



Linking lifestyle to customer lifetime value: An exploratory study in an online fashion retail market

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ARTICLE INFO

Keywords:

Lifestyle
Customer lifetime value
Segmentation
Latent class model

ABSTRACT

This study explores how lifestyle can explain the heterogeneous customer lifetime values (CLVs) among various market segments. We develop a latent class model of purchase frequency, lifetime duration, and purchase amount to infer segment-level CLV. Customers' membership to each segment is presumed to depend on their lifestyle patterns. The proposed model is then applied to the transaction and lifestyle data of customers in an online fashion retail market. The empirical analysis reveals four customer segments that each has a unique lifestyle pattern: *Individualistic Innovators*, *Rational Followers*, *Self-actualized Experts*, and *Integrated Shoppers*. These segments differ in their magnitude of average CLV, partially explainable by segment members' lifestyle characteristics. The paper finally discusses some implications for improving customer relationships and raising revenues.

1. Introduction

Customer lifetime value (CLV) is a core metric in customer relationship management. It can be useful to improve market segmentation and resource allocation, evaluate competitor firms, customize marketing communication, optimize the timing of product offerings, and determine a firm's market value (Gupta, Lehmann, & Stuart, 2004; Kumar, Lemon, & Parasuraman, 2006; Kumar, Ramani, & Bohling, 2004). Given the critical role of CLV, numerous studies aim to elucidate its drivers, which are broadly divisible into organizational and customer antecedents (Kumar et al., 2006). The latter have gained empirical generalization; Blattberg, Malthouse, and Neslin (2009) point out that customer satisfaction, cross-buying, and multichannel purchasing can increase CLV through their direct impacts on customer purchase frequency, spending, and retention.

However, despite the large body of research on this topic, studies of how lifestyle influences CLV are still scarce, primarily because data encompassing both the purchase history and the lifestyle of the same customers are not readily available. We argue that understanding the influence of lifestyle on CLV should be critical for marketers because it can explain customers' motivation to engage in certain behaviors (Plummer, 1974) and therefore clarify why some customers are profitable, whereas others are not. In particular, the influence of lifestyle is likely to be more salient for certain categories such as fashion and

luxury goods. Individuals' fashion lifestyles tend to govern their spending in that category (Darden & Reynolds, 1974; Gutman & Mills, 1982; Li, Li, & Kambele, 2012). Further, Lee et al. (2014) and Kim, Ko, Xu, and Han (2012) confirm the positive association between CLV and consumers' attitudes toward fashion brands. However, these studies neither comprehensively examine the effect of lifestyle nor use actual purchasing data to infer CLV.

This study aims to bridge this gap by investigating how different lifestyle patterns can lead to CLV heterogeneity. The main objective is to identify several customer segments by CLV levels and subsequently examine how the lifestyle characteristics of these customers explain this difference. We employ a latent class model based on customers' behavioral traits presuming that segment memberships are determined by their lifestyle characteristics. The data used in this study comprise customers' purchases of fashion-related products and self-reported lifestyle information.¹

The main contributions of this study are twofold. First, to our knowledge, it is the first to explore the influence of lifestyle on CLV using actual purchase history and lifestyle data. The results thus add to the literature on the drivers of CLV by explaining the differences among customer segments. Second, the lifestyle patterns of customer segments could provide marketers with a richer understanding of their customers, allowing them to better customize their offerings to enhance both customer relationships and revenues.

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¹ The lifestyle data are obtained as secondary data provided by a focal firm. Therefore, we refer to the existing literature to assess the external validity of the lifestyle measures included in the data.

2. Theoretical background

2.1. Lifestyle

Lazer (1963) introduces lifestyle as a concept to describe the consumer patterns marketers can use as a segmentation scheme. It describes the way people live their lives in terms of the nature of their home, the possessions they own, the interests and activities they pursue, and how they socialize (Gunter, 2016). Thus, lifestyle concerns how people allocate time among activities and how they allocate money among expenditures (Kaynak & Kara, 2001).

Scholars have proposed different methodologies to measure the lifestyle construct. Early studies used measures of activities, interests, and opinions (AIO) to classify people into several lifestyle patterns. For example, Wells and Tigert (1971) report 14 consumer types including *Price Conscious*, *Fashion Conscious*, *Homebody*, and *Community-Minded* using this approach. The Values and Lifestyles (VALS) program is another popular typology among practitioners (Mitchell, 1983). This system combines activity profiles with a range of psychological constructs such as aspirations, beliefs, desires, hopes, and values, resulting in eight segments within four broader drive orientations: the *Integrated*, *Outer-Directed*, *Inner-Directed*, and *Need-Driven* types. Another popular approach is the List of Values (LOV) model (Kahle & Kennedy, 1988), which derives a lifestyle typology based on Rokeach's (1973) proposed value system such as self-respect, security, and a sense of belonging.

Marketing researchers acknowledge that lifestyle could add to the richness of their understanding of consumer behavior, complementing common demographic and psychological typologies. Demographic variables can be useful to describe heterogeneous purchasing behaviors among customers, but lack relevant information about the motives underlying buying decisions. Psychological characteristics could provide richer consumer insights, but the findings may be less generalizable to a large population and are often difficult to implement (Plummer, 1974). In this regard, lifestyles summarize a set of activities, values, needs, and beliefs that may activate customers' attention and drive behavioral intentions, helping marketers understand why a customer engages in certain behavior and develop more targeted marketing programs.

How consumer behavior is explainable by lifestyle has been addressed in many studies (Table 1). Researchers have found that lifestyle is associated with media use (Reynolds & Darden, 1971; Tigert, 1969; Villani, 1975), affects buying and consumption behavior (Brunso et al., 2004; Cosmas, 1982; Perm, 1990), and influences store attribute evaluation and patronage (Gutman & Mills, 1982; Huddleston et al., 1990; Ogle et al., 2004). Swinyard and Smith (2003) show that Internet shoppers can be classified into four lifestyle segments that have different spending levels and purchasing patterns. In addition, lifestyle explains the difference in attitudes and preferences toward vacation activities (Gonzalez & Bello, 2002; Madrigal & Kahle, 1994; Matzler et al., 2007).

2.2. Lifestyle and fashion shopping

According to Visser and du Preez (2001), the influence of lifestyle is likely to be more salient on purchasing decision of fashion products. Here, fashion is defined as a style that a large proportion of the population adopts at a particular time, especially in categories related to appearance such as clothes, hair, and make-up. Individual buying decisions in the clothing category tend to be driven by lifestyle components such as self-expression and self-identity motives (Gunter, 2016). That is, when deciding on fashion items, consumers are inclined to consider how the alternatives can help them attain social status or express themselves to influence others' perceptions. Thus, fashion choices are expected to depend on consumers' opinions about or interest in various issues, how they spend money, and with whom they spend time.

However, empirical studies report mixed results on the extent to which lifestyle can explain fashion-related behavior. Some researchers suggest that lifestyle does not successfully predict clothing purchases (Huddleston, Ford, & Bickle, 1993), possibly because they measure lifestyles on generic scales that often lack the necessary focus to predict the purchases of a specific product category, especially clothing (Wind & Green, 1974). By contrast, other studies show that lifestyle can be useful to explain consumers' choice heterogeneity for fashion-related products and retail stores (Darden & Reynolds, 1974; Kamakura & Wedel, 1995). Similarly, Gutman and Mills (1982) find that lifestyle is associated with customers' fashion shopping orientations and store patronage. Additionally, Shim and Kotsiopoulos (1993) indicate that

Table 1
Summary of lifestyle-related studies.

