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Developing a Convenience Store Product Recommendation System through Store-Based Collaborative Filtering

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Abstract: Providing personalized product recommendations in offline retail stores, especially small-format offline retail businesses such as convenience stores, poses a great challenge. To address this issue, this study aimed to find a solution by shifting the perspective on recommendation methods and altering the target of recommendations. In this study, recommending products was defined as suggesting products that should be introduced and displayed within the store. This recommendation system proposes products that individual stores have not yet introduced but are anticipated to be purchased by customers. Building upon this, we developed a store-based collaborative filtering recommendation system. Furthermore, various rules and logic pertinent to store operations and business considerations for convenience stores were integrated to implement this recommendation system. The accuracy and effectiveness of the system were demonstrated through its application in actual convenience stores. Results from the pilot implementation of the system showed that 88% of the newly recommended products in individual stores were sold within a week, and the sales revenue was 1.75 times higher than the average sales of those products across the entire stores. Survey results on business owners' satisfaction yielded a score of 4.2 out of 5, indicating a high level of contentment. This research holds significance in extending the scope of personalized recommendation studies from primarily online platforms to offline retail businesses such as convenience stores. The study also suggests avenues for future research to address some of the identified limitations.

Keywords: recommendation models; store-based recommendation models; implementation of recommender system

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1. Introduction

Recently, the retail industry has been collecting various traces of customers' shopping journeys to provide personalized recommendations based on these data. Furthermore, efforts have been made to develop more sophisticated personalized recommendations to not only attract customers to the shopping space but also enhance purchases within that space. However, these efforts have primarily focused on the online e-commerce domain, and personalized product recommendations for offline stores have proven challenging despite various attempts.

To achieve customized product recommendations for offline customers, it is crucial to gather basic customer information and purchase journey data. Furthermore, accurately identifying the customer's current location and providing appropriate products in a timely manner are essential. In the mid-2010s, some companies with high brand loyalty attempted offline target marketing using location-based systems (LBS) such as beacons and mobile coupon distribution. However, due to technological constraints, customer resistance, and challenges related to return on investment (ROI), these systems had limitations in terms of effectiveness. Especially for companies operating multiple stores such as convenience stores, collecting customer information is difficult due to the diverse range of visitors. While investing in systems and infrastructure for collecting customer information and target marketing is possible, actual instances of such investments are rare, and even when investments are made, there are few success stories resulting in increased sales and profits.

In this study, we aimed to find a solution by shifting the approach from targeting individual customers to targeting stores in the existing personalized product recommendation models. Traditional personalized recommendation models recommend products with a high likelihood of purchase or selection based on customer purchase/selection history, preferences, and evaluations. In this study, a model was developed to recommend products based on individual store similarity. Store similarity was calculated based on each store's category-specific sales history. This store-based model predicts products that customers visiting a particular store would want to purchase, even if those products are not currently stocked in that store. These recommendations were validated based on actual sales generated by the store. The contribution of this study lies in the expansion of personalized recommendation research, primarily conducted on online platforms, to offline businesses such as convenience stores.

While recommendation system algorithms continue to evolve and diversify, limitations still exist in terms of data analysis and algorithms. Moreover, successful implementation in real business scenarios requires additional domain-specific rules and logic based on the fundamental recommendation algorithms. In this study, a store-specific product recommendation model based on convenience store product and sales data was developed. This model was then integrated with domain-specific rules and logic to validate its effectiveness.

In South Korea, there are approximately 50,000 convenience stores, with over 95% of them operated through individual franchise agreements with the headquarters. Generally, each store carries around 2500 to 3500 SKU products, with some variation depending on the store's location and size among the approximately 20,000 products offered by the company. When a new convenience store opens, Company E selects products based on pre-defined categories for commercial regions. However, this simplistic approach of categorizing based solely on store location does not fully capture the unique characteristics of each individual store. Additionally, after the initial product selection, store owners must decide which new products to introduce from a pool of around 100 different products each month. They usually rely on recommendations from their surroundings or basic product information provided by the company. The store-specific recommendation model in this study recommends products that have succeeded in similar stores with comparable customer types and sales patterns. Moreover, the study integrates domain-specific rules and logic to implement a recommendation system for convenience stores and attempts to validate its effectiveness.

