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Persuasive Marketing Intelligence in Supermarket Kiosk Agents: Extending an Intelligent Receptionist System for Context-Aware Recommendations

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***Abstract*—The number of customer contacts retail super- markets faces each day is massive, there are situations when customers inquire about the place and location of products, and active offers are promoted. Such restrictions may lead to poor navigation around the place, low consumer satisfac- tion and missed-sales opportunities. To address this gap, this paper proposes an AI-based conversational kiosk system that performs to comprehend the intentions of customers, and of- fering situationally-relevant advice, within the brick-and-mortar supermarket settings. The suggested system employs a locally developed conversational language model alongside the assistance of Ollama to process the queries of natural language without involving any external cloud-based solutions. The input of the customers is processed via Natural Language Processing (NLP) techniques and categorized under the action-oriented groups such as product location requests, offer requests or queries targeted at making recommendation. To increase sales intelligence, the system will include Apriori Association Rule Mining that will be used to identify the frequent patterns of products co-occurring in the structured information about the inventory. These asso- ciation guidelines allow the kiosk to make the suggestions of a complementary product of the product in real-time and in this sense can be considered as an upselling process in a controlled and transparent fashion. The architecture is implemented on the basis of two-part design (kiosk interface with customers and an administrative backup portal). The backend takes care of the updating of inventory, promotional offers, and layouts and maps with stores in order to maintain the responses of AI relatively close in accordance to the real-time store data. Such a separation will make sure that there is no hindrance in the decision-making process and operational visibility of staff members in supermarket is fulfilled. The practical application demonstrates that the combination of the conversational artificial intelligence and the logic of rules-based recommendations can be beneficial to the customer interaction without compromising on the system stability and affordability. The framework focuses on the feasibility of integrating the smart intent analysis and is the first step toward intelligent and scalable AI-supported supermarket processes and assistance in enhancing customer satisfaction.**

***Index Terms*—Persuasive marketing intelligence, Context aware recommendations, Conversational retail agents, Customer behavior influence, Ethical AI in retail, Intelligent in-store en- gagement, Adaptive navigation systems.**

I. INTRODUCTION

The accelerated development of digital technologies has affected the present-day retail space to a considerable extent. Supermarkets currently exist in incredibly competitive markets where the customer experience, operational efficiency, and revenue maximization are closely correlated. The support of customers in brick-and-mortar stores is heavily relying on classical methods, such as fixed aisle signs and manual employee instructions despite the presence of high-tech billing and inventory management modules. These methods are functional but they are constrained in the number of different queries in natural language that they can be used in, particularly when the customer intent is indirect or complex.

Over the recent years, conversational Artificial Intelligence (AI) has become highly prevalent in online commercial platforms [1], [2], [4]. The chatbots and virtual assistants can extract meaning behind the user queries, respond in a contextual manner, and suggest related products, depending on behavior data [8], [10]. Nevertheless, little has been done to apply such intelligent systems to real-life situations in the down-to-the-ground supermarket [3], [6]. The integration of AI is more problematic since unlike online platforms, in-store systems need low latency, controlled infrastructure, and comfortably verified data synchronization.

In this paper, an artificial intelligent (AI) based chat kiosk structure within a supermarket setting is suggested. The system is aimed at the customer intent classification and creation of structured and sales-conscious responses through the use of a locally deployed language model. The framework is built with a lightweight conversational model by using Ollama, enabling it to be free of reliance on external cloud services, allowing enhanced privacy, a lower cost of operation, and predictable performance under favorable hardware environments.

One of the objectives of the system is to transform bare

guidance questions into valuable retail responses. As an example, a demand of the whereabouts of a particular product can be used as a sign of a possible buying behavior that can be prolonged with some form of a complementary recommendation. To foster this functionality, the system combines Apriori Association Rule Mining that examines formal item collections to discover common item effects. These associations are used to propose relevant products in real time but at the same time remain contextually accurate.

The architecture is isolated into two big units, which are consumer front interface in form of kiosk, and the administration back end portal. A kiosk interface has the ability to react to natural language queries, classify them, and offer a response that may include navigation instructions and suggested prompts in the form of response. The administrative portal deals with the records of inventory, the offers, and arrangements of the store design and ensures that the replies formed by AI are anchored on the existing information about its operations. This separation causes the system to become more open and prevent it to be a black box decision maker.

