
Enhancing Customer Service in Shopping Malls with an Advanced Chatbot-Integrated Concierge Device

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Abstract:

Purpose: The primary objective of this study is to enhance customer service in shopping malls by introducing an innovative solution: a Concierge device equipped with an advanced chatbot assistant. The aim is to simplify mall navigation for customers by offering information on store locations, services, promotions, and events.

Design/Methodology/Approach: The Concierge device features a monitor displaying an interactive mall map that users can navigate to find store details, locations, and opening hours. A chatbot integrated with the device provides a personalized shopping experience, recognizing customers via onboard cameras and adjusting interactions based on their emotions. The device also visualizes routes to stores and highlights promotions along the way. Key services such as toilets and ATMs are easily located through the device, which uses the chatbot to suggest nearby points.

Findings: Preliminary research indicates that this advanced assistant enhances the customer shopping experience by providing tailored information and seamless navigation. The device effectively routes users to destinations while promoting additional services and events, ultimately improving shopping mall service efficiency.

Practical Implications: Implementing this Concierge device in shopping malls can significantly improve customer satisfaction by providing accurate, real-time information and personalized guidance. Retailers and service providers can expect increased customer engagement and better promotion of their products and services through this system.

Originality/Value: This solution integrates state-of-the-art emotion recognition and chatbot technology with interactive maps, offering a unique and innovative approach to shopping mall navigation. By providing personalized service and improving customer engagement, it adds significant value to the current shopping mall customer service landscape.

Keywords: Concierge Assistance, Customization, Training Requirements, System Integration, Customer Service Protocols, Device Operation.

JEL codes: C45, L81, L86, D83, M15, M31.

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1. Introduction

Concierge (Shin and Jeong, 2020) will be a device located in a shopping mall with a built-in assistant (chatbot) whose purpose will be to help mall customers:

- will help show the way to a selected store, service, or place,
- will advise you about promotions,
- will inform you about events taking place in the gallery.

The concierge will also be equipped with cameras, thanks to which he will recognize a user he has already met and greet him again, as well as be able to acknowledge his emotions.

The application that will run on the device's monitor will contain an interactive gallery plan with a list of stores, allowing you to display:

- detailed description of the selected store (store information, opening hours),
- location of the selected store on the gallery plan,
- promotion in the gallery,
- events taking place in the gallery.

An essential element from the functionality point of view is the combination of the visualization of the gallery plan with messages sent by the bot:

- if the user asks about a place or store where he can buy a given product, the bot should indicate a list of stores and display the route to the store closest to the user's location, along with marking promotions on the road to the destination,
- If the user asks about a special point, e.g., a toilet, an ATM, or an elevator, the bot should indicate a list of such places and display the route to the one closest to the user's location.

2. Literature Review

Reading customer emails and understanding their needs can be time-consuming, particularly when the email has to be manually forwarded to the appropriate person if sent to the wrong department (Decker *et al.*, 2022). AI can significantly reduce response times by scanning and labeling emails and offering automated suggestions, references, and solutions to draft effective responses. As AI algorithms improve and learn from extensive datasets, they can also draft responses for call center employees.

DigitalGenius provides a solution as one of its primary customer service tools

(Earley, 2016). This technology categorizes and directs emails to the correct recipient, using past solutions to make responses quicker and more efficient. With DigitalGenius, the student preparation company Magoosh improved customer response times by 50%, now responding within 24 hours.

Moreover, the company claims that over 83% of emails can be sorted and labeled using their tools. Uber's Customer Obsession Ticket Assistant (COTA) accurately addresses thousands of daily tickets across 400 cities, routing them to the right team through natural language processing (Stanley and Clune, 2017). COTA's algorithms recommend three potential solutions to customer service agents, who choose the most suitable. Uber noted that COTA increased efficiency by 10%.