Article	Lifestyle measure	Consumer behavior	Methodology
Tigert, 1969	AIO	Media choice	Cluster analysis
Reynolds & Darden, 1971	AIO	Media choice	Cross-classification
Reynolds & Darden, 1972	AIO	Retail purchase	Simple aggregation
Villani, 1975	AIO	Media use	Regression analysis
Thomas & Crocker, 1981	VALS	Product purchase, entertainment experiences	Cluster analysis
Gutman & Mills, 1982	AIO	Store patronage, shopping behavior	Cluster analysis
Cosmas, 1982	AIO	Product use	Cluster analysis
Perm, 1990	LOV	Product use	Cluster analysis
Huddleston, Ford, & Mahoney, 1990	Lifestyle of the elderly	Importance of the retailer's attributes	Regression analysis
Thompson & Kaminski, 1993	AIO	Service quality expectations	Regression analysis
Madrigal & Kahle, 1994	LOV	Vacation activity preferences	Cluster analysis
Kamakura & Wedel, 1995	AIO	Fashion purchases	Latent class model
Gonzalez & Bello, 2002	AIO	Tourist behavior	Cluster analysis
Swinyard & Smith, 2003	The Internet lifestyle	Online shopping behavior	Cluster analysis
Ogle, Hyllegard, & Dunbar, 2004	Outdoor recreational activities	Retail visit intention	Regression analysis
Brunso, Scholderer, & Grunert, 2004	LOV & food-related lifestyles	Shopping and consumption behavior	Structural model
Matzler, Füller, & Faullant, 2007	Ten lifestyle orientations	Satisfaction and loyalty to ski resorts	Cluster analysis
Li et al., 2012	Fashion lifestyles	Willingness to pay for luxury fashion brands	Regression analysis
Park, Lee, & Chung, 2013	VALS	Online shopping behavior	CHAID

different lifestyles lead to heterogeneous fashion-oriented behavioral patterns among customers.

2.3. CLV and lifestyle

CLV refers to the present value of all the future cash flows from a customer (Pfeifer, Haskins, & Conroy, 2005). The magnitude of CLV is determined by four components: lifetime duration, revenues, costs, and the discount rate (Blattberg et al., 2009). Among these, the first two relate closely to customers' behavioral traits. Lifetime duration pertains to the length of time that a customer remains active, which the defection rate affects directly. Revenues encompass purchase frequency and purchase amount, which customers' purchase rate and average spending govern. Accordingly, assessing CLV involves estimating the unobserved defection rate, purchase rate, and average spending, which are all significantly influenced by customer satisfaction (Hallowell, 1996), loyalty programs (Reinartz & Kumar, 2000), cross-buying behavior (Kumar, George, & Pancras, 2008), and multichannel purchasing (Thomas & Sullivan, 2005).

Despite the large body of the literature on the antecedents of CLV, few studies have explicitly addressed whether and how lifestyle influences CLV. Nevertheless, as previously described, they indicate that it could be the case, especially in the fashion retail market. Some studies provide deductive reasoning for the differences in revenues and relationship duration among lifestyle segments, leading to the anticipation that lifestyle indicators should explain CLV. For example, Shim and Kotsiopoulos (1993) suggest that customers with different degrees of fashion involvement should generate different revenues for firms. Similarly, Gutman and Mills (1982) point out that the difference in spending may be attributable to fashion leadership heterogeneity across customers. Furthermore, a correlation may exist between lifestyle and both spending and purchase frequency for online customers, where those with a stronger hedonic purchase orientation and lower risk perception tend to buy more frequently and spend more money (Swinyard & Smith, 2003). Moreover, lifestyle may increase the

duration of a customer relationship with a retail firm if the importance of various store attributes varies among customers belonging to different lifestyle segments (Huddleston et al., 1990). Accordingly, those who perceive that a retailer has excellent performance on some important attributes are anticipated to be more satisfied and eventually stay for a longer period (Hallowell, 1996).

3. Research framework

3.1. Conceptual model

As Fig. 1 illustrates, this study investigates whether multiple segments characterized by different levels of CLV exist and, if this is the case, how customers' lifestyle can explain this difference. For this purpose, we classify customers into a number of latent segments based on their purchase rate, lifetime duration, and average spending. Customers in the same segment should share similar behavioral traits, while those in different segments should have different values in at least one of the traits. This behavioral heterogeneity is expected to induce CLV variability among segments. Further, we posit that lifestyle characteristics, at least partially, determine customers' membership in each segment.

3.2. Lifestyle characteristics

We consider a number of psychographic and behavioral variables elicited from secondary survey data as the components that constitute one's lifestyle. Among others, four constructs representing values and self-image are documented in the consumer behavior literature: *self-esteem*, *self-actualization*, *belongingness*, and *brand consciousness*. Self-esteem is defined as “a self-attitude in which self-worth is conditional on (perceived) personal competence, performance, and attainment of desired states and ideals” (Karanika & Hogg, 2016, p. 760). A desire to maintain self-esteem motivates individuals to engage in conspicuous or compensatory consumption (Kim & Gal, 2014), particularly in product categories that convey symbolic meanings. Self-actualization can be

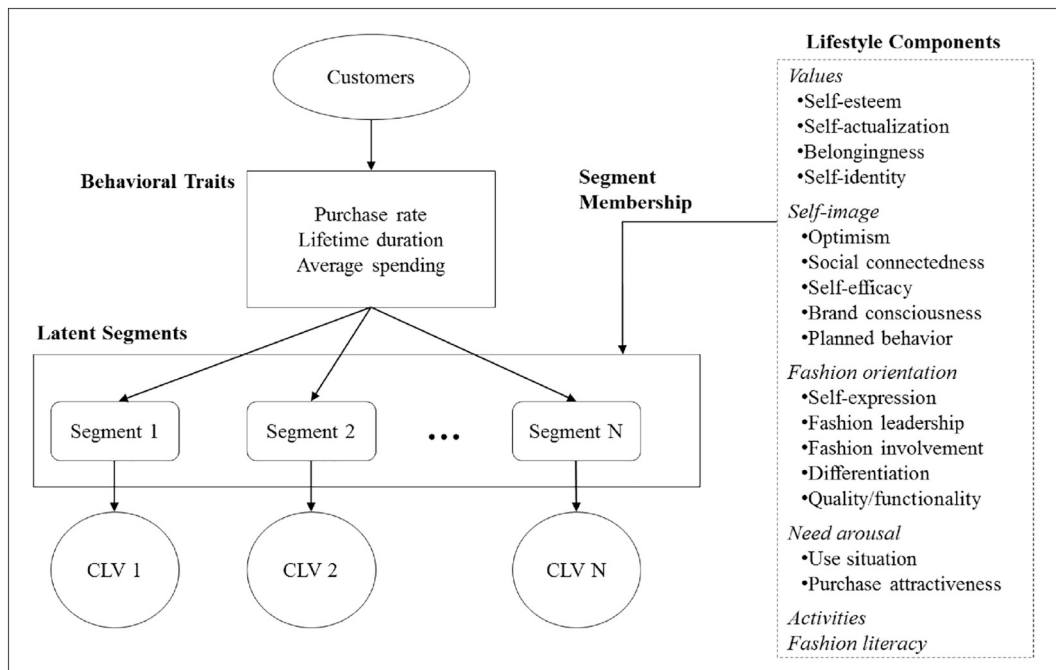


Fig. 1. Analytical framework.

regarded as the tendency to actualize, as much as possible, individual capacities (Goldstein, 1939). Self-actualizing individuals are growth oriented who constantly strive to improve themselves and pursue knowledge through information acquisition (Maslow, 1954). Hausman (2000) indicates that higher self-actualization needs may prompt consumers to engage in impulse-buying behavior.

Further, belongingness is closely related to the concept of need for affiliation, which can be defined as a desire to be in the company of and accepted as a group member by other people (Schachter, 1959). Strong affiliation needs drive individuals to acquire or consume products that help enhance their relationships with others (Mead, Baumeister, Stillman, Rawn, & Vohs, 2011). Kim, Forsythe, Gu, and Jae Moon (2002) suggest that these needs can be effectively gratified by the consumption of apparel products. Therefore, individuals with strong affiliation needs are anticipated to spend more on clothing. Brand consciousness represents the degree of a consumer's willingness to buy well-known brands (Nan & Heo, 2007). As reported by Yi-Cheon Yim, Sauer, Williams, Lee, and Macrury (2014), this construct is positively associated with attitudes toward luxury brands, indicating that brand-conscious consumers are price-insensitive. Giovannini, Xu, and Thomas (2015) support this finding by showing that brand consciousness leads to higher buying motivation and loyalty toward luxury fashion brands. As such, it is expected that brand-conscious consumers spend more on fashion products than those who are brand-unconscious.

