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Improving smart deals system to secure human-centric consumer applications: Internet of things and Markov logic network approaches

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Abstract

Considering the increasing inclination of modern consumers to frequent large retail chains capable of promptly fulfilling their diverse needs, there is a noticeable surge in the prevalence of contemporary shopping complexes. Subscription services, customer-focused strategies, and efficient supply management are driving the progression of intelligent commerce within these expansive retail platforms. The Internet of Things (IoT) presents the foundation for "smart" retailers that can monitor inventory levels, diminish equipment failures, and provide better customer experience. Many models, as one of the widely used methods in this domain, Markov Logic Network (MLN), can simultaneously use activity knowledge and data by unifying probability and logic. In this research, we determine a smart deals system (SDS), consider the improved machine learning algorithms to meet performance, and develop secure human-centric consumer applications to render the system workable. From the results, and based on the percentage of efficiency, around 10% of clients are connected randomly, which has a minor impact on the outcomes from LR (logistic regression). Similar outcomes are delivered when the number of customers in the scope of 30–40% is connected for NB (Naive Bayes). Hence, prospective shopping sales will increase along with the efficiency and speed at which it operates.

Keywords Smart deals system · Markov logic · Internet of Things · Human-centric application · Smart shopping · Consumer satisfaction

1 Introduction

These years, more sophisticated tools have been introduced to massive supermarkets, including RFID-equipped smart shelves, RFID-equipped mobile virtual purchasing assistants, Artificial intelligence (AI) readers and labels, and intelligent carriages. The Internet of Things (IoT) allows these sophisticated appliances or items

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in a supermarket to be interconnected. The IoT has affected every aspect of life and caused its evolution and change. Fields such as business, retail, or human-centered applications health almost try to adapt themselves to new technologies, and the IoT is no exception. The smart system of mega shopping centers is a new technology that has a short life and has achieved many improvements and evolved in this short period of time. This technology has increased the efficiency of residents. It has completed the possibility of effective management based on needs and human-centric applications using different AI techniques with the lowest cost. In addition to the convenience of managing smart mega shopping centers and the convenience of buyers, the remarkable thing is that the smart system will save considerable energy costs. Significant advances in technology have entered various fields of human life and have been able to create fundamental changes in various industries. Innovative technology has also been able to provide the ground to prevent energy wastage and a wise attitude towards sustainable construction so that a commercial building with the highest quality and security can be built for the well-being and comfort of customers with a human-centric perspective and energy consumption can be reduced with controlled planning. Information security and related systems have multiplied due to the IoT development. In this framework, ambient intelligence and cloud computing is expected to offer the human consumer high-quality services and unknown buying. Physical or electronic elements, such as scanners, are also envisioned.

As a result of the use of the IoTs, in enormous shopping centers, analyzing the obtained data, the taste of the target market and customers who are different in terms of age, gender, income, taste, and education level. Parameters can be identified, and the goods or provide exemplary service for each customer so that by providing better, faster, and higher quality services, they can gain more market share than their competitors [1]. Smart Deals Systems (SDS), considering the IoT, is a system that uses IoT technology to enable businesses to create and manage deals, discounts, and promotions in real time. It allows businesses to track customer behavior, analyze data, and create personalized offers tailored to each customer's needs. The system also provides insights into customer preferences and buying habits, allowing businesses to target their promotions better and increase sales. Additionally, the system can be used to monitor the performance of campaigns in order to optimize them for maximum efficiency.

New prospects to tackle these problems are being created by developing AI approaches for SDS prospects with human-centric applications. Technology-based service innovation and delivery choices have grown significantly during the past ten years. Numerous businesses provide their clients and staff with self-service choices for better, more effective, personalized services [2]. Those challenges are applied to find a way to solve how to reduce costs, increasing customer satisfaction and loyalty based on human-centric application. The current research aims to study and discover the needs of consumers, analyze the process of the human-centric framework of consumer behavior, and prioritize the factors influencing this process by making the SDS more intelligent based on IoTs technology and improving the potential sales of the shopping center, which this analysis. It is done with the help of the Markov logic network model. To address the above limitations of SDS based human-centric approach. We propose a novel Markov Logic Network (NMLN) framework for the

SDS systems network. First-order logic and the numerical strength of Markov networks are combined in MLNs, a probabilistic visual framework. MLNs represent a group of logical claims. Artificial intelligence, machine learning, and data analysis are just a few applications for MLNs. MLNs are probabilistic relational learning that incorporates first-order MLN components. In areas where relationship information is essential, they help address ambiguity and reasoning. MLNs offer a framework for managing intricate dependencies and interactions between entities. In addition, more significant MLN sales allow for better modeling of their problem area compared to alternative approaches. By using probabilistic reasoning, MLNs can deal with uncertainty. Compared to deterministic methods, the property of MLNs enhances the robustness and correctness of their model. Here are some necessities that Markov can handle in SDS: They are dealing with Uncertainty and Ensuring Scalability and Justification based on theory. This would help readers better understand the rationale behind their research and the potential impact of their contributions. In this research, we answer the following questions:

- Does consumer behavior change using IoT technology in the proposed framework compared to traditional shopping methods?
- What factor of purchase pattern derived from the proposed system affects potential sales?
- What is the complete design of the SDS network's corresponding functions in detail?

We have made an IoT technology based on the MLN network to test the functions of the SDS network based on human-centric applications in some mega shopping centers. We have also closely monitored the reading range to guarantee that only the items in an intelligent cart can be read. We also give a security analysis and performance evaluation to prove that this system is practical. AI racks equipped with weight and motion tracking sensors help employees with information generated from RFID tags. So that they can better manage and optimize the movement of products and the lack of goods in production centers and shelves by using related applications. Finally, we consider a customer satisfaction human-centric framework based on reducing time and energy, and the SDS network based on IoT can be determined better to control the volume of product sales and payment transactions. This paper is pioneer research in the procedure of SDS human-centric applications in shopping centers. We list our contributions as follows:

- To enhance links in an SDS, by employing IoT-based RFID technology to automatically read tags and barcodes of goods within an allowed range.
- We address the IoT-enabled security systems that can be used to monitor customer activity in the shopping center to reduce losses due to theft and improve overall security.
- Providing a data-semantic hybrid driving method with uncertainty handling helps parties make informed decisions.

- Addressing a probabilistic approach called MLN to model human-centric applications and system interactions to represent the various factors influencing customer behavior, such as preferences and past purchases.

The remaining article is organized as follows. A literature analysis of the SDS human centric and market and related works are presented in Sect. 2. The preliminaries and presents the survey method of the SDS network and other research solution approaches in Sect. 3. presents challenges and discussion have been addressed in Sect. 4. We present a discussion part in Sect. 5. Finally, conclusion and future research directions are addressed in Sect. 6.

