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[Original Article]

The fashion consumer purchase patterns and influencing factors through big data - Based on sequential pattern analysis -

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Abstract

This study analyzes consumer fashion purchase patterns from a big data perspective. Transaction data from 1 million transactions at two Korean fashion brands were collected. To analyze the data, R, Python, the SPADE algorithm, and network analysis were used. Various consumer purchase patterns, including overall purchase patterns, seasonal purchase patterns, and age-specific purchase patterns, were analyzed. Overall pattern analysis found that a continuous purchase pattern was formed around the brands' popular items such as t-shirts and blouses. Network analysis also showed that t-shirts and blouses were highly centralized items. This suggests that there are items that make consumers loyal to a brand rather than the cachet of the brand name itself. These results help us better understand the process of brand equity construction. Additionally, buying patterns varied by season, and more items were purchased in a single shopping trip during the spring season compared to other seasons. Consumer age also affected purchase patterns; findings showed an increase in purchasing the same item repeatedly as age increased. This likely reflects the difference in purchasing power according to age, and it suggests that the decision-making process for purchasing products simplifies as age increases. These findings offer insight for fashion companies' establishment of item-specific marketing strategies.

Keywords: purchase pattern, fashion industry, big data, sequential pattern analysis, network analysis

I. Introduction

In modern society, services utilizing information technology (IT) and information-based technology have become trendy, leading to the accumulation of a large amount of big data. Companies with advanced IT technology and software are attempting to utilize data to offer personalized services across different industries and meet customer demands. In pursuit of this goal, data integration is being implemented in various sectors, including fashion, tourism, and information and communication. By refining and extracting collected data, deriving keywords, and analyzing resultant values, analysis using big data can predict perceptions and trends related to specific words or phenomena (Saravana Kumar, Eswari, Sampath, & Lavanya,

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2015). Big data analysis can generate unique insights that differentiate it from small-capacity data analysis, enhance data reliability through multiple methods, and visualize and present vast amounts of complex data. In addition, companies are implementing customer relationship management (CRM) systems to effectively meet customers' needs based on the acquired data. A customer management system allows companies to manage the purchase history of each customer by digitizing data. Data are accumulated on what products consumers purchase, where they buy them, what time of day they shop, which sites they visit, and how they get there (Fletcher, 2003). Based on consumer purchase data, companies classify customers and identify their preferred products. Thus, consumers' purchase behavior is revealed through a scientific approach. Fashion companies also employ big data in various ways to create value. Firms gather a large amount of data to identify fashion trends and analyze consumer preferences, which enables them to establish product development and marketing strategies (Dong, Zeng, Koehl, & Zhang, 2020). Additionally, they utilize big data to plan production and manage inventory. In other words, the value of big data in the fashion industry lies in the ability to maximize corporate profits by predicting trends, reducing risks, and producing an appropriate amount of popular products (DuBreuil & Lu, 2020). In fact, a famous fashion company in Korea planned its products by analyzing fashion product search data from consumers and reviews written by consumers and achieved high sales volume (Seo, 2020). The global company ZARA leverages real-time analysis of sales data collected from its stores worldwide to forecast product demand and manufacture fashionable products (Sorescu, 2017). Companies selling fashion products on online shopping platforms evaluate consumer purchasing patterns, curate personalized product recommendations, and drive purchases by offering targeted promotions (Kim, 2022). As the scale and diversity of data continue to expand, an increasing number of studies focusing on big data have emerged in the academic field (Choi & Lee, 2020; Huh & Lee, 2019).

Research is being conducted using various methodologies related to big data. Typical approaches in various fields include sequential pattern analysis, which analyzes consumer behavior patterns; association analysis, which predicts consumers' purchasing behavior; and text mining and network analysis methods, which facilitate the understanding of the relationships between variables (Li & Law, 2020; Nakahara & Yada, 2012; Yoshimura, Sobolevsky, Bautista Hobin, Ratti, & Blat, 2018). Looking at the trends in big data research related to the fashion industry, the research primarily focuses on extracting key fashion keywords and investigating perceptions and responses to fashion topics through text mining and network analysis, respectively (An & Park, 2020). The extant literature also includes studies related to big data in the literature. However, research based on the actual purchase big data of consumers is insufficient. Therefore, this study aims to analyze consumers' purchasing patterns using big data from fashion companies. Based on four years' worth of actual purchase data of specific brands, sequential pattern analysis and network analysis were performed. Sequential pattern analysis may analyze the order and type of purchase patterns by including time information in purchase data. There will also be a difference in purchasing patterns depending on the consumer's age and purchasing season, which can affect the consumer's purchase pattern. Through this, it is expected to establish a marketing strategy by deriving results that have not been observed through existing surveys and interview methods.

II. Background

1. Consumer purchase pattern

Consumers make purchases through a series of decision-making processes in which they recognize problems, conduct information searches and evaluate alternatives, make a selection, and finally purchase the most suitable products to address them (Kardes, Cronley, & Cline, 2014). Decision-making experiences are stored in one's memory and utilized when making similar product purchases. Customers develop behavioral patterns that include repetitive use of specific brands and purchases of specific products. Consumers form specific patterns in their buying behavior to minimize cognitive resources (Hoyer, MacInnis, & Pieters, 2012). Therefore, purchase patterns can be defined as the regularity and tendencies of consumer behavior during the purchasing process. Companies seek to analyze consumers' buying patterns to develop products and formulate marketing strategies. In academia, research is also being conducted to analyze behavioral patterns to enhance the understanding of consumer consumption behavior. Moe and Fader (2004) studied customer revisit behavior toward Internet shopping malls, and their results showed that there were various types of visitation patterns among customers over time. Unique visitation patterns were also found to be closely related to consumers' product purchase behavior.

Donnellan, Macdonald, and Edmondson (2020) explored consumer buying patterns with a focus on the emergence of social media. According to their findings, consumers' purchasing patterns are formed by the social media they use (Rahman, Fung, & Liu, 2014) examined whether consumers' intrinsic values form distinctive buying patterns and found that consumers develop unique purchasing patterns based on their pursued values. Additionally, Singh, Katiyar, and Verma (2014) confirmed that retail environmental characteristics influence consumers' purchasing patterns. Jung, Park, Lee, and Choi (2012) observed consumers' purchase patterns related to fashion products and found that consumers who purchase apparel and shoes tend to purchase hats next. Thus, it can be seen that consumers form unique buying patterns related to product purchase behavior.

