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Community-based management for low-digitalized communities using cross-cutting purchasing behavior

Yuya Ieiri[1✉], Kaishu Yamaki[2] & Reiko Hishiyama[3]

The need for community-based management to revitalize the economy of commercial areas by using consumer behavior analysis focusing on transactions has increased. Low-digitalized shopping communities, commercial communities that include retailing that have not introduced digital technologies, require community-based management using consumer behavior analysis. However, low-digitalized shopping communities cannot collect cross-cutting consumer behavior data using digital technologies such as point of sales (POS) systems. This difficulty obscures the novel management potential of applying such customer behavior analysis to community-based management. Our study aims to bridge the gap between low-digitalized shopping communities and community-based management using customer behavior analysis. To achieve this purpose, this study proposed a novel management approach using data collected using paper-based community currencies and its analysis method. Two field experiments were performed in low-digitalized shopping communities in Japan using two types of community currencies: from-to (FT) and customer attributes (CA). This study illustrated the possibility of community-based management in low-digitalized shopping communities and extending conventional retailing management methods using customer behavior analysis to community-based management.

[1] Graduate School of Information, Production and Systems, Waseda University, 2-7 Hibikino, Wakamatsu-ku, Kitakyushu 8080135 Fukuoka, Japan. [2] School of Knowledge Science, Japan Advanced Institute of Science and Technology, 1-1 Asahidai, Nomi 9231292 Ishikawa, Japan. [3] School of Creative Science and Engineering, Waseda University, 3-4-1 Okubo, Shinjuku-ku 1698555 Tokyo, Japan. ✉email: yuya.ieiri@aoni.waseda.jp

Introduction

With the increase in online shopping and global retail chains, the role of commercial areas as communities has declined. In the United Kingdom, the government considers the high vacancy rate in High Streets and shopping centers a severe problem and insists on the importance of regenerating such commercial areas (BBC News Business 2013, 2019). The vacancy rate in traditional shopping streets is increasing, and joining communities to promote revitalization has become increasingly important in Japan (Buck and Mao 2019; Ito 2018). This loss of local wealth in a community negatively impacts social capital and associated well-being indicators (Hopkins 2013; Wilkinson and Pickett 2011). The New Economics Foundation proposed "Plugging the Leaks" and mentioned that circulating money within a community is necessary to revitalize the regional economy (Ward and Lewis 2002). Therefore, the need for community-based management to revitalize the economy in commercial areas has increased. Houston and Nevin (1981) highlighted the importance of community-based management and argued that municipal governments should develop promotional efforts for downtown areas as unifying agents beyond those of individual stores. Such community-based management is required not only in commercial areas but also in other communities, such as tourist destinations (Liang 2021).

Consumer behavior analysis is a management approach used to revitalize an economy. Consumer behavior includes contact with information, access to funds, contact with stores, contact with products, transactions, consumption, disposition and communication (Peter et al. 1999). There are different management approaches for each of these seven behaviors. Transactions are an important consumer behavior that is directly related to purchasing behavior. Researchers have studied consumer behavior from different perspectives by focusing on transactions in individual stores (Bhaduri and Fogarty 2016; Gil Saura et al. 2017; Kocas et al. 2018; Shabanova et al. 2015). Such an analysis of consumer behavior is helpful for the management of municipalities, as commercial areas have certain customer segmentations. Analyzing the tendencies of customer groups is effective in community-based management of business parks as well as in the management of individual stores. Matsumoto et al. (2012) thus proposed the concept of 'Machi-POS' ('Machi' means a town in Japanese) and developed a platform for sharing point of sales (POS) information between restaurants in an area, which improved inventory management.

Understanding the trends of customer groups through an analysis of consumer behavior is useful in many communities, regardless of the progress of digitalization. However, applying the analysis of consumer behavior to low-digitized buying groups is difficult. Low-digitized buying communities are trading communities that include stores that have not yet adopted digital technologies. In such low-digitized communities, it is difficult to collect overarching data on consumer behavior using digital technologies such as POS systems. For example, several retail sectors around the world have struggled to adopt technologies such as POS systems (Sourav and Emanuel 2021). Additionally, there are also street food stalls and other stores that do not use technology and instead use traditional cash transactions. The difficulty of collecting overarching shopping behavior data in communities including such low-digitalize stores obscures the novel management potential of applying customer behavior analytics to community-based management. Therefore, technology-free data acquisition and analysis methods are required as an effective alternative.

Technology-free data acquisition methods include questionnaires, interviews (Kaneda and Inagaki 2020), and paper-based community currencies (Kichiji and Nishibe 2008). Questionnaires and interviews made it possible to collect data from the community without significant effort. These approaches are often applied to simulation analyses by modeling customer behavior (Kaneda et al. 2020). However, it is not easy to collect reliable data on purchasing behavior, such as POS data. On the other hand, the use of a paper-based community currency requires the cooperation of the community, but enables reliable data collection on purchasing behavior, e.g. at the POS. Despite these valuable aspects, community currencies have been used to promote local consumption, community cohesion and volunteering. Community currencies have not been used primarily for data analysis. This type of analysis is often limited to the circulation of local currencies (Kichiji and Nishibe 2008; Kurita et al. 2012).

Similar to the analysis of POS data, the data collected with the community currency has the potential to be used in the analysis of consumer behavior. This application is an innovative approach to analyzing consumer behavior in communities with low levels of digitalization. Consumer behavior analysis based on data from paper-based community currencies can also be applied to communities with issues such as the cost of adapting information and communication technology tools and the lack of skilled personnel in technical technology (Sourav and Emanuel 2021). Based on this background, this study aims to bridge the gap between low-digitalized shopping communities and community-based management using customer behavior analysis, including transactions and cross-cutting purchasing behavior log data, in commercial areas. This study examined the following research questions:

1. How can such low-digitalized shopping communities realize community-based management?
2. How can conventional retailing management methods using customer behavior analysis expand for community-based management?

This study proposes a novel management approach using data from the community currency. The community currency enables the collection of data such as the type of customers, their purchases and the type of stores they frequent. In addition, this study extends the traditional approach to analyzing customer behavior for individual stores to community-based management. Moreover, an extended analysis is applied to compare the customer behavior data collected through the community currency. Because establishing novel data and analysis methods is crucial for new management strategies (Hoffman et al. 2022), this study is important for practitioners who manage shopping communities and researchers in commercial areas. Especially for practitioners managing shopping communities, conducting community management using a community currency as used in this study will provide valuable knowledge for revitalizing and strengthening the community, regardless of the level of digital technology adoption. For researchers in the management of commercial areas, this study demonstrates the feasibility of a new research approach by applying consumer behavior analysis methods to retail stores in shopping community management.