2 Literature and related works

In recent years, Investigation of IoT techniques has been a popular topic in market and purchasing. However, SDS with human-centric applications has not been well-investigated. Several research articles have been published recently regarding enhancing customers' shopping experiences. In recent investigation [3] focused on RFID technology that records information about the location of shopping carts in a supermarket and uses observational data from customer visits to estimate the overall structure of the store; Then, it provides a Robust MLN model to analyze the number of sales [4]. The concepts of payments and smart shelves were also covered throughout their work. RFID equipment can be used to detect smart carts and shelves and record the items' position and condition. In order to investigate the human-centric character of their qualities and user concerns, some representative SDS are provided below [5], including analysis and practically accessible systems. These systems were chosen according to customer behavior and AI application. In another study [6], the SDS areas were defined as a matrix, and then the shopping center structure was added to the model as a random Bayesian network. By visualizing this structure of sales areas, store management can be informed of the impact of customer visits on sales results. Also, in other related work [7], they proposed the usage of MLN to recognize everyday living routines in smart home health care as an essential human-centric action recognition technique. Employing logic structure and probabilistic analysis, they produced a classifying model [8]. The MLN utilizes logic statements to represent the classification models between sensing devices and actions. MLN was prepared to achieve higher recognition reliability by utilizing customer feedback and expected activity. The IoTs connect smartphones, sensors, LED displays, and even clothes to the Internet, enabling them to interact and exchange information [9]. In today's world, the IoTs have been utilized in all aspects of life, and inventory management is no exception. While the number and variety of products and customers are increasing daily, inventory management has become increasingly complex [10]. The biggest problem of store owners is optimizing inventory management along with increasing sales and reducing operating costs. In another investigation [11], They presented an interactive purchasing model and an intelligent inventory management system integrating IoT and cloud computing. It provides efficient access, tracking of orders, and monitoring and purchase of products with minimal human-centric application intervention [12]. This system provides real-time asset monitoring and tracking of the entire supply chain, an essential step in developing an optimized logistics chain and an interactive shopping marketplace. Recent advances in RFID technology and tracking customer movements in shopping centers have facilitated the recording this information in databases [13]. The data that includes the movement paths of customers in supermarkets are sequence coordination data known as shopping path data. These data can help analyze customer behavior based on human-centric applications and tracking service satisfaction and provide helpful knowledge in combination with the SDS statement [6]. In another study, the smart cart can be helpful for customers to make purchases in the SDS network. This smart cart is designed based on a standard shopping platform with a powerful engine and several peripheral devices, such as a laser scanner and RFID tag reader, which can be used to provide information about the products in the shopping cart to the customer in the user interface. In addition to the reasonable cost, these computers have acceptable performance, upgradeability, and high flexibility and can be coordinated with tablets and RFID tag readers [14]. A smart shopping cart can provide an efficient user interface for customers to promote sales services effectively. A smart shopping cart can provide an efficient user interface for customers to promote sales services effectively [15]. In this design, using facial recognition technology in the user interface of the shopping cart, customers can be identified, and the information related to each customer's purchase can be categorized based on the purchase history. RFID tags allow these shopping carts to automatically identify the different products that are added to them and show their related information in the user interface [16]. Finally, these smart cards can do the bill payment service, and the information saved on the purchase will be sent to the store's cloud server. Digitally, consumer services, and applications were built for an RFID ecosystem by [17]. The majority of businesses currently use barcodes for supermarket marketing. However, the trend is toward using RFID rather than barcodes because RFID can read data from a distance, giving it IoT-related properties and connecting all the items in smart shopping. A flexible, robust, and expandable framework of the SDS using IoTs has been proposed, including three layers: perception, data management, and application. The perception layer refers to the ability to perceive and communicate with intelligent objects. The data of this layer of information of smart objects inside the store are collected and processed if necessary and then sent to the cloud computing platform. Contact between intelligent objects and cloud computing platforms is done through wide networks, including the internet, wireless networks, AI communication, or mobile phone communication. The cloud computing platform forms the central part of the data management layer [18]. This layer has several primary functions, including storing and managing heterogeneous information, providing unlimited computing capabilities, providing methods for data processing, updating, warehousing, and trust control to ensure data security. Based on the previous layers, the application layer can also provide semantic services, modeling and event detection, and intelligent programs such as shopping guides, extracting data on customers' purchase paths and reminding of product shortages [19]. These three layers are integrated to build the SDS framework. The critical design needs, from the problems of the human-centric framework to the SDS and the persons utilizing it, influence both services and features. The customer, the tasks they do, and the resulting issues are the main subjects of the human-centric viewpoint. Any intelligent purchasing that engages with the network and influences or is influenced by it is considered human-centric [20]. It introduces a human-centered approach to system design. It goes through all the terms associated with this technique, actors carrying out tasks, actors' worries causing system limitations, and their interrelationships.

Checking performance validity in intelligent systems is also very important; Because if the components of an intelligent system perform inappropriately at any level, it will damage the output of the entire system, and those results cannot be relied upon. The research is among the previous research in evaluating the reliability of a communication system with creative human-centric using data mining. In general, the introduction of information and communication technology in various business fields has caused changes in the factors affecting economic growth and development; Therefore, the development of essential functions and innovation in them will improve the level of application of information-related technologies and business intelligence.

3 Proposed problem

With the emergence of new technologies, and the replacement of classic systems and human factors with more efficient systems, the cost of development and operation time is decreased, efficiency is optimized, and flexibility and accuracy are increased. Today, most devices connected to AI technologies are directly used by humans. However, with the arrival of a new trend, devices connected to the Internet are intelligent enough to perform assigned tasks automatically without human intervention. The complexity of these devices can range from simple RFID tags and sensors to a complex network of connected devices managed by other intelligent devices. The IoTs is a technological revolution that provides future computing and communication, and its development requires the support of some innovative technologies. The IoTs is a new method that combines different aspects of different technologies and approaches.

Based on the stated content, the need for an SDS human-centric based on IoT technology becomes necessary; Therefore, this research presents an intelligent sales system using IoT technology. This sales system improves customer service and operational operations in the store. Increasing the speed of inventory and in-store processes will help in the real-time processing of processes. New forms of mobile device interaction based on digital customer-centric application cards through smartphones will increase, and digital payments will also become more widely operated. This system will allow retailers to gain deeper insight into in-store operations and how to manage them proactively. The proposed system monitors the inventory of shelves and different intelligent departments that automatically inform employees when the inventory of goods is reduced to a certain amount or when the goods on the shelf need to be sorted. They are arranged. Wearable and portable devices help employers to provide better services. Shopping can be done while moving, which reduces waiting time and energy and satisfy customers. The information collected

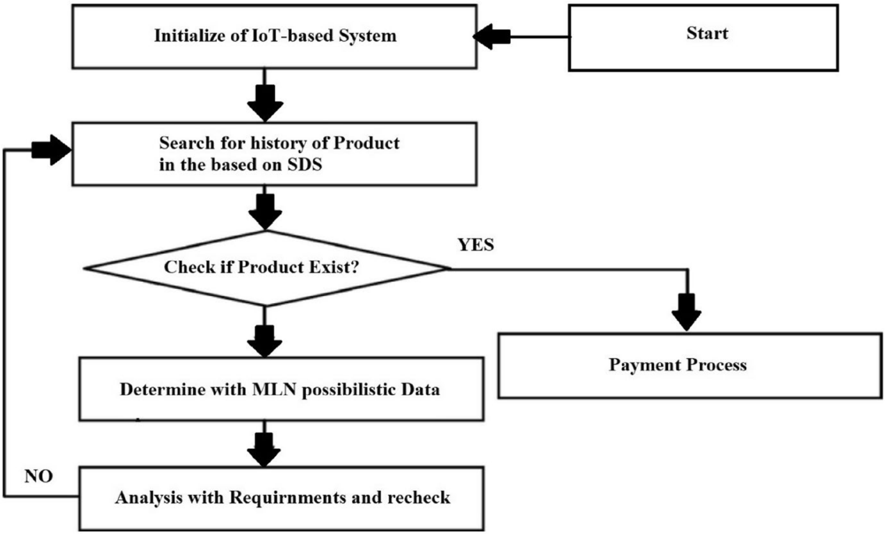

Fig. 1 Flow diagram of searching and process of smart deals systems

from the store plays a significant role in improving the efficiency of operations, better understanding customers, and providing personalized experiences. Customers can have dynamic prices, personalized offers, and customized products and services. IoT will allow complete, more efficient supply lines, automated and personalized shopping experiences, and reduce workplace employee hurt danger. The key to creating an effective flowchart for demonstrating numerical solutions is to break down the process into manageable steps and to use clear, concise labelling to explain each step. With the right approach, a flowchart in Fig. 1 can be a powerful tool for communicating complex numerical solutions in a way that is easy to understand.