2. Factors influencing on consumer purchase pattern

Consumers evaluate and purchase products based on product selection criteria. These criteria consist of various characteristics and psychological factors that consumers consider when purchasing a product and are used to evaluate and compare alternatives (Kardes et al., 2014). In the case of fashion products, unlike other products, subjective values such as aesthetics, trendiness, and social interaction play a more significant role in influencing consumers' product selection criteria (Easey, 2009). Therefore, since intrinsic characteristics of consumers play a more crucial role, it suggests that an individual's intrinsic traits can have a stronger impact on fashion purchase behavior.

Particularly, it has been found through research that the purchasing behavior of consumers is significantly influenced by demographic characteristics, most notably by age. In the case of A, differences in clothing purchasing behaviors were influenced by demographic attributes, lifestyle, and various psychological factors. In another study by Kim and Lee (2010) that focused on the silver generation, it was noticed that the design elements preferred by these individuals showed variations depending on their age. Furthermore, in research by Shin and Kim (2013), it was revealed that through fashion, consumers' self-images are formed, and due to variations in the ideal image pursued based on age, there are differences in the fashion items they choose to purchase.

Consumers, based on their age, often share a common historical, social background, and culture. This process naturally leads them to have similar societal values and consumption behaviors corresponding to their age groups (Lury, 1996). Consequently, one could argue that unique consumption values emerge with age. As a result, intrinsic factors contribute to age-specific consumption patterns. According to actual corporate reports, not only do consumers' brand preferences vary with age, but their favored items also differ (Korean Federation of Textiles Industries [KOFTI], 2022a). Therefore, it seems plausible to expect distinct purchase patterns based on the age of the consumers.

In addition, since fashion products reflect seasonal characteristics, it is believed that consumers' purchasing behaviors can vary depending on the season. Chung and Kim (2001) conducted a study on the dressing trends of women in their 20s and 30s in South Korea, and found that consumers had different item preferences based on the season. In Hwangbo, Kim, and Cha (2018) research, it was observed that consumers' preferences for fashion items varied depending on the season. For fashion products with strong seasonality, distinctive purchase patterns were identified. Examining the report from the Korean federation of textiles industries, it's evident that the items consumers purchase differ between the first and second halves of the year (KOFTI, 2022b). Particularly in South Korea, which is characterized by its clear division of the four seasons, summers tend to be hot and muggy, whereas winters are typically dry, with temperatures that can below freezing. Thus, it appears that purchase patterns inevitably change according to the seasons.

In the above studies, it was found that the purchase pattern varies according to age and season. However, it will be necessary to check whether this effect appears in the actual purchase data as well.

In addition, as consumers are weakening their age distinction psychologically and physically in recent years, and the seasonal distinction is disappearing due to climate warming, it will be necessary to investigate how purchasing patterns appear differently depending on age and season.

3. Big data and purchase pattern

Fashion products serve as significant tools for self-expression, leading to multiple purchases within a single season. To stay updated with the latest fashion trends, consumers buy new items periodically. As a result, the fashion industry observed more frequent product purchases compared to other industries (Easey, 2009; Kim, Jeong, & Lee, 2020). Recognizing this, fashion companies analyze consumer purchase data to discern unique purchase patterns. They then offer tailored services or suggest fashion items that align with specific styles. Essentially, these companies aim to harness the potential of consumer-based big data.

The main goal of big data analysis is to gather insights on consumer behaviors, patterns, and preferences from enormous datasets, facilitating informed decision-making and business improvements. As more companies acknowledge and leverage the benefits of big data, the big data industry continues to grow rapidly. Big data is characterized by a large volume, fast processing speed, and diverse formats. The proliferation of personal computers and smartphones has resulted in an increase in data related to consumer behavior. Owing to advancements in data storage and analysis technologies, the field of big data has garnered significant attention (McAfee & Barton, 2012). In the past, the concept of big data was defined broadly. However, recent definitions of big data describe it as a collection of structured and unstructured data that encompasses data collection, storage, retrieval, visualization, and analysis methods. The International Data Association described big data as a groundbreaking technological and architectural advancement, aiming to efficiently mine valuable insights from extensive datasets at an economical rate, facilitated by rapid data accumulation, exploration, and analysis (Parise, Ivyer, & Vesset, 2012). In summary, big data can be defined as the utilization of new processing and analysis methods to extract value from large-scale data. at a low cost.

Big data analysis involves extracting valuable insights from large volumes of relatively low-value data. This process includes not only the analysis of data but also the stages of data collection and cleaning. The analytical procedures and methods for big data can be basically divided into data collection, cleaning, analysis, and visualization (EMC Education Services, 2015). However, it is imperative to exercise caution when drawing conclusions based on big data because it primarily consists of observational data collected for purposes unrelated to the analysis objectives.

Data mining refers to the technological process utilized to derive valuable insights from extensive sets of data. It is widely employed in various fields, including statistics, machine learning, pattern recognition, and artificial intelligence (Hand, Heikki, & Padhraic, 2001). Linoff and Berry (2011) defined data mining as the process of exploring and analyzing large-scale data using computer programs to discover meaningful patterns or rules. Chun (2012) defined data mining as the process of extracting value from various types of large-scale data, with a focus on performing tasks related to database operations. It involves extracting potentially useful information that has not been previously discovered and using it to create decision support models for predicting future behavior based on past analysis (Berson, Smith, & Thearling, 1999). Data mining can be described as an exploratory analysis of large-scale data, which distinguishes it from traditional statistical techniques.

Previously, high-performance IT devices were necessary to analyze large volumes of data. However, with the development of technology and the emergence of various software, data mining techniques have become popular. As a result, many companies utilize these techniques to extract meaningful information from vast amounts of data and strategically leverage it (Berry & Lindoff, 2004). Data mining can be described as an analytical approach primarily aimed at deriving new hypotheses or rules from data rather than simply validating the given hypotheses (Kudyba, 2014).

