applied sciences

MDPI

Article

The Analysis of Customers' Transactions Based on POS and RFID Data Using Big Data Analytics Tools in the Retail Space of the Future

Marina Kholod [1], Alberto Celani [2,*] and Gianandrea Ciaramella [2]

[1] AI, Neurotechnology and Business Analytics Laboratory, Plekhanov Russian University of Economics, Stremyanny Lane, 36, Moscow 117997, Russia; kholod.mv@rea.ru

[2] Architecture Built Environment and Construction Engineering (ABC) Department Politecnico di Milano, Polytechnic University of Milan, Leonardo da Vinci Square, 32, 20133 Milan, Italy; andrea.ciaramella@polimi.it

* Correspondence: alberto.celani@polimi.it

Abstract: In today's business landscape, the volume of transaction data is rapidly increasing. This study explores the integration of Point of Sale (POS) and Radio-Frequency Identification (RFID) technologies to enhance the analysis of customer transactions using big data tools. By leveraging these technologies, businesses can extract valuable insights to improve processes, optimize inventory, and boost customer satisfaction. The research employs an object—subject management approach, which facilitates real-time decision-making by merging retail transactions of the clients with their movement patterns. An experiment involving around 7000 customers demonstrates the effective collection and processing of POS and RFID data, highlighting the benefits of integrating these data streams. Key metrics, such as time spent in different store sections, provide deeper insights into consumer behavior. The findings reveal the potential of these technologies to transform retail services, offering opportunities for demand forecasting, risk management, and personalized customer experiences. The study concludes that merging POS and RFID data opens new avenues for developing management solutions aimed at enhancing customer engagement and the operational efficiency of the retailer. Future research will focus on further elaborating these solutions to maximize the benefits of integrated data analysis.

Keywords: real estate; space management; retail; POS data; RFID data; big data; trade and service company; retail transactions

Citation: Kholod, M.; Celani, A.; Ciaramella, G. The Analysis of Customers' Transactions Based on POS and RFID Data Using Big Data Analytics Tools in the Retail Space of the Future. *Appl. Sci.* **2024**, *14*, 11567. https://doi.org/10.3390/app142411567

Academic Editor: Pedro Couto

Received: 17 October 2024
Revised: 4 December 2024
Accepted: 7 December 2024
Published: 11 December 2024

1. Introduction

In the modern world, the volumes of data generated by retail transactions are growing at an incredible rate [1]. A retail transaction is a transaction using a bank account. The most common example of a retail transaction in the modern economy is a banking operation to pay for goods and/or services of a trade and service enterprise using a bank payment card [2].

This transaction is carried out using a POS terminal [3,4]. During the implementation process, a complete technological process is carried out from authentication of the cardholder to approval or refusal in the operational center of the payment system and the implementation or non-implementation of this very transaction [5].

In this article, we will go further and consider aspects of the analysis of customer retail transactions based on POS (Point of Sale) and RFID (Radio-Frequency Identification) data using big data tools. This has become possible due to the widespread use of POS and RFID technologies, which are used to automate and record sales in retail and service enterprises [6–8]. Such data play a key role in extracting valuable information that can be used to improve business processes, optimize inventory, and increase customer satisfaction from retail transactions within a retail and service enterprise [9].

Analysis of retail transactions based on data obtained using POS and RFID systems and the use of Big Data tools allow us to identify patterns and trends that are not visible with traditional approaches to analysis and, in fact, are not particularly applicable due to the large volume of such data [10]. Using powerful algorithms and machine learning to process large volumes of data opens up new opportunities for retail forecasting, risk management and informed decision making [3,11–16].

Analyzing retail transactions is a complex process that requires a deep understanding of both retail principles and advanced technologies [17–19].

POS systems are terminals or points of sale that not only process payments but also collect important transaction data, such as the time of the transaction (purchase), the items purchased, the payment methods, and the customer's (buyer's) personal information. This data can then be analyzed to identify purchasing trends and consumer behavior.

RFID technologies enable the automatic identification of objects, people, and animals using radio waves [20]. In the context of retail transactions, RFID tags can be used to track the movement of customers and goods, which helps in inventory management, logistics, and the organization of customer flows/visits in physical or online space [21].

Big Data tools play an important role in processing and analyzing the huge amounts of data collected through POS and RFID. They include various technologies, such as databases, cloud platforms, analytics tools, and machine learning. These tools enable real-time data processing, pattern detection, and deep analytical reporting [22,23].

These technologies are used for demand forecasting, which is the analysis of historical sales data to predict future demand for products; inventory management, which is the optimization of inventory levels in warehouses by analyzing sales data and product movement; and personalization of offers, which is the creation of personalized offers for customers based on their purchasing history and preferences.

These technologies are transforming the retail industry, making it more efficient, accurate and customer-centric. In the future, we can expect to see even more development of these tools and their application to improve retail services and customer satisfaction.

Based on the analysis of RFID and POS data in this paper, valuable insights were gained into customer behavior and store operations. Tracking customer journeys through RFID revealed key patterns, such as movement paths [11] and time spent in different sections of the store. For example, customers tended to spend more time in high-traffic areas, like the dairy section, which can inform product placement and staffing decisions. Additionally, the integration of RFID and POS data allows for more accurate inventory forecasting, helping to avoid stockouts and overstocking. These insights can also be used to create a more personalized shopping experience, including tailored promotions and recommendations, ultimately enhancing customer satisfaction and boosting sales.

2. Materials and Methods

2.1. The Use of RFID and POS Data in Retail Management Studies

In order to increase the efficiency and flexibility of retail management, the emergence has occurred of opportunities to adapt the organization's operating activities to constantly changing market conditions. Why is RFID (Radio Frequency Identification) technology so prevalent in the retail industry and why is it so important? Normally, RFID can provide real-time data, reduce product loss, reduce inventory loss, increase revenue, improve information quality, improve customer service, improve operational performance, and improve the security of tagged products, all while reducing costs [24,25]. On the other hand, there are challenges in implementing RFID in the retail sector, such as lack of standardization, higher costs, employee resistance, and business process revision. The most common issue that needs to be addressed before implementing RFID in the retail sector is the privacy issue [23]. Therefore, in order to anonymize the collected RFID data in the experiment conducted in this research, RFID tags were attached to the shopping carts, and not to the clients or goods. Due to the huge amount of data used by RFID, data integration issues are also very tedious, so the business process needs to be redesigned.

RFID is a contactless wireless technology that reads and records RFID-marked shopping carts in the air using radio frequency waves [26]. RFID tags have a data storage capacity of up to 2 kilobytes (KB). Just as barcode technology collects data from a tag or sticker and stores it in a database, RFID does the same. On the other hand, RFID has several advantages over barcoding. For example, RFID tags and logos can be read from a long distance, while barcodes require scanning from a close distance to read [12]. RFID tags are faster to read than barcodes and allow multiple tags to be recognized simultaneously, while barcodes require the scanning of each label or tag separately. Thus, Figure 1 shows that the actual information on financial transactions of clients in the store in POS data and tracking of customer movements using RFID technologies are integral elements of the retail management system. The management subject in real-time, with the help of "machines", collects data on its clients, based on the analysis of which, through a flexible integration architecture, management decisions are developed and made regarding changes to the management system [15,27].