3.1 Model survey instruction

The IoTs allow retailers to build a vastly improved ecosystem that connects the physical and digital worlds and enables two-way, real-time communication with consumers inside and outside the store. Today, smartphones are increasingly available everywhere. Retailers seek new ways to connect with customers and improve their shopping experience. For example, tracking human-centric customers' paths in the store using sensors can help managers improve store designs and product placement strategies. Therefore, the IoTs significantly decrease delays and costs by creating an integrated, accurate, reliable, and up-to-date database. Security issues are comprehensively covered, and inventory management [21] is automated and intelligent. All these factors indicate the improvement of shopping inventory management performance and will determine significant competitive advantages for them in the market. Figure 2 illustrates a plan for the SDS where the Internet of Things equipment is present in the entire store on the shelves and carts and checkout and exit gates. The volume of product sales and payment transactions is essential in such

Fig. 2 Schematic structure of proposed SDS based on the Internet of Things

a system. Shopping employees can more carefully monitor current work and follow the list of activities that must be done through an application. The manager can also know the quantity and quality of the shop's products and manage the store more intelligently. Customers can identify and enter the shop through the application or web platforms. Upon arrival, the store sends a welcome message to the customer, and the entrance gate sensor registers the customer's entry and assigns a unique ID to each customer. This sensor monitors the number of customers inside the store and records information about frequent visitors, such as purchase dates and personal preferences, in the central system. Human-centric application in intelligence sales networks in smart shopping involves utilizing technology to enhance the customer experience while maintaining a personal touch. This can include using data analytics to personalize recommendations and promotions and utilizing chatbots and virtual assistants to provide quick and efficient customer service. However, it is essential to remember that technology should only partially replace human interaction, as many customers still value speaking with a knowledgeable sales associate. A successful intelligence sales network in smart shopping should balance utilizing technology and maintaining a human touch.

Well, the customer movement analysis in a smart sales system based on IoTs is quite fascinating. With the help of sensors and cameras placed strategically throughout the store, the system can track and analyze customer behavior, such as which products they are looking at, how long they spend in certain areas of the store, and even how they move around the store. This information can then be used to optimize store layout and product placement to increase sales and improve customer experience. At the moment they enter the store, it can suggest the best route to reach the exact location of the desired products and inform them of the availability or absence of those products in the shop; Also, to provide better and more effective services to each customer and to inform them of the store's special offers and discounts based on the number of visits, amount and purchase records of each customer. Based on Fig. 3, smart cards can provide data about store products to consider customer expectations based on human-centric services. Stores are full of various products,

Fig. 3 Smart cards control the goods data based on IoTs

and it will be challenging to follow these products and find them. This means that customers must spend much time searching for products. In this system, with the help of the IoTs, the time of customers and store owners can be saved. Many benefits can be achieved by equipping the store with sensors that help the seller and customer find the location of a specific product. When the customer reaches the desired shelf, he can scan all the products with his smartphone, see the complete product information, and search for related comments on the websites. Digital displays can also read sensors and inform customers about product descriptions, benefits, and nutritional value of foods. Passive RFID chips are installed on all goods; Therefore, when the customer chooses a product, takes it from the shelf, and puts its cart, the chip is activated, and the unique code of the product is sent to the controller system. The smart shelf registers a decrease in the number of products. If the shelf is empty, the inventory of the warehouse is checked, and the employees are informed through the application to fill the shelf again.

3.2 Model formulation

The following primary objectives should be met by our suggested smart shopping network: (1) The intelligent cart must be able to read things added to or withdrawn from the cart accurately. One cart should not be capable of recognizing an item placed in another cart close. (2) The server should maintain the condition of the goods in the shop. The products may be seen, and the item supply can be modified on the database with the help of RFID sensors put on the racks. (3) Before the departure door, we suggest placing RFID scanners that can scan every object in the smart card and verify with the server to see if anything has been accounted for. A dishonest consumer who tries to exit the store without paying will fail the verification process.

Many more services, including navigation, branding, and coupon advice, can be accomplished in the future in addition to the primary objectives. The smart cart's features can easily be expanded to include advertising and discount suggestions, and navigating is possible by using localization to locate a shopping cart.

IoT-based approaches have benefits, including rich real-time data, ambient insights, and personalized suggestions when combined with MLNs. However, difficulties come from data complexity and privacy issues. Other ML methods offer more widely applicable strategies, although they may need assistance capturing the complex relationships in IoT data and involve more work in developing features. The smart sales system's unique requirements and trade-offs determine whether IoT-based techniques and other ML models should be used.

3.2.1 Markov logic network (MLN)

Markov logic network (MLN) analysis is utilized to validate the performance of the proposed system [22]. MLN is a probabilistic logic that allows for uncertain inference by incorporating the principles of a Markov network into first-order logic. The MLN L is a set of pairs (f_i, ω_i), where f_i is a formula in first-order logic (FOL) and ω_i is an actual number. Together with a limited set of constants $C = \{c_1, c_2, ..., c|c|\}$, it defines a Markov network. $M_{L,C}$ defines as follows:

- $M_{L,C}$ contains one binary node for each possible grounding of each atom appearing in L. The value of the node is 1 if the ground atom is true, and 0 otherwise.
- $M_{L,C}$ contains one feature for each possible grounding of each formula f_i in L. The value of this feature is 1 if the ground formula is true, and 0 otherwise. The weight of the feature is the ω_i associated with f_i in L.

Let X be the set of all grounded elements more precisely, F be the set of all first-order clauses in the MLN, ω_i be the weight associated with clause $f_i \in F$, $\wp_i$ be the set of all possible groundings of clause f_i with the constants in the domain. Then, the probability of a possible world x is defined as:

$$\begin{aligned} P_\omega(X = x) &= \frac{1}{Z} \exp\left(\sum_{f_i \in F} \omega_i \sum_{g \in \wp_i} g(x)\right) \\ &= \frac{1}{Z} \exp\left(\sum_{f_i \in F} \omega_i n_i(x)\right) \end{aligned} \tag{1}$$

where the subscript w represents a set of clause weights, $g(x)$ equals 1 if g is satisfied and 0 otherwise, $n_i(x)$ denotes the number of true groundings of f_i in x, and it is as follows:

$$Z = \sum_{x' \in X'} \exp\left(\sum_{f_i \in F} \omega_i n_i(x)\right)$$

is the normalizing constant.

A Markov network's structure is a graphical representation of the mutual effects of the variables to be modeled. This method is based on conditional probability calculations. In this research, the MLN is addressed to analyze the number of sales to achieve the potential sales and the supply of alternative goods sold in the shopping. Therefore, in this section, we define the effects of different first-order logic applications on SDS.

