learning algorithms to improve the accuracy and reliability of demand predictions, for instance. Companies are using machine learning to sense retail demand through the science of demand forecasting. The competitive advantages include improved inventory management and better visibility on logistics and transportation. Machine learning techniques are used to sense demand. This paper has identified that, in the literature, the supervised, unsupervised, and deep learning machine learning algorithms are among those used in demand sensing. There is a gap in the literature regarding attention paid to other machine learning algorithms used to sense demand.

Practitioners are beginning to use statistical model-based and academic demand forecasting research-based machine learning algorithms for demand sensing in various use cases: energy forecasting, intermittent demand, new product demand forecasting, transportation and logistics, finance, and retail. Cases of demand sensing Machine learning algorithms, including strategies from clustering, frequent pattern analysis, collaborative filtering, decision trees, and Bayesian modeling, have been improved and tested successfully for demand sensing. Research engineers have used machine learning to build models and sense demand to forecast and predict near-future demand-related behavior. The operational areas in retail, logistics, and inventory management, where sense-and-respond models demonstrate successful application, include stock replenishing, transportation scheduling, and proactive maintenance for demand-driven production planning. Research and case study evidence show that a reduced forecast error rate is achievable in some applications, reducing the costs of working capital in non-value-added and low-value-added processes.

3.1. Application Areas

Machine learning approaches are now applied in retail demand sensing in various areas. These areas include demand forecasting, promotion planning, and inventory optimization. In order to reduce lead times along the supply chain, real-time data processing and analysis are crucial to improve responsiveness. Predictive analytics are receiving a growing level of attention from the research community. The retail demand forecasting problem is analyzed to make future predictions of sales figures by considering historical sales data. Different studies show that predictive models for demand forecasting and replenishment provide better price and inventory recommendations in traditional brick-and-mortar formats and e-commerce businesses.

As a highly dynamic and immediate updating of sales, stock, and other internal data needs to be conducted in e-commerce businesses for real-time forecasting, machine learning techniques are being perceived as potentially critical contributors to the effectiveness of demand planning and management. Case studies illustrate that this is already the case in some retail formats. Machine learning, more generally, is showing clear early signs that it may improve on human and statistical forecasts, potentially also in longer-term forecasting. By and large, these demand-related and trend sections are a source of excitement and potential innovation, which points to future development as the sophistication of analytical techniques continues to improve.

4. Developing AI Models for Real-Time Insights

Data-driven decision-making is key for enhancing retail supply chain operations. Supply chain managers can use a wealth of data to both optimize routing and planning, enabling them to increase revenue, enhance the quality of their service, and strategically price their products. In the last few years, AI techniques have evolved dramatically and achieved significant breakthroughs in the automated creation of new models for analyzing data. In this section, we go one level deeper to review the AI methodologies and proposed AI models that are specifically targeted for real-time application and focused on the development of new models for data-driven retail demand sensing.

AI models for decision-making via prediction can be developed through a few stages. First, an original concept is received by identifying the required input data, constraints, assumptions, and outputs. Once formulated as a mathematical model or AI model, a development stage is conducted to build the model to predict demand. Finally, the demand model can be deployed for prediction. The design stage is typically implemented through four major steps: data collection/pre-processing, model building, parameter determination, and validation and interpretation. The demand sensing accuracy in this model is estimated from alternative multi-seasonal store sales data. The best practices for data collection and preprocessing are identified, ensuring any AI model can learn as well as possible if supplied with a robust and unique data set. Furthermore, proposed models can be augmented to exhibit 'representativity' by ensuring they maintain data integrity and remain relevant over time. Techniques employed for 'latching data' together can involve many diverse techniques in various fields such as machine learning, statistical forecasting, complexity science, and pattern recognition, including but not limited to reinforcement learning, kernel methods, support vector machines, decision trees, deep learning, and the associated techniques such as convolutional networks for computer vision, recurrent networks for sequential time series, and decision trees, among others.

4.1. Data Collection and Preprocessing

Supply chain planning and execution in the retail landscape are challenged by the need for high-quality forecasting in the face of ever-increasing uncertainty. AI-driven approaches such as demand sensing promise to help retailers better understand, anticipate, and act on changes in demand across channels and within local and global contexts. This is especially important in the rapidly changing context of a global pandemic and its aftermath. This subsection dives deeper into the essential components of data collection and preprocessing for AI models.

Data Collection Often, multiple data sources are employed for AI modeling: from legacy enterprise and demand planning systems to more recent analytics of consumer online behavior. Furthermore, effective demand sensing should account for external economic, social, and meteorological factors that influence demand. In these contexts, for example, data sources might include macroeconomic indicators to surface high-level demand signals. To effectively train AI using these reams of data, consideration should be given to quality over quantity. For example, key data sets should be carefully curated with preference for relevance to the immediate context and features of likely higher predictive value.

Preprocessing Data preprocessing before feeding into AI supply chain and demand models involves several cleanup steps. Successful demand prediction is contingent on high-quality data free from noise, conflicting information, and inconsistencies. High-quality data can be prepared using sanitization, transformation, feature extraction, and enrichment. At the basic level, sanitization is used to clean data, removing anomalies and inconsistencies that can degrade model performance. Key elements of data sanitization include anomaly detection, data munging, and determining data relevance. Furthermore, data can be cast such that each feature is normalized as close as possible to a Gaussian or normal distribution. This entails removing skew through variance stabilizing techniques. Data governance and compliance with principles of sensitivity and privacy are crucial components of this stage, ensuring suitable handling, storing, and redistribution in sensitive industry contexts. Given two identical neural networks, the one trained on data preprocessed with these techniques could perform significantly better for demand forecasting tasks.