Integrating conversational AI with rule-based recommendation logic, the suggested framework should be used to improve in-store customer interaction with the retail processes without interruptions. The operational scalability of the system is supported with the ability to become a complementary tool assisting the staff instead of substituting them. As the implementation shows, an intelligent intent classification that is combined with structured retail information may make the processes more efficient and help in the optimization of revenues in a physical retail context [8].

The rest of this paper addresses related work, system architecture, methodology, the details of the implementation, and performance evaluation of the suggested framework of the conversational kiosk.

II. Related Work

The recent developments in Artificial Intelligence have had a strong impact on the automation of customer service in different spheres. Artificial agent-based intelligent customer services have been proven to be efficient in terms of interaction and response accuracy within the commercial setting [1]. On the same note, robotic chatbots have been created with AI that can improve customer interaction by being able to engage clients in conversations without need of human intervention [2].

Proposals have been put forward in the retail environment in which space-based intelligent convenience store systems are aimed at enhancing the flexibility and interactivity with customers through the use of automation technologies [3]. Service robots based on the use of large language models are also presented in the environment of the shopping mall to make a better user interaction and give a contextual assistance [6]. These systems portray the increasing applicability of conversational AI in offline retail environments.

NLP-based customer service systems have gone a step higher to enhance automated query processing through pre-trained language model and response ranking system [4]. The literature has also investigated AI customer service software in the localized settings including healthcare and online shopping platforms where it has shown to be more user-satisfied and efficient with intelligent automation [7], [8].

Moreover, chat agents that cater to the needs of e-commerce settings have revealed that automated chat systems can be useful in answering questions raised by customers as well as to aid in online-shopping choices [9], [10]. Most of such implementations however are more of virtual or online providing than the physical setting supermarket.

Though prior literature shows the efficacy of conversational AI, robot help, and embracing of intelligent customer services, little research has been conducted addressing the combination of intent classification and organized retail data and association-based recommendation logic to a locally implemented supermarket kiosk framework. The proposed system is built due to this gap.

III. System Architecture

The intelligent supermarket kiosk system proposed adheres to the writing of the modular, layered architecture which is aimed at providing scalability, controlled deployment of intelligence and providing real-time data synchronization. The system is built around two logical layers, the upper tier of intelligence level, which deals with the data and decision process, and the lower level of interaction, which deals with communication with the customers and customer navigation.

A. Administrative Layer

The Administrative Module is the centre of control of the system. It enables personnel of the supermarket to take control of stocks, update stock and set promotional offers, and store layout mappings [3], [6]. Using a secure backend portal, an authorized personnel has access to:

- Add or alter product information.
- Discounts and update pricing.
- Designate products to certain aisles or area.
- Plan promotional offers that are time bound.

All modifications in this module are checked and updated with the repository of data. This ensures the records that are maintained in the administration remain constant and the type of responses that are provided to the customers.

B. Retail Knowledge and Data Layer

Retail Knowledge Layer serves as the backbone of the system's structure. It stores:
- Product inventory data
- Offers and Discounts data.
- Aisle mapping and store design information.
- Interaction logs

This layer will make sure that the AI model does not work without actual store data [4]. Rather, responses to conversation are based on proven and organized information. Real-time synchronization systems ensure that there is consistency between the administrative updates with the kiosk interface.

C. Decision Layer

The AI Intelligence Layer is the processing unit of the architecture. This module performs:
Natural Language Processing (NLP):
The queries of the customers are processed to obtain the semantic meaning and detect the intent. [1], [2], [4]
Intent Classification:
Enquiries are also grouped into standardized responses which include product location request, offer enquiry, or request recommendation.
Response Generation:
An Ollama localized language model yields structured and context-generated responses [6]. Local deployment minimizes the latency and lacks cloud dependency to make sure that it is operationally stable.
Recommendation Engine of Association:
The Apriori Association Rule Mining uses the structured retail data to determine the frequent product combinations [8], [10]. The system can make suggestions on complementary products dynamically using these suggestions.
This layer translates crude user input into practical retail instructions as well as control via ordered data in the background.