For smart deals systems, Markov Logic Networks can be crucial for expanding their capabilities and tackling specific problems. As fresh data enters available, MLNs can grow and change over time. MLNs may continuously update their knowledge and enhance their predictions and suggestions in an SDS where client preferences and economic conditions constantly change. IoT data and other pertinent information can be incorporated by MLNs to provide customized sales recommendations that match each customer's tastes and effective sales tactics, thus improving sales performance and client satisfaction.

3.2.2 First-order logic

First-order logic (FOL) is a standard framework for representing propositions about the universe that is utilized in computer science, and mathematics [23]. In FOL, a paragraph's or statement's predicate can only allude to one subject. In first-order logic, the four symbols are:

Constant: A constant is an item with a permanent value that never changes. Constants are often defined in first-order logic by the lowercase characters at the start of the vowel (e.g., a, b, c). Variable: A replacement with any value is referred to as a variable. Variables are often indicated by lowercase characters in the center of the vowel in first-order logic (e.g., x, y, z).

Function: A function is a formula that accepts one or more variables and produces a result. Functions are denoted in first-order logic by the uppercase characters at the start of the alphabet (e.g., F, G, H). The squaring of x, for instance, could be represented by the function F(x).

Predicate: A predicate is a declaration that has two possible outcomes: correct or incorrect. Predicates are often defined by uppercase characters in the spelling center in first-order logic (e.g., P, Q, R). Predicates are applied to indicate how different objects relate to one another. For instance, the sentence "x is greater than y" might be represented by the predicate P(x, y). Therefore, according to these four crucial factors in FOL, we will now discuss the definitions of this research based on these four factors, as shown in the table below. Table 1 represents relationships between customers, products, and their characteristics in an SDS. In Eq. (2), we say that all customers prefer a specific product type. In Eq. (3), a customer buys a product if and only if they like it and can afford it. In Eq. (4), at least one product has a promotion. Finally, in Eq. (5), for all customers, a product with a discount for them exists. Equation (6) states that if a customer purchases a product, then the product's inventory level decreases by one. Customers who spend more than \$100 in a single transaction receive a 10% discount. They will receive a notification for this discount in Eq. (7). Equation (8) states that if a customer enters a specific aisle, they receive

Table 1 Various activities between customers and their characteristics in an SDS

Activity	FOL	
Preference	$\forall x \forall y;$ $Customer(x)$ $\rightarrow HasPreference(x, y);$	(2)
Afford to pay	$\forall x \forall y;$ $Customer(x) \wedge Product(y)$ $\rightarrow Purchases(x, y)$ $\leftrightarrow Likes(x, y) \wedge CanAfford(x, y)$	(3)
Promotion	$\exists y;$ $Product(y) \wedge HasPromotion(y)$	(4)
Discount	$\forall x;$ $Customer(x)$ $\rightarrow \exists y(Product(y)$ $\wedge HasDiscount(x, y))$	(5)
Inventory Control	$\forall x, y;$ $Customer(x) \wedge Product(y)$ $\wedge Purchases(x, y)$ $\rightarrow DecreasesInventoryLevelByOne(y)$	(6)
Incentives	$\forall x, y, t;$ $Customer(x) \wedge Transaction(t)$ $\wedge Product(y) \wedge Contains(t, y)$ $\wedge Spends(x, t, \$amt) \wedge \$amt > 100$ $\rightarrow ReceivesDiscount(x, t, 10\%)$ $\wedge ReceivesNotification(x, t)$	(7)
Smart Cart	$\forall x, y, a;$ $Customer(x) \wedge Aisle(a)$ $\wedge Enters(x, a) \wedge OnSale(y, a)$ $\rightarrow ReceivesNotification(x, y)$	(8)
RFID Tags	$\forall x, y;$ $Customer(x) \wedge Product(y)$ $\wedge PicksUp(x, y)$ $\rightarrow ReadsRFIDTag(x, y)$	(9)

a notification on their phone about a product on the sale corridor. Equation (9) expresses that if a customer picks up a product, then the product's RFID tag is read by a reader. By expressing these relationships in a formal language, we can reason more precisely and draw logical conclusions about how SDS will improve the shopping experience.

Based on the suggested method of improving the pseudo-log-likelihood while doing generative weight learning for a defined collection of clauses [22, 24, 25]. Several methods have been put in to improve the conditioned log-likelihood for discriminative learning. A weight learning approach that focuses on the scenario where MLNs only have non-recursive clauses. Because there is only one objective hypothesis in each sentence in this specific situation, each clause's grounding will have just one grounding objective hypothesis. As a result, provided the background atoms, each query atom is independent. In order to maximize the conditional log-likelihood penalized by a L2 norm constraint, we employed a MAP technique and took into account MLNs that only contained no recursive equations:

Table 2 The structure of Pseudo-code of MLN learning algorithm

```
function: Initialize Sturctual Learning (FGH, MLN, PQR)
    inputs: PQR, a set of predicates.
            MLN, a section of Markov Logic Network
            FGH, a parallel of data function
    outputs: Adjusted the Markov Logic Network
    Attach whole unit section from PQR to MLN
    for each non-unit section in MLN (Optional)
        Test all possible symbol inversion pairings for actual x and y
        to retain the one that produces the highest value (MLN, FGH)
   Section ← {whole sections in MLN}
   LearnWeeights (MLN, FGH)
  Outcome ← highest value { MLN, FGH}
    repeat
        Sections ← FindbestSections(PQR,MLN, Outcome, FGH)
        if Sections ≠ 0
    for each non-unit sections x,y in MLN
      Raise x,y from the MLN only if minimizes the highest
      value (MLN, FGH)
    return MLN
```

$$\begin{aligned} f(\omega) &= \log P(Y = y|X = x, \omega) - \lambda||\omega||_2^2 \\ &= \sum_{i=1}^{n} \log P(Y_i = y_i|X = x, \omega) - \lambda||\omega||_2^2, \end{aligned} \tag{10}$$

With

$$P(Y_i = y_i|X = x, \omega) = \frac{\exp\left(\sum_{i\in F_{yi}} \omega_i n_i(x, y[Y_i = y_i]\right)}{\exp\left(\sum_{i\in F_{yi}} \omega_i n_i(x, y[Y_i = 0]\right) + \exp\left(\sum_{i\in F_{yi}} \omega_i n_i(x, y[Y_i = 1]\right)}, \tag{11}$$

where Fy_i is the set of clauses concluding on the target atom Y_i, and $n_i(x, y[Y_i, y_i]$ is the number of true groundings of the ith clause when the atom Y_i is set to the value Y_i.

Depending on the MLN network, we have devised a search approach that is quicker and more thorough. Following the definitions from the previous section, Table 2 displays the structural learning method for the MLN system in pseudo-code.

In this research, the MLN method is applied by considering random data to validate the proposed system's performance, and the system's efficiency is concluded with conditional probability. For this purpose, first, several questions are asked as examples, which show the status of the operation of the store system equipped with Internet of Things equipment. These situations are described conditionally, and their probability of validity will be measured using the MLN method.

4 Results and analysis

In this section, to check the working steps of the system, the "Wu Mart" as a mega shopping center that has established a smart shopping card is considered. This store offers fresh food, including fruits, dairy products, meat, vegetables, seafood, hygiene products, valuable products, and household appliances. The purpose of this store is more than providing the goods customers need. The shop's customers can get the products they need at competitive prices and special discounts; Therefore, the human-centric of this shop has access to superior quality and better prices simultaneously. Customer orientation, as the central axis of the shopping activity, means paying serious attention to the wishes and views of customers. To do this, an unpaired two-sample t-test was used to compare the mean total amount of shopping cart, and number of unique items in the shopping cart between individuals using IoT in their shopping experience and those who do not use IoT.