Companies can place chatbots on their websites to handle simple customer queries 24/7. They can also escalate queries they cannot answer to the relevant department. IBM Watson Assistant, a no-code visual tool, enables anyone to build robust AI chatbots (Chow *et al.*, 2023). It can answer questions, integrate with existing customer service platforms, and learn from past interactions to improve responses (Ebenezer *et al.*, 2019). Optimum, an internet, TV, and mobile provider use chatbots to analyze customer keywords and better understand their needs (Chakraborty *et al.*, 2022).

Virtual assistants like Google Assistant and Siri are often mistaken for chatbots but focus on specific customer journey aspects to provide a personalized experience (Balakrishnan and Dwivedi, 2024). Voice assistance becomes crucial when inquiries are too complex for text or email.

Challenges such as diverse accents, background noise, and unclear pronunciation complicate voice support. AI algorithms for speech recognition can improve routing, providing a more seamless customer experience (Li and Liu, 2021). Deep learning models predict emotional tones when customers react negatively and redirect calls to human agents.

Cogito's tool, based on behavioral science and deep learning, analyzes real-time conversations to assess customer sentiment using tone and volume (Wang *et al.*, 2020). This insight helps representatives improve call quality, reducing callback rates by 10% and increasing customer satisfaction by 28% (Amadeo *et al.*, 2023).

AI can offer personalized content and services to enhance customer value, helping companies increase sales and retain customers. Accenture reported that 41% of U.S. consumers abandoned brands due to a lack of personalization (Daugherty *et al.*, 2019).

Amazon leverages machine learning to recommend products based on customer order history, while Home Depot provides design trends and recommendations specific to customer locations. Netflix uses personalized graphics to showcase

titles with familiar actors or genres. The data gathered from these services reveals patterns that guide businesses in enhancing products.

Machine learning helps companies identify trends and improve products for better customer satisfaction. Air Canada used customer conversations and browsing sessions to identify issues with its booking platform and prioritize problem-solving.

EasyJet provides travel recommendations based on previous trips, while Twiddy offers rental pricing suggestions based on demand trends. Microsoft Dynamics 365 uses advanced AI in NLP to assist customer service agents and managers make better decisions, providing data insights to enhance customer engagement (Wei *et al.*, 2023).

3. Research Methodology

To make it possible to use the model and train it online alternately, the `OnlineMNBClassifier` class was developed in the system being created. This class has functionalities that allow loading a model, using it for prediction, training with the generation of a new label, training using a known label, and two novelty detection algorithms (situations when the data does not belong to any of the classes that were previously used for training (Maciura *et al.*, 2023)).

Newness detection algorithms are crucial in the system being developed and, at the same time, its most challenging element. In the system being developed, there is a need for the system to automatically detect the situation when a new person appears and automatically use their facial image for training (updating the model). The `OnlineMNBClassifier` class has the following methods:

- a constructor that initializes components creates a model, or loads an existing one,
- `getAvailableLabel` – a method that allows you to detect the next "free" label in the model using the functionality of the MNB classifier in the scikit library – `learn`,
- `load` – method that loads the classifier from the file (as well as the names of people),
- `save` – method that saves the current state of the classifier to a file (as well as the names of people),
- `update_model_new` – method to update the model with new samples along with generating a new label,
- `update_model_existing` – method to update the model with new samples for a previously known label,
- `check_novelty` – a simple (but best-performing) method that returns the values needed to detect new features,

- `check_novelty_new` – novelty detection method based on the SVM model,
- predict class prediction based on a sample.

The biggest challenge in the online face recognition training system was to develop a novelty detection algorithm, i.e., a situation where samples from a new, unknown class arrive. Most often, in such a situation, the model responds with 100 percent certainty that the sample belongs to class X, where X is the label of one of the previously learned classes (which is not true).

The predictions of the remaining classes are most often equal to 0 or close to 0. So we can see that this problem is complicated, and the projections of other classes are so small that these numbers do not fall within the range of real numbers for the float type (Maj *et al.*, 2022). The scikit-learn library for MNB models provides the `predict_log_proba` method, which, instead of prediction, returns logarithms from predictions (most often negative values or 0 - for prediction equal to 1), so you can analyze these algorithms instead of these tiny numbers (Maj *et al.*, 2023).