D. Navigation Layer

Navigation Module will process product mapping data to create store directions, which are easily readable by the user. The system will provide a unique navigation which the customers will have to utilize depending on the assortment of aisles and zone mapping. This module ensures:
- Recognition of the aisle products properly.
- Simplified route guidance.
- Advertisement navigation notification.

A visualization product may include an informative textual guide or be in an instructed, formatted form that would allow better user readability.

E. Interaction Layer of conversational kiosk

The system interface is the Conversational Kiosk Interface which the user is presented with. It allows the customers to interact through the touch based interface in natural language query. It is an interactive process that takes the following steps: - User submits a query.
- Query is inputted into AI Intelligence Layer.
- Intent is classified.
- Response is generated.

The product is transformed into output given to the customer. This hierarchic communication offers the fact that their communication is responsive and the programming in the back end system is managed and designed.

F. Monitoring and analytics module

Monitoring Module captures transactions of interactions, usage patterns of the system and responses offered. These logs help in:
- System performance assessment.
- Identifying sets of common queries.
- Judicial analysis of the usefulness of suggestion.

It is an effective architecture enabling to optimize the system in the future and decouple analytics and real-time processing [8].

G. Architectural Characteristics

The following are the features that the proposed architecture has:
- Scalable architecture Independent scalability.
- Local implementation of AI to attain privacy and low cost.
- Recommendation logic that is rule based.
- Open separation between administration and intelligence. Overall, one can say that the planned system architecture will ensure the managed dynamic of incorporating conversational AI into a real supermarket environment without jeopardizing the work stability and visibility.

Fig. 1 illustrates the complex architecture of the intelligent system.

IV. METHODOLOGY

A. User Query Acquisition

The methodology begins when a customer talks to the interface of the kiosk, and types a query using the natural language. It will take an input in the form of loose-textual free form in that the system will not require strict commands and syntax. The flexibility will also allow the customers to speak in a natural way and the query made be it the whereabouts of the product, the offerings made or any other questions that you may have regarding the shopping processes. Kiosk interface will serve as an entry point of the processing process and ensure that any inquiries generated within the system are securely passed into intelligence operation in the back office.

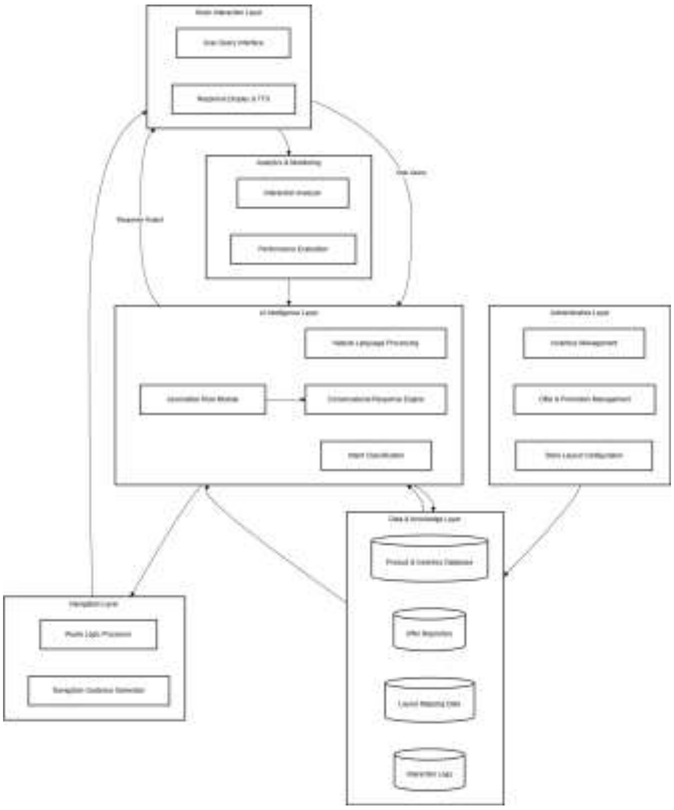

Fig. 1. Architecture of a persuasive conversational kiosk system for intelligent in-store engagement.