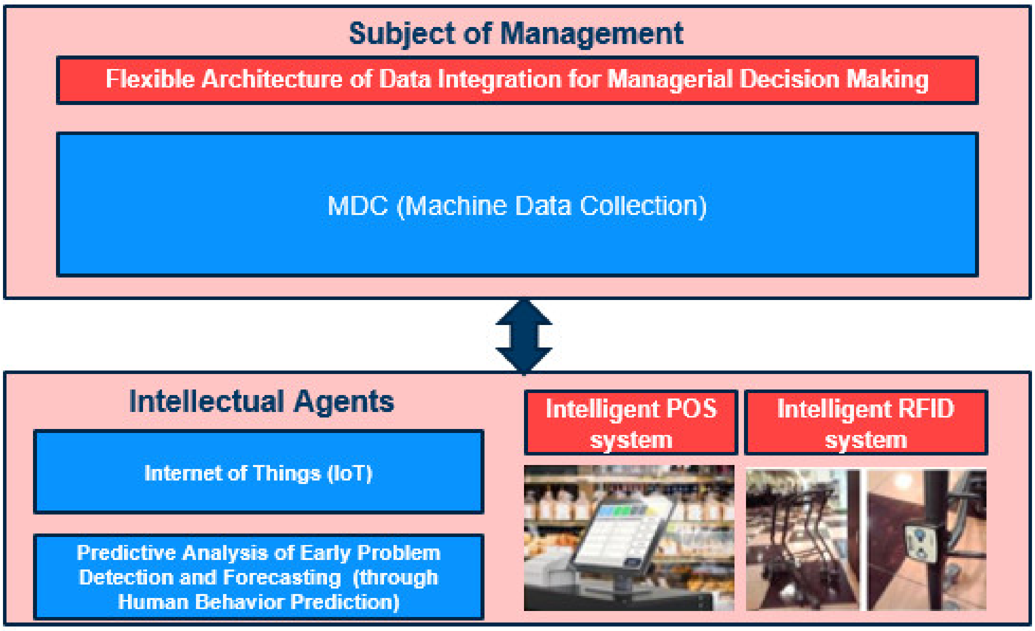

Figure 1. The interaction between the managerial subject and intellectual agents of the POS and RFID systems of the retailer.

Fundamental RFID and POS analytics analyzes various variables depending on the specific goals and objectives of the company. Some of the most common variables that may be analyzed are:

1. Sales: Analyzes sales data, including total sales, number of items sold, average order value, sales dynamics over time, and other sales-related metrics.
2. Inventory: Examines inventory data, including the number of items in stock, inventory levels, inventory turnover rate, and other metrics related to inventory management.
3. Buying behavior: Analyzes buying behavior data, such as popular items, purchasing patterns, purchasing frequency, customer preferences, and other factors that can help understand customer preferences and needs.
4. Prices and discounts: Examines data on product prices, discount levels, the effectiveness of various promotions and campaigns, and their impact on sales and buying behavior.
5. Supply data: Data on the supply of goods is examined, including information on suppliers, delivery times, quality of deliveries and other parameters related to the supply of goods.

6. Location data: Data on the movement of goods within a store or warehouse, as well as on the movement of goods within the supply chain, is analyzed.

These are just a few examples of variables that can be analyzed as part of fundamental RFID and POS data analytics. Depending on the specific needs and goals of the company, other variables may be identified for analysis.

When it comes to the model of managerial decision making, the state of operational activities involving big data, intellectual agents, and predictive modeling has advanced significantly due to the convergence of various technologies and methodologies (Figure 2). Intellectual agents of POS and RFID systems (in our case) collect data from multiple streams, including transactional data and RFID data, which fixes the tracking information, allowing the withdrawal of a set of measurements on customers trajectories [28–32]. As for the model of the technical and economic parameters, these involve the capabilities of the retail store to generate such flow states for the clients, in which they are fully immersed in a shopping activity, experiencing full involvement in the shopping process, visiting the maximum number of supermarket sections and, as a result, making the biggest possible purchase [17].

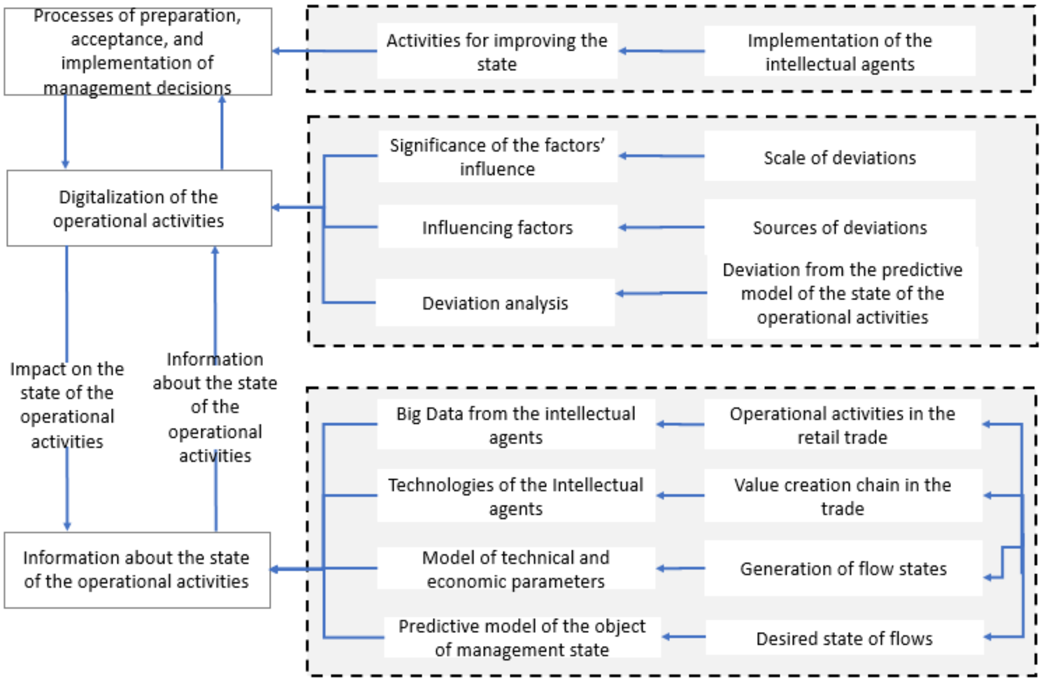

Figure 2. Model of managerial decision making based in the digitalization of operational activities through the intellectual agent systems—RFID and POS.

Streams of POS data contain information about the transaction itself (date, time, product, price and quantity, product category and manufacturer) and customer demographic information (gender, age, income or its proxy estimate through other demographic indicators, such as place of residence or education). If collection and analysis of POS data from the point of view of financial transaction analytics is obvious, how can technologies for collection and analysis help in this analytic's RFID data? With RFID data, a manager gains real-time insight into the behavior of customers, which it can use to reduce shrinkage and inventory loss, increase revenue, improve customer information, enhance customer service and operational performance, and improve the security of branded products, all while reducing costs [33]. On the other hand, there are difficulties in implementing RFID in the retail sector, such as lack of standardization, higher costs, employee resistance, and revision of business processes. The most common problem that needs to be addressed before implementing RFID technology in the retail sector is the privacy issue. Due to the huge amount of data generated by using RFID technologies, data integration problems are also very tedious, so the business process needs to be redesigned. To overcome all these difficulties, tag passwords, blocking tags, regulating tags, distance estimation, shielding tags, authentication between tags and readers, and manual system configuration can be used.

RFID is a contactless wireless technology that reads and records RFID-tagged or smart labeled products in the air using radio frequency waves [34].