The best-performing algorithm for novelty detection so far is to find the logarithm of the second maximum response by finding the second maximum logarithm of the reaction. Inside the system, this value will be calculated for several samples, averaged, and then thresholded, and in this respect, it will be estimated whether the samples from the tracked face are new or not. These values are returned by the `check_novelty` method in the class described earlier.

The second method for novelty detection is to use the SVM model. First, the model was trained on half of the data (53), and then the model's responses were tested on this half and the other half of the classes for which it was not trained.

The 20 highest logarithms of responses sorted in non-ascending order form the training vectors for the SVM model for novelty detection and the generated novelty labels (0 or 1). The SVM model is then trained on such vectors. Unfortunately, the novelty detection algorithm using the SVM model works worse on new data from outside this set than the first, most straightforward novelty detection algorithm. More experiments in this direction are planned (Maciura *et al.*, 2023).

4. Research Results and Discussion

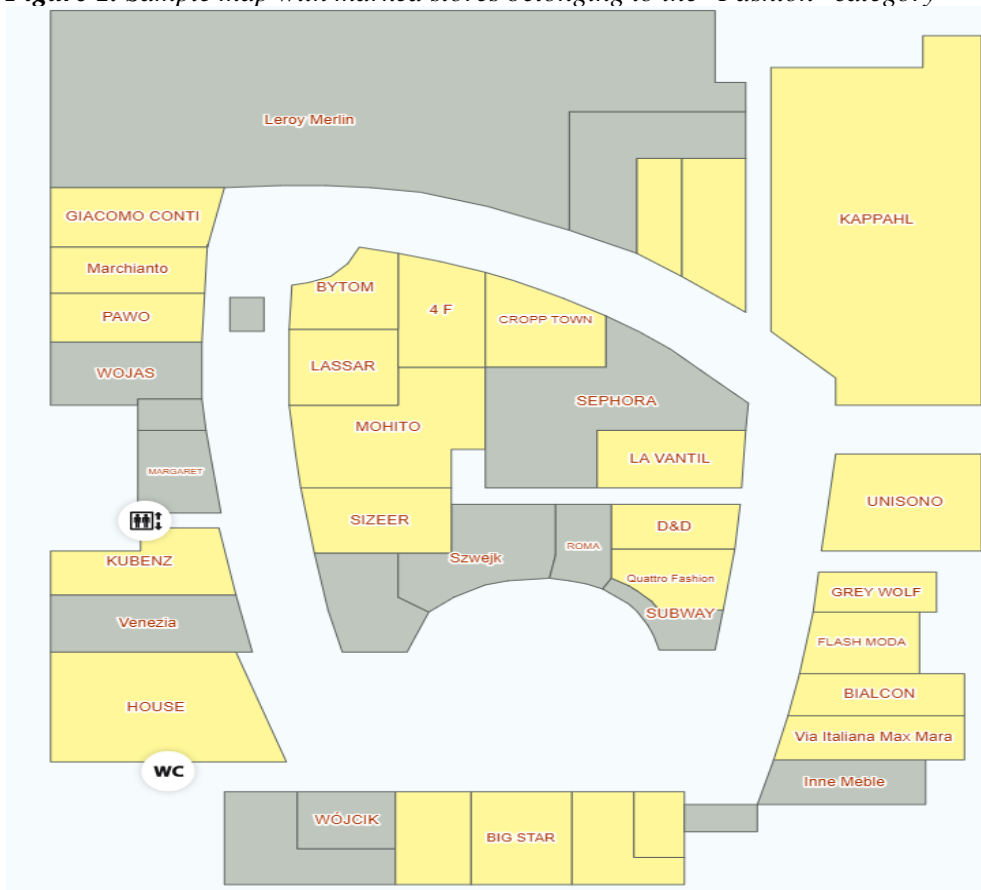
This part will describe how to build subsequent functionalities and extensions regarding the Concierge device's assistant. Regarding the device's functioning, we assume it will be placed in large-format stores. To carry out the tasks, we will assume that it is a device placed in a shopping mall as a totem, allowing users to obtain additional information. In the first approach, we believe that the totem is

placed in a specific place in the gallery. A user approaching the totem can obtain information about stores and the products they are looking for.