4. Sequential pattern analysis and purchase pattern

Sequential pattern analysis, which employs an association rule analysis algorithm, is a method for discovering the most frequently observed patterns in data (Zaki, 2001). By analyzing consumers' purchase data, it is possible to predict their future behavior. For example, if a large number of consumers purchase a t-shirt and pants, we can predict that customers who own the t-shirt are more likely to buy the pants in the future, and vice versa.

Sequential pattern analysis includes time information in the purchase data. Therefore, it is more accurate than association analysis because it can analyze whether t-shirt or pants purchases occur first. In other words, by reflecting the order of each customers' product purchases and extracting a pattern, you can determine what percentage of consumers who purchased a t-shirt will purchase pants in the future. Pattern analysis using an association rule algorithm has been used in many studies because it can accurately analyze consumer purchase patterns. Through the sequential pattern analysis method, Choi and Nam (2019) found that there are various browsing and non-purchasing browsing patterns depending on the shopping website consumers use. Likewise and Nam (2022) used sequential pattern analysis to reveal the conversion paths of online consumers to purchase products. The results indicated that different genders explored products differently and their purchase patterns differed. Furthermore, the study found that product browsing patterns lead to purchase differences between single and married consumers. Nakahara and Yada (2012) revealed that consumers' product purchase patterns vary depending on their spending time and shopping route. From the results of Yada's study, we found that consumption patterns differed between the short-, medium-, and long-duration consumer groups. Moreover, out of many sections at the grocery store, shoppers who spent the most time at the agricultural section had the highest purchase rates. This type of pattern analysis using association rules can be useful for discovering distinctive patterns in consumer purchasing behavior. In addition, it is valuable for analyzing large amounts of transaction data. Therefore, insights into the purchasing behavior of fashion consumers will also be confirmed through the analysis of consumers' sequential purchasing patterns. Through this, fashion companies will be able to develop marketing strategies.

III. Research Method

1. Study purpose

This study is a study using actual big data of consumers provided by fashion companies, and it will be the starting point to study the purchase patterns of consumers using big data, and can contribute to the efficient marketing strategies of fashion companies. The specific research objectives to reveal consumers' purchasing patterns are as follows.

1) Identify consumers' purchase patterns by brand,
2) Identify consumers' purchase patterns by season,
3) Identify consumers' purchasing patterns by age.

2. Brand characteristics

To analyze the consumption patterns of consumers, we used data from two women's brands that are one of major large fashion companies in Korea. The data expands from 2017 to 2021. The two brands are selected by the fashion company and are among the top in terms of sales contributions. Both brands are internationally renowned women's designer brands. They are directly imported and operated by a Korean fashion company. Both brands are semi-luxury with high-quality and unique designs. Due to the protection of the company's internal information, we cannot mention the specific brand names, so we intend to refer to each brand as A and B. Brand A has about 24 types of items. This brand develops products with a French chic concept and casual style items are popular. Brand B has about 20 types of items. Brand B develops products with a modern New York style concept and formal casual items are popular. Each brand has an online, mobile, and offline stores nationwide. Consumer data includes information on items purchased by date. On the other hand, age is available only for consumers who have entered their age. The consumer data received from the company has been encrypted with a new code, making it impossible to identify individuals.

3. Data collection and analysis methods

This study employed the sequential pattern analysis method of the sequential pattern discovery using evidence class (SPADE) algorithm, which searches for the proportion of observations that simultaneously contain a particular item at the same time among all observations (Zaki, 2001).

In this study, four years of transaction data of two brands were obtained from fashion company which is one of Koran major large conglomerates. While 1,295,052 transaction data points were obtained, 236,624 were from customers who withdrew their membership under the Personal Information Protection Law. As we could not identify their purchase data, we coded the data in R to exclude them, and the final dataset used in this study contained 893,928 data points. R was used to code the data in a form suitable for sequential data mining. Finally, the purchase date, purchase item, and coded customer identification variables were analyzed using the SPADE algorithm. Only data with a support level > 1% were extracted. The results of the sequential pattern analysis based on the SPADE algorithm were saved in the form of buying patterns, support levels, and pattern sizes 〈Table 1〉. To secure the company's internal information, data that could predict the brand's product sales and the number of customers by age were blinded. A network analysis was performed to examine the structural linkages between the items.

The term "pattern size" refers to the size of a product and indicates the number of products included in a specific pattern. For instance, a pattern size of 1 corresponds to a single product, whereas a pattern size of 2 represents two product purchase (e.g., you buy a t-shirt on January 10 and then buy another t-shirt on January 20). A comma, such as {t-shirt, t-shirt}, means that the product purchase was made on the same day, and since this is a purchase pattern for two products, the pattern size is displayed as 2. Support can be interpreted as the percentage of consumers. For example, if the t-shirt has a support

<Table 1> Example of sequential pattern structure

Buying pattern	Support	Pattern size
{t-shirt}	0.269293	1
{t-shirt} → {t-shirt}	0.078856	2
{t-shirt} → {t-shirt} → {t-shirt}	0.036209	3
{t-shirt} → {t-shirt} → {t-shirt} → {t-shirt}	0.020285	4

of 0.269, it means that 26.9% of all consumers purchased the t-shirt at least once.

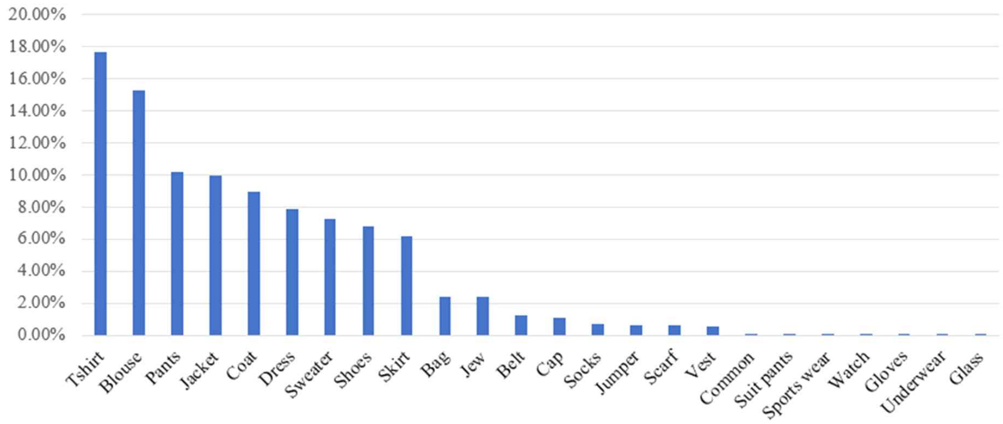
Ⅳ. Results

1. Brand A characteristics and patterns

A total of 314,674 transaction data points were analyzed. The top-selling items over the four-year period were t-shirts, blouses, pants, and jackets 〈Fig. 1〉. Consumers of the brand made 310,000 transactions, of which 61,000 and 250,000 were online and offline purchases, respectively. The brands' most popular items were t-shirts and blouses. However, in order to protect the information of fashion companies, the specific number of sales by fashion item could not be presented, and only comparisons of sales were made possible.