RFID data contains information such as the customer identification number, date, time (recorded every second along the customer's route within the retail and service enterprise), X and Y variables recording the coordinates of each customer on the plane of the sales area, basket number, department, section visited by the customer, time spent in these sections and the status of her movement (categorical data that show whether the customer moved or stopped on her way through the sales area) [35].

2.2. Description of the Experimental Setting and Experimental Environment for POS and RFID Data Collection

To collect such data, a certain technical and experimental environment is needed. The technical environment for collecting RFID data consists of the following elements of the equipment, which was sourced from: POS terminal, RFID responders and RFID readers, installed around the perimeter of the store (Figure 3).

Figure 3. Technical set-up of the experiment for collecting POS and RFID data.

The experiment, which was run in one of the supermarkets of one of the major retailers, examined around 7000 clients based on more than two million records of their movements and purchases. After initial processing of the data on the servers using open source data extraction and processing tool Musashi [36], a sample was created, which was processed using BI systems.

The results of the experiment yielded POS and RFID data, which are streaming data organized in a tabular structure. To use this data for intelligence analysis, visualization, and modeling, it is necessary to implement the stages of preprocessing and data processing. During the implementation of the preprocessing stage, which takes a lot of time, all data stream lines were manually checked to identify distortions or extreme values during automated data collection caused by equipment failures. Then, at the processing stage—for two data streams via a key identifier, the client ID—an algorithm was written using open-source platform Musashi that allows the merging of the two streams into one common dataset, which contains information about both products and clients. Merging POS and RFID data through a common customer identifier involves integrating two distinct data streams to create a cohesive system that enhances retail operations and customer experience. The architecture for merging POS and RFID data through a common customer identifier involves integrating sales transaction and customer data from POS systems with real-time item tracking and interaction data from RFID systems. The logic of the algorithm is based on integrating two distinct data streams—POS data and RFID data—using a unique customer identifier (such as a loyalty card number). This integration is achieved through Musashi, which facilitates the merging of these two data sources into a unified dataset. The algorithm extracts, transforms, and loads the data (ETL process) via middleware, linking customer transactions (from the POS system) and real-time item tracking (from the RFID system). The integrated data is stored in a centralized data warehouse or data lake for further processing and analysis. These insights are utilized by retail management systems and CRM applications to enhance operations and customer engagement, while robust security measures and compliance protocols ensure data protection (Figure 4).

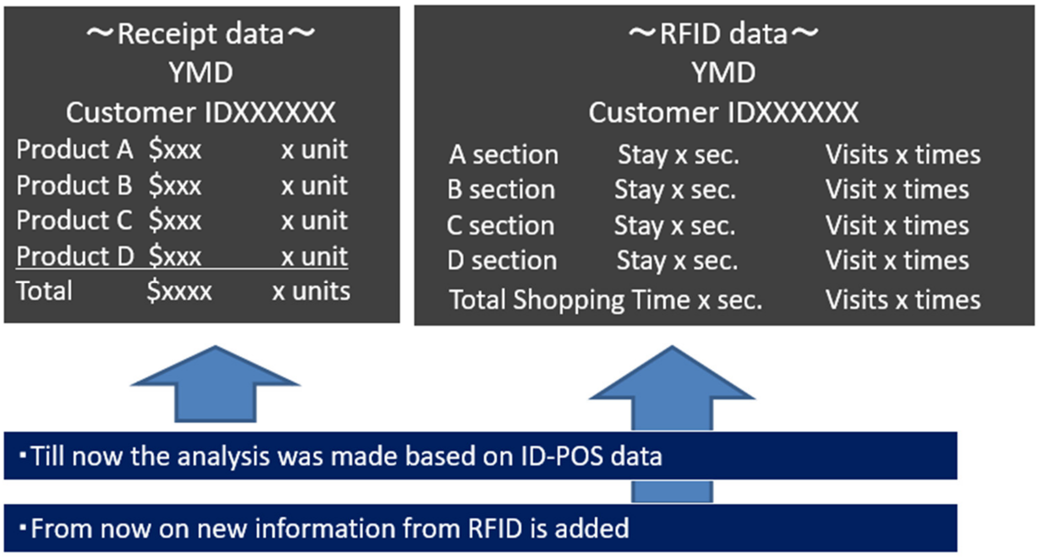

Figure 4. Architecture of POS and RFID data when merging their flows through a common customer identifier.

2.3. Store Area Decomposition

Store layout decomposition involves breaking down the physical arrangement of a retail space into distinct zones and components to optimize customer flow, product placement, and overall shopping experience. This process begins with identifying key areas, such as entry points, high-traffic zones, product displays, checkout counters, and customer service areas. By analyzing how customers navigate through these spaces, retailers can strategically position products to maximize visibility and accessibility, encouraging impulse buys and efficient shopping. Additionally, understanding the natural flow of customer movement helps in designing pathways that reduce congestion and enhance the ease of navigation. Effective store layout decomposition also considers the placement of promotional signage and the integration of technology, such as digital kiosks or interactive displays, to engage customers and provide seamless access to information. Ultimately, this approach aims to create an inviting and intuitive shopping environment that aligns with consumer behavior, driving sales and improving customer satisfaction.

The experiment was conducted in the store, consisting of 16 departments, 25 sections, 2 entrances, a central aisle and checkouts (Figure 5). Data were collected during working hours from 9:00 to 18:00 within 2 weeks in one of the supermarkets of the major retailer.

Department 'A' contains 3 sections (Household Goods; Books, Magazines; Cleaning Products). Department 'B' consists of six sub-areas (Fast food; Spices, sauces; Butter, flour, sugar, salt; Pasta, cereals; Sweets; Yogurt, jams). Department 'C' includes three sections (Candies; Chocolate, cookies). Department 'D' consists of 2 sections (Wine, whiskey, vodka; Beer). Department E is 'Entrance', 'F' has 2 sections for fish, 'G' stands for 'Ready-made food', and 'I' is dairy foods. Department 'J' has different types of beans. 'K' has 'frozen foods'. 'Drinks' are sold in 'L'. 'M' specializes in 'Meat' goods, 'Register' is found in 'R', 'Ceremonial Goods' are present in 'S', and department 'V' contains two sections (Vegetables and Vegetables (green)).