A collection method was constructed for crosscutting consumer behavior log data and analysis methods by focusing on two types of paper-based community currencies. Field experiments on traditional Japanese shopping streets called "shotengai" were conducted for four weeks to assess the effectiveness of the proposed method. Shotengai is shopping street where various stores have been in business for many years. Currently, there are over 10,000 shotengai in Japan. A fact-finding investigation of shotengai in 2018 conducted by The Small and Medium Enterprise Agency (2018) reported that approximately 68% of shotengai struggled financially. In addition, it became clear that the number of visitors was decreasing in almost 55% of shotengai. Additionally, people in some shotengai are aging, and technology is not being widely introduced. Thus, traditional Japanese commercial areas, shotengai, are low-digitalizazion shopping communities that require community-based management utilizing cross-cutting purchasing behavior log data.

Related literature

Consumer behavior analysis with transactions. Consumer behavior data using transactions are a crucial asset in retail management. Some studies examined retail store management by focusing on transaction data (Tan et al. 2022; Van Ittersum et al. 2013; Zhang et al. 2014). Zhang et al. (2014) combined customer video tracking and transaction data at retail stores to investigate the effect of social elements of retail store visits on shoppers' product interaction and purchase likelihood. Van Ittersum et al. (2013) focused on smart shopping carts and revealed the influence of real-time spending feedback on customers' purchasing behavior in retail stores. Tan et al. (2022) investigated transaction data based on differences in the use of augmented reality in retail store management.

POS systems were developed from mechanical cash registers at the beginning of the 20th century Sularto15. Researchers have analyzed consumer purchasing behavior using various approaches and POS data (Sano and Yada 2015; Trivedi 2011; Williams et al. 2014). Consumer purchasing behavior analyses that consider identification (ID), including consumer attributes and individual POS data, have been attempted by linking points cards to online services (Amemiya et al. 2018; Ishimaru et al. 2021).

Most conventional studies are limited to the analysis of consumer behavior for management in individual stores, as it is difficult for purchasing groups with a low level of digitalization to collect comprehensive data on purchasing behavior.

Collection of cross-cutting consumer behavior data. Over the years, many researchers have attempted to collect crosscutting consumer behavior data from commercial areas (Timmermans 2009). Questionnaire surveys are the most commonly used method for collecting behavioral data from consumers (Sisiopiku and Akin 2003). Kaneda and Inagaki (2020) focused on a shopping district in Nagoya, Japan, and identified shop-around corridor patterns using questionnaire data. Global Positioning System have also been used to develop location-based services (Flamm and Kaufmann 2007). In addition, fixed-point observations such as video recording (Denzler and Niemann 1997) and image processing technology (Sexton et al. 1995) have been used to collect behavioral data.

Regional consumer data helps in constructing behavior models for local people. Using such data and behavior models, some studies have clarified downtown dynamics using agent simulations (Kaneda et al. 2020). In short, consumer behavior surveys have been used to examine behavior in the community rather than in individual stores and include methods such as interviews, questionnaires, digital sensing, and social media (Kaneda and Inagaki 2020). However, these data collection approaches have no apparent relationship with purchasing behavior because they do not guarantee customer purchasing behavior. Thus, these methods are unsuitable for consumer behavior analyses that focus on transactions in commercial areas.

Matsumoto et al. (2012) proposed the concept of 'Machi-POS' ('Machi' means a town in Japanese) and developed a platform for sharing POS system information between restaurants in an area, which improved inventory management. However, this management approach is limited to targeted stores in the same area or

Table 1 Related studies using community currency.

Research	Target country	Currency style	QIS[a]	NA[b]	CBA[c]
Seyfang (2001)	UK[d]	LETS[e]	✓		
Graugaard (2012)	UK	Paper-based	✓		
Kurita et al. (2012)	Japan	Paper-based	✓		
Kichiji and Nishibe (2008)	Japan	Paper-based	✓	✓	
Mattsson et al. (2023)	Kenya	Electronic		✓	
Our study	Japan	Paper-based			✓

[a]QIS stands for questionnaires and interview surveys.
[b]NA stands for network analysis.
[c]CBA stands for consumer behavior analysis.
[d]UK stands for the United Kingdom.
[e]LETS stands for the local exchange trading scheme system.

connected stores in commercial areas. Moreover, this approach is unsuitable for low digitized buying communities, including those that cannot use POS systems. Therefore, the Machi-POS approach has not yet been used for community-based management of low-digitized shopping communities. To realize a novel community-based management based on consumer behavior analysis, a data collection method for overarching consumer behavior that can be applied to different regions and stores is required.

The proposed method of data collection with community currencies does not require the introduction of technology for individual stores or customers. Community currencies are one of the most important approaches to promote local consumption and community cohesion, and 3,418 community currency projects have been validated in 23 countries worldwide (Seyfang and Longhurst 2013). Various efforts have been made to promote commercial areas using such community currencies. Table 1 summarizes some related studies. As confirmed in Table 1, applying consumer behavior analysis to data collected using community currencies has not yet been attempted. This is because most conventional analyzes of consumer behavior are retail-centric and do not focus on community management. Therefore, this study aims to extend the method of consumer behavior analysis from retail stores to the community and realize community-based management by analyzing consumer behavior using community currency data. In contrast to previous studies, the proposed approach enables a novel community-based management of shopping communities with a low degree of digitalization.

Methods

Data collection using community currencies. There are various methods of collecting data on overarching consumer behavior. One of these methods is the use of a community currency. Community currencies usually only spread within the targeted trading area, and trading areas create community currencies. Community currencies have been utilized in various contexts, such as the local exchange trading scheme (LETS) (Williams et al. 2001), the recovery of a local community (Graugaard 2012), and sustainable regional development (Seyfang 2001). However, as can be confirmed from Table 1, the mainstream approach to analyzing data collected from community currencies is distribution analysis using questionnaires, interviews, and network analysis. This type of distribution analysis is mainstream because community currencies are tools to promote local consumption and cohesion. Thus, there has yet to be an attempt to collect data on cross-cutting consumer behavior using community currency and apply counselor behavior analysis methods. Adding