2. Literature Review

As personal data have rapidly increased and become more accessible, recommendation systems are widely applied across various online platforms. Especially for online shopping malls, movie and music content providers, news websites, bookstores, and research-related sites, recommendation systems are essential. From the perspective of sellers/suppliers, providing appropriate recommendations that induce actual purchases has a direct impact on revenue generation, underscoring the importance of accurate product recommendations. Consequently, research to enhance the accuracy and efficiency of recommendation systems has been actively pursued [1].

The concept of recommendation systems was initially proposed by Karlgren in 1990 [2]. In 1994, the University of Minnesota Group Lens research team developed the first automated recommendation system "Group Lens" using the UCF algorithm. In 1997, content-based collaborative filtering (CF) algorithms were introduced for information retrieval [3]. In 1998, an approach using collaborative filtering with singular value decomposition for classification tasks was introduced [4]. In 2002, item-based CF algorithms were proposed [5], and Linden et al. [6] established the widely known Item-to-Item CF method used in Amazon's recommendation system. Alfred and Lovstakken [7] increased the accuracy of recommendation systems using implicit user interaction data. Fan et al. [8] presented a recommendation algorithm utilizing multi-user similarity. Rong et al. [9] proposed an improved user-similarity-based algorithm for collaborative filtering. Since 2015, deep neural networks have been applied to enhance recommendations in large-scale content. In 2016, Google introduced the high-performance YoutubeDNN model by integrating classic recommendation system architectures [10]. Subsequent developments include VAE-CF considering user preferences [11], RNN-based recommendation systems considering user preference changes [11], and the RKSA model using the Transformer architecture to consider item relationships [12]. Recent research in recommendation systems has primarily focused on improving algorithm accuracy, with online customers being the main target [13–15].

This study differs from previous research in several ways. It implements and validates a recommendation system using user-based collaborative filtering based on the hypothesis that if a specific store prefers certain products, similar preferences may be present in other stores. While prior studies mainly focused on recommending products to individual online customers, this study aims to recommend products to offline stores. Therefore, unlike previous research that emphasized enhancing the efficiency and accuracy of recommendation algorithms, this study focuses on effectively implementing a recommendation system based on changes in the recommendation target.

In a similar context, Joe and Nam [16] implemented and validated a recommendation system for SKU recommendations in offline fashion stores of the same brand. Their study proposed methods for handling SKU recommendations at the store level for distribution companies dealing with the same brand across different countries and regions using collaborative and hybrid filtering. Their models, based on sales data from 52 stores, 24 items, and 404 SKUs of the 'K' brand over a 3-week period, achieved recommendation precision of 9.9% for collaborative filtering and 10.8% for clustering-based recommendations.

This study proposes and validates a recommendation model for offline stores similar to that of Joe and Nam [16] but with three key differences. Firstly, this study utilizes much more data, including sales data from over 6000 convenience stores for a year. Secondly, it considers various business characteristics of customer purchasing behavior and system implementation in similarity evaluation. Lastly, the recommendations are validated based on actual sales generated by the store.

3. Method of the Study

3.1. Overview of Research Method

The aim of this study was to implement a model that recommends products expected to be purchased by customers visiting each convenience store (Company E) and integrate it with the existing ordering system to validate its effectiveness in real stores. The recommendation model consists of a store-based collaborative filtering model, which is a modification of the user-based collaborative filtering model, and a top-N recommendation system that recommends the top N products through various business logics and sorting methods tailored to the convenience store business. The constructed recommendation model was implemented within Company E's ordering system, enabling store owners to select and place orders for the recommended products. The ordered products were then delivered to the stores and displayed for sale. Subsequently, the performance of the recommendation system was evaluated based on the sales results of the recommended products. The overall research process is illustrated in Figure 1.