In addition to these general constructs, four variables specific to the fashion domain are derived from the data: *fashion leadership*, *fashion involvement*, *differentiation*, and *fashion literacy*. Fashion leadership is the extent to which a customer is willing to be the first to try and persuade others to buy new fashion products (Goldsmith, Freiden, & Kilsheimer, 1993). Fashion leaders tend to engage in risk-taking behaviors such as buying new products or adopting new styles, leading to higher expenditure on fashion because those who adopt new fashion earlier pay higher prices (Bitran & Mondschein, 1997). Studies also indicate that fashion leadership is positively correlated with impulse buying (Beaudoin, Moore, & Goldsmith, 2000) and purchase frequency (Cho & Workman, 2014). Fashion involvement is “the extent to which consumers view fashion-related objects or activities as a central part of their lives” (O’Cass, 2004, p. 870). This induces several needs, positive attitudes, and purchase intentions (Kim et al., 2012; Yoo, Khan, & Rutherford-Black, 1999), suggesting that highly involved consumers tend to buy more frequently and spend more money on the category.

Differentiation or need for uniqueness refers to “the trait of pursuing differentness relative to others through the acquisition, utilization, and disposition of consumer goods for the purpose of developing and enhancing one's self-image and social image” (Tian, Bearden, & Hunter, 2001, p. 52). This psychological trait may give rise to unpleasant feelings when an individual perceives her/himself as similar to others. The avoidance of unfavorable feelings resulting from similarity perception occurs through counter-conformity behaviors such as adopting new innovations and unpopular styles (Snyder, 1992). Consequently, strong differentiation intentions should lead to purchases of new fashion products, particularly when currently used ones have become popular among the majority of people. Finally, fashion literacy refers to the subjective knowledge of fashion attributes and perceived ability to deal with fashion problems. O’Cass (2004) asserts that fashion clothing knowledge reduces perceived risks when consumers consider buying from the category, suggesting that those with higher fashion literacy should be more confident when making buying decisions. Moreover, perceived self-ability can prompt individuals to engage in a certain behavior more intensely because it induces a perception of being capable to organize and execute courses of action (Barling & Beattie, 1983), leading to the prediction of a positive correlation between fashion literacy and purchase frequency.

4. Methodology

4.1. Outline

As Table 1 shows, most studies use cluster analysis to classify customers into lifestyle segments and subsequently link these segments to certain behavioral characteristics. The major advantage of this approach is that the resulting segments are easily interpretable in terms of lifestyle patterns. However, this often leads to weak associations between segment membership and behavior for at least two reasons. First, some components of the lifestyle construct do not explain behavior, but are critical to shaping clusters. Researchers can remedy this issue by first examining the discriminant power of these components and then selecting only those with significant effects in the subsequent cluster analysis (Gonzalez & Bello, 2002). Second, the number of segments is usually determined in ad hoc fashions for ease of interpretation and favorable segment sizes. To overcome this shortcoming, researchers can use a latent class model, which provides more rigorous likelihood-based criteria for choosing the most appropriate segment number (Kamakura & Wedel, 1995).

Another popular approach links the lifestyle component directly to consumer behavior using multiple regression analysis (Li et al., 2012; Ogle et al., 2004). This straightforward approach gives a clear picture of the significant components and their direction. However, it may be unsuitable in settings where other variables mediate the link between lifestyle and buying behavior (Brunso et al., 2004). For example, when CLV serves as the dependent variable, factors such as brand attitudes and purchase intention may play a mediating role in the lifestyle–CLV link (Kim et al., 2012; Lee et al., 2014). In this study, we account for these limitations and develop a latent class model that generates a number of segments according to different levels of CLV such that lifestyle influences customers' membership in each segment.

4.2. Research model

The proposed model assumes the presence of K latent customer segments characterized by different purchase rates, lifetime durations, and average spending. Since these behavioral traits are direct determinants of CLV, average CLV should vary across segments. Let p_{ik} denote the “prior” probability that customer i ($i = 1, 2, \dots, I$) belongs to segment k ($k = 1, 2, \dots, K$), given by

$$p_{ik} = \frac{\exp(\beta_k' d_i)}{\sum_{l=1}^K \exp(\beta_l' d_i)} \quad (1)$$

where d is a vector of the lifestyle components and a constant term. Further, β_k denotes a coefficient vector that represents the effect of lifestyle components on customer membership in the respective segment.

Following the Pareto/NBD model² (Schmittlein, Morrison, & Colombo, 1987), conditional on segment membership in segment k , repeat purchase frequency x_i and the defection time τ_i of customer i follow a Poisson and exponential distribution with purchase rate λ_k and defection rate μ_k , respectively:

$$x_i \sim \text{Poisson}(\lambda_k) \quad (2)$$

$$\tau_i \sim \text{Exponential}(\mu_k) \quad (3)$$

² Other possible specifications are the BG/BB model (Fader, Hardie, & Berger, 2004) and BG/NBD model (Fader, Hardie, & Lee, 2005), which have more parsimonious structures. Nevertheless, we use the same assumption as that in the Pareto/NBD model because the computation of CLV is straightforward in this setting. Computational complexity is not a serious issue in our context because we apply the finite mixture model to account for consumer heterogeneity instead of integrating over the Gamma heterogeneity distribution.

By repeat purchase frequency, we mean the number of store visits needed to purchase one or more products. Accordingly, x_i represents the number of purchases made by customer i across different product categories. Further, let m_i be the customer's average purchase amount, which follows a lognormal distribution with mean $\log(\eta_k)$ and variance σ_k^2 . Here, η_k can be interpreted as the average spending of customers in segment k .

$$m_i \sim \text{Lognormal}(\log(\eta_k), \sigma_k^2) \tag{4}$$

The unconditional likelihood function of all customers is

$$\begin{aligned} \ell(\lambda, \mu, \eta, \sigma^2 \mid \text{data}) &= \prod_i \sum_k P_{ik} \ell(\lambda_k, \mu_k, \eta_k, \sigma_k^2 \mid \text{data}) \\ &= \prod_i \sum_k P_{ik} \ell(\lambda_k, \mu_k \mid x_i, t_i, T_i) \ell(\eta_k, \sigma_k^2 \mid m_i) \end{aligned} \tag{5}$$

where

$$\ell(\lambda_k, \mu_k \mid x_i, t_i, T_i) = \frac{\lambda_k^{x_i} t^{x_i-1}}{\Gamma(x_i)} (\mu_k)^{(1-z_{ik})} e^{-(\lambda_k + \mu_k)(z_{ik} T_i + (1-z_{ik})y_{ik})}, \tag{6}$$

$$\ell(\eta_k, \sigma_k^2 \mid m_i) = \frac{1}{\sqrt{2\pi} \sigma_k m_i} e^{-\frac{(\log(m_i) - \log(\eta_k))^2}{2\sigma_k^2}}. \tag{7}$$

Here, t_i and T_i denote the time elapsed since the last and first purchase, respectively. z_{ik} is an indicator function equal to 1 if the customer is still active at the end of the observation period and 0 otherwise. When $z_{ik} = 0$, y_{ik} denotes the time at which the customer defects. Further, given the data, we assign a customer to a segment using the posterior membership probability given by

$$P_{ik \mid \text{data}} = \frac{P_{ik} \ell(\lambda_k, \mu_k, \eta_k, \sigma_k^2 \mid \text{data})}{\sum_{m=1}^k P_{im} \ell(\lambda_m, \mu_m, \eta_m, \sigma_m^2 \mid \text{data})} \tag{8}$$

We estimate the model using a Markov Chain Monte Carlo (MCMC) simulation. Given the segment-level parameter estimates $\{\lambda_k\}$, $\{\mu_k\}$, $\{\eta_k\}$, and $\{\sigma_k^2\}$ as well as the discount factor δ , the average CLV of the k -th segment is (Abe, 2011)

$$CLV_k = \frac{\lambda_k \eta_k e^{\sigma_k^2/2}}{\mu_k + \delta} \tag{9}$$

5. Data and lifestyle measurements

5.1. Data description

We obtained the data for the empirical analysis from an online shopping mall company through a data contest organized by the Joint Association Study Group of Management Science in Japan (company name is withheld for confidentiality purposes). The mall's customers can purchase fashion products such as apparel, shoes, bags, and accessories from more than 900 independent tenant shops through the mall's commercial website. The company conducts an annual survey to collect data on customer value and lifestyles, usually in March. The sample consists of 3052 customers (960 men) who responded to the survey during the collection period. Fig. 2 shows the composition of customer ages in this sample.