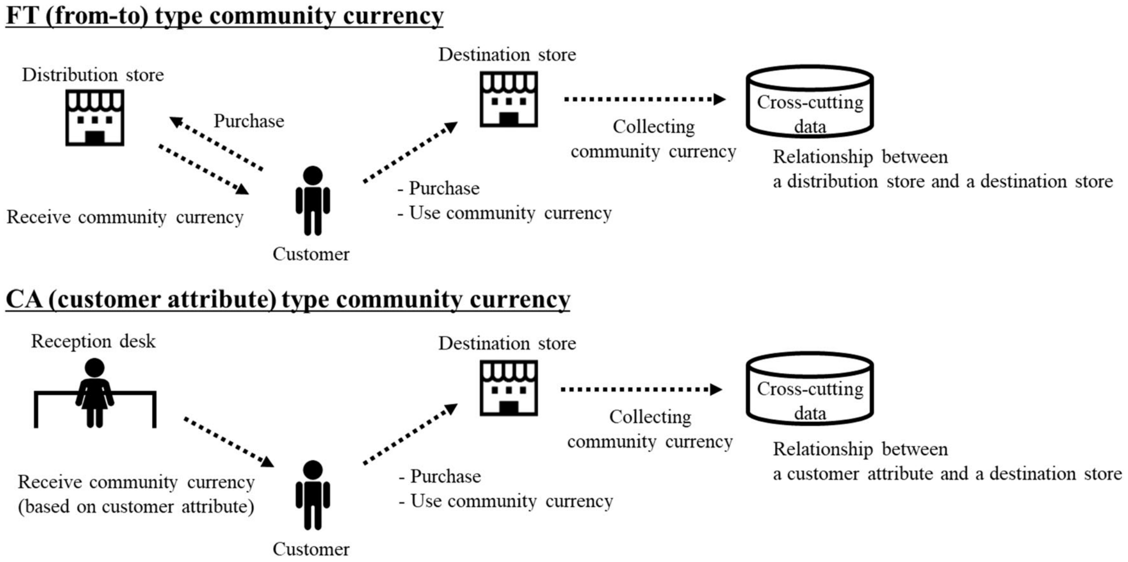

Fig. 1 Distribution flow of FT and CA community currencies. This diagram shows the flow of distribution of FT and CA community currencies and the characteristics of the collected data.

Table 2 Characteristics of each type of community currency.

Type of community currency	Obtained data	
	Relationship between stores	Relationship between CA and a store
FT-type (Paper-based)	✓	
CA-type (Paper-based)		✓
Electronic-based	✓	✓
Type of community currency	Requirements for introduction	Introduction cost
FT-type (Paper-based)	- Making paper-based community currencies	Low
CA-type (Paper-based)	- Making paper-based community currencies - Establishing a specific reception desk	
Electronic-based	- Making electronic-based community currencies - Digital device for customers to use the currencies - Digital device for stores to receive the currencies	High

identifiers to community currencies makes it possible to collect various cross-cutting consumer behavior data.

There are two types of community currencies: paper-based currencies, a classic variety that does not require technology, and electronic-based currencies that use digital applications. The studies above focused on paper-based community currency (Lietaer and Hallsmith 2006). In contrast, Knowles et al. (2014) focused on electronic-based community currencies, but did not collect cross-cutting consumer behavior data. The paper-based community currency enables the collection of overarching data on consumer behavior for each business area without the need to introduce separate technologies for stores and customers. There are two possible distribution methods for customers: in stores and at special reception desks. This study focuses on two types of paper-based community currencies, based on the differences between the two distribution methods. (see Fig. 1).

(FT) currency is distributed in stores in a commercial area. Recording the identification (ID) of the community currency distributed at the store allows for an analysis of the co-occurrence relationship between stores used by customers (distribution and destination stores). The customer attribute (CA) currency is distributed to a specific place. Distributing community currency with IDs associated with customer attributes allows for analyzing the relationship between stores and customer attributes.

Table 2 summarizes the characteristics of data collection methods using these two types of paper-based and electronic-based community currencies. Compared to paper-based community currencies, electronic community currencies can collect a wider variety of data. However, the introduction of electronic-based community currencies is more complicated than that of paper-based community currencies in commercial areas. In addition, the combination of the two types of paper-based Community currencies (FT-type and CA-type) made it possible to collect various data similar to those of the electronic Community currencies.

Consumer behavior analysis for community-based management. ABC and association analyses are typical methods for analyzing consumer behavior data, including transactions. ABC analysis is a method for classifying items that have a significant impact. ABC analysis can classify objects into groups A, B, and C as the most important, moderately important, and least important objects, respectively, (Yu 2011). The classification scheme is based on the Pareto principle or 80/20 rule (Pareto 1896). Association analysis is a method of analyzing item relationships based on co-occurrence relationships in transaction data (Agrawal et al. 1994). Thus, it is compatible with POS data, and Usami et al. (2017) clarified the characteristic purchasing behavior by applying association analysis to POS data. This study extends these analysis methods and constructs a consumer behavior analysis method for community-based management. The main processes of ABC and association analysis are summarized in Table 3 for each of the two

Table 3 Detail process of ABC and association analysis.

	FT-type	CA-type
ABC analysis	1. Focus on the time of distribution and use of community currencies and derive the number of times that store k is used (S_k). 2. Divide S_k by twice the number of circulated community currencies to derive R_k, the visit frequency ratio of store k. 3. Identify stores with R_k in the top 20% in the community.	1. Focus on the customer attribute CA and derive the number of times the community currency is used at store k, described as $C_{CA,k}$. 2. Divide $C_{CA,k}$ by the total number of circulated community currencies to derive $R_{CA,k}$, the visit frequency ratio of store k. 3. For each customer attribute CA, identify the stores in the community with $R_{CA,k}$ in the top 20%.
Association analysis	1. Remove the data where the local currency is distributed and used at the same store from the whole data and focus on the remaining data. 2. Derive the total number of community currencies distributed at store k and the total number of community currencies used at store k. 3. Derive the degree of support, the degree of certainty, and the index for examining the validity of the relevance as indicators for discussing the relationship between two stores.	Not applicable.

types of community currencies (FT and CA) on which this study focuses. This section explains the procedures used in the analyses.

Using ABC analysis to identify stores frequently visited by customers in commercial areas using the ABC analysis is essential for community management. The method of applying the ABC analysis to cross-cutting consumer behavior data collected using FT-type community currencies is as follows. Let $C_{i,j}$ be the number of community currencies distributed in-store $i(i = 1, 2, \ldots, n)$ and used in-store $j(j = 1, 2, \ldots, n)$. Let S_k be the number of times store k was used, which was obtained based on FT-type community currencies, and the following equation was derived:

$$S_k = \sum_{i=1}^{n} C_{i,k} + \sum_{j=1}^{n} C_{k,j} \tag{1}$$

This formula adds up the number of times a store k is used when the community currency is distributed, and the community currency is used. Assuming that the visit frequency ratio (%) of store k is R_k, the following equation is derived:

$$R_k = \frac{S_k \times 100}{2 \times \sum_{i=1}^{n} \sum_{j=1}^{n} C_{i,j}} \tag{2}$$

$\sum_{i=1}^{n} \sum_{j=1}^{n} C_{i,j}$ is the total number of circulated community currencies. With one community currency, FT-type community currencies can collect transaction data twice, once when the community currency is distributed and once when used. Thus, the visit frequency can be determined by dividing S_k by twice the total number of circulating community currencies. For example, assume that the number of distributed community currencies at store e is 30 and that of used community currencies is 50. If the total number of circulated FT-type community currencies is 400, then the values of S_e and R_e are 80 and 10%, respectively.

