Brand Fandom Dynamic Analysis Framework based on Customer Data in Online Communities

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Received February 16, 2023; accepted June 20, 2023; published August 31, 2023

Abstract

Brand fandom refers to a collection of consumers with strong emotions toward a brand. Studying the dynamics of brand fandom can help brands understand which services or strategies influence their consumers to become a part of brand fandom. However, existing literature on fandom in the last three decades has mainly used qualitative methods, and there is still a lack of research on fandom using quantitative methods. Specifically, previous studies lack a framework for locating fandoms from online textual data and analyzing their dynamics. This study proposes a framework for exploring brand fandom dynamics based on online textual data. This framework consists of four phases based on the design thinking model: Preparing Data, Defining Fandom Categories, Generating Fandom Dynamics, and Analyzing Fandom Dynamics. This framework uses techniques such as social network analysis and process mining, combined with brand personality theory. We demonstrate the applicability of this framework using case studies of two Korean home appliance brands. The dataset contains 14,593 posts by consumers in 374 online communities. The results show that the proposed framework can analyze brand fandom dynamics using textual customer data. Our study contributes to the interdisciplinary research at the intersection of data-driven service design and consumer culture quantification.

Keywords: brand fandom, data-driven, design thinking, dynamic analysis framework, online community, service design.

A preliminary version of this paper was presented at ICONI 2022, and was selected as an outstanding paper. This version includes further analysis of dynamic results and an additional experimental verification.

http://doi.org/10.3837/tiis.2023.08.015 **ISSN : 1976-7277**

1. Introduction

Brand fandom refers to a collection of consumers who display a common commitment to a particular brand's product, activity, or philosophy of consumption, usually with a strong emotional attachment to the brand [1]. Brand fandom is created based on individuals' passion for a brand to influence organizations to change services, products, or strategies [2,3]. Service-Dominant Logic emphasizes paying attention to consumer groups from the perspective of "entering the consumer's life" [4]. However, existing service research has focused on individual customers. Research on brand fandom, as a form of collective consumers, in the service literature is still vital. The literature proposes that service research should go beyond the individual customer's experience and explore the relationship between individual consumers and consumer groups [5]. Researchers believe that the service literature on collective consumers needs further development, including with regard to brand-fandom-related topics.

Owing to the development of information and communications technology and the invigoration of consumers in online communities, the intensity and extent of online fandom productivity has surpassed that of offline fandom. Consequently, many companies invest time and capital to manage brand fandom through social networks [6]. Simultaneously, advances in information technology have enhanced fandoms' visibility, and social media and online communities have created new socializing and interactive practices for fandoms, resulting in an increase in lively fandom activities. Through tools such as social network analysis, researchers can examine fandom activities quickly.

Consumer attitudes and behaviors are intrinsically dynamic. Zhang and Chang [7] define consumer dynamics as "the temporal changes of consumer attitudes and behaviors." Understanding consumer dynamics is crucial for comprehending consumer behavior, which further helps companies formulate appropriate action plans for doing business [8]. Over the past decade, companies have deliberately collected consumer data by fully utilizing technological developments. The abundance of online consumer data has driven the development and application of quantitative methods for consumer dynamics, which has helped reveal many complex consumer dynamic issues. Lopes et al. [9] employ a netnography approach to understand the interactive dynamics of collective consumers, using both online and offline data. Berger et al. [10] examine how to unite individuals of collective consumers using online textual data. Therefore, online data provide abundant resources for understanding the dynamics of online fandoms.

However, the number of studies on fandom used quantitative methods is still limited. There is a need to improve fandom research that uses online customer data through quantitative methods. In addition, consumer dynamics theory is still a new field that has not been fully recognized [7]. Previous studies lack a framework for locating fandoms from customer textual data and analyzing their dynamics.

The main contributions of this study are as follows. First, we propose a framework that can be applied to analyze the dynamics of brand fandom. Second, we analyze the brand fandom dynamics of two Korean home appliance brands, which enriches experimental research on brand fandom. Third, our framework is a novel attempt to apply the digital method to fandom research. Most existing studies on collective consumer research are qualitative, and few have used quantitative analysis. Larger samples and more accurate consumer data can be analyzed using online textual data. This study has potential reference value for developing the fandom theory and improving service strategies based on online community data.

The remainder of this paper is structured as follows: Section 2 provides a summary of related work, Section 3 describes our proposed framework, Section 4 elaborates on a case application to evaluate the framework, and Section 5 presents the conclusion and suggestions for future research.

2. Related Works

2.1 Brand Fandom in Online Communities

The concept of fandom originated in pioneering research in the media consumer field in the 1990s [11,12]. In terms of brand-related consumption, Fuschillo [13] indicates that fandom is a group of “lead users” who first adopt new technologies and services. Consumer research further defines the active users of these brands and categorizes them into the domain of collective consumers. Collective consumers is an umbrella term that applies to groups of consumers who have a shared commitment to a product category, brand, or consumption theory [14]. A notable feature of collective consumers is that their consumption is not initiated by the brands but is motivated by the consumers’ need to discover ideal brands and acquire the best products and services at favorable prices [15]. Brand fandom is a type of collective consumers that refer to a group of loyal users or admirers of a brand who engage in group activities to achieve collective goals, or express mutual emotions and commitments [16]. Overall, brand fandom is a collection of loyal consumers who display a strong emotional attachment to their favorite brands and continuously develop strong brand loyalty [17].