Additionally, the user will be recorded via cameras placed on the device, so the next time he visits, he will be greeted as a known person, and, depending on the data he has, he will be greeted, e.g., by name. Among the functionalities of the assistant itself, the user will be shown the stores he is interested in on the map and the route to them.

Additionally, based on the database, stores along the way with promotions in their offer will be indicated - this will be a combination of the bot's functionality with the user's panel. Additionally, the assistant will mention upcoming events planned in the gallery. Further, it is intended to additionally place a totem in one of the stores (e.g., construction stores) to indicate the location of specific products in the store space. This solution is supported by the lack of such functionalities and the need to ask store employees about the products they seek.

Figure 1. Sample map with marked stores belonging to the "Fashion" category



Source: Own creation.

The first stage is to build an assistant that, based on the user's query about specific products, will determine the stores where they can be found. At this point, it will only be based on determining the type of store based on the information in the database tables.

During subsequent work, products proposed by individual stores will be downloaded for more detailed analysis and return more accurate results. The accepted store types based on an example shopping mall are as follows: Building supplies, Cafes and restaurants For children, Fashion, Multimedia, Footwear and leather goods, Services and others, Interior furnishings, Health, and beauty.

We will start building these assistant functionalities by defining the user's intentions. Below are example queries for given product categories. Intentions were divided according to the type of store. The remaining products will be added after obtaining additional data, and the lookup tables functionality will be used for this purpose.

For example, a user can ask, "Where can I buy shoes?" In addition to regular shops, there will be specific places in the mall, such as toilets, ATMs, or rooms for mothers and children - hence the idea of search_room.

After defining a set of new intentions and adding them to the assistant's domain, you need to determine the histories and explain the actions the assistant should perform when a given intention occurs. At this point, stories will be described and each intention will have its counterpart in the form of an action.

As you can easily see, each action involves downloading objects from a given category from the database. Additionally, based on their location in the gallery and the position of the totem, the closest store is determined using the Euclidean metric.

This is to avoid confusion when the totem is moved. Then, a response containing the acquired information is sent back to the user. The figure below shows the conceptual design of the website where the chat widget is placed. Figure 3 presents the concierge device.

5. Conclusions, Proposals, Recommendations

The introduction of a developed assistant to operate the Concierge device in a shopping mall has the potential to significantly improve customer experience and efficiency of service in public places.

Our study shows that combining the advanced functions of an interactive gallery plan with an intelligent assistant allows for quick and personalized customer service, which translates into increased customer satisfaction and loyalty.

Figure 2. Putting a chat on the website and guiding the user to the store



Source: Own creation.

Figure 3. Concierge Device



Source: Own creation.

Recognizing customers and monitoring their emotions allows for more personalized service, which can help build customer bonds and increase loyalty. The assistant, supported by an interactive gallery plan, enables quick and accurate provision of information to customers, which shortens search time and improves service efficiency.

Integration of the visualization of the gallery plan with the assistant's messages allows you to quickly and intuitively find the necessary information. It facilitates navigation in the gallery, contributing to a positive shopping experience for customers. Despite the promising results of our study, there is potential for further development of the Concierge assistant, e.g., by implementing more advanced speech recognition functions or developing customer interactions through mobile applications.

These conclusions suggest that a developed assistant for operating the Concierge device may be a valuable tool supporting customer service in shopping malls and other public places, improving customer experience and increasing service efficiency.

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