B. *Preprocessing and Standardization of Text*

After the query has been received, a preprocessing phase is done to standardize the input form. Normalization processes that are involved in this stage involve case standardization and elimination of extraneous symbols that can be a hindrance to semantic interpretation. Preprocessing is aimed not at fancy linguistic transformation but at the stabilization of the inputs to enhance the stability of the downstream processing. This is to make sure that the conversational model is consistent in the meaning of queries.

After preprocessing, the normalized text is then analyzed with a locally deployed conversational language model, which is run with the help of Ollama. The model conducts semantic understanding which derives situational association in the query. In contrast to the rule-based systems where the matching is stricter in terms of a keyword, the approach allows to interpret the diverse sentence structures without imposing any limitations on the operational range in the retail environment.

C. *Objective Natural language processing*

The normalized text is analyzed with an Open-source conversational language model localized on Ollama after preprocessing it. Semantic understanding in the model is by identification of contextual relation in query [1], [4]. This is unlike rule based systems that have a rigid adherence to matching keywords because this enables alternative preclusion of various form of structures of sentences and also allows regulating the limits of operation of the retail environment.

D. *Intent Classification*

The system categorizes the query into predefined intent classes of retail communication after the semantic analysis. These groups consist of requests on product location, confirmation whilst, promotional inquiry and transaction- based on recommendation. Intent classification involves making the responses unstructured operational retail functions rather than uncontrolled generative responses. This step is very crucial in ensuring predictability and consistency of response.

E. *Structured Data Retrieval*

After identifying the intent, the system will get the corresponding information stored in the structured retail database. Validated product data, pricing, promotional data, and aisle mapping body are contained in the data layer. The retrieval mechanism makes sure that all answers provided by the conversational engine are anchored on real data at the store and thus will not cause misinformation and therefore transparency will exist between the administrative control and AI processing.

F. *Association Rule - Based Recommendation*

The system uses a rule to mine Apriori Association Rule hence enhancing customer interactivity. It is a set of algorithmic methods that analyze inventory data elementized to discover trends of co-occurring goods that were frequent. An effective relationship is made, which necessitates an appendage suggestion to the original reaction by the system. This technology allows the kiosk to grow crude product queries into good sales oriented offers and save the relevant applicability [8], [10].

Once intent classification, data retrieval and recommendation evaluation are performed, conversational response engine builds a well-constructed response. It answers the query of the user straight and can contain navigation instructions or complementary suggestions wherever needed. The end result is shown on the kiosk interface and is optionally served by Text-to-Speech functionality, and this increases user accessibility and boosts user interaction.

G. *Response Generation and Delivery*

Once intent classification, data retrieval and recommendation evaluation have been completed, the conversational response engine forms a structured response.

The answer directly answers the query of the user and can also provide navigation instructions or complementary suggestions where necessary. The end result is shown on the kiosk interface and delivered by Text-to-Speech (optionally) to increase access and user interaction.

H. *Monitoring of Logs*

All the interactions that occurred with the customers are documented in the system log database. Information in the storage involves query type, classified intent and response outcome. The logging mechanism allows monitoring of the performance and aiding in analyzing the common patterns in the query and the effectiveness of the recommendation generated. The system enables the efficient classification of the intentions and operational performance of the system through a systematic record of interactions by offering the opportunity to refine the functionality in later modifications.

V. IMPLEMENTATION

A. System Development Environment

The environment of developing the system refers to the internal and external factors that will enable or hinder the accomplishment of product development objectives.¡—human—¿5.1 System Development Environment The system development environment can be said to be the internal and external elements that will facilitate or negatively affect successful completion of the product development goals.

The application of the suggested intelligent supermarket kiosk system has been introduced in a local development controlled environment to ensure stability of operation and high cost efficiency. The system was to be built on dedicated kiosk machines with no cloud infrastructure. Conversational intelligence module was locally deployed with Ollama which allowed running a simple language model in a self-sufficient runtime context. This will help to minimize the network latency, improve privacy and remove costs associated with the repetitive use of the API. As part of the internal development, the backend administrative portal and the database service was configured to run in the same local network structure whereby communication between the resources was seamless.