2. Brand A entire sequential pattern analysis

We observed five types of purchase patterns from Brand A. The two most frequently observed patterns for each purchase type are shown below (Table 2). Among the five types of pattern size, pattern size 1, which involves buying only one item, was the most common. The pattern of buying only t-shirts was the most frequent (26%) across all transaction data. The second type is a pattern size with two purchases, with the most frequent pattern observed being t-shirt → t-shirt. This means that a customer who bought a t-shirt tends to buy another t-shirt as well. Pattern size 3 has three purchases, and the most frequent pattern observed is t-shirt → t-shirt → t-shirt. Pattern sizes 4 and 5 also showed the most patterns of continuous purchase of t-shirts. In the case of brand A, it was found that t-shirts and blouses were important purchase items. This appears to exist in certain types of items that consumers are loyal to. To determine whether these patterns were due to seasonal bias, we conducted a sequential analysis that reflected the seasonal cycle.



<Fig. 1> Brand A sales of items

<Table 2> Brand A entire sequential pattern

Pattern	Support	Pattern size
<{t-shirt}>	0.269293	1
<{t-shirt},{t-shirt}>	0.078856	2
<{t-shirt},{t-shirt},{t-shirt}>	0.036209	3
<{t-shirt},{t-shirt},{t-shirt},{t-shirt}>	0.020285	4
<{t-shirt},{t-shirt},{t-shirt},{t-shirt},{t-shirt}>	0.012647	5

3. Brand A seasonal sequential pattern analysis

To conduct a sequential analysis that reflects the characteristics of the seasons, we used March–May for spring, June–August for summer, September–November for fall, and December–February for winter. We found four types of pattern sizes in spring and three types of pattern sizes in summer, fall and, winter 〈Table 3〉. In all four seasons, pattern size 1 purchases of a single product were the most common. In the spring season, 19% of all consumers purchase a t-shirt at least once. For pattern size 2, {blouse, blouse} was the most common purchase pattern: approximately 8% of consumers purchased two blouses on the same day. For pattern size 3, {blouse, blouse} → {blouse, blouse} was the most common purchase pattern at 2.27%. For pattern size 4, {blouse, blouse} → {blouse, blouse} was the most observed purchase pattern at 1.14%.

The most common purchase observed during the summer is blouses: 23% of consumers purchased blouses at least once during the summer season. In pattern size 2, {blouse} → {blouse} was the most common purchase pattern (5.43%). For pattern size 3, the pattern of buying {blouse} → {blouse} → {blouse} was observed the most at 1.91%. The most common purchase observed in fall and winter is t-shirts. In the

<Table 3> Brand A seasonal sequential pattern

	Pattern	Support	Pattern size
Spring	{blouset}	0.199156	1
	{blouse, blouse}	0.083164	2
	{blouse, blouse} → {blouse}	0.023534	3
	{blouse, blouse} → {blouse, blouse}	0.014803	4
Summer	{blouse}	0.231779	1
	{blouse} → {blouse}	0.054359	2
	{blouse} → {blouse} → {blouse}	0.019107	3
Fall	{t-shirt}	0.259389	1
	{t-shirt} → {t-shirt}	0.044668	2
	{t-shirt} → {t-shirt} → {t-shirt}	0.012177	3
Winter	{t-shirt}	0.228942	1
	{t-shirt} → {t-shirt}	0.041933	2
	{t-shirt} → {t-shirt} → {t-shirt}	0.012979	3

fall and winter seasons, 25.9% and 22.8% of consumers purchased a t-shirt at least once, respectively. In both fall and winter, the most common purchase patterns are {t-shirt} → {t-shirt} (4.46%, 4.19%) for Pattern Size 2 and {t-shirt} → {t-shirt} → {t-shirt} (1.43%, 1.21%) for Pattern Size 3.

The items observed in the purchase patterns during the spring and summer seasons were consistent, as well as in the autumn and winter seasons. In the spring and summer seasons, purchase patterns were formed around blouses, while in the fall and winter seasons, purchase patterns were formed around t-shirts.

4. Brand A sequential patterns analysis by age

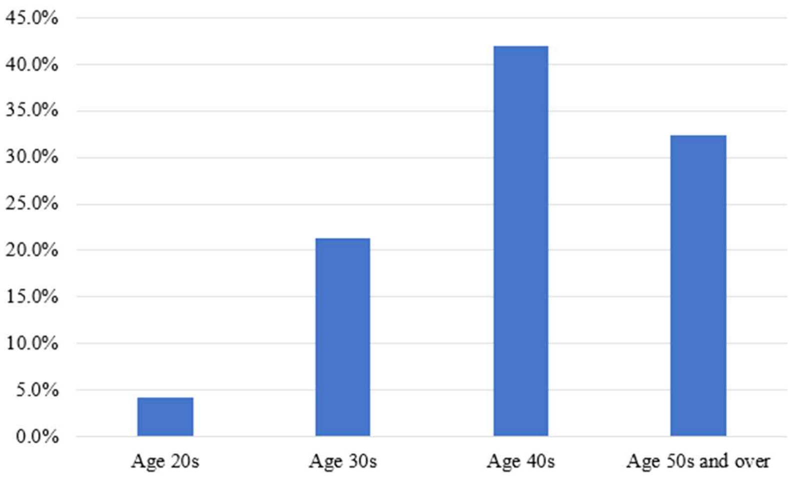
The percentage was checked to find out the composition of consumers of brand A by age. As a result of checking the age differences, most consumers were in their 40s. The following figure shows the percentage of customers by age for brand A 〈Fig. 2〉. However, in order to protect the information of fashion companies, the specific number of sales by fashion items could not be presented. And only comparisons of sales were made possible.