As a collective concept, brand fandom distinguishes itself from the individual loyal consumer in two aspects. First, brand fandom usually seeks out other fans who are equally engaging and enthusiastic about the brand. They gather in online and offline communities to share their consumer experiences [18]. Second, brand fandom does not simply absorb the information it receives, but tends to express its opinions in the consumer collective, thus influencing the fandom community’s overall perception and behavioral dynamics [19]. Therefore, brand fandom is a more potent form of collective experience [20]. Obiegbu et al. [19] propose that fandom is a reinforcing expression of loyalty that includes repeated purchases of a branded product (behavioral loyalty), positive feelings toward a brand (attitudinal loyalty), and participation in brand activities within a fandom community (experiential loyalty). Consequently, researching brand fandom will help organizations understand consumer behavior and brand loyalty [21]. Parallel to increased consumer activities on the Internet, research in the field of online consumers and digital fandom has provided advantages for brand marketing. First, networking is a significant feature of fandom [22]; fans connect and mobilize each other online, forming a huge network of connections. Based on this feature and crowd power, fandom can create a new level of purchasing power and new markets for brands by strengthening associations and resource combinations across groups in the network. Second, through network-based technologies, brands can investigate the creation of online fandoms to understand consumer trends [23]. For instance, by using the social network analysis technique, we can identify “lead users” in the fandom construction. Brands utilize the strong influence of “lead users” on the overall fandom community and collect “lead users” data to predict the success of products [24]. Third, fandoms’ online reviews and social media posts have provided abundant textual data for consumer research [13,25]. Arvidsson and Caliandro [26] perform social network analysis to understand Louis Vuitton’s brand fandom communication by analyzing their posts on Twitter. Overall, brands can use network-based technologies to analyze fandom textual data online to achieve marketing effects [27].

2.2 Consumer Dynamics

Temporal changes in consumer attitudes and behavior are dynamic processes [7]. Marketing decisions largely depend on an accurate understanding of consumers, regarding not only their current behavior but also changes in behavior in the temporal dimension. Observing consumer behavior from a dynamic perspective can help better understand the consumers; thus, it is necessary to study the dynamics of brand fandom. Parmentier and Fischer [28] point out that studying the dynamics of fandom allows researchers to capture the time when a general consumer becomes loyal, which may provide specific evidence of the increase and decrease in a brand's customer base.

Consumer dynamics include two key features: one is to change chronologically, and the second is to reflect consumers' activities, behavior, or attitudes [7]. The emerging literature has addressed how consumer movements have changed over time [29,30,31,32]. Scholars have also studied the influence of algorithms on the daily behavior, sequence of actions, and thinking of popular culture fandom on social media [33]. With the development of information technology and an increase in social network users, the massive increase in online consumer data and variety of technologies have made it possible for researchers to study the patterns of consumer dynamics more flexibly. For example, Lopes et al. [29] use conversations on social networks to track the emotional dynamics of collectives. Although current literature generates findings on consumer dynamics and collective consumers, studies on brand fandom dynamics are limited. Specifically, there is a dearth of research on fandom dynamics using online consumer data.

2.3 Process Mining

Process mining has emerged as a sub-discipline of data science and process science [34], which refers to a model that automatically constructs and interprets the behaviors observed in an event log. It is characterized by a combination of business process mining techniques and event log data that can effectively observe behaviors that occur in chronological order [35]. In addition, some scholars have optimized the process mining model for fuzzy mining, such that an unstructured process can be simplified and aggregated [36]. Therefore, infrequently executed activities can be excluded and essential processes can be better understood.

Fig. 1 shows the structure of the process mining model [34]. First, event log data are extracted from unstructured data. Second, a type of process mining is selected according to the following requirements: discovery, conformance, and enhancement. Finally, the process mining model determines the dynamics of the unstructured data. Event log data should include three types of information for process mining: cases, timestamps, and activities. Process mining has been applied to various domains in previous studies, including discovering and improving service behavior [37], understanding customer browsing dynamics using a booking site [38], analyzing hospital treatment processes [39], building customer journey maps [34], and improving the design process of data interactive learning systems [40]. The common denominator of these studies is that behavioral dynamics are associated with the process mining model.