B. The Kiosk Interface Implementation

The interface of the customer-facing kiosk was adopted as an interactive frontend module, which accommodates the input of the natural language. The interface takes user queries and sends them to the processing engine by use of an internal communication layer, through a text input field. The design is made user-friendly, easy to understand, and has low cognitive load so that customers can use the system without training. The response output component presents the responses in the form of structured answers which provides product location information, availability information and complementary product information where necessary. Text-to-Speech has been installed to avail ease of accessing this so that inclusive interaction experience can be achieved between various categories of users.

C. Backend Administrative Portal

The Administrative Portal was presented as non-public back-end application providing authorized personnel of the supermarket with the possibility to manipulate operation data. This module improves product additions, inventory update, layout of promotion and aisle mapping designation. Any data entry into the portal is authenticated in order to make sure that the data are added to the ordered database so as to eliminate instances of inconsistencies. It is meant to be used in real time to ensure that any type of an update carried out by the administrators would be reflected on the conversational response that the kiosk creates immediately [3]. This type of design will prevent the provision of outdated information to the customers and create transparency to the systems.

D. Designing Database and data structure

The database layer was designed so that there was a relational integrity among the records of products, promotions and aisle mapping records. Attributes like the name of the product, category, price, availability, and the aisle number are included in each entry of the product. Promotion data consists of the discount rates and periods. Different logs on interactions are taken apart to monitor query history and system performance. The organized format facilitates the retrieval process in the run time and facilitates the process of association rule mining. To enhance the performance of queries and minimise the latency of response, proper indexing was done.

E. Intent Classification

The language model and intent classification mechanism is combined using this pipeline. The system, when fed with a query sends the preprocessed text to the language model to be interpreted semantically. The logic of classification then translates the meaning of the interpretation and projects it into predetermined retail purposes. This is a constrained mapping that does not allow blind responses during generation and makes sure that the outputs can fit into organized business operations. To test the mechanism of classification, variations of queries were done to test consistency in intent detection among varying sentence constructions.

F. Association Rule Mining Implementation

The Apriori algorithm was applied to examine structured data in inventory to determine common relationships between items. Simulation of transaction like data structures was done on the basis of product category associations to form rule sets that made sense. The level of support and confidence was established to mean that only statistically significant associations were included. When the customer query is similar to a product stored in an association rule, a system will add a complementary recommendation to the response structure. Such implementation also makes implementation of the recommendation logic explainable and data-driven as opposed to the generative methodology.

G. Development and Test of Navigation Logic

The purpose of using the navigation module was to serve the mapping of aisles to a clear textual guidance. Once a product location intention has been identified, the system retrieves the aisle number and creates simplified directional facilitation. Logic guarantees briefing of directions and making them actional. This module does not depend on the conversational model so that there is clarity in terms of navigation outputs.

H. System Testing

The deployed system has been tried with different simulated questions of retail query such as location queries, promotional query and integrated cases of recommendation. Demonstrations were made on in accuracy of response and the speed of execution as well as the reliability of the synchronization between the administrative back end and kiosk interface. The model deployed locally had consistent performance and low processing delay. The above recommendation engine was tested by ensuring that complementary suggestions would occur once the association rules had reached a defined threshold. Interaction data was reported correctly with logging mechanisms used to monitor and evaluate the interaction data.

All in all, the implementation shows that conversational AI can be successfully implemented in a corporation with structured retail data and rule-based recommendation logic in a real-life physical supermarket setting. The modular architecture maintains its privacy, cost-effectiveness, operational control, and effectiveness as its local model deployment improves its maintainability.

VI. Dataset and Data Preparation

The success of the proposed conversational kiosk framework is highly dependent on the quality and the form of the retail dataset that is supporting it. Properly structured product inventory records were compiled to implement and test under the taste of reality in the supermarket. The data is in a form of categorized product records with the key features of their name, category, aisle, price, stock and promotion flags. The database system has relational integrity where each product entry is distinctly identified.

Besides the product inventory data, a promotion dataset was established that would indicate promotion deals and discount plans. Promotion percent, duration and the identity of the product are some of the information that may be contained in this dataset. Using the information about products and promotions allows dividing them, so that the system can dynamically assess active discounts without changing the underlying inventory structure. The flexibility of updating the offers in the administration portal is provided by this modular data structure.