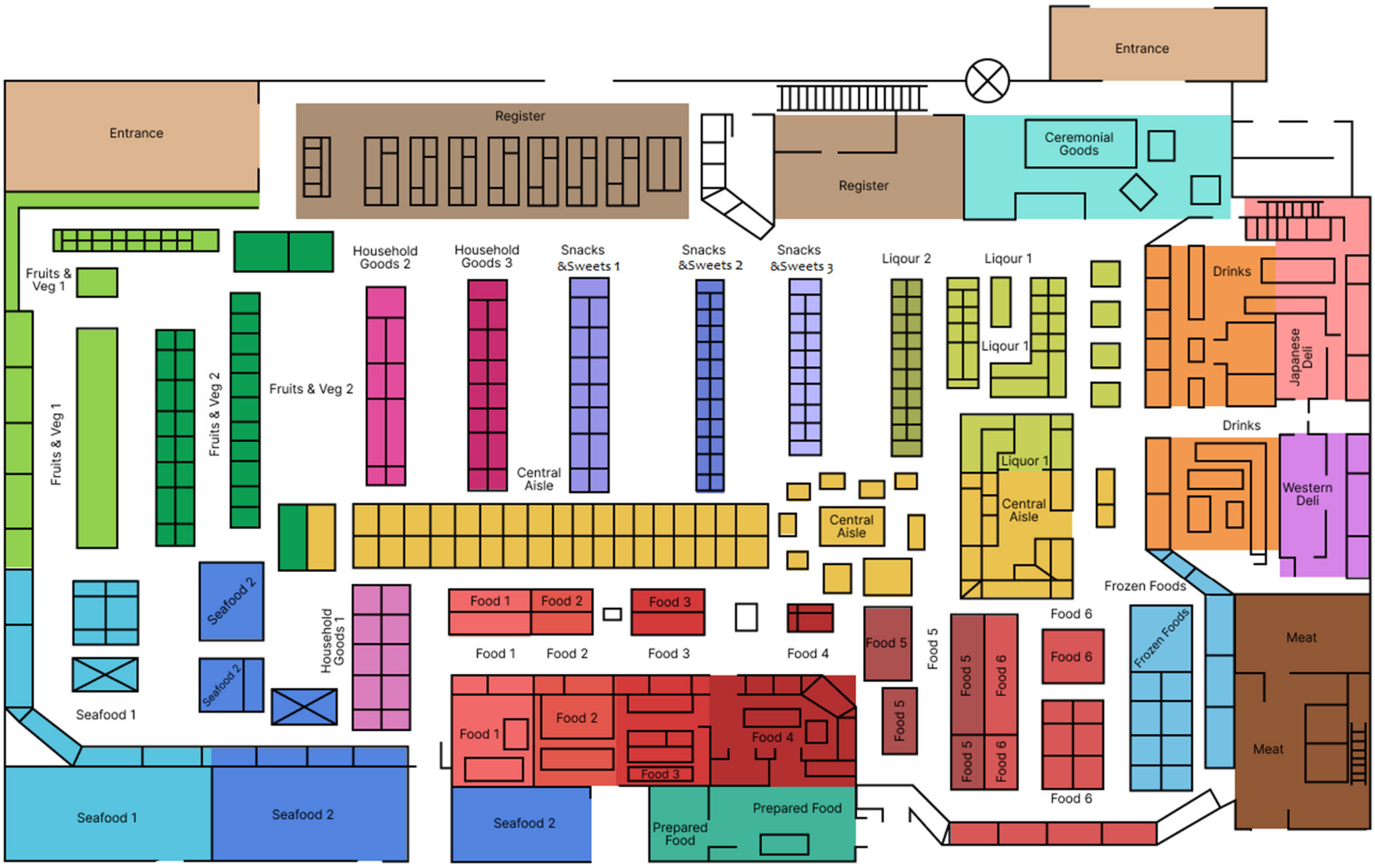

Figure 5. Decomposition of the store by departments and sections.

Designing the layout of the store involves organizing various departments to optimize workflow, customer experience and operational efficiency. The grid style layout is the most traditional retail store layout. It is used in supermarkets, stores and many big box retail stores when a store contains many goods (especially different kinds of products), or when a retail location needs to maximize space, as in the case of our supermarket. The layout, with the section abbreviations which are further used in the analysis, is shown in Figure 6.

Table 1 provides a more detailed breakdown of the departments and sections within them.

The shopper will have to walk past all of the impulse items, increasing their chances of picking up something extra on their way to their necessities.

Grid layouts are perfect for introducing customers to a wide variety of products because they allow them to browse several aisles while only selecting a few pieces. They are the best layout for stores with a lot of stock, like supermarkets.

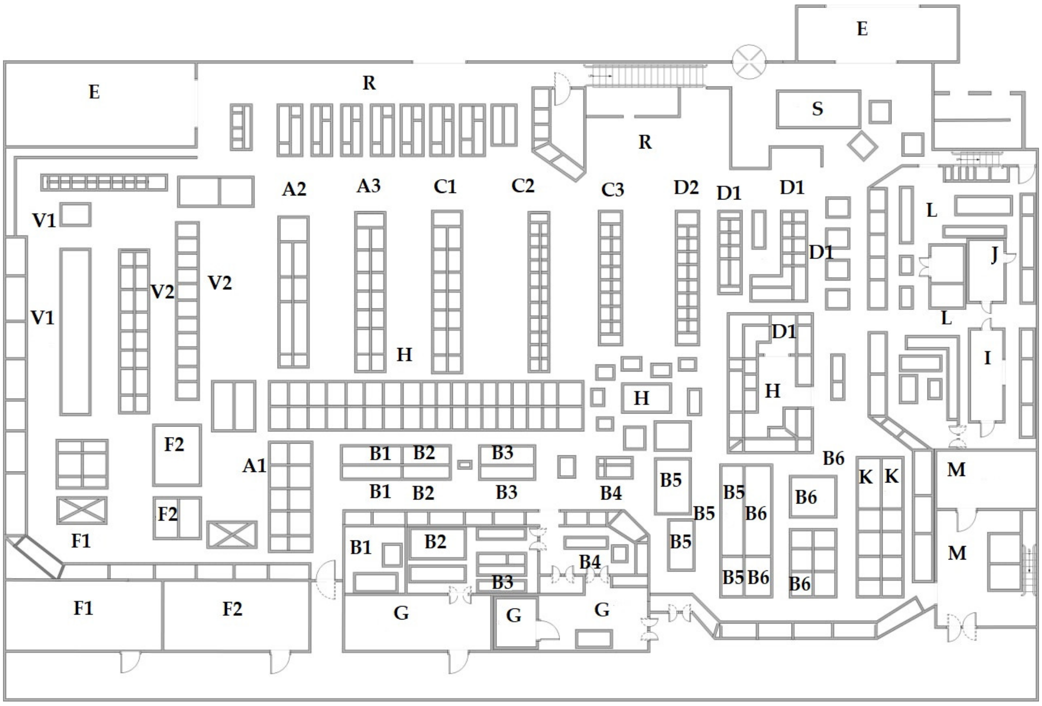

Figure 6. Grid layout of the store and section abbreviations.

Table 1. Departments, sections and products of the supermarket.

Department	Section	Product	Department	Section	Product
E	E	Entrance	B	B1	Food1 (Fast food)
V	V1	Fruits and Veg1		B2	Food2 (Spices, sauces)
	V2	Fruits and Veg2		B3	Food3 (Butter, flour, sugar, salt)
F	F1	Seafood1		B4	Food4 (Pasta, cereals)
	F2	Seafood2		B5	Food5 (Sweets)
G	G	Prepared Food		B6	Food6 (Yogurt, jams)
M	M	Meat	C	C1	Snacks and Sweets1 (Candies)
K	K	Frozen food		C2	Snacks and Sweets2 (Chocolate, cookies)
I	I	Western Deli		C3	Snacks and Sweets3 (Snacks)
J	J	Japanese Deli	D	D1	Liqour1 (Wine, whiskey, vodka)
L	L	Drinks		D2	Liqour2 (Beer)
S	S	Ceremonial Goods (Holiday Products)	H	H	Central Aisle
A	A1	Household goods1	R	R	Registers
	A2	Household goods2	S	S	Ceremonial Goods (Holiday Products)
	A3	Household goods3			

3. Experimental Results: Measuring Key Customer Transaction Metrics Based on POS and RFID Data

The collected RFID dataset consists of such data as customer ID number, dates, time, coordinates of a customer on axis X and Y, ID number of every basket in the store, position, movement time, and type of movement.

Below is a visual image of x and y axis positions on store floor map (Figure 7). The x axis 150 and y axis 300 in the graph map below represent a customer position, and the identification number of this customer is 5110203. The customer's location is in the Vegetable Department and specifically in section V2 during her customer journey through the store.