5. Challenges and Future Directions

Despite the promise of AI, there are several challenges that must be addressed to support the robust deployment of AI in demand sensing. There are significant data silos in retail supply chains, including finance, sales, marketing, and operations, that lead to supply chain complexity. Building horizontally integrated solutions as opposed to vertically integrated solutions to support demand-driven supply chains will necessitate additional layers in model complexity. With algorithmic transparency and interpretability, these complexities are antithetical. In several use cases, most AI algorithms are black boxes and, consequently, interpretable explanations are scant. Data privacy and ethics are also barriers to adopting AI. Training data for AI is taken in the form of customer sales and marketing data.

Bias in sales and marketing data is difficult to avoid so long as it is linked to particular attributes of customers such as sex, race, or salary. Unexpected and sudden shocks are challenging for contemporary AI systems to comprehend. AI has been able to forecast a supply chain for a sleek production period where the market is constant, but not so well for us in a volatile and uncertain world where emergent retail therapy is expected. This further complicates demand prediction as many current approaches are not adaptive by design. There are several ways in which current approaches to machine learning, in general, might be augmented. In demand sensing, advances in machine learning such as continual learning and transfer learning could improve long-term retail sales. Long-term retail sales and demand are likely to be enhanced by improving demand sensing algorithms further to manage real-time demand estimations. In addition, machine learning research might reach the next phase where learning models are designed not merely to predict or classify, but to establish their own real-time learning strategies. Adopting advances in machine learning for demand-driven supply chains, however, will necessitate cooperation and dialogue between supply chain practitioners and machine learning researchers. This is because state-of-the-art demand-driven supply chains require connectivity, interoperability, and collaboration between stakeholders such as data scientists, ETL developers, and DevOps.

5.1. Ethical Considerations

Algorithmic bias is a phenomenon closely related to the provision of unfair predictions. The effects may be particularly detrimental in applications for public services, policing, judicial systems, and lending. However, the same phenomenon may apply in demand forecasting or other applications in supply chain management. Any company should be ethically clear to prohibit unfairness and thus ensure algorithmic fairness. In model development, it is, therefore, important to be transparent about unfairness, and this is why it is recommended to provide reasons for a reduced predictive power because of the above-specified constraints when explaining the implementation of demand-side forecasting by using AI. In a retail context, neglecting these considerations may lead to ethical issues and social consequences. For instance, a European clothing retailer launched a fraud detection system that mistook thousands of legitimate purchases for fraudulent. Consequently, they blocked access to goods and funds used for purchases for a substantial number of real consumers. A British outlet revealed that, during March 2020, retail giant Amazon began sacking dozens of employees in the UK due to suboptimal performance detected by AI-powered timekeeping systems. Amazon's timekeeping system is programmed to automatically decide which workers to lay off based on an algorithm. Furthermore, a report implies that large retailers, such as Tesco and Great Universal Stores, use predictive capability to detect which of their customers represent a poor credit risk. The report indicates that the consequence of wrongly classifying customers as poor payers triggers issues of discrimination. The potential risks of deploying AI in the context of retail are immense.

In view of the ethical risk, companies and research institutes should be very careful with the development of AI systems. This implies that a clear understanding of the different aspects of ethical and societal risk and the mapping of the use of AI technologies to these various aspects is needed to promote ethical innovations. To overcome the potential ethical dilemmas, several solutions are proposed, including legal protection like the implementation of a general AI ethics governance or governmental action as well as industry initiatives. These aim to promote self-regulation, for example, through developing a technology oversight board and guidelines. Moreover, transparency is suggested as another method to guarantee accountability. In effect, this idea is also mentioned in proposing the use of blockchain technology for AI accountability in retail. This solution is based on the application of a blockchain platform that can deliver an informative flow of goods and services for operations like the data discovery phase or supply chain management. At the same time, this platform would ensure compensation and the product traceability of AI-based applications in retail as direct and consensus-based proof of AI operations.

6. Conclusion

AI has the potential to positively transform retail supply chains by making them more efficient and responsive. This is especially important in retail due to large inventories and highly time-sensitive products. Demand sensing is crucial for understanding the latest demand and detecting changes in it to support strategic decision-making in retail supply chains. The integration of demand sensing technology in AI/Machine learning can lead to more accurate forecasting by capturing granular level patterns. However, this is not without challenges, the most important of which is data quality and transparency of AI generated predictions. AI makes use of large quantities of data, but also by that needs data which describes the actual situation. With the increasing use of AI approaches in demand prediction, data quality problems are becoming increasingly critical.

Moreover, data-driven predictive models are regarded as black boxes in the classical sense, which can be a significant lever in influencing overall predictions. Last, but not the least is the societal perspective which should also be cofounder. There are clear challenges of the use of algorithms. It can violate one's personal privacy or be used unethically. Further research is needed to overcome these challenges and an interdisciplinary standpoint. Combining research in the fields of AI/Machine learning and supply chain management is important in order to make fast progress in the field. In the future, we anticipate that retail demand sensing will focus on increasing the data acquisition and data use by incorporating numerous sources of videos, images, voice recognition, and smart cards in addition to traditional point-of-sales data.

To be able to cope with these complex and non-structured data sources, demand AI technologies will have the capacity to use natural language processing tools, looking at images and videos using machine learning and deep learning to deliver performance without having to use large amounts of curated data. Moreover, a large potential and achieving a higher level of demand sensing would be through collaboration among retailers, consumers, manufacturers and smart cities, leading to higher and faster predictability while incorporating the sentiment of every one of these entities. We hope this highlights the potential demand of AI in retail. It also provides a good perspective on the challenges and the necessary tools that are to be developed to be able to be competitive and build a sustainable scientific advantage in the future.