In addition to lifestyle-related information, the data comprise customers' purchase history from April 2015 to March 2016. The left panel of Fig. 3 depicts the distribution of customers' purchase frequency. The average purchase frequency is 6.71 and maximum is 42. Approximately 60% of customers (1838 people) made fewer than six purchases during the period. The number of product categories purchased ranged from one to 19, with a large proportion of customers buying from four or five categories. The right panel of Fig. 3 reports the distribution of purchase amounts per transaction. Average customers spent about 8277 yen per transaction (range: 666–71,000 yen), indicating considerable heterogeneity in customer spending.

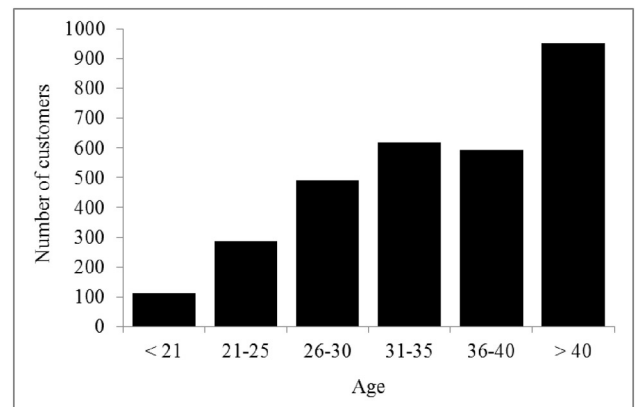


Fig. 2. Distribution of age among customers.

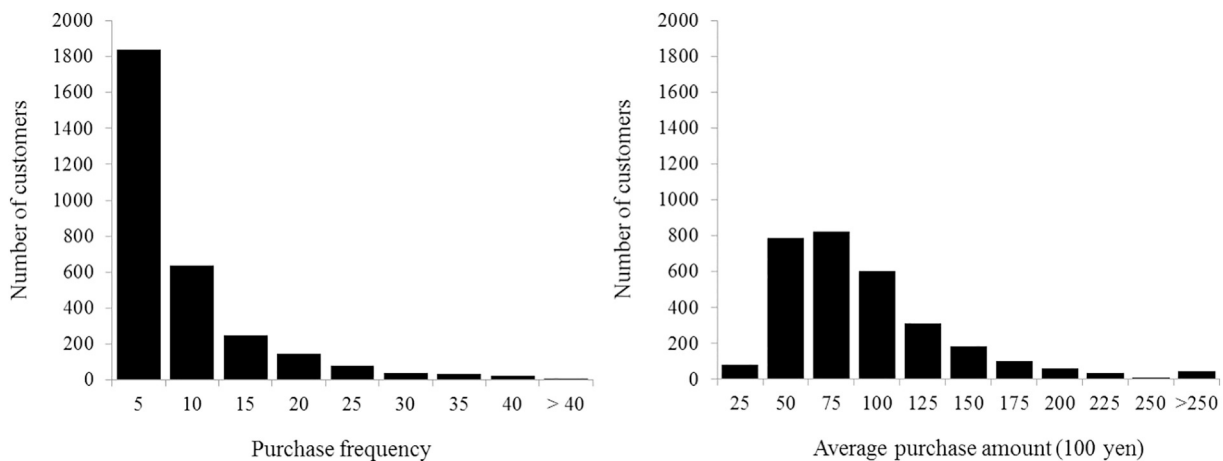


Fig. 3. Distribution of purchase frequency and purchase amount.

Table 2
PCA results: values.

Item	Loading	Eigenvalue	Variance proportion	Cronbach alpha
Self-esteem		5.12	0.21	0.79
Performance, reputation	0.81			
Competition, victory	0.81			
Promotion	0.70			
Fame	0.59			
Self-actualization		1.69	0.17	0.73
Cutting-edge	0.47			
Competence	0.61			
Expertise	0.68			
Ambition	0.60			
History	0.64			
Belongingness		1.61	0.14	0.62
Security	0.70			
Possession	0.41			
Friendship	0.69			
Recognition	0.55			
Self-identity		1.18	0.13	0.61
Sensibility	0.72			
Capability	0.46			
Individuality	0.72			

5.2. Lifestyle measures

The lifestyle data comprise 109 items classified into eight broad categories, six of which were included as lifestyle measures in this study: *values*, *self-image*, *fashion orientation*, *need arousal*, *social activities*, and *fashion literacy*. Two categories, *happiness* and *perceived behavioral changes*, were excluded from the analysis because of a lack of relevance to the topic.³ Sixteen values including promotion, fame, competence, friendship, and personality were measured using a four-point Likert scale (1 = not important, 4 = important). A principal component analysis (PCA) was conducted to reduce the dimensionality, resulting in four factors with eigenvalues above one (Table 2). The first factor is composed of such values as performance, reputation, competition, and fame, which are closely related to the concept of self-respect (Gentina, Huarng, & Sakashita, 2018; Karanika & Hogg, 2016). Thus, we interpret this construct as reflecting a customer's self-esteem. The second factor encompasses values associated with individuals' motives to improve themselves or their capabilities (i.e., cutting-edge, competence, expertise, and ambition), making it reasonable to consider this construct as representing the degree of self-actualization (Goldstein, 1939; Maslow, 1954). The next factor includes security, friendship, and recognition values that are related to motivation to belong to social groups and gain recognition from others, some of which have been used to measure the need for social belonging (Schreindorfer & Leary, 1996). Accordingly, this factor can be regarded as representing belongingness. The fourth factor comprises values related to customers' perception of how they should present themselves to others (e.g., sensibility and individuality), representing one facet of self-concept or self-identity (Sirgy, 1982).

Self-image contains 14 items on how customers think about themselves, measured using a four-point Likert scale (1 = disagree, 4 = agree). The items were factor analyzed with eigenvalues as the basis for determining the number of factors. We omitted one item whose factor loadings were all less than 0.4 (Table 3). The analysis resulted in five factors: optimism, social connectedness, self-efficacy, brand consciousness, and planned behavior. Optimism concerns customers' evaluation of their current condition and expectation of future condition (Van Raaij & Gianotten, 1990). The social connectedness

factor is composed of two items reflecting the extent to which customers want to be connected with the rest of the world (Schachter, 1959). Self-efficacy contains three items that describe customers' perception of their capability to organize and execute certain courses of action (Bandura, 1986). Brand consciousness is measured using three items describing price sensitivity and interest in fashion brands (Nan & Heo, 2007). Planned behavior comprises two items describing whether customers decide product categories or items before visiting a store.

Further, fashion orientation concerns how customers think about fashion and the meaning of fashion to them. Twenty-nine items were used to measure the construct on a four-point Likert scale (1 = disagree, 4 = agree), seven of which were omitted for the same reasons as above. As shown by the PCA in Table 4, these items can be reduced to five factors. Nine items on the perceived role of fashion as a tool to express one's identity or appearance constitute the self-expression factor (Cardoso, Costa, & Novais, 2010). Four items describing customers' susceptibility to fashion trends and motivation to buy new fashion products converge to a factor interpreted as fashion leadership (Goldsmith et al., 1993). Further, being composed of four items representing customers' interest in fashion, the third factor is regarded as a measure of fashion involvement (Kim et al., 2012). In line with Tian et al. (2001), three items describing the need for uniqueness is regarded as representing the factor of differentiation. The last two items pertain to how customers attach importance to the quality and functionality of fashion products and thus, the associated factor is labeled quality/functionality.