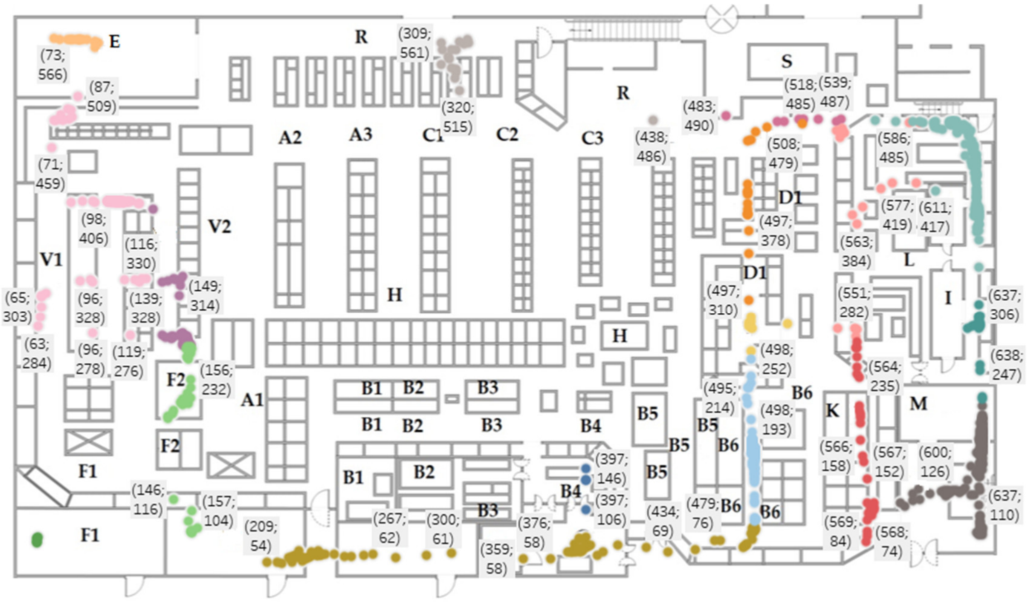

Figure 7. Demonstration of X, Y coordinates of customer #5110203 in the map of the supermarket with different coloring according to the section.

The travel time in the dataset refers, as mentioned before, to the duration time of the shopping trip. The duration time is displayed in seconds, as shown in Figure 8 below. Customer number 5110203's shopping journey started from her entrance and ended at the checkout and the duration time is shown spent in each "sustained" position during his trip. Figure 8 shows that the customer spent 1 s at each "sustained" position, i.e., moved fairly quickly along the outer perimeter of the sales area and stopped only at section J for 10 s. When examining the financial transaction, this customer actually bought only milk and salad (which she did not spend much time buying and, judging by the data, simply grabbed them from the shelf).

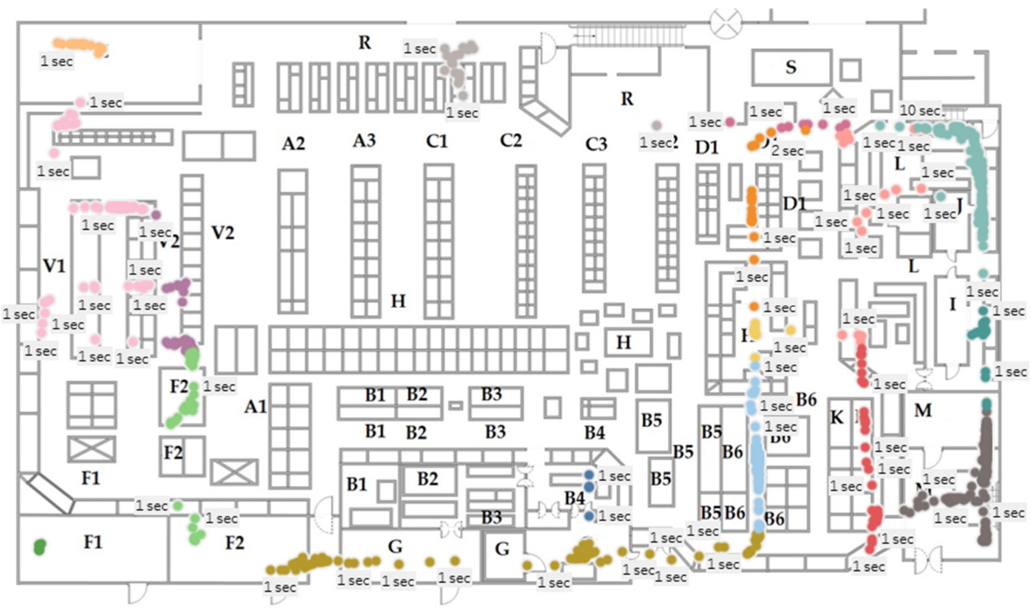

Figure 8. Demonstration of "sustained" time at some of the stop points of customer #5110203 on the map of the supermarket.

It is important to identify the customer's movement around the store, such as her stopping to look at goods, buying specific goods in any department or keeping moving along her path.

The stop points are actually fixed in the data by "sustained" status, while moving status is marked as "migration" (Figure 9).

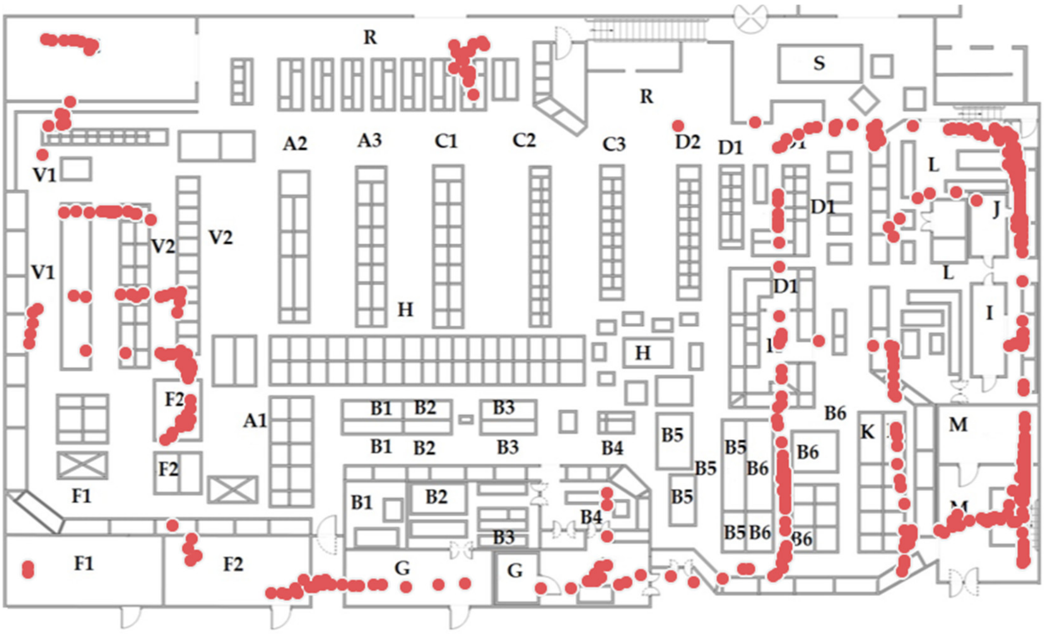

Figure 9. Customer stop points, marked with red dots, during her shopping trip (the example of customer #5110203).

The same customer #5110203 with her non-stop movement during her shopping is shown in Figure 10.