For service organizations, the top group in the ABC analysis results is defined as 20% of the total (Flores and Whybark 1986). Therefore, the study considers a commercial area as a type of service organization and identify ($[\frac{n}{5}]$) stores, equivalent to 20% of all stores in the commercial area, as stores that consumers frequently visit based on R_k.

The method of applying the ABC analysis to the cross-cutting consumer behavior data using CA-type community currencies is as follows. Let $C_{CA,j}$ be the number of community currencies customers use with attribute CA at store $j(j = 1, 2, \ldots, n)$. Let $R_{CA,k}$ be the visit frequency ratio (%) of store k for customers with the attribute CA, and the following equation is derived:

$$R_{CA,k} = \frac{C_{CA,k} \times 100}{\sum_{j=1}^{n} C_{CA,j}} \tag{3}$$

$\sum_{j=1}^{n} C_{CA,j}$ indicates the total number of community currencies customers use with the attribute CA. In the case of CA-type community currencies, transaction data are collected for only one community currency. Thus, the visit frequency of store k can be determined by dividing $C_{CA,k}$ by the total number of circulating community currencies. As a specific example, it is assumed that the number of community currencies used at store e is 50 for CA-type community currencies that focus on customers with a particular customer attribute ex. If the total number of circulated CA-type community currencies for customer group ex is 400, the value of $C_{CA,k}$ is 50, and the value of $R_{CA,k}$ is 12.5%. As with FT-type community currencies, the study identifies $[\frac{n}{5}]$ stores, equivalent to 20% of all stores in the commercial area, as stores that consumers frequently visit based on $R_{CA,k}$.

Central place theory, a theory of urban geography that shows the spatial structure of an area (Christaller 1966), highlights the importance of determining the center of service supply in commercial areas. Based on the central place theory, community-based management and regional design utilizing the center of service supply in commercial areas have received widespread attention in recent years (King 2020). These discussions on the central place theory support the significance of applying an ABC analysis to community-based management.

Clarifying the relationships between the stores used by customers in commercial areas is essential for community-based management. Previous studies show the importance of examining store relationships, including location relationships (Brown 1987; Getis and Getis 1968).

The following method applies association analysis to cross-cutting consumer behavior data collected using FT-type community currencies. The data for $C_{i,j}(i \neq j)$ are analyzed to examine the relationships among stores in commercial areas. Let D_i be the total number of FT-type community currencies distributed at store i, and U_j be those used at store j. The following equations were used:

$$D_k = \sum_{j=1}^{n} C_{k,j}(k \neq j) \tag{4}$$

$$U_k = \sum_{i=1}^{n} C_{i,k}(i \neq k) \tag{5}$$

$\sum_{k=1}^{n} D_k$ and $\sum_{k=1}^{n} U_k$, and the total number of circulating FT-type community currencies is the same.

Assume that $SUP_{i\Rightarrow j}$ indicates the degree of support, which is the probability of the occurrence of data on the total number of consumers who purchased at stores i and j. In particular, $i \Rightarrow j$ implies that when customers use store i, they also use store j. This shows the rate of co-occurrence between the stores that appear in the collected data and is derived as follows:

$$SUP_{i\Rightarrow j} = \frac{C_{i,j} + C_{j,i}}{\sum_{i=1}^{n} D_i}(i \neq j) \tag{6}$$

The numerator in the equation above represents the number of transactions using stores i and j. The denominator of the above equation is the total number of circulated community currencies. As shown in the equation, $SUP_{i\Rightarrow j}$ does not depend on the order of i and j.

$CONF_{i\Rightarrow j}$ represents the degree of certainty, which is the probability of consumers who purchased something at both stores i and j among all consumers who purchased something at store i. This shows the strength of the relationship between these two stores and was calculated as follows:

$$CONF_{i\Rightarrow j} = \frac{C_{i,j} + C_{j,i}}{D_i + U_i}(i \neq j) \tag{7}$$

The numerator in the above equation represents the number of transactions using stores i and j. The denominator in the above formula indicates the total number of distributed and used community currencies related to store i. As can be observed from the definition of the degree of certainty, $CONF_{i\Rightarrow j}$ depends on the orders of i and j.

$LIFT_{i\Rightarrow j}$ is an index for examining the validity of the relevance derived from the degree of certainty, as follows:

$$LIFT_{i\Rightarrow j} = \frac{CONF_{i\Rightarrow j}}{\frac{D_j + U_j}{\sum_{i=1}^{n} D_i}}(i \neq j) \tag{8}$$

$LIFT_{i\Rightarrow j}$ indicates the degree of correlation between the usage of stores i and j, and the numerator in the above equation indicates the degree of certainty. The denominator in the above equation shows the value obtained by dividing the number of community currencies associated with store j by the total number of community currencies. Furthermore, as determined by substituting $CONF_{i\Rightarrow j}$, the value of $LIFT_{i\Rightarrow j}$ does not depend on the order of i and j. The co-occurrence relationship between stores in a commercial area was clarified through association analysis using the above three indicators.

As a specific example, assume that the total number of circulating FT-type community currencies is 300, the number of community currencies distributed at store $e1$ is 30, and the number of community currencies used at store $e1$ is 50. At that time, the values of D_{e1} and U_{e1} are set to 30 and 50, respectively. In addition, it is assumed that the number of community currencies distributed at store $e2$ is 40 and the number of community currencies used at store $e2$ is 20. The values of D_{e2} and U_{e2} are 40 and 20, respectively. In addition, the number of community currencies distributed at store $e1$ and used at store $e2$ is 10, and the number of community currencies distributed at store $e2$ and used at store $e1$ is 20. In such a situation, association analysis is applied to the example data to consider the relationship between stores $e1$ and $e2$. At that time, the value of $C_{e1,e2}$ was 10, $C_{e2,e1}$ was 20, and $SUP_{e1\Rightarrow e2}$ was $30/300 = 0.1$. Furthermore, the value of $CONF_{e1\Rightarrow e2}$ is $30/80 = 0.375$ and the value of $LIFT_{e1\Rightarrow e2}$ is $0.375/(60/300) = 1.875$.

Study 1: Field study using FT-type community currencies

Design. A field experiment was conducted in a commercial area to assess the effectiveness of community-based management using an FT-type community currency. A field experiment was conducted from November 29 to December 13, 2020. The stores agreed to cooperate after being informed about the content of the experiment. There were no direct incentives for participating in the experiment. Participation in the stores was voluntary. The data collected in this experiment was only shared within the research group (college, town hall and commercial area) under strict control. An unspecified number of customers were informed about the content of the experiment through posters and flyers.

This experiment was conducted in shopping districts around the Shin-Okubo and Okubo stations in Tokyo, Japan. These areas are multinational and the trends in consumer behavior within the communities are not clear; therefore, the community wanted to revitalize the communities by clarifying the trends. In addition, the location of the site is convenient for the college, which is the base for empirical research, allowing for field research on foot. For these reasons, these areas were selected as fields for Study 1.