Need arousal is a construct related to situations in which customers recognize the need for new clothes, measured using eight statements on the timing at which customers are likely to decide to purchase from the product category on a four-point Likert scale (1 = disagree, 4 = agree). Factor analyzing these items resulted in two factors: use situation and purchase attractiveness (Table 5). The former relates to situational changes that require customers to use different fashions (Belk, 1975), whereas the latter relates to the needs arising from increasing product category attractiveness and affordability (Seetharaman et al., 2005).

To assess activities, customers were asked whether they had participated in 10 social activities during the past year (Table 6), which is a common way to elicit the activity aspect of one's lifestyle (Wells & Tigert, 1971). These variables were measured on a binary scale (1 = yes, 0 = no). As the table reports, 61% of customers went on vacation and 51% attended a Valentine's Day party, whereas only 12% attended a Halloween party. The last lifestyle indicator lists seven items on the ability to cope with problems that may occur when dealing with fashion. For example, one item reads, "I am not good at coordinating clothing items." These items were measured using a binary scale (1 = agree, 0 = disagree). We reverse coded the scores and interpreted the sum within a customer as representing fashion literacy. Table 7 summarizes the average values for the items, showing that customers have a high ability to identify brand differences and choose clothes for different occasions, but are relatively unable to coordinate clothing items.

The individual-level factor scores for the estimated factors of values, self-image, fashion orientation, and need arousal were used as independent variables in the latent class model. Further, the activities variable was created by taking the sum of the social activity items for each customer (i.e., the number of activities in which respondents participated). Because the lifestyle data were obtained as secondary data, some constructs have rather low internal reliability measures. Therefore, although we refer to previous studies when interpreting the constructs, caution may be needed when assessing the results.

6. Results

6.1. Segment number

We considered several models with between two and seven

³ The procedure for selecting the items can be found in the web appendix.

Table 3
PCA results: self-image.

Item	Loadings	Eigenvalue	Variance proportion	Cronbach alpha
Optimism		2.31	0.19	0.91
I think I am financially comfortable	0.48			
I am pessimistic about my current condition	−0.90			
I am pessimistic about my future condition	−0.89			
Social connectedness		1.77	0.16	0.76
I always want to know a lot of people	0.78			
I always cherish my friends	0.79			
Self-efficacy		1.39	0.15	0.64
I think I have enough free time	0.53			
I know a lot about PCs and the Internet	0.74			
I like to customize the products I have bought	0.52			
Brand consciousness		1.28	0.13	0.72
I often engage in impulse buying	0.59			
I have a great interest in fashion brands	0.66			
I would spend my time finding the best price	−0.42			
Planned behavior		1.14	0.13	0.73
I like to keep everything very simple	0.71			
I always prepare lists before shopping	0.76			

Table 4
PCA results: fashion orientation.

Item	Loading	Eigenvalue	Variance proportion	Cronbach alpha
Self-expression		4.28	0.17	0.72
Fashion can express one's personal identity	0.51			
Clothing is a means to exert one's originality	0.57			
Fashion is a part of lifestyle	0.60			
I always mind how people see my fashion	0.41			
I often care about other people's fashion	0.45			
Buying clothes is a great stress reliever	0.47			
Clothing can increase or decrease one's value	0.62			
I have clothes of the same items with different colors	0.42			
I have my favorite brand	0.46			
Fashion leadership		2.01	0.14	0.61
I always want to try new products earlier than others	0.62			
I am very susceptible to new fashion trends	0.67			
I am very motivated to try new fashion	0.60			
I am good at adapting new fashion to my style	0.54			
Fashion involvement		1.71	0.13	0.60
I don't pay attention to house dresses	−0.43			
I often buy clothes that are on promotion	−0.60			
I don't mind wearing clothes that are outdated	−0.66			
I think quality and functionality are more important than brand	−0.52			
Differentiation		1.40	0.13	0.58
I like to dress differently from the other people around me	0.73			
I don't care about traditional fashion	0.66			
I always want to have something that other people don't	0.43			
Quality/functionality		1.23	0.12	0.56
I am concerned about the materials and country of origin	0.67			
I always choose clothes that look comfortable	0.69			

Table 5
PCA results: need arousal.

Item	Loading	Eigenvalue	Variance proportion	Cronbach alpha
Use situation		2.91	0.24	0.69
When the season changes	0.57			
When I meet different people	0.74			
When my clothes are outdated	0.72			
When I prepare for a vacation	0.65			
Purchase attractiveness		1.12	0.21	0.67
When I see a nice outfit	0.66			
When I have the money to spend freely	0.64			
When clothes are on sale	0.58			
When I need it for a change	0.62			

Table 6
Summary of social activity participation.

Event joined	Mean	SD
Valentine's Day party	0.51	0.50
Cherry-blossom viewing	0.35	0.48
Barbeque party	0.35	0.48
Music festival	0.17	0.38
Sunbathing	0.26	0.44
Vacation	0.61	0.49
Fireworks festival	0.36	0.48
Halloween party	0.12	0.32
Wedding party	0.27	0.44
Christmas party	0.32	0.46

Table 7
Summary of fashion literacy.

Fashion problem	Mean	SD
I am not good at coordinating clothing items	0.63	0.48
I don't really know the difference among brands	0.95	0.21
I have no idea about fashion trends	0.86	0.35
I don't know the clothes that suit me	0.64	0.48
I don't know how to dress for different occasions	0.87	0.34
I have no idea how to maintain clothing items	0.79	0.41
I often can't find the best clothing products	0.85	0.36

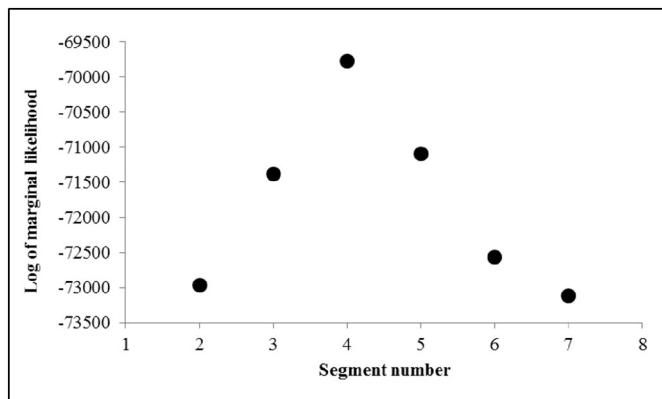


Fig. 4. Model comparison.

segments in the empirical analysis. The optimal segment number was determined by examining the goodness of fit of each model. We estimated the model parameters using the MCMC method with 10,000 iterations, where the first 5000 were “burned in” to eliminate the influence of the initial values. Subsequently, we compared the accuracy of each model in terms of the log of marginal likelihood. The model with four segments performed the best (Fig. 4) and thus we present the results of this model hereafter.

6.2. Segment characteristics

Table 8 presents the estimation results for the segment membership coefficients. The coefficients of the first segment were fixed to zero values for the identification.⁴ Therefore, they should be interpreted

⁴ Multiplying Eq. (1) by $\exp(-\beta_k' d_i) / \exp(-\beta_k' d_i)$ does not change the probability or the likelihood. However, this multiplication changes the value of the parameters, where the k -th segment parameters become 0. Therefore, we have to fix the parameter vector of one of the segments to make the model identifiable.

Table 8
Parameter estimates of the segment membership coefficients.