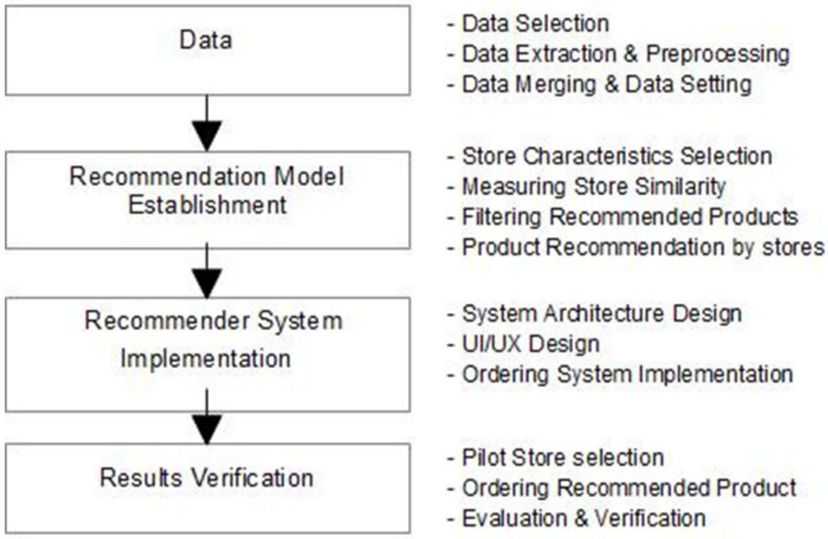

Figure 1. Overall research process.

3.2. Data Composition

The data used in this study were extracted from the databases of Company E's operational system and POS (Point of Sales) system, covering the period from 1 January 2022 to 31 December 2022, for the duration of one year. This data can be categorized into two types: master data, which include reference information, and various transaction data used for store operations.

The master data include store master data containing store codes, store names, store locations, store types, store opening dates, and store sizes. Additionally, there is promotion master data, which hold information on promotion codes, promotion names, promotion types, promotion periods, and the stores where the promotions apply. Furthermore, the product master data comprise product codes, product names, product categories, product attributes, and product suppliers. They also include store-specific product master data containing products available at each store. As for transaction data, they involve sales performance data generated from each store's POS system, inventory movement data for each store, and product ordering data for each store. Customer data that could be identified for individual purchases in each store accounted for less than 5% of the total purchase data, making it challenging to consider customer data for assessing store similarity. Therefore, these data were excluded.

Data preprocessing was conducted in this study prior to data analysis, involving the selection and extraction of relevant items from the entire dataset, removal of inaccurate or incorrect data, and data modification to enhance data accuracy. Outliers primarily originated from sales quantities within the POS data. Data exhibiting distinct patterns from the typical customer sales patterns due to special store sales (such as B2B sales) or specific purpose-driven customer purchases (e.g., bulk purchases for event preparation) were eliminated. Additionally, new items were added for analysis, including daily totals of transaction data, store-specific sales summaries, and recommendation scores. Finally, new database tables, encompassing metric tables and category conversion tables necessary for model generation, were created during the model creation phase. Subsequently, essential data from each table were merged to construct the analysis dataset. As a result, operational and transaction data of approximately 400 million records from Company E were leveraged for analysis.

3.3. Recommendation Model

In this study, user-based collaborative filtering, a type of collaborative filtering, was chosen as the initial approach for developing the product recommendation model. The approach for establishing the product recommendation model is shown in Figure 2.