Next, a sequential pattern analysis was conducted to examine consumption patterns according to age. Three types of pattern sizes were observed in those in their 20s, four types of pattern sizes in their 30s, five types of pattern sizes in their 40s, and six types of pattern sizes age 50 and above 〈Table 4〉. As age increased, more pattern sizes were observed. People in their 20s, 30s, and 40s purchased t-shirts at least once, whereas people in their 50s and older purchased blouses at least once. The most common purchase patterns for each pattern size are as follows: People in their 20s, 30s, and 40s most often purchased t-shirts in a row. For individuals aged 50 years and older, the pattern of continuously purchasing blouses was the most frequently observed.

By age group, consumers in their 50s and above consistently purchased blouses in sequence, different from other age group who bought t-shirts. This indicates that consumers aged 50 and above have a distinct purchasing pattern compared to consumers from other age groups.

5. Brand B characteristics and patterns

Over the four-year period, brand B sold dresses and sweaters the most, followed by blouses and pants 〈Fig. 3〉. The brand conducted 340,000 transactions, with approximately 136,000 online purchases and more than 240,000 in-store transactions. Overall, the brand's most popular items are dresses and sweaters, and their



<Fig. 2> Brand A consumer age distribution

<Table 4> Brand A sequential pattern by age

	Pattern	Support	Pattern size
Age 20s	{t-shirt}	0.240458	1
	{t-shirt} → {t-shirt}	0.039313	2
	{t-shirt} → {t-shirt} → {t-shirt}	0.017176	3
Age 30s	{t-shirt}	0.265879	1
	{t-shirt} → {t-shirt}	0.062129	2
	{t-shirt} → {t-shirt} → {t-shirt}	0.024697	3
	{t-shirt} → {t-shirt} → {t-shirt} → {t-shirt}	0.013043	4
Age 40s	{t-shirt}	0.290121	1
	{t-shirt} → {t-shirt}	0.090526	2
	{t-shirt} → {t-shirt} → {t-shirt}	0.041883	3
	{t-shirt} → {t-shirt} → {t-shirt} → {t-shirt}	0.022473	4
	{blouse} → {blouse} → {blouse} → {blouse} → {blouse}	0.010341	5
Age 50s and over	{blouse}	0.244608	1
	{blouse} → {blouse}	0.078175	2
	{blouse} → {blouse} → {blouse}	0.039666	3
	{blouse} → {blouse} → {blouse} → {blouse}	0.023634	4
	{blouse} → {blouse} → {blouse} → {blouse} → {blouse}	0.015701	5
	{blouse} → {blouse} → {blouse} → {blouse} → {blouse} → {blouse}	0.011073	6

sales are mainly offline. However, in order to protect the information of fashion companies, the specific number of sales by fashion item could not be presented, and only comparisons of sales were made possible.

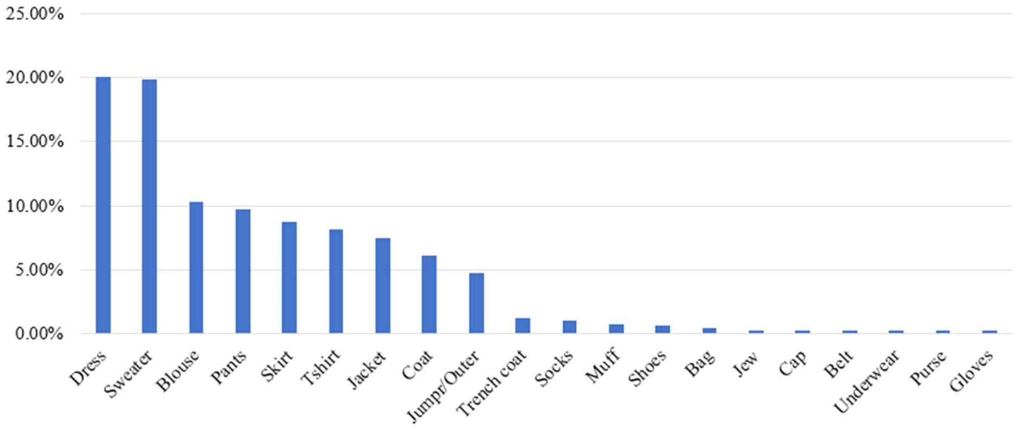
1) Brand B entire sequential pattern analysis

For brand B, we observed six types of pattern sizes 〈Table 5〉. The two most common patterns for each pattern size are as follows: Among the five types of pattern sizes, pattern size 1, in which consumers purchase only one item, was the most common. Among all consumers, 29.5% purchased a t-shirt at least once. Pattern size 2, {dress}→{dress}, was the most common purchase pattern (8.57%). For pattern size 3, {dress} → {dress} → {dress} was the most common purchase pattern (4.17%). For pattern size 4, {dress} → {dress} → {dress} → {dress} → {dress}, was the most common (2.44%). Pattern size 5 had the most observed purchase pattern of {dress} → {dress} → {dress} → {dress} → {dress} → {dress} (1.56%). Finally, pattern size 6 had the highest pattern of buying {dress} → {dress} → {dress} → {dress} → {dress} → {dress} → {dress} (1%).

This brand found that dresses were an important purchase item. As in Brand A, it was confirmed that there were items that consumers are loyal to in brand B.

2) Brand B seasonal sequential pattern analysis

Five and four types of pattern sizes were observed in spring and summer, respectively 〈Table 6〉. In the fall and winter, three pattern sizes were observed. In all four seasons, the most pattern size 1 (a single product purchase) was the most common. In the spring season, 23% of all consumers purchased dresses at least once. For pattern size 2, the purchase pattern {dress, dress} was the most common. For



<Fig. 3> Brand B sales of items

<Table 5> Brand B entire sequential pattern

Pattern	Support	Pattern size
{dress}	0.295923	1
{dress} → {dress}	0.085754	2
{dress} → {dress} → {dress}	0.041705	3
{dress} → {dress} → {dress} → {dress}	0.024463	4
{dress} → {dress} → {dress} → {dress} → {dress}	0.015681	5
{dress} → {dress} → {dress} → {dress} → {dress} → {dress}	0.010842	6

pattern size 3, {dress, dress} → {dress} was the most common purchase pattern at 3.19%. For pattern size 4, the {dress, dress} → {dress → dress} purchase pattern was observed the most (2.01%). For pattern size 5, the {dress, dress} → {dress, dress} → {dress} purchase pattern was observed the most (1.08%).