Figure 2 shows the location and category of stores in the target commercial area and an outline of the paper-based FT-type community currency used in the experiment. Some stores in the target area are members of the purchasing association, others are not. Therefore, it is difficult to accurately count the number of stores whose main business is the customers at stake in this experiment. Nevertheless, the authors identified 55 stores among the Shopping District Association stores whose main business is customers. Seventeen stores participated in this experiment, and the number of participating stores in the community was approximately 31%.

As shown in Fig. 2, there are some differences in the positional relationships between the stores targeted in the experiment. However, the size of this commercial area is moderate, and shop-around behavior is possible on foot in this area. Restaurants refer to businesses that provide food and beverages to customers, general merchandise businesses that provide goods other than food and beverages, and service businesses are businesses that provide services other than goods to customers. In this study, the commercial areas comprised a mix of different businesses. Therefore, the commercial area covered by this experiment was suitable for evaluating the collection of data on overarching consumer behavior using the proposed method. The FT community currency used in this experiment was a 200-yen tender, and the 4-digit number assigned to each tender corresponded to the distribution business. In addition, customers can only use one tender of the community currency for each transaction, which provides the exact frequency of their purchase behavior.

For this experiment, customers received a FT community currency in exchange for a purchase of more than 200 yen at the target stores. This FT community currency could be used in all target stores of the experiment, regardless of which store it was spent in. Once the community currency was used, it would no longer be distributed to customers. After the experiment, the FT-type community currencies were collected in the target stores. Through the procedure described above, the distributing store is identified by the 4-digit number that is uniquely described for the FT-type community currency. By recording the community currency, the store in which each community currency of type FT was used can be determined. This data corresponds to the overall

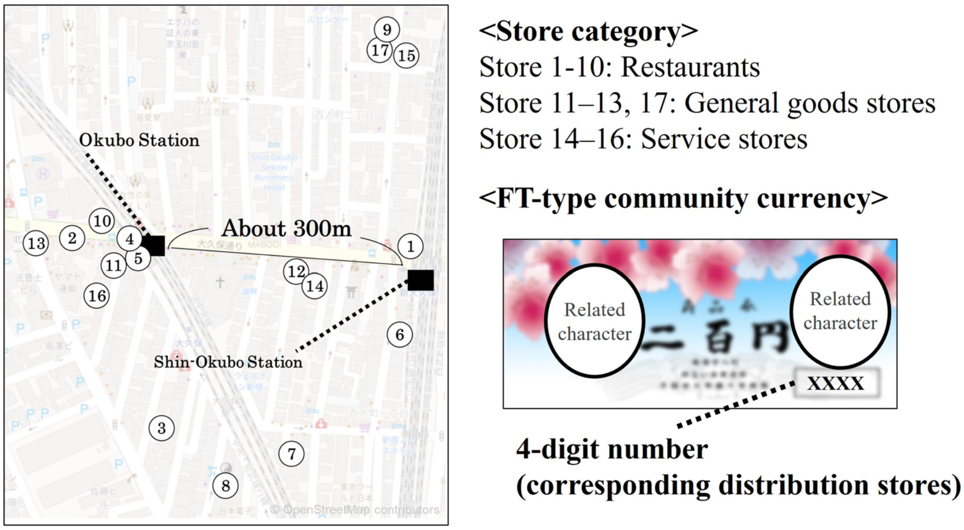

Fig. 2 Outline of the field experiment with details of stores and FT-type community currency. This diagram describes the characteristics and location information of participating stores related to Study 1.

Table 4 S_k and R_k in Study 1.

	S_k	R_k		S_k	R_k
Store 1	89	8.9	Store 10	95	9.5
Store 2	10	1.0	Store 11	41	4.1
Store 3	76	7.6	Store 12	117	11.7
Store 4	93	9.3	Store 13	42	4.2
Store 5	89	8.9	Store 14	24	2.4
Store 6	46	4.6	Store 15	16	1.6
Store 7	110	11.0	Store 16	12	1.2
Store 8	4	0,4	Store 17	42	4.2
Store 9	90	9.0			

Table 5 Results of association analysis in Study 1.

Store(i, j)	$SUP_{i\Rightarrow j}$	$CONF_{i\Rightarrow j}$	$LIFT_{i\Rightarrow j}$
Store(10, 11)	0.172	0.756 ($i=10$) 0.872 ($i=11$)	3.836
Store(12, 14)	0.081	0.232 ($i=12$) 0.667 ($i=14$)	1.913
Store(3, 12)	0.056	0.423 ($i=3$) 0.159 ($i=12$)	1.214

consumer behavior data with transactions in the target community.

Results and discussions. Experiments collected cross-cutting consumer behavior data for 498 transactions using an FT-type community currency. Kichiji and Nishibe (2008) conducted a network analysis targeting 2,771 transactions. Kichiji and Nishibe (2008) focused on 272 subjects, regarded these subjects as nodes and attempted to manage the community by applying network analysis. Community management was attempted by focusing on the aggregates of these 272 subjects as a community. This experiment attempted to realize management through consumer behavior analysis, focusing on the aggregate of 17 stores as a community. Referring to the size of the literature (Kichiji and Nishibe, 2008), approximately 173 transactions (2,771 × (17/272)) is the number of transactions necessary to discuss the target community in this experiment. The 498 transactions collected in the experiment are sufficient for a valid discussion.

First, ABC analysis was applied to the collected data. The values of S_k and R_k for Stories 1–17 are shown in Table 4. The ABC analysis identifies three ($[\frac{17}{5}]$) stores frequently visited by consumers, accounting for 20% of all stores (17 stores) in the commercial area. Stores 7, 10, and 12 were identified as frequently visited. As shown in Fig. 2, the three stores are not positioned near each other. Thus, frequent visits may not result from the location but rather from the nature of these stores. Stores 7 and 10 were restaurants, and store 12 was the only pharmacy among the 17 stores targeted. From the collected data, approximately 74% of the community tenders used in store 12 were distributed from the other stores. This indicates that store 12 serves as a hub connecting stores in the target commercial area.

This experiment included a total of 300 data points for $C_{i,j}(i \neq j)$. Thus, association analysis was applied to the remaining 198 data points for $C_{i,j}(i \neq j)$. Table 5 describes the combination of the top three with the largest values of $SUP_{i,j}$, $CONF_{i,j}$ and $LIFT_{i,j}$. These combinations were the primary co-occurrence relationships among stores in commercial areas, obtained through association analysis. From the viewpoint of positional relationships, store 10 was relatively close to stores 11, and store 12 was relatively close to store 14. Thus, close proximity between stores can positively affect co-occurrence relationships. Stores 3 and 12 were far apart, suggesting that closeness was not the only factor in this co-occurrence relationship. Table 5 includes two of the three combinations containing store 12 because the store has many visitors from other stores, as shown in the ABC analysis. Interestingly, many consumers who purchased at store 10 also visited store 11. Store 10 is an Indonesian restaurant, and store 11 deals with Indonesian products. This commonality likely resulted in significant co-occurrence.