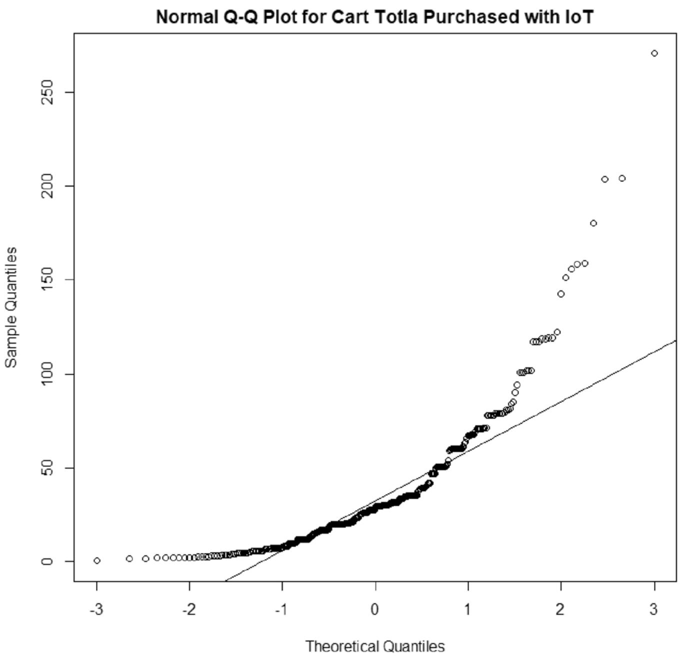

Fig. 4 Normal Q–Q plot for overall shopping expenditure, individuals using smart carts

4.1 Preliminary analysis

One of the objectives of this study is to investigate whether the overall shopping expenditure differs when IoT is used compared to when it is not used. Before conducting the t-test, a Fisher's F-test is used to test the homoscedasticity of the data. Moreover, in Figs. 4, and 5, QQ plots are used to check the normality assumption of the data, whereas the F-test is used to check the homogeneity of variance assumption between the two groups. The plot suggested that both groups had similar distributions and no significant deviations from normality. However, to ensure that the variances of the two groups were homogeneous, a Fisher's F-test is conducted.

The F-test showed that the variances of the two groups were significantly different ($F=0.514$, $p<0.05$), indicating heteroscedasticity. Therefore, a Welch t-test is used to compare the means of the two groups, as it is a more appropriate test when the variances of the groups are different.

The results of the Welch t-test showed that there is no significant difference in the total purchase value between the two groups (p value = 0.6967). The mean total purchase value for the individuals using smart carts is 36.72, and for those who do not use IoT, it is 33.79. The 95% confidence interval for the difference in means is −12.09 to 17.95, which contains zero, suggesting no significant difference. Additionally, Fig. 6 presents a box plot comparing the total purchase value between the two groups.

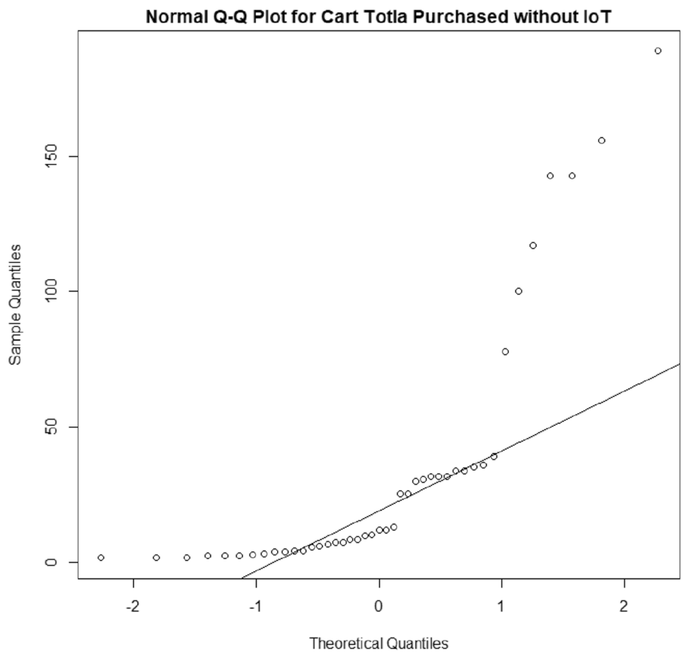

Fig. 5 Normal Q–Q plot for overall shopping expenditure, individuals not using smart carts

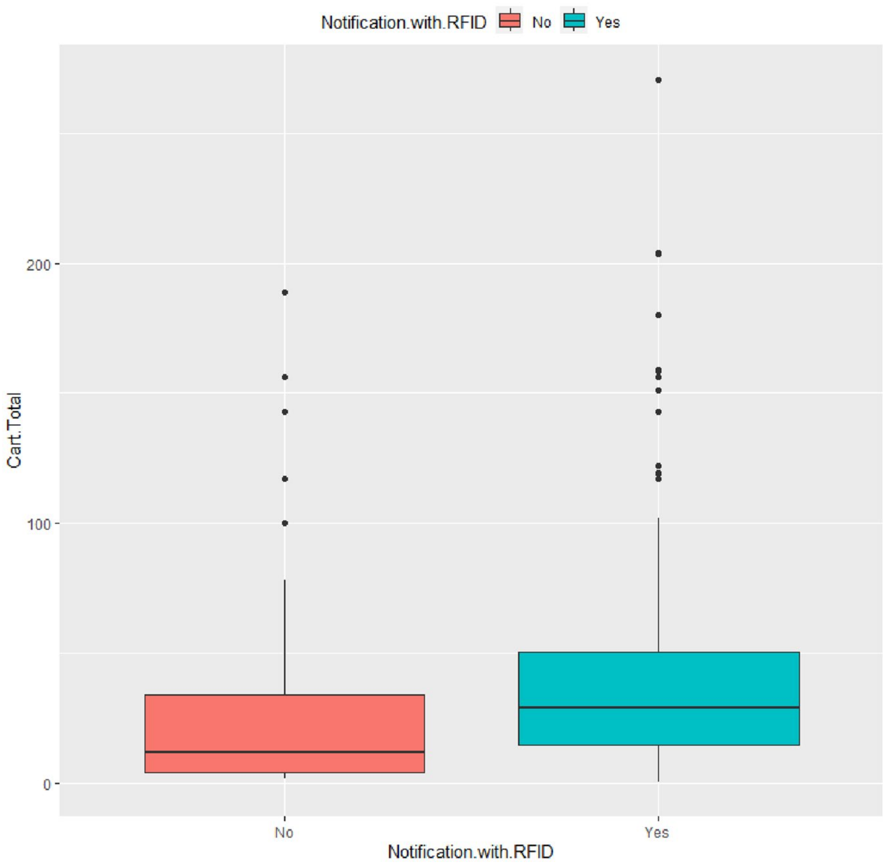

Fig. 6 Boxplots for overall shopping expenditure

4.2 Number of unique items

For the number of unique items in the cart when the shopping is finished, a similar analysis is performed. First, QQ plots are used in Figs. 7, and 8 to check the normality assumption of the data.