The most common purchase pattern observed during the summer season was dress purchases: 34.5% of all customers purchased dresses at least once during the summer. For pattern size 2, {dress} → {dress} was the most common purchase pattern (7.34%). For pattern size 3, the pattern of buying {dress} → {dress} → {dress} was observed the most (2.26%). For pattern size 4, the pattern of buying {dress} → {dress} → {dress} → {dress} → {dress} was observed the most at 1.26%. In the fall and winter seasons, sweaters were the most commonly observed consumer purchase. Unlike in the summer, 25.8% and 25.1% of consumers purchased sweaters at least once in the fall and winter, respectively. In both fall and winter, the most common purchase patterns were that {sweater} → {sweater} was (5.47%, 4.70%) for pattern size 2, and {sweater} → {sweater} → {sweater} was (1.02%, 1.54%) for pattern size 3.

Based on the seasons, dresses were important purchase items during spring and summer, while sweaters were important in the fall and winter. Additionally, it was evident that purchase items could be distinctly categorized into two season groups such as spring-summer and fall-winter. This may be because climate warming has weakened the distinction between the four seasons.

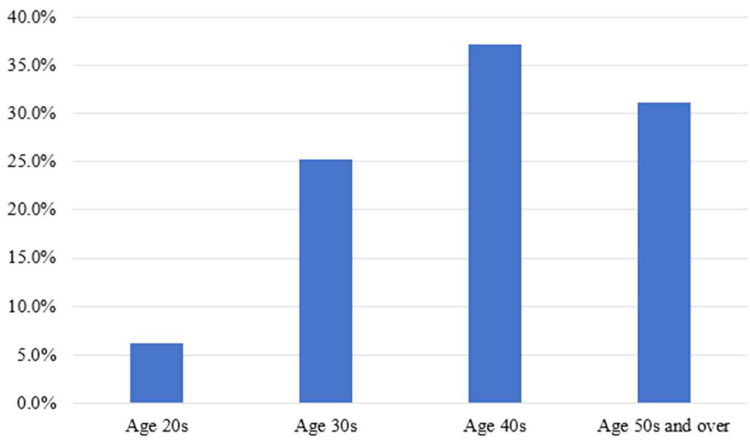
<Table 6> Brand B seasonal sequential pattern

	Pattern	Support	Pattern size
Spring	{dress}	0.238085	1
	{dress, dress}	0.106193	2
	{dress, dress} → {dress}	0.031985	3
	{dress, dress} → {dress → dress}	0.020183	4
	{dress, dress} → {dress, dress} → {dress}	0.010839	5
Summer	{dress}	0.345737	1
	{dress} → {dress}	0.073411	2
	{dress} → {dress} → {dress}	0.026615	3
	{dress} → {dress} → {dress} → {dress}	0.012614	4
Fall	{sweater}	0.258401	1
	{sweater} → {sweater}	0.054795	2
	{sweater} → {sweater} → {sweater}	0.019075	3
Winter	{sweater}	0.251518	1
	{sweater} → {sweater}	0.047038	2
	{sweater} → {sweater} → {sweater}	0.015467	3

3) Brand B sequential patterns analysis by age

The percentage was checked to find out the composition of consumers of brand B by age. As a result of checking the age differences, most consumers were in their 40s. The following figure shows the percentage of customers by age for brand B 〈Fig. 4〉. However, in order to protect the information of fashion companies, the specific number of sales by fashion items could not be presented. And only comparisons of sales were made possible.

The following table shows the percentage of customers by age for brand B. Most consumers were in



<Fig. 4> Brand B consumer age distribution

their 40s. Sequential pattern analysis was conducted to examine consumption patterns by age. The purchase patterns by age are as follows: 3, 4, 6, and 6 types of pattern sizes were observed in the 20s, 30s, 40s, and 50 and above groups, respectively 〈Table 7〉. The number of pattern sizes increased with age. People in their 20s, 30s, and 40s purchased dresses at least once, whereas people age 50 and above purchased sweaters at least once. The most common purchase for those in their 20s, 30s, and 40s was dresses, while for those in age 50 and above it was sweaters. Similar to A, as the pattern size increases, a pattern of purchasing the same product is observed. For example, a pattern size of five in the 50s group means that the percentage of consumers who purchase a sweater in five shopping situations is 1%.

By age group, consumers in their 50s and above consistently purchased sweaters in sequence, different from other age group who bought dress. This indicates that consumers aged 50s and above have a distinct purchasing pattern compared to consumers from other age groups.

6. Network analysis results

In addition to sequential pattern analysis, a network analysis between items recognized by consumers was

<Table 7> Brand B sequential pattern by age

	Pattern	Support	Pattern size
Age 20s	{dress}	0.317006	1
	{dress} → {dress}	0.059854	2
	{dress} → {dress} → {dress}	0.024834	3
	{dress} → {dress} → {dress} → {dress}	0.014191	4
Age 30s	{dress}	0.347345	1
	{dress} → {dress}	0.086958	2
	{dress} → {dress} → {dress}	0.039236	3
	{dress} → {dress} → {dress} → {dress}	0.021534	4
	{dress} → {dress} → {dress} → {dress} → {dress}	0.012957	5
Age 40s	{dress}	0.284443	1
	{dress} → {dress}	0.095084	2
	{dress} → {dress} → {dress}	0.049015	3
	{dress} → {dress} → {dress} → {dress}	0.029477	4
	{dress} → {dress} → {dress} → {dress} → {dress}	0.019674	5
	{dress} → {dress} → {dress} → {dress} → {dress} → {dress}	0.013681	6
Age 50s and over	{sweater}	0.289361	1
	{sweater} → {sweater}	0.089858	2
	{sweater} → {sweater} → {sweater}	0.042681	3
	{sweater} → {sweater} → {sweater} → {sweater}	0.024047	4
	{sweater} → {sweater} → {sweater} → {sweater} → {sweater}	0.015292	5
	{sweater} → {sweater} → {sweater} → {sweater} → {sweater} → {sweater}	0.010796	6