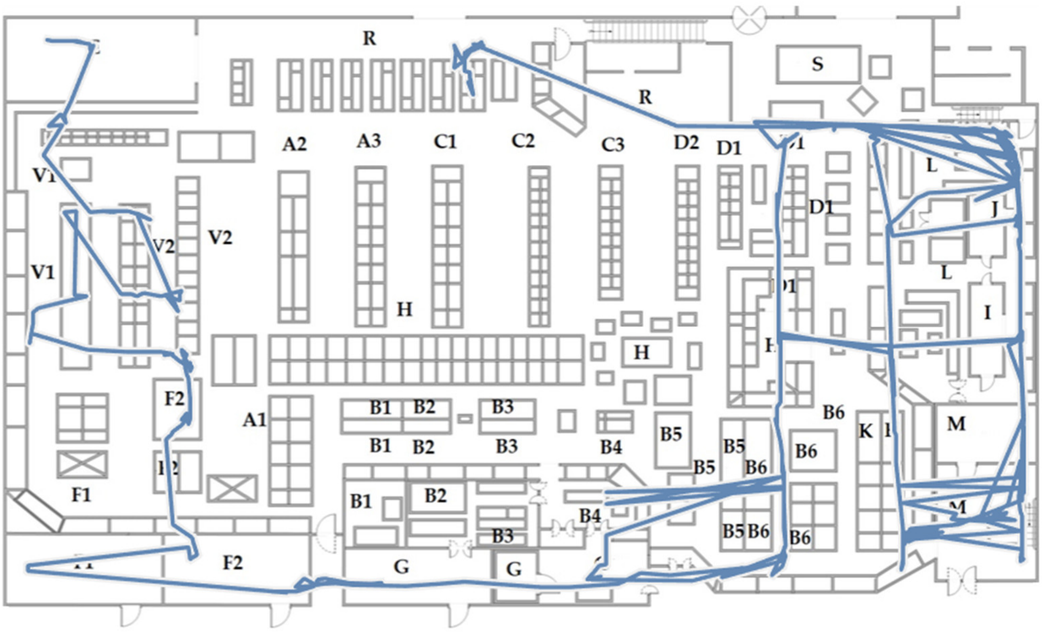

Figure 10. Customer movements ("migration") marked with blues lines during her shopping trip (example of customer #5110203).

If we combine the information visualized in Figures 9 and 10, we obtain the customer trajectory with stop points and movement combined, which is pictured in Figure 11.

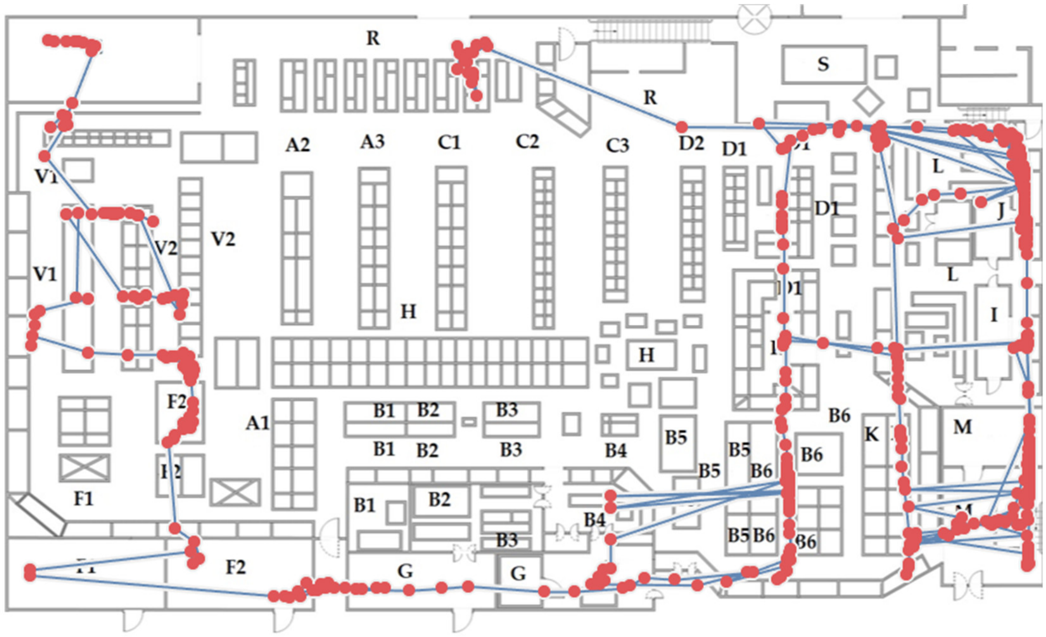

Figure 11. Customer trajectory (with stop points—red dots, and movement—blue lines) during her shopping trip (example of customer #5110203).

Based on the above data, measurements of key metrics were made, i.e., the time spent by the client in each section and in each of the departments. (Figure 12). The distribution of time spent in sections, calculated using POS and RFID data, can be visualized as a histogram showing the percentage of customers across various time intervals. On the x-axis, intervals like 0–2 min, 2–4 min, etc., represent the duration of time customers spend in each section, while the y-axis indicates the proportion of the total customer sample within each interval. Typically, there is an initial spike in the 0–2-min range, reflecting quick purchases, followed by a significant proportion of customers in the 8–14-min range, indicating standard browsing behavior. Fewer customers fall into the 20–40-min range, often engaging in detailed comparisons or waiting for assistance, with a small percentage spending 46+ min, possibly due to consultations with shop assistants or bulk purchases. Identifying peak intervals helps optimize staffing and promotional activities, while the tails of the distribution provide insights into improving store navigation and customer engagement, ultimately aiding in resource allocation and enhancing the shopping experience.

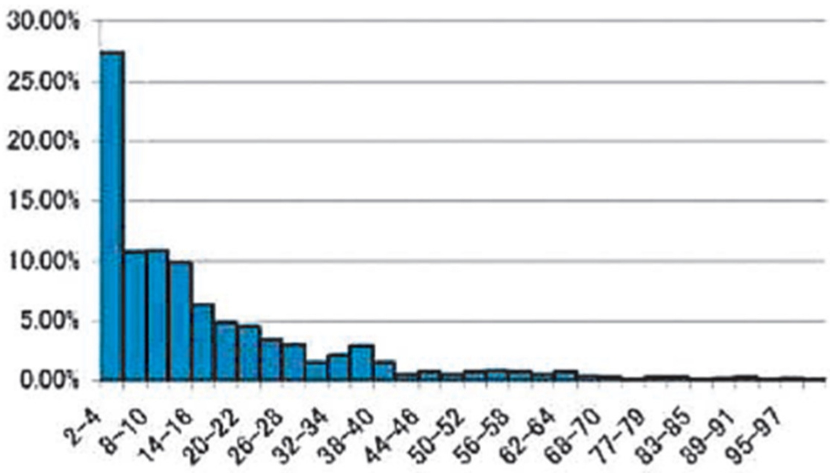

Figure 12. Distribution of time spent in sections, calculated based on POS and RFID data as a percentage for the entire sample of customers (x-axis—intervals of time values, y-axis—proportion of customers in the sample).

In order to carry out such calculations, the processing of two data streams was carried out according to the scheme described above, i.e., the two streams are connected using a key identifier, which is the client number. If we visualize all the routes of all the clients inside the sales area for the entire period of the experiment (4 weeks), we will obtain the image in Figure 13. From this image, it is clear that the sections on the perimeter of the store are highly trafficked, while the inner sections are not very much walked in, excluding section B6.