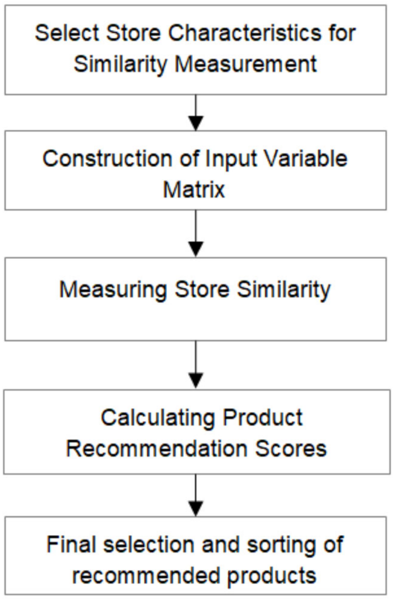

Figure 2. Recommendation model.

Select Store Characteristics for Similarity Measurement: Defining the characteristics of similar stores is crucial for utilizing user-based collaborative filtering. Store similarity can be delineated through various methods, such as by physical attributes such as store size and location and operational characteristics such as handled products and services, as well as customer attributes such as gender and age group. In this study, the recommendation system aims to suggest products that are well sold in similar stores to a specific Store A, which currently does not offer those products. While Company E classifies stores into N commercial areas based on geographical location, there exists substantial variance among stores within each commercial area.

Taking these factors into consideration, this study deemed the most plausible and rational factor for determining store similarity using Company E's current data to be the sales trend of products within stores. This information reflects customer purchasing behavior and commercial area attributes. However, comparing the sales trend of each SKU across all stores to determine similarity would be inefficient, as it would necessitate processing a sales quantity matrix of over 10,000 SKUs for approximately 6000 stores. Consequently, product categories representing individual SKU attributes and sales time slots were chosen as pivotal factors for determining similarity. Thus, store similarity was calculated based on the sales proportion of product categories and sales time slots among all products.

Construction of Input Variable Matrix: To perform similarity calculations, we constructed an input variable matrix based on Store x category proportions and Store x time slot sales proportions. In this context, categories represent sets of SKUs with similar attributes, and, specifically, we composed the input variable matrix for similarity calculation using 180 intermediate categories derived from Company E's product classification rules.

Measuring Store Similarity: In collaborative filtering recommendation techniques, user similarity is utilized to select neighbors for the target user. Various metrics such as Euclidean distance, Pearson correlation, cosine similarity, and mean squared differences are employed for calculating similarity [17]. In this study, users were defined as stores, and store similarity was computed based on category-wise revenue proportions. Furthermore, we utilized cosine similarity as there was no bias in the measurements of the revenue figures for the 180 categories used in the similarity calculation.

Calculating Product Recommendation Scores: Typically, a product recommendation model selects the top N items that are expected to be most preferred by the target customer and presents them as a list of recommended products [18]. In traditional movie or document recommendations, preference can be predicted using evaluation scores such as satisfaction scores or preference scores provided by customers [19]. However, in this study, we employed a user-based top-N item recommendation technique [20]. The calculation of recommendation scores for products involved the following steps: First, based on the similarity matrix calculated from store data, we selected the top 30 most similar stores. Next, from these stores, we identified the 500 products with the highest daily sales volume. Finally, we computed the recommendation score by taking the weighted average of the store similarity scores and the sales frequency of each product. The reason for using sales frequency as a weight was to prioritize recommending products with higher sales. The formula for calculating the product recommendation score is as follows:

Recommendation Score of Item 1 for Store A

Final Selection and Sorting of Recommended Products: In the existing product recommendation system, items are recommended and sorted for individual users based on the recommendation scores calculated by the algorithm. In this study, while still utilizing the recommendation scores as a basis, we introduced exclusion criteria to remove products that lack business significance. Firstly, products currently being managed by the store and those with inventory were excluded. Secondly, products that were currently out of stock but had a purchase history within the maximum ordering lead time were excluded. Thirdly, considering the potential rapid changes in product sales due to promotions in convenience stores, products within the ordering lead time from the end of a promotion were also excluded. Through these processes, recommended products tailored to each individual store were integrated into the store ordering system.