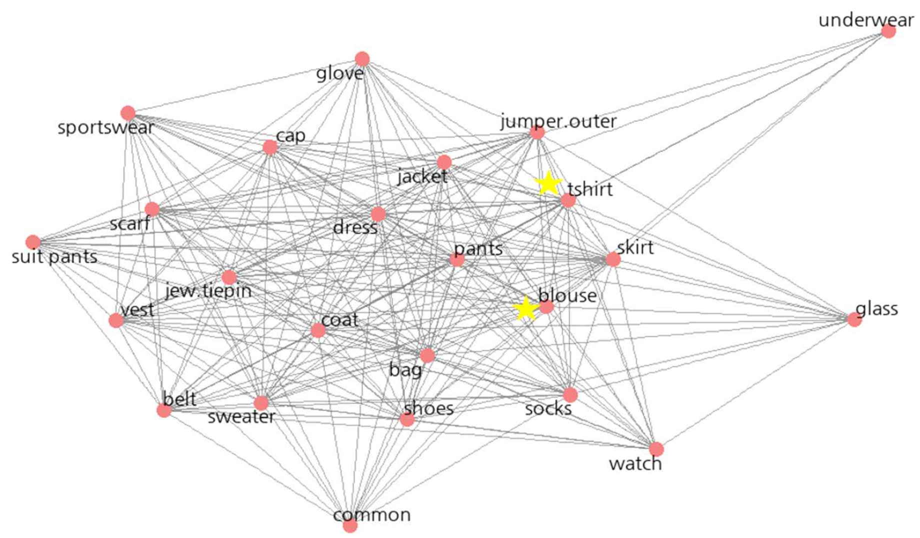
performed to confirm the item purchase pattern. The network analysis was performed to examine the structural linkages between the items. For Brand A, we observed the highest centrality of t-shirts and blouses 〈Fig. 5〉. High centrality means that the item is centered and a purchase pattern of purchasing other items is made. This indicates that the consumer is purchasing a product that includes a t-shirt or blouse. For example, a consumer who buys a skirt is likely to buy a t-shirt as well.

In the case of brand B, dresses and sweaters were found to have the highest centrality 〈Fig. 6〉. Therefore, in the case of customers using brand B, it can be said that the purchasing behavior, including dresses or sweaters, is most often observed.

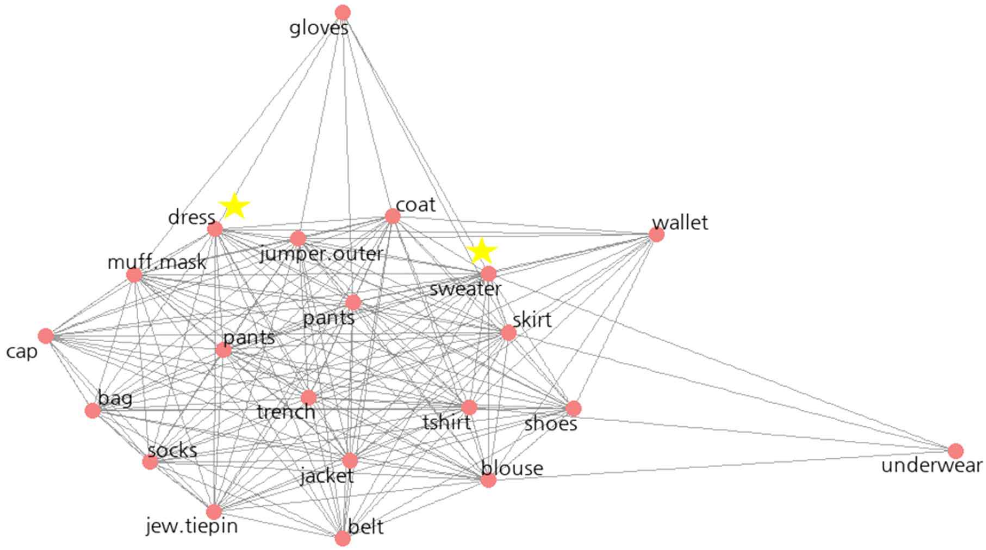
V. Conclusion

In this study, we conducted a sequential pattern analysis and network analysis based on consumer transaction data to examine the purchase patterns of fashion consumers were conducted. The overall purchase pattern was analyzed, followed by seasonal and age-specific purchase patterns. The results of the overall pattern analysis showed that purchase patterns were formed around popular brand items. In the case of brand A, we observed a pattern of increasing pattern size centered on t-shirts was observed, whereas in the case of brand B, a pattern of increasing pattern size centered on dress was recorded. Therefore, it seems that customers are loyal to brands with regard to certain types of items. In other words, the representative items are creating the image of brand. This is consistent with research findings suggesting that a brand's impression has a positive influence on the consumers' decision-making process. According to previous study, consumers tend to overlook the inherent attributes of a product but rely more on the superficial level of the brand such as the brand's image or impression when purchasing an item (Fill & Turnbull, 2016; Zhang, 2015). Furthermore, the brand's icon enables consumers to distinguish the strength of the item amongst others, leading to a higher purchase rate (Henderson & Cote, 1996). This suggests that iconic items recognized by consumers can play a significant role in shaping purchase patterns.

To examine whether consumers' purchase patterns differed by season, a sequential pattern analysis for



<Fig. 5> Brand A co-occurrence network structure



<Fig. 6> Brand B co-occurrence network structure

spring, summer, fall, and winter were conducted. Both brands showed similar purchase patterns across different seasons. The items observed in the purchase patterns during the spring and summer seasons were consistent, as well as in the autumn and winter seasons. For brand A, the purchase pattern centered around blouses in the spring and summer, while it focused more on t-shirts during the autumn and winter. This aligns with previous research findings that indicate consumers' purchasing preferences vary based on the season (Chung & Kim, 2011). It also suggests a potential shift in the way consumers view seasonal products nowadays. The traditional four-season division seems to be merging into two broader categories as the first and second halves of the year. This observation is consistent with previous research and recent business reports, suggesting that consumers nowadays are less bounded by strict seasonal purchasing patterns. This is also attributed to the recent lack of clear changes in the four seasons. However, an important result of verifying the difference in purchasing patterns according to season is that purchases are centered on popular items for both brands.