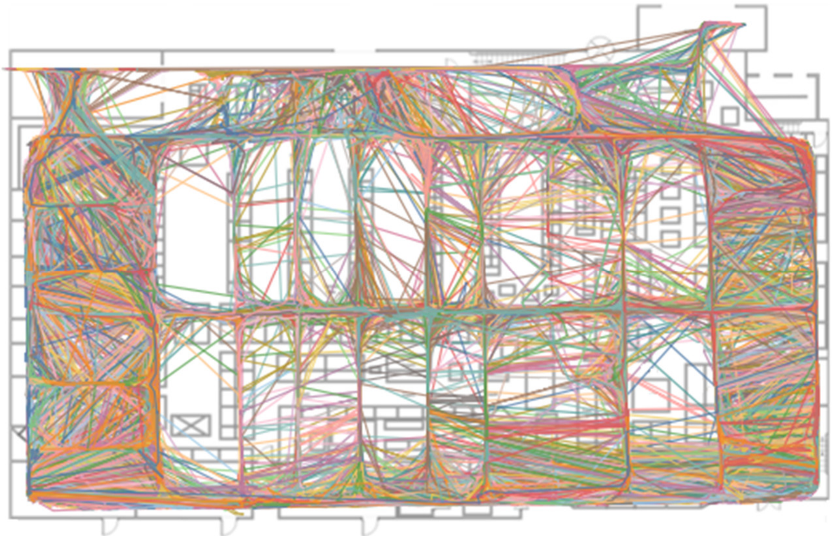

Figure 13. Visualization of the trajectories of all customers inside the sales areas for the entire period of the experiment (4 weeks).

4. Managerial Implications and Discussion

Fundamental analytics of RFID and POS data provide companies with valuable information that can be used to make a variety of management decisions. One such decision can be related to inventory management. We do not have the data on the store inventory available for this study, however RFID and POS data allow the setting up of at least approximate inventory levels of categories to prevent stock-outs or overstocks, as we know the well-shopped and under-shopped sections in the supermarket. Based on these insights, optimal order points and replenishment periods can be determined, which helps reduce inventory costs and improve customer service. As for the latter, the conclusions made based on visualizations of RFID and POS data help to improve the design of supermarket sections to improve their trafficability. Moreover, the detailed information on traffic for each section allows the grasping of the peculiarities of each section performance and improve this. Another managerial implication can be related to customer demand forecasting. Analyzing sales and purchasing behavior data can help develop demand forecasts for products. This allows companies to plan production, purchasing, and marketing activities in line with expected demand, which increases efficiency and reduces risk. As a result, sales efficiency can be improved. Analyzing sales and shopping behavior data can help identify the most successful products, popular product categories, and effective sales channels. This information allows optimization of the assortment, development of marketing strategies, and improvement of sales processes to achieve better results. Overall efforts towards sectional performance improvement lead to increased customer satisfaction. This also allows improvement of store efficiency based on the results of in-store movement analysis and shopping behavior data. This type of analysis helps to optimize shelf placement, improve store design, determine optimal placement of advertising materials, and improve overall store efficiency.

5. Conclusions

The analysis of RFID and POS data provided valuable insights into customer behavior and store operations. The RFID dataset, which includes customer IDs, timestamps, movement coordinates, and product interactions, was used to track customer journeys throughout the store. A detailed examination of this data revealed key patterns, such as customer trajectories—the path taken by customers in the store was visualized by combining RFID movement data with time stamps. For example, customer #5110203 was tracked as moving swiftly through the store, with notable stops in certain sections, like the dairy area. These movements were categorized as either "sustained" (stopping to shop) or "migration" (moving without stopping). Another key metric, which is time spent in sections, was also computed from the data. The amount of time customers spent in different departments was calculated, revealing that certain areas, like the dairy section, saw longer engagement, while others experienced quick movements. A histogram of time distribution across customer visits showed that most customers spent between 8–14 min in the store, with a smaller group spending 20–40 min or more. This insight can be used to optimize staffing and customer engagement strategies. The overall visualization of customer movement was demonstrated by aggregating data from all customers over a 4-week period, and a comprehensive map of customer trajectories was created, providing an overview of traffic patterns within the sales area. This helps identify high-traffic areas and sections that require further optimization.

The integration of RFID and POS data offers significant potential for future retail spaces. By continuing to track and analyze customer movement, stores can optimize store layouts. With a clearer understanding of customer movement, retailers can redesign store layouts to improve traffic flow and enhance the shopping experience. High-traffic areas can be stocked with popular products, while under-shopped sections can be reimagined to boost engagement.

By correlating customer behavior with sales data, stores can better predict inventory needs, avoiding stock-outs or overstocks. This is particularly useful for managing high-demand products or adjusting stock levels in under-performing sections. Therefore, inventory management can be improved.

As retailers gain more insights into customer preferences and behavior patterns, they can tailor the shopping experience to individual customers. Personalized promotions, targeted marketing campaigns, and recommendations based on past behavior will likely enhance customer satisfaction and drive sales. By doing so, personalized shopping experience can be provided.

Advanced analytics using RFID and POS data can lead to better demand forecasting and implementation of dynamic pricing. Retailers can predict product demand more accurately, enabling dynamic pricing strategies and optimized stock replenishment. This can improve operational efficiency and reduce costs.

In conclusion, combining RFID and POS data can dramatically improve store efficiency, inventory management, and customer satisfaction. By leveraging business intelligence tools and machine learning, retailers can not only optimize their operations but also create a more personalized and engaging shopping environment for their customers.