3.4. Recommender System Implementation

The configuration image of the recommendation system implemented in this study is shown in Figure 3. The data collected from the business systems were stored in a big data DB in the public cloud system. After batch processing, the store-specific recommended candidate product data were combined with business rules to generate the final recommended products, which were then provided through the ordering system.

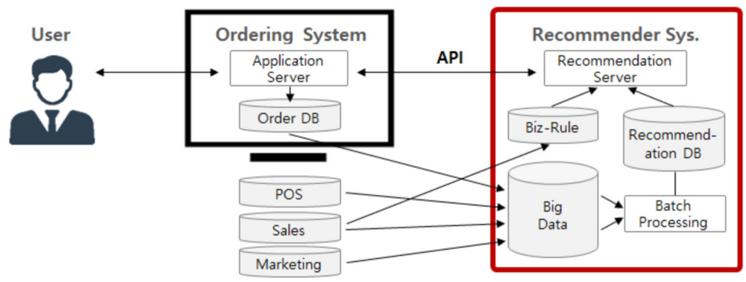

Figure 3. Overall system architecture.

Within the ordering system, the implemented product recommendation screen displays up to 10 SKU products per category and time slot in a pop-up window on the main ordering screen. This allows the store owner to select products and enter the order quantity. The target products are periodically updated for a specific period, and a "Do not show again today" feature is added to prevent the pop-up window from being displayed continuously.

3.5. Results Verification

The purpose of a recommendation system is not only to accurately recommend items that users are highly likely to choose but also to provide users with sufficient satisfaction, thereby enhancing trust in the system and encouraging long-term usage. Therefore, the criteria for a good recommendation system should include not only the accuracy of recommendation performance but also psychological and interface factors.

This study is based on a model that recommends products within convenience store stores and implements it within the ordering system to validate its performance. Rather than focusing on advanced algorithms to improve recommendation performance, the study prioritizes the implementation of a realistic and efficient system based on the data, data structure, and existing system currently managed and configured by Company E. The goal is to focus on the applicability and usability of the system.

As reviewed in the previous literature, we used the user-based model that is the most widely used collaborative filtering technique with a store-centric approach. So, we defined this model as a store-based collaborative filtering model. To evaluate the accuracy of the recommendation system, the study planned to implement this user-based model and use precision as the evaluation metric for the first verification. Additionally, user satisfaction was assessed through surveys and interviews to evaluate recommendation satisfaction and system usage satisfaction.

4. Results

4.1. Results of Store-Based Collaborative Filtering

This paper utilized store-based collaborative filtering, with store similarity calculated based on the similarity of category-based sales. Initially, we compared the recommended products for the store with the highest similarity and the store with the lowest similarity in order to assess the precision of store similarity measurement. In the case of Store A, we selected 15 recommended products from the top 30 stores with the highest category-based similarity. These 15 recommended products were filtered based on the exclusion criteria mentioned earlier. Table 1 displays the top 15 recommended products for Store A.

Table 1. Recommended products for Store A (top 15).

Rank	Product Code	Product Name	Scores
1	123734	Chicken breast ricotta salad	43.5
2	016104	Thick Buckwheat Tea 340 mL	37.0
3	840169	Aloe pet 340 mL	30.4
4	000022	Corn Silk Tea 340 mL	29.6
5	123697	Tandanji hot chicken tender salad	19.9
6	840190	Tandanji grilled chicken breast salad	19.6
7	012176	Blue zero soda 250 mL	16.5
8	016098	Milk chocolate biscuit 102 g	12.7
9	112783	Kim Rabbit Fresh Strawberry Sandwich	11.0
10	005314	Burdock tea 500 mL	10.2
11	008765	Orange mango 200 mL	8.8
12	008758	Sour love plum 42 g	7.4
13	016135	Choco-chip donut 38.3 g	7.4
14	006830	Coconut milk plus 290 mL	5.8
15	040350	Noodle Fit Spicy Udon Flavor Cup	5.6

Table 2 presents the top 15 recommended items for Store B, which is the most similar store to Store A. Upon reviewing the items listed in Tables 1 and 2, it is evident that 10 items are being recommended identically. The 66.7% item duplication rate between the most similar stores is a result of the application of exclusion criteria such as inventory considerations.