Study 2: field study using CA-type community currencies

Design. Additional field experiments were conducted from 12 to 23 November, 2018 and from 14 to 25 January, 2019 to evaluate the effectiveness of community-based management using CA-type community currencies. As in Study 1, stores agreed to participate in the experiments after reviewing their content. Furthermore, participation was voluntary and there were no direct incentives for taking part in the experiment. The data collected in this experiment was only shared within the research groups (college, town hall and business park) under strict supervision.

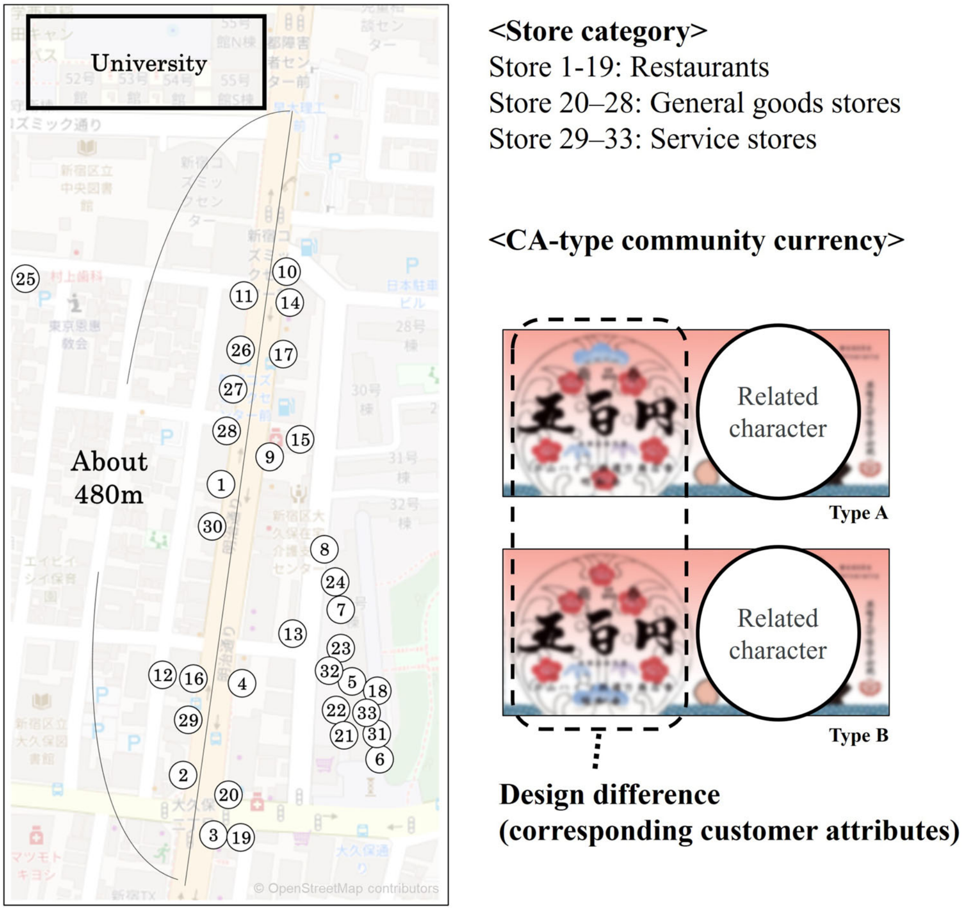

Fig. 3 Outline of the field experiment with details of stores and CA-type community currency. This diagram describes the characteristics and location information of participating stores related to Study 2.

An unspecified number of customers were notified about the contents of the experiment through posters and flyers. This experiment focused on a shopping district near Waseda University in Tokyo, Japan. Although these shopping districts were located near the university, the problem in the community was that they were poorly recognized by university students and faculty members, which led to a low visit frequency. Therefore, the community wanted to clarify the consumer behavior of university students and faculty members and attempt community management. Therefore, these areas were selected as fields for Study 2. Figure 3 shows the location and category of stores in the target commercial area and an outline of the paper-based CA-type community currency used in the experiment.

As shown in Fig. 3, the university and target commercial areas are close. Therefore, this commercial area allows shop-around behavior on foot by university-related people. One of the purposes of this experiment was to manage the target community by clarifying the consumer behavior of university students and faculty members. Thus, this experiment attempts to collect cross-cutting consumer behavior data by focusing on the two consumer attributes of students and faculty members at a university. A commercial area consists of a mix of stores and is therefore a suitable location for evaluating the collection of cross-sectional data on consumer behavior. The CA-type community currency used in this experiment was a 500-yen tender. By matching the slight differences in the design of the community currency to the differences in consumer characteristics, it was possible to collect cross-sectional data on consumer behavior based on customer characteristics. As in Study 1, customers can use only one community currency tender for each transaction to estimate the exact frequency of purchases with the community currency.

In the experiment, customers earned points while engaging in shop-around behavior using the walk-rally application "Machi-Navi" (Ieiri et al. 2019). They exchanged points and community currency at a specially set up reception in the college. The receptionist distributes the community currency according to the customer's characteristics. Recording the CA-type community currency used in each store after the trial period enabled an understanding of the overarching data on consumer behavior with transactions in the target community during the field trial period.

Results and discussions. The field experiment collected cross-cutting consumer behavior data for 338 transactions using CA-type community currencies. As in Study 1, the validity of this number of transactions was examined. Study 2 focused on an aggregate of 33 stores in a community. Referring to the size of the literature (Kichiji and Nishibe 2008), approximately 336 transactions (2,771 × (33/272)) is the number of transactions necessary to discuss the target community in this experiment. The 338 transactions collected in the experiment are sufficient for a valid discussion.

To describe data considering customer attributes, which consist of data specific to CA-type community currency, the customer attributes of university students were set as *st*, and the customer attributes of faculty members were *fa*. The values of S_k and R_k for

Table 6 S_k and R_k in Study 2.

	S_k	R_k		S_k	R_k		S_k	R_k
Store 1	6	1.8	Store 12	0	0.0	Store 23	3	0.9
Store 2	3	0.9	Store 13	10	3.0	Store 24	0	0.0
Store 3	5	1.5	Store 14	62	18.5	Store 25	1	0.3
Store 4	6	1.8	Store 15	1	0.3	Store 26	2	0.6
Store 5	1	0.3	Store 16	10	3.0	Store 27	0	0.0
Store 6	2	0.6	Store 17	14	4.2	Store 28	0	0.0
Store 7	0	0.0	Store 18	0	0.0	Store 29	0	0.0
Store 8	61	18.2	Store 19	5	1.5	Store 30	0	0.0
Store 9	36	10.7	Store 20	1	0.3	Store 31	0	0.0
Store 10	74	22.0	Store 21	2	0.6	Store 32	0	0.0
Store 11	30	8.9	Store 22	1	0.3	Store 33	0	0.0

Table 7 $S_{st,k}$ and $R_{st,k}$ in Study 2.