A Fisher's F-test is conducted to check for homogeneity of variances, and the results indicated that the variances between the two groups were significantly different ($F = 1.993$, $p < 0.05$). Therefore, a Welch's t-test was used to compare the mean number of unique items in the cart between the two groups. The results of the t-test indicated a significant difference between the two groups ($t = 3.1218$, $df = 63.262$, $p < 0.05$, 95% CI [1.72, 7.82]). Specifically, the individuals who are using smart carts had a higher mean number of unique items in the cart (mean = 10.75) compared to individuals who do not use IoT (mean = 5.98). The statistical results are presented in "Appendix". Additionally, Fig. 9 presents a box plot comparing the total number of unique items in carts.

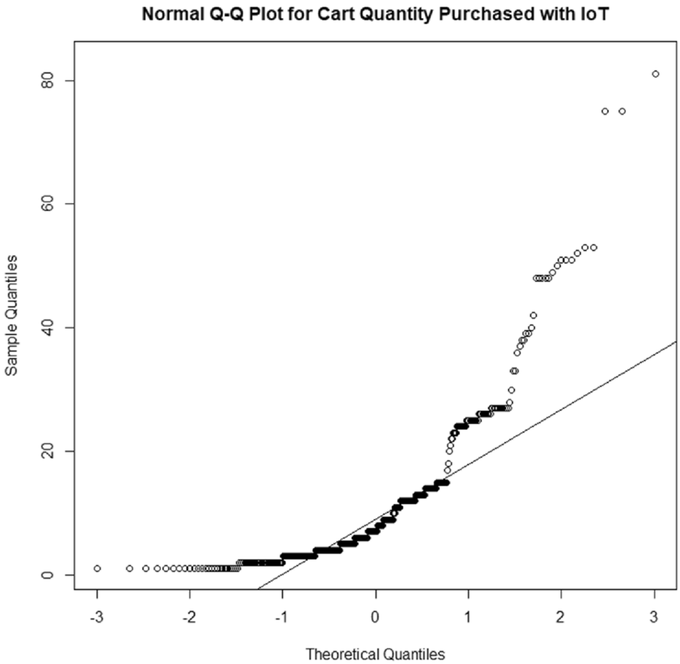

Fig. 7 Normal Q–Q plot for number of unique items, individuals using smart carts

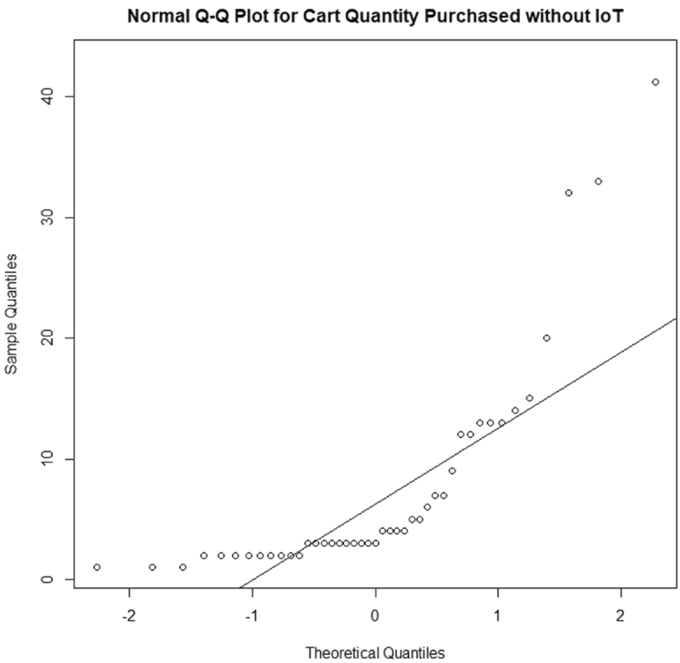

Fig. 8 Normal Q–Q plot for number of unique items, individuals not using smart carts

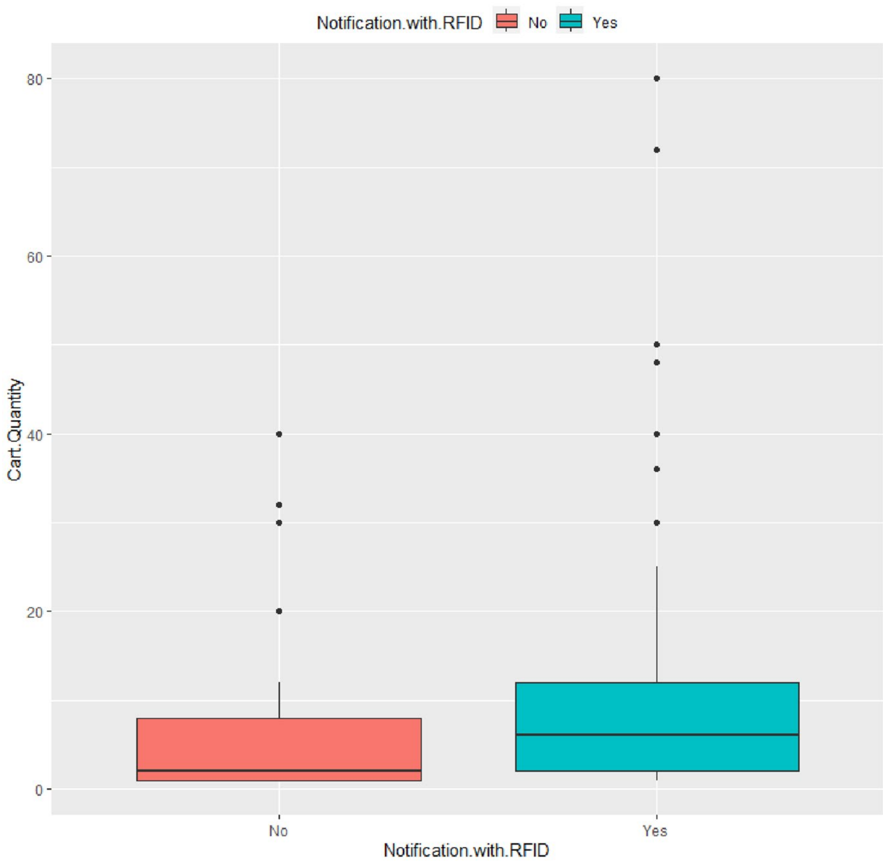

Fig. 9 Boxplots for number of unique items in carts

Based on our analysis, we found that while the total amount of dollars in each shopping cart did not significantly differ between individuals who are not using smart carts and those who are using smart carts equipped with IoT technology, the number of unique items in the cart was significantly higher among the latter. This indicates that the use of IoT in shopping carts has a positive impact on customer satisfaction by facilitating the discovery of desired items and creating a more diverse shopping cart without increasing the monetary cost. Therefore, it can be concluded that the use of IoT in shopping carts provides a more human-centric shopping experience, meeting the evolving expectations of modern-day consumers. The findings suggest that the integration of IoT technology in shopping carts has the potential to create a paradigm shift in the way we approach retail shopping, with a greater focus on customer convenience and satisfaction.