Table 3 presents 15 recommended items for Store C, which is the least similar store to Store A. Upon reviewing the items in Tables 1 and 3, only one item, "Burdock Tea 500 mL", is recommended identically, resulting in a very low duplication rate. In conclusion, the analysis of the recommended items in Tables 1–3 indicates that the similarity measurement based on category-wise sales, as employed in this study, is appropriate.

Table 4 presents a list of the top 10 recommended items for Store A. In addition to the exclusion criteria mentioned earlier, this list has been reorganized based on business conditions (such as uniqueness, trendiness, profitability, sales growth rate, PL status, etc.).

Furthermore, Table 4 has been further fine-tuned based on the expiration of promotions at the time of the recommendation algorithm execution. As a result, 'Thick Buckwheat Tea 340 mL' and 'Corn Silk Tea 340 mL' were excluded from the list. Additionally, 'Choco-chip donut 38.3 g' ranked higher than 'Sour love plum 42 g' due to a higher sales growth rate.

Table 2. Recommended products for Store B (top 15).

Rank	Product Code	Product Name	Scores
1	123734	Chicken breast ricotta salad	38.7
2	666022	Min Saeng Bitter Coffee 500 mL	32.4
3	253103	Ambasa can 350 mL	32.1
4	016104	Thick Buckwheat Tea 340 mL	27.7
5	840169	Aloe pet 340 mL	22.8
6	123697	Tandanji hot chicken tender salad	14.9
7	840190	Tandanji grilled chicken breast salad	14.7
8	062347	Charcoal Grilled Chicken Skewers	14.2
9	315095	Gary Cheese Crackers 100 g	11.8
10	016098	Milk chocolate biscuit 102 g	9.5
11	213604	Beyotte cookies and cream	9.2
12	005314	Burdock tea 500 mL	7.7
13	008765	Orange Mango 200 mL	6.6
14	016135	Choco-chip donut 38.3 g	5.5
15	006830	Coconut milk plus 290 mL	4.4

Table 3. Recommended products for Store C (top 15).

Rank	Product Code	Product Name	Scores
1	350109	Pastel-dol lighter	14.1
2	511047	Seoul Jangsu Makgeolli	13.8
3	551233	Taewharu Makgeolli	13.1
4	010414	Crayon Shin-zzang Candy	9.4
5	920067	Sosung alcohol	9.3
6	230053	Metalrochi lighter	8.1
7	000022	Haru mineral water 500 mL	7.7
8	129378	Good day bottle 360 mL	6.9
12	005314	Burdock tea 500 mL	6.8
10	008758	Epresso hot americano coffee	4.6
11	023379	Big ice americano coffee	4.2
9	675367	Long wheat snack	3.8
13	159733	Good day alcohol pet 640 mL	3.8
14	915709	Grinded pear juice 500 mL	3.7
15	000015	Haru mineral water 2L $\times$ 6	3.0

Table 4. Finally recommended products for Store A (top 10).

Rank	Product Code	Product Name	Score	Sales Growth Rate	PL /PB	New Prod.	Days after Order
1	123734	Chicken breast ricotta salad	43.5	NaN	0	0	NaN
2	840169	Aloe pet 40 mL	30.3	17.6	0	0	45
3	123697	Tandanji hot chicken tender salad	19.9	92.3	0	0	NaN
4	840190	Tandanji grilled chicken breast salad	19.6	13.2	0	1	NaN
5	012176	Blue zero soda 250 mL	16.5	22.5	0	1	NaN
6	016098	Milk chocolate biscuit 102 g	12.7	−33.2	0	0	NaN
7	005314	Burdock tea 500 mL	10.2	10.8	0	1	NaN
8	008765	Orange mango 200 mL	8.8	NaN	0	0	NaN
9	016135	Choco-chip donut 38.3 g	7.4	35.6	0	0	NaN
10	008758	Sour love plum 42 g	7.4	7.83	0	0	NaN