Lifestyle variable	Individualistic innovators	Rational followers	Self-actualized experts	Integrated shoppers
Constant	0	1.57	-3.18	0.04
Values				
Self-esteem	0	0.17	-0.16	0.09
Self-actualization	0	0.13	0.25	0.12
Belongingness	0	0.27	0.19	0.34
Self-identity	0	-0.32	-0.53	-0.32
Self-image				
Optimism	0	0.32	0.30	0.24
Social connectedness	0	-0.05	0.04	0.17
Self-efficacy	0	0.28	0.30	0.25
Brand consciousness	0	-0.21	0.11	-0.07
Planned behavior	0	-0.15	-0.12	-0.15
Fashion orientation				
Self-expression	0	-0.62	-0.49	-0.45
Fashion leadership	0	-0.48	-0.34	-0.36
Fashion involvement	0	-0.13	-0.15	-0.12
Differentiation	0	0.83	0.86	-0.23
Quality/functionality	0	0.34	0.65	0.40
Need arousal				
Use situation	0	-0.08	-0.03	0.03
Purchase attractiveness	0	0.32	0.18	0.13
Others				
Activities	0	0.26	0.27	0.32
Fashion literacy	0	0.34	0.62	0.36

Note: Bold font indicates significant estimates evaluated based on 95% HPD interval.

relative to this segment. Not all lifestyle components are significant in explaining customers' membership of different segments. Self-esteem, social connectedness, planned behavior, fashion involvement, and use situation are insignificant for the second segment, revealing that no difference exists in these variables between the first and the second segment. From the estimates, the resulting segments are interpretable as *Individualistic innovators*, *Rational followers*, *Self-actualized experts*, and *Integrated shoppers*.⁵

Individualistic innovators attach great importance to values such as sensibility and individuality. They seem to have their own sense of fashion, which is critical for them to express who they are to others. When buying fashion products, they are likely to consider brand as the most crucial attribute, while quality and price promotions appear to be less influential. Further, they are highly inclined to keep up with new fashions, and adopt new models at an early stage of product introduction. However, despite having unique fashion preferences, this group has the lowest participation rate in social activities among the segments, perhaps because most prefer indoor activities.

Rational followers are more optimistic about current and future conditions than those in the other segments. They perceive themselves as being able to make rational decisions when shopping for fashion products and prioritize quality over brand. For these customers, clothing is more about essentials than a means of self-expression. Further, they are less motivated to adopt new fashions at an early stage, but would rather do so after observing early adopters or after the initial prices decrease.

Self-actualized experts have a desire to gratify self-actualization needs. They wish to improve self-competency and expertise. Indeed,

⁵ We provide the demographic profiles of each segment in the web appendix.

Table 9
Segment size and behavioral traits.

Segment	Size	Purchase rate	Defection rate	Spending
Individualistic innovators	145	11.97(2.20)	0.56(0.14)	7836(318)
Rational followers	1690	2.45(0.35)	0.78(0.26)	6910(289)
Self-actualized experts	233	15.44(1.87)	0.55(0.16)	7765(361)
Integrated shoppers	984	6.84(0.76)	0.62(0.11)	7601(209)

Posterior standard deviations are in parentheses. Average spending is in Japanese yen.

Table 10
Segment-level CLV.

Segment	Average CLV	Total CLV	Share of CLV
Individualistic innovators	186,725	27,075,186	12.42%
Rational followers	24,676	41,701,628	19.14%
Self-actualized experts	242,709	56,551,188	25.95%
Integrated shoppers	94,111	92,605,238	42.49%

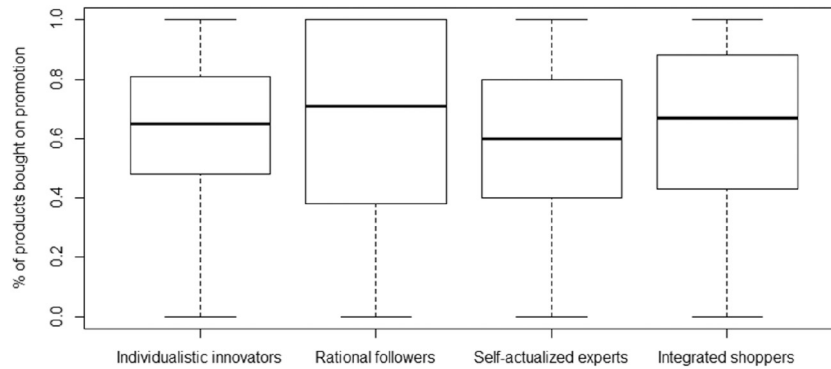


Fig. 5. Deal attraction to segment members.

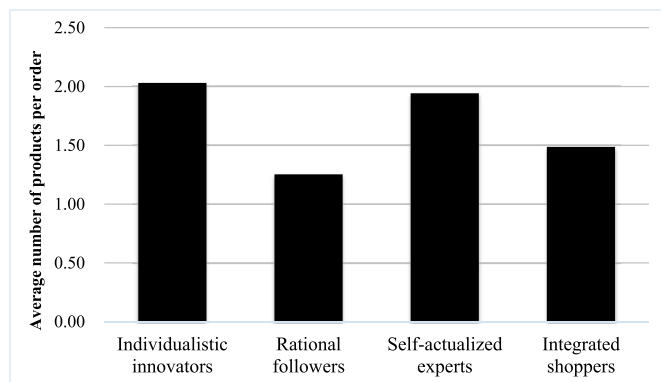


Fig. 6. Average number of products bought on each purchase occasion.

they perceive themselves as good decision-makers when deciding on clothing products and think they can handle many fashion-related things. Further, product quality and functionality appear to be the most influential attributes for these customers, and they are inclined to have a different appearance from other people.

Integrated shoppers have greater social relationship needs than those in other segments. Being connected and having strong ties with others are important for them. They strive to assimilate within society or into groups to which they belong to gain recognition. Further, they are actively involved in community events and participate in many social activities.

6.3. Behavioral traits of each segment

Table 9 reports the size and behavioral trait estimates of the segments. The individualistic innovator segment is the smallest, with 145 members (4.8%). The largest segment is rational followers (1690 members, 55.4%). The estimates of the behavioral trait parameters reveal that self-actualized experts are frequent buyers with the highest purchase rate among all segments ($\lambda=15.44$, $SD = 1.87$). Individualistic innovators follow in second place with a purchase rate of 11.97 ($SD = 2.20$). Rational followers have the highest defection rate

($\mu = 0.78$, $SD = 0.26$), implying that such customers have 1.28 years of remaining expected lifetime on average. Integrated shoppers have a longer expected lifetime, with a defection rate of 0.62 ($SD = 0.11$). By contrast, individualistic innovators and self-actualized experts are expected to stay with the firm for longer periods. With regard to average spending, individualistic innovators spend more money per transaction than customers in the other segments ($\eta=7836$, $SD = 318$), whereas rational followers spend the least (6910, $SD = 289$).

The heterogeneity in average spending could be attributed to several factors including customers' attraction to promotional deals and the number of products purchased per order. Fig. 5 depicts the distributions of the percentage of products on promotion bought by each customer in each segment and Fig. 6 shows the average number of products per order for each segment. Rational followers are more inclined to buy products on promotion (median = 0.71) than those in the other segments. Furthermore, customers in this segment buy an average of 1.25 products on each purchase occasion, which is the lowest. This explains why rational followers have the lowest average spending. In contrast to this segment, self-actualized experts have the lowest tendency to use price promotions (median = 0.60). However, this segment has lower average spending ($\eta=7765$) than individualistic innovators ($\eta=7836$), although the latter appear to buy products on promotion more frequently (median = 0.65). This is perhaps because individualistic innovators purchase more products in each transaction than self-actualized experts (2.03 vs. 1.94, see Fig. 6).

6.4. Segment-level CLV

The average CLV⁶ of each segment is calculated using Eq. (9). The results in Table 10 shows that rational followers have the lowest

⁶ The estimates of CLVs should be interpreted with caution because the data cover customers' purchases for only one year, which might have resulted in the overestimation of the defection rates. However, we conjecture that the potential bias should not have caused serious problems in the interpretation of the results because CLV heterogeneity appeared to be prominently determined by the differences in purchase rates and spending rather than in lifetime duration. We thank an anonymous reviewer for pointing out this issue.