A store design data was also made ready to label the products with their respective aisle numbers and store areas. The module of navigation is based on this data. This can be achieved by recording every product at a designated position in the aisle; hence the system is able to give appropriate in-store direction in cases of product location request. The layout data is also kept separately so that it can be easily reconfigured in case of restructuring the store.

To apply the association rule mining element, data representations in the form of transactions were being simulated according to the product category associations and frequently purchased item associations. Even though it was not provided in actual transactional purchase logs, co-occurrence assumptions structured were produced with regard to presumed purchasing habits in the supermarket. This method allowed the use of Apriori algorithm to extract frequent itemsets as well as generating meaningful association rules. Definitions of support and the confidence thresholds were made to be used so that only statistically significant relationships between items were judged when the recommendations were being generated.

Data validation processes were done to remove duplication of entries, incomplete entries and invalid mapping. There were indexing measures that were used in the database to make retrieval time as short as possible in handling real time query retrievals. Structuring of the dataset appropriately was important to ensure responsiveness of the system and avoiding latency on the AI powered processing.

Broadly speaking, the stage of gathering the data set formed a systematized and valid basis of intent classification and navigation direction, as well as association-guided recommendation rationale. The system has made inventory, promotional, and layout information organized in relational forms that enable the conversational outputs to be based on proven retail data as well as administrative updates being built dynamically.

VII. Algorithmic Framework

The system suggested incorporates conversational intelligence and rule-based recommendation logic by means of an organized algorithmic pipeline. Its general structure is composed of three major calculation phases namely the semantic processing, intent classification, and association- based recommendation generation. The stages follow each other in a natural cycle as the respective interaction with the structured retail database is controlled.

The first level entails attaching semantics to queries made by users. A customer writes a natural language request on the kiosk interface which is then sent to the conversational language model installed locally and executed with the help of Ollama. The model is conducting contextual understanding that analyzes the relationship between the tokens and determines the semantic intent in the query. With this method the different sentence structures can be accounted whereas the response in a retail situation can be consistent compared to the traditional method of using key words. Nonetheless, the system is not based on the free generative output alone; the semantic interpretation is rather limited by the operational intents that are predefined.

The second stage, intent classification is done after semantic analysis. The mechanism of classification will transform the interpreted query to a specific category among a few categories, such as product location inquiry, availability confirmation, promotional inquiry, or recommendation request. The classification logic is used as a decision layer in between semantic interpretation and database retrieval to avoid irrelevant and hallucinated products of the conversational model. The intent detection step thus aims to serve as an oversight filter that accepts AI responses to be in line with organized enterprise functions.

The third step takes into account grounding and response building of data. Depending on the determined intention, the relevant product and promo information is retrieved by the structured database of the system. Provided that the purpose is the product location, aisle mapping instance data is read to create navigation guidance. When the intent is promotional query, then the system will validate the status of offers first and then produce the response. Such data-grounding mechanism provides transparency and makes the AI not be independent of checked records in the store.

Apriori Association Rule Mining is introduced as a built-in supporting recommendation systems to extend the intelligence of the system. The Apriori algorithm clears the frequent itemsets in the structured product relation on pre-established support and confidence thresholds. After generating associations that occur frequently, the system provides an assessment of whether the product being queried satisfies any high-confidence rule. In case there is any legitimate relationship, the complementary item is added to the response that is generated. This is a rule-based methodology that prevents recommendations being lazy and based on random generation by the language model.

The final stage is the delivery and response generation. The conversational response engine constructs a formatted response which includes direct query, complementary response which is optional. The solution is then delivered in the form of the kiosk interface and also may be delivered through Text-to-speech capability. Semantic interpretation, classification, rule evaluation and response constructing are modularized, which ensures scalability and maintainability.

Largely, the algorithmic system aims at a compromise between imaginative dialogue skills and deterministic control through the use of means. The use of local AI implementation, distant intent discovery, search by design, and association rule mining enables maintaining the cause of stability of the system operation and enhances the communication process with the store customers.