4.2. Pilot Implementation Results of the Product Recommender System

The goal of this study was not only to implement the recommended algorithm as mentioned in the introduction but also to evaluate and validate the system's functionality in actual stores. To accomplish this, the implemented recommendation model was integrated into Company E's order system, and a pilot operation was conducted. For the pilot operation, stores with well-performing order operations were selected to apply and assess the recommendation system in real-world scenarios. The pilot operation took place from 13 March to 9 April 2023, spanning four weeks. Each store was instructed to order three or more products from the top 10 recommended products based on the store owner's judgment. The ordered products were promptly displayed and sold. Table 5 provides an overview of the proposed recommendation system's pilot operation.

Table 5. Overview of the proposed recommendation system's pilot operation.

Cat.	Contents
Op. Period	13 March 2023~9 April 2023 (4 weeks).
No. of Stores	8 stores.
New Prod. Order	Order 3 or more of the recommended top 10 SKUs by each store.
Order Way	Order every Monday through the recommended ordering screen in the ordering system.
Performance Criteria	1. Sales status of recommended/ordered items (1 week); 2. Average daily sales of recommended items (4 weeks).
Comparison criteria	Average sales volume per store for each product.
Evaluation criteria	1. Percentage of recommended introduced products that are sold (1 week); 2. Average daily sales of recommended products by store vs. overall average daily sales by all handling stores.

Among the eight stores participating in the pilot operation, including Store A, four stores placed orders for the recommended products for a duration of 4 weeks, two stores placed orders for 3 weeks, and Store F placed orders for 2 weeks. Store K used the recommendation system only in the first week and was excluded from the evaluation. In total, 91 SKUs recommended and ordered from seven stores were used to evaluate the pilot operation results. Table 6 presents the number of ordered SKUs each week on Mondays and the number of sold SKUs for each week.

Table 6. Orders and sales of SKUs.

Store Name	1 Week		2 Weeks		3 Weeks		4 Weeks		1~4 Weeks
	Order SKU	Sales SKU	Order SKU	Sales SKU	Order SKU	Sales SKU	Order SKU	Sales SKU	Unsold/Total SKU
A	4	4	4	4	4	3	4	2	0/16
B	4	4	4	4	4	3	3	2	0/15
C	4	4	4	4	4	3	4	4	0/16
D	4	4	4	1	4	1	4	3	0/16
E	0	0	4	4	2	2	2	2	0/8
F	0	0	0	0	4	2	4	4	0/12
G	0	0	0	0	4	4	4	4	0/8

Out of the total 91 newly introduced SKUs across the seven stores, 80 SKUs were sold within 1 week, while 15 SKUs had no sales during that week. Throughout the entire 4-week pilot operation period, all SKUs were sold at least once. While opinions may vary regarding the sales criterion within 1 week, considering that Company E sells approximately 500 SKUs on average per day and each store manages around 3500 SKUs, the average sales period for newly introduced products was considered as 1 week.

Based on this 1-week sales period, the accuracy of the recommendation system can be calculated as follows:

$$\text{Accuracy} = \text{Number of Sold SKUs}/\text{Number of Recommended Ordered SKUs} = 80\ \text{SKUs}/91\ \text{SKUs} = 0.88$$

The accuracy of the recommendation system calculated in this way is 88%. However, due to the nature of offline stores, this approach alone may not be sufficient to determine the system's effectiveness. To further evaluate the performance of recommended products, the average daily sales quantity of newly introduced products in each store was compared with the overall average sales quantity of those products being sold across all stores. Table 7 presents the results of this comparison.

Table 7. Comparison: average daily sales versus overall average sales.