	$S_{st,k}$	$R_{st,k}$		$S_{st,k}$	$R_{st,k}$		$S_{st,k}$	$R_{st,k}$
Store 1	2	2.4	Store 12	0	0.0	Store 23	0	0.0
Store 2	0	0.0	Store 13	0	0.0	Store 24	0	0.0
Store 3	0	0.0	Store 14	3	3.6	Store 25	0	0.0
Store 4	0	0.0	Store 15	0	0.0	Store 26	0	0.0
Store 5	0	0.0	Store 16	5	6.0	Store 27	0	0.0
Store 6	0	0.0	Store 17	0	0.0	Store 28	0	0.0
Store 7	0	0.0	Store 18	0	0.0	Store 29	0	0.0
Store 8	1	1.2	Store 19	0	0.0	Store 30	0	0.0
Store 9	31	37.3	Store 20	0	0.0	Store 31	0	0.0
Store 10	25	30.1	Store 21	0	0.0	Store 32	0	0.0
Store 11	16	19.3	Store 22	0	0.0	Store 33	0	0.0

Table 8 $S_{fa,k}$ and $R_{fa,k}$ in Study 2.

	$S_{fa,k}$	$R_{fa,k}$		$S_{fa,k}$	$R_{fa,k}$		$S_{fa,k}$	$R_{fa,k}$
Store 1	4	1.6	Store 12	0	0.0	Store 23	3	1.2
Store 2	3	1.2	Store 13	10	4.0	Store 24	0	0.0
Store 3	5	2.0	Store 14	62	23.3	Store 25	1	0.4
Store 4	6	2.4	Store 15	1	0.4	Store 26	2	0.8
Store 5	1	0.4	Store 16	10	2.0	Store 27	0	0.0
Store 6	2	0.8	Store 17	14	5.5	Store 28	0	0.0
Store 7	0	0.0	Store 18	0	0.0	Store 29	0	0.0
Store 8	60	23.7	Store 19	5	2.0	Store 30	0	0.0
Store 9	5	2.0	Store 20	1	0.4	Store 31	0	0.0
Store 10	49	19.4	Store 21	2	0.8	Store 32	0	0.0
Store 11	14	5.5	Store 22	1	0.4	Store 33	0	0.0

stores 1-33 without considering customer attributes are shown in Table 6. Conversely, data considering customer attributes (students and faculty members) are shown in Table 7 with values of $S_{st,k}$ and $R_{st,k}$ for stores 1-33, and in Table 8 with values of $S_{fa,k}$ and $R_{fa,k}$ for stores 1-33. The ABC analysis identifies six ($\lceil \frac{33}{5} \rceil$) stores frequently visited by consumers in Study 2, accounting for 20% of all stores (33 stores) in the commercial area.

Most of the collected data were from purchasing behavior at restaurants. This bias may have occurred because the target customers were those related to the university. The target commercial area was not near the target customers' residences but rather near the school or workplace. Therefore, the data collected mainly shows the purchase of food and drink rather than general goods or services. The insight that people tend to buy food and drink can be applied to various local government practices. For example, it might be a good idea to invite restaurants when the practitioners managing the shopping community are considering locating new businesses. It is important for community revitalization that people associated with the college purchase general goods or services. To realize the behavioral induction, the shopping community administrators can promote stores that sell general goods or services by distributing coupons to stores that sell food and beverages.

As shown in Table 6, stores 8, 9, 10, 11, 14, and 17 were frequently visited. Looking at customer attributes, as shown in Tables 7 and 8, stores 1, 9, 10, 11, 14, and 16 were frequently visited by students, whereas stores 8, 10, 11, 13, 14, and 17 were frequently visited by faculty members. Interestingly, most of the customers in store 8 were students, while most of the customers who visited store 9 were faculty members. In addition, a comparison between students and faculty members revealed that students preferred to visit certain stores. Understanding the differences in store usage based on differences in customer characteristics allows for more accurate community-based management that focuses on customer segmentation.

General discussion

Paper-based community currencies have made it possible to collect cross-cutting consumer behavior data in low-digitalized communities. These two field practices revealed that consumer behavior analysis using such data enables novel community-based management of low-digitalized communities. This section describes the theoretical and practical implications of the findings obtained by integrating the two field studies.

Theoretical implication. This study had two significant theoretical implications. First, it confirms that the consumer behavior analysis methods for retail stores can be extended to community methods. Second, this study demonstrates that the theory supporting consumer behavior analysis in retail stores holds when targeting communities.

Previous management research using consumer behavior data on transactions focused on the purchase of products at a specific retail store (Tan et al. 2022; Van Ittersum et al. 2013; Zhang et al. 2014). By contrast, this study considers the entire commercial area as one retail store and focuses on store purchases in a specific community. In other words, this study makes it possible to extend research on management using consumer behavior data, including transactions in retail stores, to research community-based management. This study considers extending ABC and association analyses to consumer behavior analysis methods for the community.

This study identified stores frequently visited by consumers in commercial areas using ABC analysis. This extends the findings of previous studies that identified best-selling products in retail stores using consumer behavior data, including transactions with community-based management. Shabanova et al. (2015) determined the best-selling products in retail stores and realized effective inventory management of products. Extending this contribution to community-based management would allow for the effective distribution of shared community products, such as community-based event leaflets and original community souvenirs, to stores with high-frequency visits. Kocas et al. (2018) demonstrated that discounting the best-selling products in retail stores improved sales. Applying this to management at the community level, it can be assumed that discounts in stores that are frequently visited by consumers will increase overall sales in the community. Furthermore, it is essential for retail store management to segment customers based on customer characteristics and identify the buying tendencies associated with them (Bhaduri and Fogarty, 2016; Gil Saura et al. 2017). CA-type community currencies enable segmentation based on a community's customer attributes. Therefore, identifying stores that are visited frequently according to each customer attribute reinforces the expansion of the ABC analysis.

Furthermore, this study identified store associations in commercial areas using association analysis. This extends the findings of previous studies that identified product associations in retail stores using consumer behavior data, including transactions, to community-based management. Aydınoğlu and Krishna (2019) demonstrated the importance of solid associations between consumption components within the novel context of price promotions. Jain et al. (2021) supported product discount pattern planning to increase retail sales by identifying associations between products in retail stores. Applied to community-based management, identifying connections between stores could lead to new ideas of cooperation between stores, such as distributing coupons to customers who store at both connected stores in a commercial area.

These theoretical findings on extending ABC and association analyses to consumer behavior analysis methods for communities are meaningful for researchers aiming at community management. Many other consumer behavior analysis methods exist for retailers, such as Recency, Frequency, and Monetary value (RFM) analysis (Parikh and Abdelfattah 2020) and trend analysis (Ramansh et al. 2020). By extending these methods to the consumer behavior analysis of communities, it will be possible to realize new research and approaches contributing to community management.