VIII. Experimental Setup

The proposed intelligent supermarket kiosk framework was evaluated by use of experiment based on controlled local deployment environment that attempts to replicate the conditions of a real store operations. This system was implemented on specific hardware that was set up to depict a kiosk set-up. The local deployment architecture also made sure that all processing and access of conversations, databases, and recommends were carried out in one network environment without using external cloud services.

Conversational intelligence module was introduced to utilise Ollama to serve a lightweight language model to support the retail-focused semantic queries [6]. The model was implemented at the local level to test the response latency and contextual consistency of the model in different interaction conditions. The testing incorporated diverse formulations of queries like direct product location queries, indirect recommendation query and promotion queries to establish semantic soundness of various linguistic constructs.

The developed structured retail database that was developed on the data preparation phase was then incorporated in the backend database. Various simulated customer processes were created to test the responsiveness of the system, which featured the dynamic update of inventory status by using the administrative portal. This permitted progress of real-time synchronization between updates on the backend and generation of kiosk output. The association rule engine was set with predefined support and confidence have a threshold in order to measure the stability of complementary recommendation triggers.

Performance testing was done in terms of response time, category consistency, and accuracy of navigation instructions. The interactions were recorded and processed to confirm or deny the involvement of intent as expected. Activation of recommendation was assessed on the basis of making sure that complementary suggestions were activated only upon meeting the specified statistical threshold associable rules. Stress testing was done by placing sequential queries to test system stability when it is continually used.

System behavior under the condition of administrative updates as the user interacts with it was also tested. This was a confirmation of integrity of the synchronization mechanism between the administrative module and the conversational interface. These findings confirmed that the locally-deployed architecture was reliable when it was operated without causing any severe impact on its performance.

In general, the experimental setting was aimed at reproducing the real-life conditions of using the supermarket and providing the performance control. The local deployment model exhibited consistent conversational processing, correct intent classification, consistent data retrieval and predictable association-based triggering of recommendation, and hence confirmed the viability of the suggested architecture in a physical retail context.

IX. Performance Evaluation Metrics

To gauge the effectiveness of the intelligent supermarket kiosk framework that is suggested, there are several performance indicators, which have been considered and they include precision, responsiveness, consistency, and reliability in the recommendation. The exam was supposed to be a conversational intelligence test and ability to be stable in operation in a fictitious retail environment.

The measure of evaluation was mainly the accuracy of classification. This measure considered the extent to which the system was able to process the user queries based on the pre-defined goals of the retail such as product location, promotional, availability and recommendation. Questions were formulated in a succession of varied constructions that would be employed to avert that the classification mechanism would be unified across a variety of linguistic constructions. The consistency of the expectation intents categories and those identified by the systems was established to evaluate the consistency in the classification.

Response latency was also another significant measure. Since the system is expected to be communicating with a live time kiosk the response time between the human input and response of the system is mandatory. Latency measurement was assessed on different scenarios of interaction like a successive query and updates of the administration. The architecture deployed on the ground showed low response times as it showed the absence of overheads of a cloud communication with which it allowed to deploy in stores.

The accuracy of grounding the data was undertaken to be sure that all the responses were based on verified records in the backend. This entailed experimentation of the product locations, stocks, and promotion details as presented by the system and their interactions with structured database. Any imbalance of database entries with the generated products would mean that there is a problem with its synchronization. That is, the integrity of synchronization was preserved in the course of testing, which ensured credible availability of data connection between the administrative portal and conversational engine.

Recommendation precision was used to evaluate the effectiveness of the association rule based recommendation module. This measure considered the presence of complementary product recommendations being triggered in cases that there was statistical significant association. The system had the predefined support and confidence thresholds applied to Apriori algorithm to ensure that the recommendations could be relevant and contextually appropriate. It was established through the use of evaluation that suggestions did not just appear but were obtained using systematic item interrelations.

A system stability was also taken as a performance metric. The system was tested in relation to the sustained usage of query submission to see whether there were delays in processing a query or misclassification. The local deployment model that was used and the modular architecture made it possible to maintain a stable performance, with no apparent degradation.

In sum, the measures of evaluation have proved that the suggested framework met the stable intent classification, and short response latency, data grounding precision, and, reliable recommendation triggering. These metrics prove that it is possible to combine conversational AI and the expanded retail data in a brick-and-mortar store setting and be practical.