Store Name	Avg. Daily Sales Quantity		Superiority/Inferiority	
	Pilot Store	Total Store	Superior SKU	Inferior SKU
A	0.62	0.40	11	5
B	0.88	0.28	12	3
C	0.39	0.34	6	10
D	0.22	0.25	8	8
E	1.21	0.36	7	1
F	0.40	0.39	8	4
G	0.85	0.40	8	0
Total	0.63	0.36	60 SKU	31 SKU

In comparison, except for Store D, the average daily sales of newly recommended products was higher than the average daily sales of the existing products in the other six stores. Across all seven stores, the average daily sales of newly recommended products was 0.63 units, which was 1.75 times higher than the overall average of 0.36 units for the existing product composition. Furthermore, when comparing individual SKUs, 60 products achieved higher sales than in the comparison stores, while 31 products had lower sales. This indicates that approximately 66% of the recommended products demonstrated better sales performance compared to the overall sales performance.

In addition to quantitative results, qualitative evaluation was conducted by collecting user satisfaction and feedback on system usage. To identify areas for improvement, a survey was conducted. Table 8 presents the survey results reflecting user satisfaction and opinions from the seven stores after the 4-week pilot operation. The survey was conduct with a five-point Likert scale.

Table 8. User survey results.

	Questions	Results
System Reliability	Are the recommended products reliable and worth adopting?	3.7
System Usability	Selecting and ordering products was performed smoothly without any difficulty?	4.6
System Utility	Are you using the recommendation system continuously in the future?	4.3
Other Opinion	Address issues or suggestions	Total Average 4.2

Overall, there was generally positive feedback from users regarding the recommendation system, and the key feedback for the open-ended question (addressing issues or suggestions) is as follows: "We expanded our product lineup through the recommendation of cold noodle category products. The recommended products are selling well, but whether they show better performance than other new products needs further verification. If similar products within the same category are recommended, it may lead to a decrease in sales of other products. The system recommends products that were not previously considered, reducing decision-making scope and time. Concerns were raised about the potential impact on sales of similar products within the same category, such as 'oooo café latte'".

5. Conclusions

In summary, the results of the pilot operation of the product recommendation system are as follows:

- During the 4-week pilot period, all 91 newly introduced SKUs were sold, achieving a 100% sales rate;
- Out of the 91 recommended SKUs, 80 SKUs were sold within 1 week, demonstrating an 88% recommendation accuracy;
- The overall average daily sales of recommended products in the selected seven stores was 0.63, which is 1.75 times higher than the overall average;
- When compared to the average sales of identical SKUs across all stores, 66% of the SKUs recorded higher sales.

These results indicate a substantial level of accuracy and effectiveness in the pilot operation of the recommendation system. The business owners' satisfaction rating of 4.2 also reflects continued interest in the system's ongoing use.

The significance of this study lies in the expansion of personalized recommendation research, primarily conducted on online platforms, to offline businesses such as convenience stores. The study implemented and validated a store-based collaborative filtering model for product recommendation, considering users across various store locations. Store similarity was calculated based on each store's category-specific sales history. Leveraging collaborative filtering after analyzing SKU sales histories for each store, the model recommended products that were predicted to perform well in terms of sales, taking into account additional business considerations such as headquarter and store product operations.

Several areas require further attention and research. The 12% failure rate of recommended products and the underperformance of 34% when compared to overall average demand indicate the need for additional algorithm refinement and optimization. Furthermore, additional validation is needed for store similarity assessment, considering factors such as store locations, product range, and sales volume. Exploring weight adjustments for various business requirements in recommendation score calculation is necessary. Hybrid recommendation systems using cluster analysis and item-based recommendation systems using basket analysis are potential areas for further research. Moreover, a financial evaluation, such as assessing the overall sales and profitability impact of introduced products, needs to be considered for a comprehensive assessment of the recommendation system's effectiveness from a financial perspective.

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