Author Contributions: Conceptualization, M.K.; methodology, M.K., A.C. and G.C.; software, M.K.; validation, A.C.; formal analysis, A.C.; investigation, G.C.; resources, M.K., A.C. and G.C.; data curation, M.K.; supervision, G.C.; funding acquisition, G.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was performed in the framework of the state task in the field of scientific activity of the Ministry of Science and Higher Education of the Russian Federation, project "Models, methods, and algorithms of artificial intelligence in the problems of economics for the analysis and style transfer of multidimensional datasets, time series forecasting, and recommendation systems design", grant no. FSSW-2023-0004.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Acknowledgments: The authors thank Katsutoshi Yada, whose advice during the work on this paper was invaluable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ferrari, A. *Digital Competence in Practice: An Analysis of Frameworks, EUR 25351 EN*; Publications Office of the European Union: Luxembourg, 2012; JRC68116.
2. Want, R. An Introduction to RFID Technology. *IEEE Pervasive Comput.* **2006**, *5*, 25–33. [CrossRef]
3. Yada, K.; Ishibashi, K.; Ohashi, T.; Wang, D.; Tsumoto, S. How Shoppers Walk and Shop in a Supermarket. In Proceedings of the International Conference on Data Mining Workshops, Sorrento, Italy, 17–20 November 2020; pp. 114–118.
4. Amrutha, R.; Dhrishya, V.; Gopika, J.; Biji, K. RFID based POS System. *Int. Res. J. Eng. Technol.* **2020**, *7*, 716–721.
5. Alfian, G.; Octava, M.Q.H.; Hilmy, F.M.; Nurhaliza, R.A.; Saputra, Y.M.; Putri, D.G.P.; Syahrian, F.; Fitriyani, N.L.; Atmaji, F.; Farooq, U. Customer Shopping Behavior Analysis Using RFID and Machine Learning Models. *Information* **2023**, *14*, 551. [CrossRef]
6. Boto-García, D.; Mariel, P.; Baños-Pino, J.F. Intra-Household Bargaining For a Joint Vacation. *J. Choice Model.* **2023**, *47*, 100408. [CrossRef]
7. Panfilov, P.; Suleykin, A.; ElDarawany, A.; Elpashev, D. Open-Source Digital Infrastructure Capacity Prediction System for Production Company. In Proceedings of the 3rd International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency, Lipetsk, Russian Federation, 10–12 November 2021; pp. 915–920.
8. Zuo, Y.; Shawkat Ali, A.B.M.; Yada, K. Consumer Purchasing Behavior Extraction Using Statistical Learning Theory. *Procedia Comput. Sci.* **2014**, *35*, 1464–1473. [CrossRef]
9. Kholod, M.; Golubtsov, P.; Varlamov, A.; Filatov, S.; Yada, K. Modeling Customers Speed of Movement From POS- and RFID-Data. In *Smart Innovation, Systems and Technologies*; Springer: Singapore, 2019; Volume 143.
10. Takai, K.; Yada, K. A Framework For Analysis of the Effect of Time on Shopping Behavior. *J. Intell. Inf. Syst.* **2013**, *41*, 91–107. [CrossRef]
11. Hui, S.K.; Fader, P.S.; Bradlow, E.T. Research Note—The Traveling Salesman Goes Shopping: The Systematic Deviations of Grocery Paths from TSP Optimality. *Mark. Sci.* **2009**, *28*, 566–572. [CrossRef]
12. Kazagli, E.; de Lapparent, M. A Discrete Choice Modeling Framework of Heterogenous Decision Rules Accounting for Non-Trading Behavior. *J. Choice Model.* **2023**, *48*, 100413. [CrossRef]
13. Kholod, M.; Lyandau, Y.; Maslennikov, V.; Kalinina, I.; Mrochkovskiy, N. Upper Level Processes and Projects Model Building. In *Smart Innovation, Systems and Technologies*; Springer: Singapore, 2019; pp. 267–276.
14. MacGregor, J.N.; Chu, Y. Human Performance on the Traveling Salesman and Related Problems: A Review. *J. Probl. Solving* **2011**, *3*, 2. [CrossRef]
15. Panfilov, P.; Suleykin, A.; ElDarawany, A. Digital Ecosystem-Based KPI-Driven Railway Communication Network Reporting System. In Proceedings of the 13th International Conference on Management of Digital EcoSystems, virtual, 1–3 November 2021; pp. 163–166.
16. Sorensen, H. *Inside the Mind of the Shopper*; Pearson Education: London, UK, 2009.
17. Ma, L.; Cheng, S.; Shi, Y. Enhancing Learning Efficiency of Brain Storm Optimization via Orthogonal Learning Design. *IEEE Trans. Syst. Man Cybern. Syst.* **2021**, *51*, 6723–6742. [CrossRef]
18. Ju, L.; Wu, J.; Lin, H.; Tan, Q.; Li, G.; Tan, Z.; Li, J. Robust Purchase and Sale Transactions Optimization Strategy for Electricity Retailers with Energy Storage System Considering Two-Stage Demand Response. *Appl. Energy* **2020**, *271*, 115155. [CrossRef]
19. Ma, L.; Huang, M.; Yang, S.; Wang, R.; Wang, X. An Adaptive Localized Decision Variable Analysis Approach to Large-Scale Multiobjective and Many-Objective Optimization. *IEEE Trans. Cybern.* **2022**, *52*, 6684–6696. [CrossRef]
20. Roggeveen, A.; Sethuraman, R. Customer-Interfacing Retail Technologies in 2020 & Beyond: An Integrative Framework and Research Directions. *J. Retail.* **2020**, *96*, 299–309.
21. Kaneko, Y.; Yada, K. A Deep Learning Approach for the Prediction of Retail Store Sales. In Proceedings of the IEEE 16th International Conference on Data Mining Workshops (ICDMW), Barcelona, Spain, 12–15 December 2016; pp. 531–537.
22. Larson, J.S.; Bradlow, E.T.; Fader, P.S. An Exploratory Look at Supermarket Shopping Paths. *Int. J. Res. Mark.* **2005**, *22*, 395–414. [CrossRef]
23. Hui, S.K.; Fader, P.S.; Bradlow, E.T. Path Data in Marketing: An Integrative Framework and Prospectus for Model Building. *Mark. Sci.* **2009**, *28*, 320–335. [CrossRef]
24. Hui, S.K.; Bradlow, E.T.; Fader, P.S. Testing Behavioral Hypotheses using An Integrated Model of Grocery Store Shopping Path and Purchase Behavior. *J. Consum. Res.* **2009**, *36*, 478–493. [CrossRef]
25. Yada, K. String Analysis Technique for Shopping Path in a Supermarket. *J. Intell. Inf. Syst.* **2011**, *36*, 385–402. [CrossRef]
26. Kaneko, Y.; Yada, K. Fractal Dimension of Shopping Path: Influence on Purchase Behavior in a Supermarket. *Procedia Comput. Sci.* **2016**, *96*, 1764–1771. [CrossRef]

27. McCarthy, M.L.; Ding, R.; Pines, J.M.; Zeger, S.L. Comparison of Methods for Measuring Crowding and Its Effects on Length of Stay in the Emergency Department. *Acad. Emerg. Med.* **2011**, *18*, 1269–1277. [CrossRef]
28. Rogers, A.; Foxall, G.R.; Morgan, P.H. Building Consumer Understanding by Utilizing a Bayesian Hierarchical Structure within the Behavioral Perspective Model. *Behav. Anal.* **2017**, *40*, 419. [CrossRef]
29. Sano, N.; Yada, K. The Influence of Sales Areas and Bargain Sales on Customer Behavior in a Grocery Store. *Neural Comput. Appl.* **2015**, *26*, 355–361. [CrossRef]
30. Underhill, P. *Why We Buy: The Science of Shopping*; Simon & Schuster Pbks: New York, NY, USA, 2009.
31. Tamura, T.; Inaba, T.; Nakamura, O.; Kokuryo, J.; Murai, J. A Proposal on RFID Data Analytics Methods. In Proceedings of the 2010 Internet of Things (IOT), Tokyo, Japan, 29 November–1 December 2010; pp. 1–6.
32. Zhao, L.; Zuo, Y.; Yada, K. Sequential Classification of Customer Behavior Based on Sequence-to-Sequence Learning with Gated-Attention Neural Networks. *Adv. Data Anal. Classif.* **2023**, *17*, 549–581. [CrossRef]
33. Zuo, Y.; Yada, K. Using Statistical Learning Theory For Purchase Behavior Prediction Via Direct Observation Of In-Store Behavior. In Proceedings of the 2nd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE), Nadi, Fiji, 2–4 December 2015; pp. 1–6.
34. Zuo, Y.; Yada, K.; Ali, A.B.M.S. Prediction of Consumer Purchasing in a Grocery Store Using Machine Learning Techniques. In Proceedings of the Asia-Pacific World Congress on Computer Science and Engineering and Asia-Pacific World Congress on Engineering, Nadi, Fiji, 5–6 December 2016; pp. 18–25.
35. Viswanadha, V.; Pavan Kumar, P.; Chiranjeevi Reddy, S. Smart Shopping Cart. In Proceedings of the International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), Kottayam, India, 21–22 December 2018; pp. 1–4.
36. Nakahara, T.; Yada, K. Analyzing Consumers' Shopping Behavior Using RFID Data and Pattern Mining. *Adv. Data Anal. Classif.* **2012**, *6*, 355–365. [CrossRef]