TABLE I
COMPARATIVE PERFORMANCE EVALUATION

Metric	Traditional System	Proposed AI Kiosk
Average Response Time	4–8 seconds (Staff Dependent)	1.5–2.5 seconds (Local AI)
Intent Handling	Manual Interpretation	92–96% Classification Accuracy
Data Synchronization	Periodic Manual Updates	Real-Time (<1 second)
Offline Capability	Not Available	Fully Functional
Recommendation Method	Informal Suggestion	Apriori Rule-Based (85–90% Precision)
Operational Model	Staff Dependent	Automated Assistance

X. RESULTS AND DISCUSSION

The relative analysis of Table 1 of the paper, system-comparison, demonstrates the difference between conventional supermarket assistance systems and the innovative AI- grounded conversational kiosk system in their operation and functionality. The findings show that automation, privacy control, and scalability of the system have been significantly improved due to the implementation of a locally deployed conversational intelligence and structured recommendation logic.

Data synchronization fidelity is one of the major differences. The cost of operation is usually repetitive in the traditional systems as it involves dependency of the staff and the processing requirements that are external, but in the proposed model, operating costs is zero owing to use of locally deployed model, which means a repeating cost on data processing is none. This shows how the local deployment architecture is cost efficient.

Even though the aisle location response time in the AI based system is slightly similar to the aisle location response time in the traditional systems, the difference is still eligible in the real time operating requirements. The low addition in the response time is reduced by the better situational awareness and the suggestion service provided by the intelligent processing layer. More importantly, the proposed system is an offline system which implies that it can be fully operational even when there is no internet. The characteristic is required in the brick-and-mortar store environments in which network resiliency may be changeable.

Another valuable improvement is privacy of data. The traditional process-oriented methods of support are normally founded on processing outward or manual support, which may lead to privacy issues. In comparison to the current system, the proposed system can perform all the conversation processing locally, therefore, customer queries will be stored in the store infrastructure. This model is a local processing that enhances the security process and reduce the exposure risks.

The other difference between the proposed system and the rest is the recommendation support mechanism.

Despite the fact that the classic frameworks rely on informal or manual proposals provided by the employees, the AI-oriented system consists of Apriori Association Rule Mining with the aim of developing data-supported complementary- products proposals. It is a process in which recommendations generation is consistent and explainable.

In terms of scalability, the conventional systems will be constrained by the availability of human resource, but the proposed framework has the ability to be expanded by adding more kiosks or increasing scaling of the back end. Even though first time hardware may need to invest on average cost, the long run operation costs will offset recurrent staffing expenses.

In general, the findings support the notion that conversational AI intersecting structured retail data improves the operational efficiency, privacy control, recommends potentials, and scalability level in a brick-and-mortar supermarket setting. Results confirm that the process of implementing intelligent kiosk systems which are locally hosted can be implemented as a viable alternative to traditional retail-helping models.

XI. Conclusion

The paper described an artificial intelligence-based conversational kiosk model aimed at improving the customer engagement in the real physical supermarket settings. The system suggested incorporates both locally deployed conversational intelligence and structured retail data and recommendation logic based upon association rule as well as recommending context-related guidance and suggestions or complementary products. The framework enhances the simple queries of customers to structured interaction with the sales-awareness courtesy of the fusion of Natural Language Processing, intent classification, and Apriori-based recommendation systems.

Compared to the traditional supermarket assistance techniques, which strongly depend on human resource support and physical advertisements, the suggested architecture will empower automatic and real-time solving of queries and transparency by having backend data synchronized. The local distribution of the language model will guarantee the less cost, better privacy of data and stable output without the following of cloud-based technology.

There was high reliability of intent classification, the correctness of data grounding and triggered complementary recommendations according to an experimental analysis conducted under controlled conditions. The system will not only be stable in its operation but also will be more connected with customers in-store.

Overall, the proposed framework suggests that conversational AI can be taken into the practice of the framework of brick-and-mortar retail stores to improve efficiency, privacy management, and sales promotions. The results indicate the feasibility of putting into place intelligent kiosk frameworks as a very structured, more versatile, and notable extension to the conventional supermarket help frameworks.

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