During the spring season, unusual purchase patterns were observed for both brands. Purchasing behavior was observed when two core brand items of the same type were purchased on the same day. For brand A, blouses were the key item for the spring season, with consumers purchasing two of this type of item on the same day. For brand B, dresses were the key item for the spring season, and a pattern of two purchases on the same day was observed. This phenomenon may also be related to the beginning of the fashion cycle. Similar to the New Year's effect, people are motivated to change things at the point of a fresh start. In the case of fashion, the spring season is the starting point for a new style. Therefore, consumers are expected to have a greater desire to change things at this time than in other seasons. To fulfill this desire, consumers seem to buy more than one product in a single shopping transaction during the spring season compared to other seasons.

The same seasonal buying patterns were observed for both brands, which goes against the conventional perception that the types of items that consumers prefer change significantly as the season changes. Instead, it appears that there are key brand items that consumers recognize, and purchasing is centered around these core items. In other words, when purchasing three times, a purchase pattern emerges that includes popular items.

To confirm whether the purchase pattern around popular items is a phenomenon that occurs in certain age groups, additional sequential pattern analysis by age was performed. For both brands, it was found that purchase patterns were formed around popular items in the 20s, 30s, and 40s age groups. This means that the types of popular items consumed by the different age groups did not change significantly. Therefore, it would seem that fashion companies do not need to differentiate their product types to target specific age groups as 20s–40s. Developing a type of product that matches the strengths of the brand means that the product will be purchased regardless of age 20s–40s. However, it is observed that the core items that create purchase patterns from the costumers start to change from the age of 50. For instance, in the case of brand A, the age group of 20s–40s predominantly formed a purchase pattern centered around t-shirts. On the other hand, customers who are over 50 tend to change their preference closer towards blouses. This suggests that there might be a transitional phase in purchase patterns starting from the age of 50. The changes observed in the purchasing behavior of people over 50 can be attributed to a variety of factors. Usually, social and psychological aspects play a significant role in fashion purchases. It is presumed that this is because they think that they should have an elegant image different from that of young people. Keeping these preconditions in mind, such a pivotal life transition could reshape their consumption values and priorities (Lumpkin, 1984; Passyn, Dirker, & Settle, 2011).

It was also observed that a trend of more pattern sizes increasing with age for both brands. Three types of pattern sizes were observed for people in their 20s purchasing brand A as four categories for people in their 30s, five categories for people in their 40s, and six categories for people in their 50s. For brand B, four types of pattern sizes were observed in the 20s, five categories in the 30s, and six categories in the 40s and 50s. Looking at the most frequent purchase patterns for each pattern size, it can be observed that consumers repeatedly purchase the same type of item. This can be interpreted as consumers becoming more loyal to a brand's specific items as their age increases. As they age, they accumulate shopping experience and there seems to be a core branded item that they recognize. Therefore, compared to other age groups, consumers over 40 years of age seem to have a simpler decision-making process when purchasing products. This can be explained by the high repetition pattern of buying the same product repeatedly. This can be said to be because risk sensitivity increases when purchasing a new type of item as the age increases (Heckhausen, Dixon, & Baltes, 1989; Hoyer et al., 2012). Another reason may be inferred to purchase the same item several times because the higher the age is, the higher the financial stability is.

Finally, network analysis shows that t-shirts and blouses have the highest number of linked sales. Integrating this with the results of the sequential pattern analysis, we can see that consumers purchase products centered around t-shirts and blouses and then buy other items around these items. Thus, we can conclude that consumers buy other products around the brand's top-selling products.

This study is significant as it analyzes more than 1 million actual purchase data points to derive consumer purchase patterns in the fashion sector. A practical implication of this study is that, during the spring season, consumers make two or more purchases of popular item of brand on the same day. This suggests that the spring season is important from a practical perspective. Accordingly, it is essential to create a positive image of the key items that consumers consume during this time, not only because the consumption of these types of key items such as blouses and t-shirt continues throughout the summer, fall, and winter seasons but also because these items increase consumers' purchase intention. Of course, each brand will have different important signature items. As age increases, an increase in repeat purchases of key items were found.

It was also observed that approximately 1% of consumers in their 20s made four consecutive purchases that included a t-shirt, whereas we found that about 1% of consumers in their 40s made six consecutive purchases that included a t-shirt. As age increased, an increase in repeat purchase patterns for popular items was found. In a commercial context, maintaining relationships with current clients is often more financially beneficial than seeking to acquire new customers. Customers who consistently make repeat purchases are a key factor in increasing a company's operating profit margin. Therefore, it is necessary to actively develop a type of marketing program that is suitable for customers over the age of 40s who show a high repetition pattern. When reviewing existing studies, it was anticipated that consumers would exhibit dynamic purchasing patterns for clothing products, as they often use them as a means of self-expression (Shin, 2001). However, upon analyzing our research results, the most frequently observed pattern was a simple repetitive purchasing of specific items. This insight can broaden our understanding of consumers' purchase behaviors. In the future, through a sophisticated research, it will be anticipated that proposing a consumer behavior model related to these simple purchasing patterns.

The mainstream literatures suggest that customers who have high loyalty in brands tend to purchase a variety of items (Møller Jensen & Hansen, 2006). On the contrary, however, our research found that high loyalty in brands enables consumers to repurchase specific products. Prior studies have indicated that brand assets build up through brand-level communication, leading to observable brand loyalty behaviors. However, our research suggests the possibility of accumulating brand-related assets even at the item level. This implies a deeper understanding of the process by which brand loyalty develops. Moreover, it is significant academically to note that a rare big data, which is relatively unfamiliar and challenging to secure in the fashion industry, was obtained and analyzed. Lastly, big data is an observational data, in other words, it is nearly impossible to be obtained through the initial stage of research design.

Regardless of research designs, there are limitations of big data in clearly explaining the data from a social scientific perspective. Because of these limitations, various analysis methods should be used. In a follow-up study, data from various fashion brands will be secured to analyze purchase patterns that can be generalized by fashion consumers, and to identify various influencing variables.

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