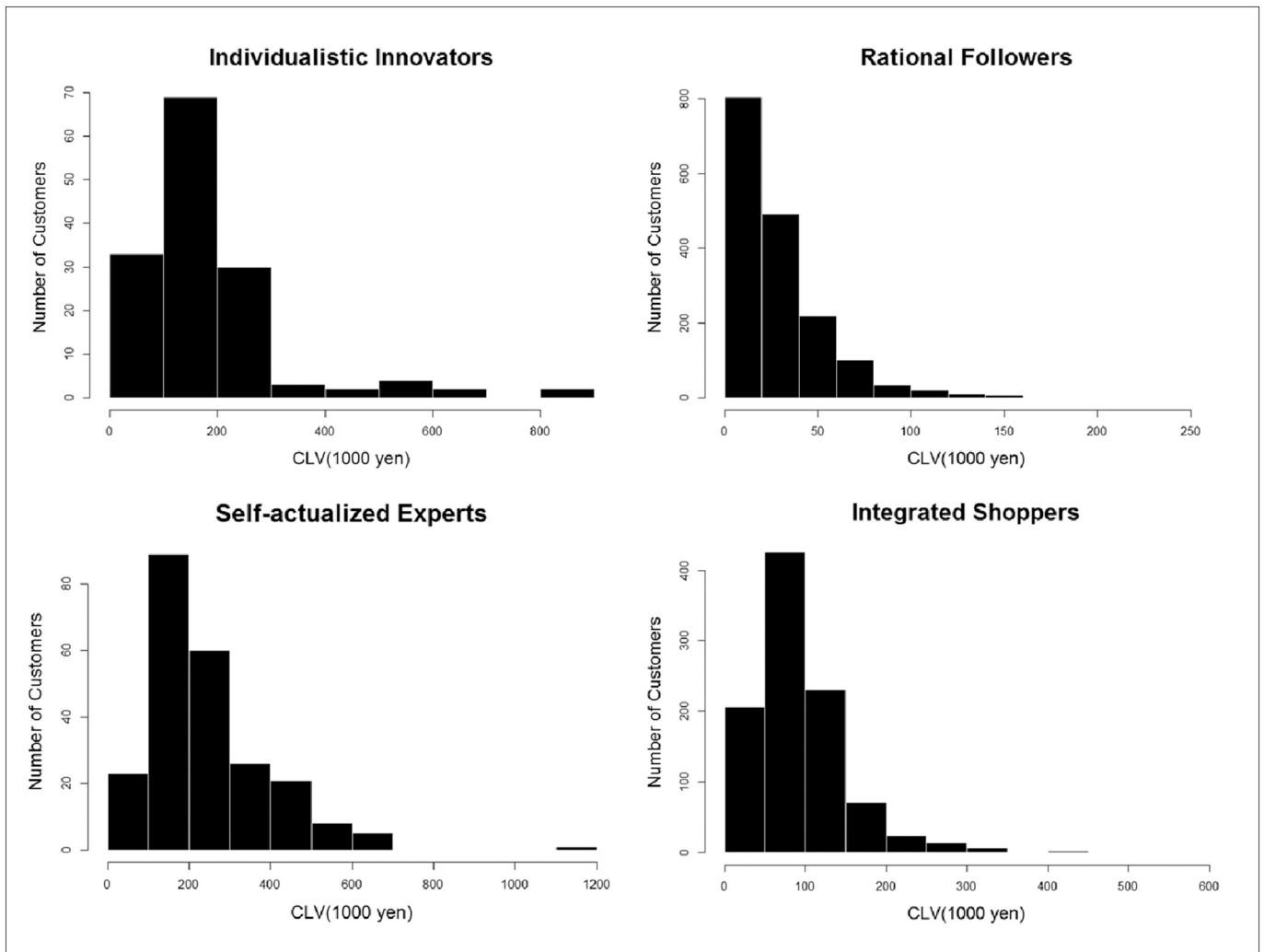


Fig. 7. Distribution of CLVs in each segment.

average CLV, as expected; this segment has the lowest purchase rate and spending and the shortest expected lifetime duration. By contrast, the average CLV of self-actualized experts is 242,709 yen, which is the highest among all segments. This might be because this segment contains many frequent buyers, although they have lower average spending than individualistic innovators. For cumulative CLV, integrated shoppers have the highest value (92 million yen) followed by self-actualized experts (56 million yen). For rational followers, although the segment is large, their cumulative CLV is only about 42 million yen.

We subsequently computed the individual-level behavioral trait parameters as follows:

$$\lambda_i = \sum_{m=1}^k P_{im|data} \lambda_m \tag{10}$$

$$\mu_i = \sum_{m=1}^k P_{im|data} \mu_m \tag{11}$$

$$\eta_i = \sum_{m=1}^k P_{im|data} \eta_m \tag{12}$$

These parameters were used to derive the CLV of each customer in each segment (Fig. 7). For individualistic innovators, while the maximum CLV is 855,392 yen, about 91% of customers have a CLV below 300,000 yen. The distribution of CLVs in the rational followers segment has a long right tail (right skewed), with a median of 17,016 yen, below

the average value. This indicates that more than half of customers are anticipated to generate CLVs less than the segment's average (i.e., 24,676 yen) in the future. For self-actualized experts, approximately 90% of customers are predicted to have CLVs greater than 100,000 yen, signifying their high contribution to the firm's future revenues. Finally, the CLVs of integrated shoppers are highly concentrated around the average value, indicating that such customers are more homogeneous in terms of CLV than those in the other segments.

7. Discussion

7.1. Discussion

The empirical analysis shows the existence of heterogeneous segments with different lifestyle characteristics. Of particular interest, each segment is unique in terms of its behavioral traits, leading to different levels of average CLV. First, individualistic innovators appear to be brand-conscious, price-insensitive, and highly motivated to adopt new fashions before others. This might be why they spend higher amounts in each transaction than other customers, which is consistent with previous findings that brand-conscious consumers prefer and are highly motivated to buy expensive luxury brands (Giovannini et al., 2015; Yi-Cheon Yim et al., 2014). Further, the results confirm our expectation that fashion leaders have higher spending because fashion products are usually priced higher at launch. These customers are also frequent shoppers, perhaps because they are inclined to buy clothes every time

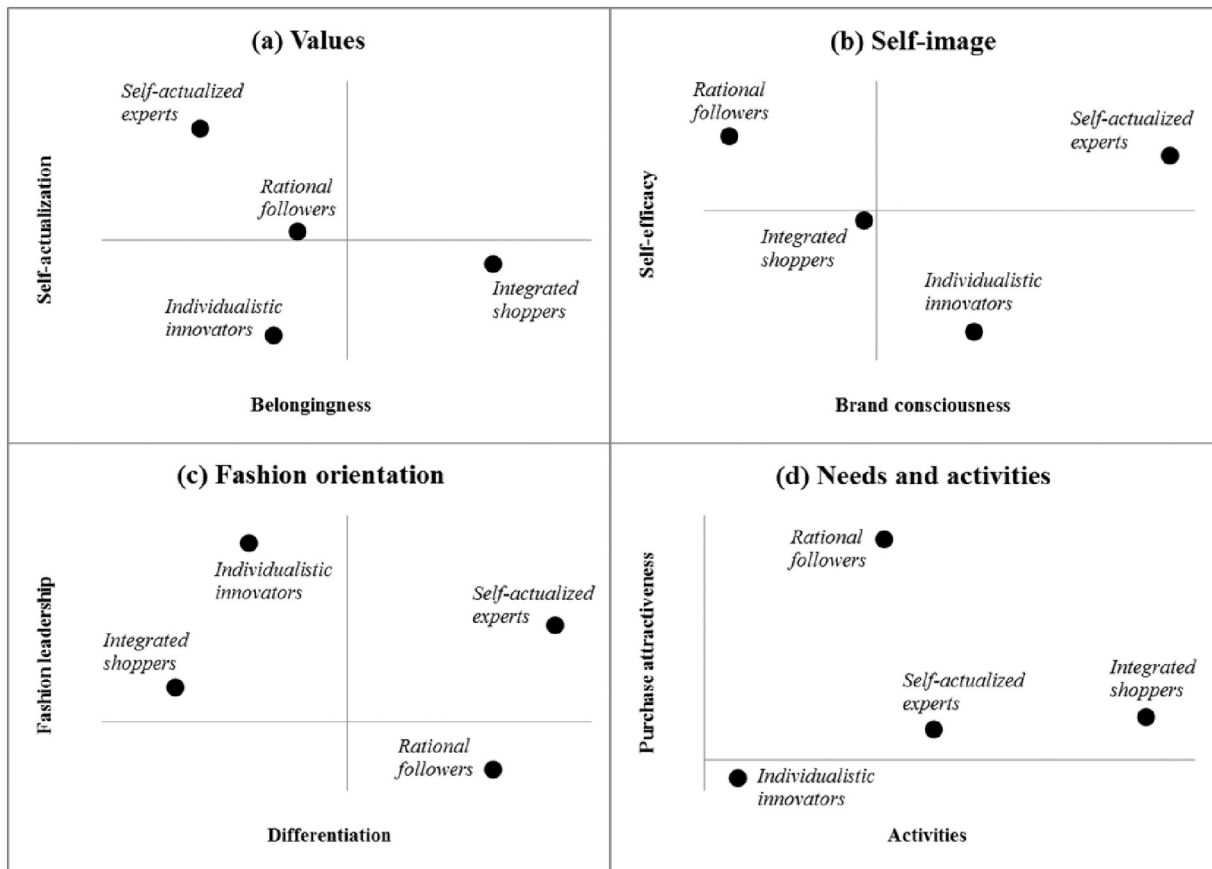


Fig. 8. Segment perceptual map along lifestyle dimensions.