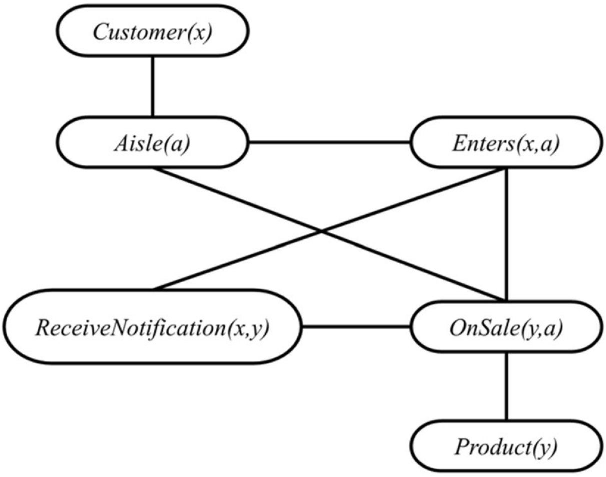

Fig. 10 MLN for Notification system of Smart Carts

4.3 Analysis System using MLN

MLNs are a probabilistic framework that allows us to reason about uncertain situations. In the context of smart shopping carts, MLNs can be used to predict when to send notifications to users during their shopping experience to improve their satisfaction. To demonstrate the usefulness of MLNs in this context, we used a dataset of customers in "Wu Mart" shopping experiences with smart carts equipped with IoT technology. The features we used to build our model can be classified in four main categories:

1. Time: includes the date and time of the purchase, as well as the day of the week and any holidays or special events.
2. Product information: includes details about the products purchased, such as the category, brand, price, quantity, as well as promotions or discounts.
3. Store information: includes details about the store's layout, and aisles.
4. IoT: includes smart shopping cart location, RFID scanned in cart.

We had access to 1417 shopping trips and recorded the time stamps of when the user added items to their cart and when they checked out. We then used this dataset to train an MLN to predict notifications of products which converge to purchase. Specifically, we modeled the relationship between the user's shopping behavior and the probability of sending a notification at each time step in our MLN model proposed in Fig. 10. The nodes in this figure are formed by all the potential ground functions in the given domain. The edges are established based on the groundings of the first-order clauses, connecting the functions. Also, the possibility that users would interact with the system, make buys, and remain to utilize the MLN-enhanced smart sales system increases each time the step in MLN exhibits more precise and relevant MLN forecasts. This results in the

Table 3 Results of various performance metrics based on train and test sets

Performance Metric	NB (%)	LR (%)	MLN (%)
Precision	66.32	45.45	94.59
Recall	75.01	22.72	79.54
Specificity	89.10	92.30	98.71
F1-score	70.21	30.30	86.41
Accuracy	86.04	77.13	94.51

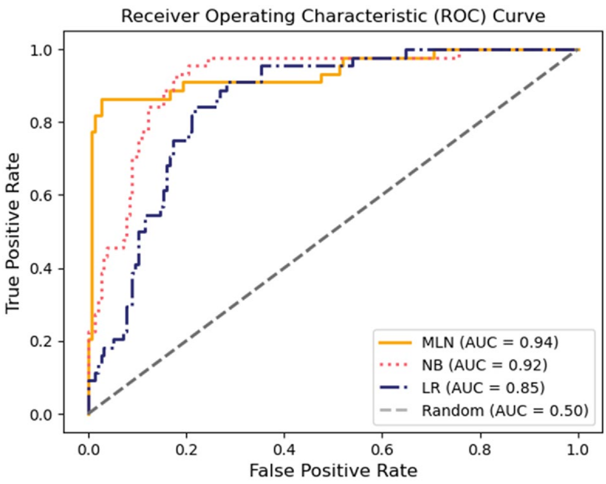

Fig. 11 Receiver operating characteristic plot for MLN, NB, and LR models

formation of predicate among nodes that appear together in a FOL depicted in Table 1, used as a set of logical rules to encode our prior knowledge. We then used the trained MLN to predict when to send notifications for a test set of 100 shopping trips. The algorithm's performance was evaluated using the area under the precision-recall curve (AUC). The AUC metric represents the area under the curve of a plot of True Positive Rate against False Positive Rate for different classification thresholds. In other words, AUC measures how well the model can distinguish between positive and negative classes. Formulated Forecasting Task Clarification:

Prediction label The prediction label in our forecasting task is whether an item is purchased or not after sending the notification. The positive class indicates a successful purchase, while the negative class represents the scenario where no purchase occurs.

Train-test split We perform a train-test split using an 80–20 ratio. Specifically, 80% of the data is used for training the models, and the remaining 20% is reserved for evaluating model performance on unseen data.

Test set size The test set consists of 100 shopping trips, providing a representative subset for assessing the generalization capability of the models.

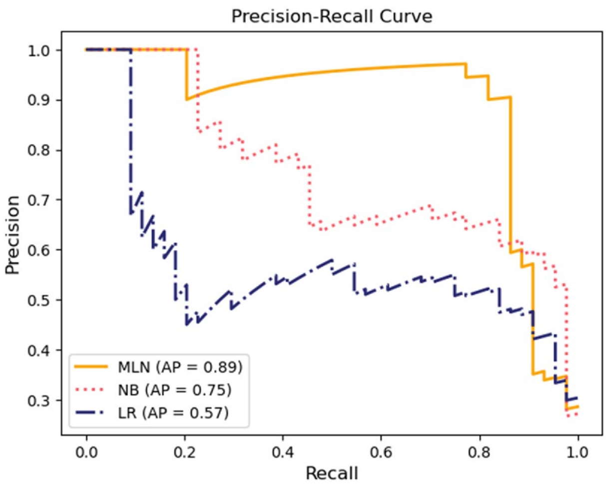

Fig. 12 Precision and recall plot for MLN, NB, and LR models

Performance Metrics on Train and Test Sets:

In response to the suggestion to report performance on both train and test sets, we agree with the importance of evaluating model generalization. The presented performance metrics, including Precision, Recall, Specificity, F1-Score, and Accuracy, are indeed computed on the test set.

In this study, five performance metrics—accuracy, precision, recall, specificity, and F1-score—have been presented to assess the models' performance based on the test set. Model accuracy reflects its overall proficiency in correctly identifying positive and negative classes, while precision gauges the model's effectiveness in predicting instances belonging to the positive class. Furthermore, recall and specificity measure the model's ability to correctly identify actual positive and negative classes. Additionally, F1-score offers a balanced evaluation by considering both precision and recall (Table 3).

Unlike LR and NB, which assume linear separability and feature independence [26], the MLN model can discern intricate patterns and correlations. Moreover, the MLN's capacity for hierarchical feature learning and its adaptability to diverse data structures enable it to uncover hidden layers of the underlying data distribution. These distinguishing features position the MLN model as a powerful tool for enhancing predictive accuracy and uncovering deeper insights in data-driven research and decision-making processes [22]. Precision/recall curves for $ReceiveNotification(x, y)$ atoms which converge to purchase are displayed in Fig. 11, indicating that MLN outperforms its competitors in accuracy, demonstrating the potential of this methodology. The purely logical and purely probabilistic approaches are prone to difficulties when inferring intermediate predicates while MLN is generally immune.