Furthermore, this study shows that the Pareto Principle (Pareto 1896), a theory that supports ABC analysis, may also hold when targeting communities. The Pareto Principle (Pareto 1896) states that 80% of the effects are produced by 20% of the causes. Applying this principle to a community, 20% of the stores that make up the community will generate 80% of the customer transactions. The results of Study 1 revealed that stores 7, 10, and 12 were in the top 20% of stores in the community, as identified in Section "Results and discussions". The visit frequency ratios (%) were 11.0, 9.5, and 11.7, respectively, with a total of 32.2%. However, when checking the results of Study 2, the experiment found that stores 8, 9, 10, 11, 14, and 17 were in the top 20% of stores in the community, as identified in Section "Results and discussions". The visit frequency ratios (%) were 18.2, 10.7, 22.0, 8.9, 18.5, and 4.2, totaling 82.5%. In other words, in Study 1, the Pareto Principle could not be supported by the community. However, in Study 2, the Pareto Principle was supported when communities were targeted. To discuss the detailed reasons why the principle did not hold in Study 1 but in Study 2, more experiments in various fields are required. This study demonstrates that the Pareto Principle can also be supported when targeting communities.

Practical implications. This study demonstrates that a novel method for collecting and analyzing cross-cutting consumer behavior data for community-based management is effective for commercial area management organizations. The proposed method is suitable for community-based management, for two reasons.

First, the proposed method does not require the implementation of special hardware or software for stores and customers to collect cross-sectional data on consumer behavior. Some stores in the commercial areas investigated in this study did not have hardware such as POS systems and showed a negative attitudes new technologies to collect consumer behavior data. An important factor hindering the adoption of digital technologies in stores and communities is the lack of staff who are knowledgeable about digital technology (Malecki 2003). Thus, although there are businesses in some municipalities that have difficulty adopting digital technology, it is a challenge to solve the problem of staff shortages that ultimately hinder the management of municipalities. Since the proposed method collects data using a paper-based community currency, it is possible to carry out community-based management, even in stores that have difficulty adopting digital technology. The proposed approach makes it possible to promote community management based on an analysis of consumer behavior, regardless of whether or not a store is struggling to adopt additional hardware or software.

Second, the proposed method realizes community-based management that transcends the boundaries between store types. Conventional management that goes beyond the boundaries of individual stores is limited to targeting stores of the same type (Matsumoto et al. 2012) or affiliated stores (Bilgic et al. 2015) due to restrictions on collectible data. Therefore, previous studies have not considered community-based management of commercial areas that include a mix of businesses. This study shows that the proposed method of data collection, which does not depend on the type of business, enables community-based management across boundaries between business types. As an application of community management in this study, it was possible to identify the traffic generators in a community. The goal of community management in this study was to increase overall consumption in the community. Identifying such traffic builders in the community can assist practitioners who manage shopping communities by developing strategies to increase visitation. This type of community management does not result in a zero-sum game, and increasing overall consumption in the community can ultimately increase retail sales as well.

Limitation. This study has several limitations that should be addressed in the future. The first is the quality of the overarching consumer behavior data collected in the community currencies. In this study, paper-based community currencies were used to enable management in communities where digitization is not as advanced. The single-use specifications of community currencies limit the data collected by a community currency. Therefore, this study only elucidates the relationship between two elements (two stores for FT-type community currency, one customer attribute, and one for CA-type community currency). Thus, there is room for improvement in the quality of the data. For instance, by applying digital community currencies, data can be collected to discuss the relationships between three or more stores and between multiple customer attributes and stores. In addition, POS data, the main target for consumer behavior analysis, includes product data, such as the types of products purchased. This data type can be collected by recording the main products purchased from paper-based community currencies. Thus, consumer behavior analysis with improved data quality can provide more meaningful community management findings.

Second, this study uses only two consumer behavior analysis methods: ABC and association analyses. Therefore, more concrete solutions are required to apply these methods to various communities. However, this study demonstrates the possibility of using consumer behavior analysis methods for community management in retail stores. This can be a trigger for applying previous research on consumer behavior analysis methods for retail stores to community management and has great potential for many proposed solutions.

Conclusion

This study focuses on two research questions: "How can such low-digitalized shopping communities realize community-based management?" and "How can conventional retail management methods using customer behavior analysis expand to community-based management?" Two research questions were answered through experiments and discussions. Regarding the first question, this study focuses on two types of paper-based community currencies to collect overarching data on consumer behavior in a low-digitized community. To confirm the effectiveness of this approach, field experiments were conducted in two commercial sectors: low-digitized retail. In these commercial areas, overarching consumer behavior data was collected for 498 FT transactions and 338 CA transactions. This provided useful information for community-based management. The proposed method enables community-based management in low-digitized shopping communities. For the second research question, the conventional consumer behavior analysis methods for retail, ABC, and association analysis was extended to community-based management. This study can be considered as a motivation for expanding theoretical research on management from individual stores to community-based management. Furthermore, the findings identified practical considerations for practitioners such as commercial area management organizations and local governments when developing commercial areas.

This research will be useful for practitioners involved in community management and researchers involved in community revitalization. Community currency is one of the methods of community management to promote local consumption, unite the community and revitalize volunteer activities. To date, consumer behavior analysis has not been applied to community currency data. This study provides a methodology for identifying modes of transportation in communities and the relationships between stores that are frequently visited together, demonstrating the potential applicability of community currencies. Practitioners involved in community management can use the proposed methodology to discuss measures to increase overall consumption and consumers in the community, regardless of the level of digitization. From the perspective of researchers seeking to revitalize communities, it is possible to extend the methods for analyzing consumer behavior in retail stores, such as ABC and association analysis, to include methods for analyzing consumer behavior in communities. This opportunity elevates conventional retail store consumer behavior analysis research to new research that contributes to community management and opens up new areas of consumer behavior and community management research.

Three significant issues need to be addressed in future studies. First, future studies should examine the management interventions presented in this study to evaluate their effectiveness in community-based management. This finding supports the applicability of the proposed method. Second, future studies should extend conventional research on retail store management beyond ABC and association analysis to community-based management. This will lead to novel analytical methods that utilize overarching consumer behavior data and enable more effective community-based management. Third, future studies should improve data quality in the use of paper-based community currencies. By developing and distributing paper-based community currencies that can be used multiple times or community currencies that record items purchased, it is possible to collect more detailed, cross-cutting data on consumer behavior. Analyzes of consumer behavior using such detailed data can provide meaningful insights into community management.

Data availability

The datasets generated and/or analyzed in the current study are available from the corresponding author upon reasonable request.

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Author contributions

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Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Correspondence and requests for materials should be addressed to Yuya Ieiri.