new products are introduced into the market, providing external validity for the positive correlation between fashion leadership and purchase frequency (Cho & Workman, 2014). Having a high purchase rate and average spending, these customers have moderately high average CLV. However, as the size of this segment is small, the cumulative CLV is the lowest among all the segments.

The second segment, rational followers, consists of price-conscious customers who value quality rather than brand when buying fashion products. They are likely to buy clothes during promotions and thus have lower spending than customers in the other segments. Further, they purchase from the category less frequently, probably because they are less interested in the latest fashion trends and would not hesitate to wear outdated clothes. Moreover, these customers have a higher probability of churning in the future. These behavioral traits make this segment less profitable for the firm.

Self-actualized experts are somewhat similar in that they are willing to have appearances different from other people and have high perceived self-efficacy. However, they have higher fashion literacy and are less responsive to price promotions. Further, they are highly motivated to gratify such self-actualization needs as improving self-competency and expertise. These reasons may explain their high purchase frequency and relatively high average spending, which eventually leads to higher average CLV than those in the other segments. This is in line with previous studies postulating that self-actualization needs and self-confidence result in favorable impacts on purchasing behavior (Hausman, 2000; O’Cass, 2004). Accordingly, customers in this segment should generate considerably high cash flow in the future, although they account for less than 8% of the population.

Lastly, integrated shoppers actively engage in social activities. They are highly motivated to pursue social relationship needs by knowing as many people as they can. They consider recognition by their

community and social groups as the most important value in their lives and choose the fashion adopted by the majority of people. As a result, these customers frequently recognize the need for fashion products because they have the opportunity to meet different people and participate in many activities. These reasons explain their moderately high purchase rate, although the rate is below those of individualistic innovators and self-actualized experts. The results indicate a positive association between need for uniqueness and purchase frequency (Kim et al., 2002). Moreover, integrated shoppers generate the highest total CLV, suggesting that they may be the main contributor of future revenues if the firm manages to nurture its members to become profitable customers.

7.2. Theoretical implications

The presented segmentation scheme results in lifestyle typologies that underlie behavioral traits and, consequently, CLV heterogeneity. Customers in different segments differ in the importance they attach to certain values, how they perceive themselves, how they view fashion, what stimulates them to recognize needs, and how they interact with society. This finding is useful to gauge customers' motivation to buy and the reasons behind heterogeneous buying behaviors. More importantly, the finding helps explain why a certain segment has higher CLV than others.

To illustrate this notion, Fig. 8 plots perceptual maps of the resulting segments along various lifestyle dimensions, where the coordinates are the factor scores of the segments with respect to the lifestyle components. The figure illustrates which lifestyle components prominently motivate customers in each segment to purchase from fashion categories as well as to decide how much and when to purchase. The gratification of self-actualization needs and differentiation appear to

induce frequent purchasing behavior by self-actualized shoppers, as panels (a) and (c) show. However, self-actualization needs do not seem to influence individualistic innovators. Rather, their fashion shopping behavior is more affected by fashion leadership (panel (c)), explaining the high average spending of these customers. Further, purchases made by integrated shoppers are likely driven by needs stemming from their high involvement in various activities (panel (d)). Thus, their choice of fashion relies on the style adopted by the majority of people in the group to which they belong (i.e., low differentiation motive). Finally, rational followers' shopping behavior appears to be governed by purchase attractiveness; specifically, the availability of price promotions (panel (d)), which explains why they have the lowest average spending among all segments. Moreover, as panels (b) and (c) show, low brand consciousness and late new fashion adoption magnify the unprofitability of these customers.

7.3. Managerial implications

Marketers would clearly benefit from linking lifestyles to customer profitability because this can provide richer insights into why a segment is profitable. This would be particularly important in the development and implementation of customer tier programs, enabling marketers to customize services to different customer tiers appropriately. For example, knowing the values and fashion orientation of self-actualized experts, a marketer could design rewards to offer to this profitable segment. Further, the proposed framework should also be useful in determining marketing communication types targeted at different segments. For example, firms may need to engage rational followers by brand values information to make them more brand-conscious and less price-oriented to increase their average spending. Further, firms can facilitate interactions among integrated shoppers who share common interests or fashion senses by establishing a community site to increase customer satisfaction and thus retention rate. Additionally, the analysis allows firms to create a feasible budget for customized marketing programs targeting different segments. That is, marketers can consider the segment-level CLV as the maximum amount to invest in each segment to retain and nurture customers.

8. Conclusion

Despite the considerable research on the drivers of CLV, few studies investigate the potential role of lifestyle because of the scarcity of lifestyle and purchase history data sourced from the same customers. Utilizing such scarce data, this study attempted to narrow the gap in the literature and explored how lifestyle can provide a richer understanding of CLV heterogeneity among customer segments. The proposed latent class model yielded multiple segments with different CLV levels, each with unique lifestyle characteristics. The results show that the relationship between behavioral traits (i.e., purchase rate, defection rate, and average spending) and lifestyle explains the CLV differences among segments. In particular, self-actualization, self-efficacy, differentiation, and fashion literacy appear to increase the probability a customer belongs to the frequent buyer segment (i.e., self-actualized experts), which generates the largest average CLV for the company. Further, customers with a high degree of fashion leadership and involvement are likely to spend more money in each transaction than other customers, leading to a great contribution of these customers to the company's future profitability. The analysis also identified that customers who tend to make rational purchase decisions and have low self-expression needs generate low CLVs because they purchase less frequently, spend less money on each purchase occasion, and are more likely to defect.

These findings can be useful to better understand the reasons behind CLV heterogeneity. The lifestyle variables reflect some of the motives behind purchasing behavior in fashion product categories. For example, the high degree of CLVs generated by self-actualized experts and individualistic innovators might have been driven by their needs to have

different appearances from others or be the first to try new fashions. By contrast, integrated shoppers would be more motivated by the need for recognition from society or the need to build new friendships when spending on fashion products. Additionally, purchases by rational followers are likely driven by utility-maximizing motives, as signified by their frequent use of promotions.

However, we also note some limitations of this study. First, we examined customers' purchasing behavior only for fashion-related products and thus the results may lack generalizability. Further examination using data for different product categories would provide external validity. Second, selection bias may be an issue because customers who responded to the survey could have distinct characteristics compared with non-respondents. For example, respondents might use the Internet more frequently than average customers. Improving the representativeness of the sample could help remedy this problem, but would entail a higher survey cost. Third, the data used in the analysis comprise customers' purchase history for only one year. Thus, the estimated segment-level CLVs should be interpreted cautiously because the values might be underestimated. Further, our segment-level model may not be useful for examining the direct effects of the lifestyle variables or their interactions. Future research may address this issue using individual-level models (e.g., Abe, 2009) to derive more generalizable theoretical findings. Finally, as the lifestyle measures were developed for business purposes, they may lack some theoretical justification. Indeed, some constructs in the data have low reliability. The collaboration between practitioners and academics to produce more reliable lifestyle data should help overcome this problem.

Acknowledgement

This research was supported by Japan Society for the Promotion of Science, KAKENHI [grant number 17H02573, 18K01875].

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jbusres.2019.02.049>.

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