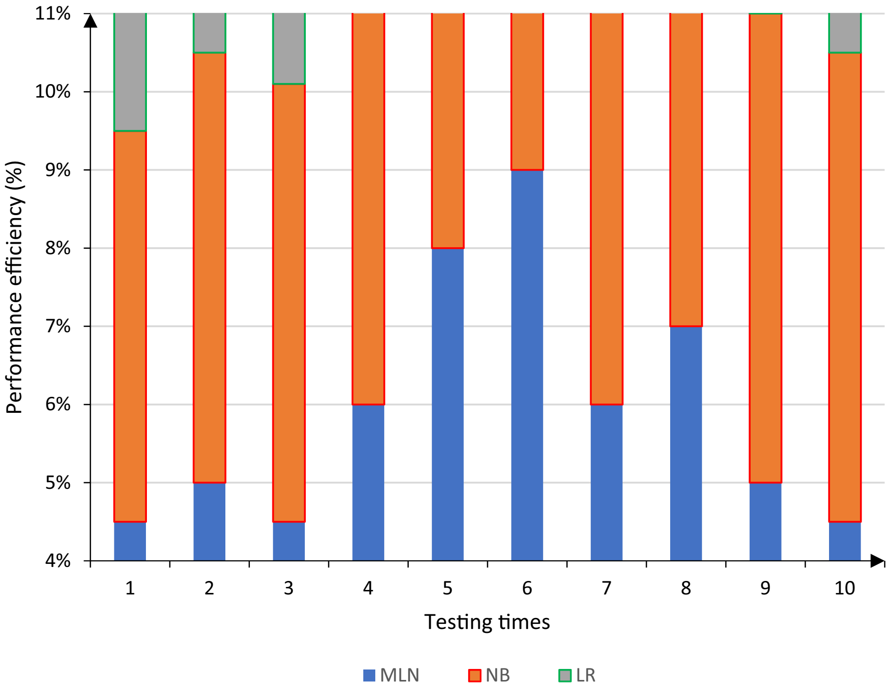

Fig. 13 Statistical analysis of performance percentage of three factors based various test times

MLN is also found to outperform the baseline models in Fig. 12, providing a more accurate and effective method for the task at hand. The IoT generates large amounts of data that are often incomplete, noisy or ambiguous, which makes it challenging to make accurate predictions. Proposed MLN model can handle these types of data by modeling them as uncertain or probabilistic, which enables them to make more accurate predictions.

This demonstrates the potential of MLN to improve the human-centric design of smart shopping carts and provide a better shopping experience for customers.

4.4 Statistic analysis of MLN

Statistical analytic methods are the cornerstone for comprehending data, seeing trends, and calculating uncertainty in SDS. The integration of MLNs with statistical techniques enables a comprehensive approach to modeling, prediction, and decision-making, leading to enhanced effectiveness, productivity, and overall performance of smart deals. Moreover, the integration of statistical analysis with MLNs allows for a rigorous analysis of data dynamics, enhancing the reliability and interpretability of the decision-making process.

During the activity of MLN, based on the percentage of efficiency, around 10% of clients are connected randomly, which has a minor impact on the outcomes from LR. Similar outcomes are delivered when the number of customers in the scope of 30–40% is connected for NB. As the number of performances increases, the accuracy maximizes. However, based on statistical analysis in Fig. 13, overall is within the performance percentage of 50%, with a precision of 8–9% as the average for MLN determined.

5 Discussion

However, one technology that links numerous elements in a network is the Internet of Things, which represents a turning point in the development of the intelligent world. The foundation of smart deals systems is human-centric performance. Users can shop thanks to this innovation effectively. Businesses and customers are both involved in the idea of programmable commerce, which enables purchases to be performed on their behalf. This is done automatically via the IoTs and other network devices. In order to prevent consumers and appliances from running out of supplies, the sensors can be designed to detect declining supplies. Overall, smart shopping based on IoTs and a human-centric approach can revolutionize the retail industry by providing personalized experiences for consumers while improving operational efficiency for retailers. However, addressing these challenges will be critical for its success. One of the biggest challenges for smart shopping is ensuring the privacy and security of personal data collected by IoT devices. Consumers are concerned about sharing their personal information with third parties without their consent. Another challenge is integrating various IoT devices and platforms to complete a seamless shopping experience. This requires collaboration between different companies and standardization of protocols. In this research, we tried to offer the best view for customer satisfaction using IoTs technology for SDS. However, every research has limitations, which may be defined as follows. While IoT-based SDS can collect vast amounts of data about human-centric behavior, they may only sometimes be able to provide personalized recommendations or experiences that genuinely meet individual needs. Also, The SDSs should be designed with a human-centric approach considering user needs, preferences, and behaviors. However, this requires a deep understanding of human psychology and behavior which may only sometimes be feasible or practical for all retailers. The practical ideas and factors managers consider developing and employing such a system are the managerial implications of an SDS. These effects have an impact on a variety of sectors, including daily operations and strategic planning. Security and privacy issues become crucial with integrating IoT devices and client data. Data security safeguards, authentication procedures, and adherence to data protection laws should all be given top priority by managers. It is crucial to clearly communicate data usage and privacy regulations to keep customers' trust. An SDS has managerial ramifications in making strategic choices, client engagement, efficiency of resources, handling performance, data security, and process enhancement. Managers are vital in maximizing the system's ability to boost customer interactions, increase revenue, and optimize business operations.

6 Conclusions and future studies

This research presents a smart deals system based on the IoTs with considering human-centric. This system allows shop employees to track their inventory online. This paper aims to solve the "smart deal systems" issue using MLN for human-centric activities assessment. The advantages of MLN and federated learning were combined in this study to create an IoT platform. The trial outcomes demonstrated that MLN could further reduce concerns about customer privacy and database security when used for smart deal systems.

In regard to statistical variability, MLN was efficient. The number of consumers participating in the SDS training process impacted the outcomes because of the small dataset gathered for this work. The volatility is prominent when fewer clients participate in the training program. In real-world situations, the clients were cut off and unable to experience the training for various reasons. Additionally, the MLN framework was quite reliable, which enabled staff to control better and optimize the movement of goods inside the warehouse and on the shelves. Our future research directions will focus on improving the current system, for instance, by Exploring the role of trust and privacy concerns in adopting IoT-based smart shopping systems and evaluating smart shopping technologies' impact on traditional retail businesses, including their competitiveness, profitability, and sustainability. Also, authors can consider how to apply the fuzzy MLN framework to more IoT areas.

Appendix

The statistical results can be found in Sect. 5, while the detailed findings are presented below:

```
> var.test(data_IoT_Yes$Cart.Total, data_IoT_No$Cart.Total)

        F test to compare two variances

data:  data_IoT_Yes$Cart.Total and data_IoT_No$Cart.Total
F = 0.51459, num df = 370, denom df = 42, p-value = 0.001353
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.312751 0.779054
sample estimates:
ratio of variances
         0.5145873

> t.test(data_IoT_Yes$Cart.Total, data_IoT_No$Cart.Total, var.equal = FALSE)

        Welch Two Sample t-test

data:  data_IoT_Yes$Cart.Total and data_IoT_No$Cart.Total
t = 0.39222, df = 47.14, p-value = 0.6967
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -12.09805  17.95850
sample estimates:
mean of x mean of y
 36.72232  33.79209

> var.test(data_IoT_Yes$Cart.Quantity, data_IoT_No$Cart.Quantity)

        F test to compare two variances

data:  data_IoT_Yes$Cart.Quantity and data_IoT_No$Cart.Quantity
F = 1.993, num df = 370, denom df = 42, p-value = 0.007592
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 1.211298 3.017309
sample estimates:
ratio of variances
          1.993019

> t.test(data_IoT_Yes$Cart.Quantity, data_IoT_No$Cart.Quantity, var.equal = FALSE)

        Welch Two Sample t-test

data:  data_IoT_Yes$Cart.Quantity and data_IoT_No$Cart.Quantity
t = 3.1218, df = 63.262, p-value = 0.002709
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 1.716845 7.822928
sample estimates:
mean of x mean of y
10.746631  5.976744
```

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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