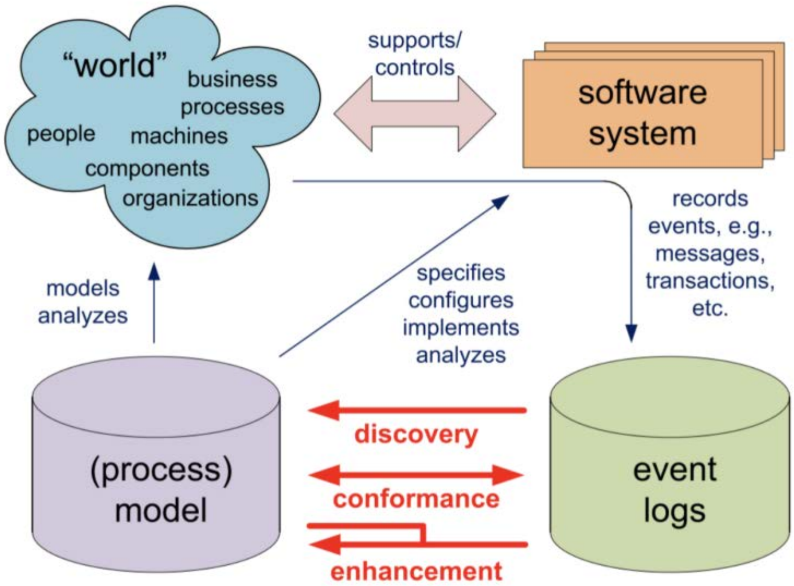

Fig. 1. Structure of process mining: Extract event log data from unstructured data, and then analyze the dynamic process using the process mining model [34].

In summary, process mining can correlate, predict, and cluster behavior dynamics based on event logs and display the significant dynamics of the data in chronological order [41]. Therefore, exploring fandom dynamics from posting data using a process-mining technique is feasible.

3. Brand Fandom Dynamic Analysis Framework

This section introduces the framework for analyzing the proposed brand fandom dynamics with a brief description of the data analysis techniques. This study explores the dynamics of brand fandom in online communities using social network analysis and process mining techniques. The primary reference supporting this framework is the double-diamond design process. The double-diamond design process originates from design research. It can also be applied to comprehensive research solutions such as services and marketing [42,43,44]. This process consists of four phases: Discover, Define, Develop, and Deliver [45].

The brand fandom dynamic analysis framework was developed in four phases based on the double diamond, shown in **Fig. 2**: Preparing Data, Defining Fandom Categories, Generating Fandom Dynamics, and Analyzing Fandom Dynamics. In the Preparing Data phase, a divergent mode of thinking was employed to seek all potential data in online communities that can be used to discover fandom dynamics. We also performed data pre-processing at this stage. Defining Fandom Categories is a convergent mode that identifies fandom categories using social network analysis. In the Generating Fandom Dynamics phase, we created a fandom dynamic using a process-mining technique. In the Analyzing Fandom Dynamics phase, we incorporated the results of fandom dynamics into marketing insights. This framework represents divergent and convergent thinking processes for analyzing fandom dynamics. Divergent and convergent processes have the advantages of creativity and iterations [42]. The four phases are presented in detail in the following sections.

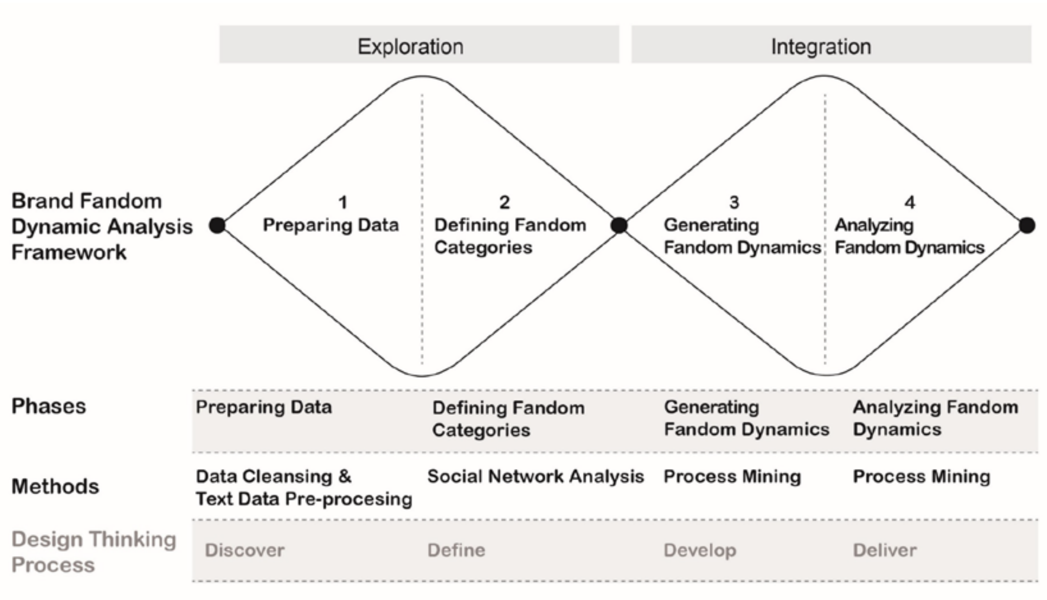

Fig. 2. Brand fandom dynamic analysis framework.

3.1 Data Preparation

We verified the applicability of our framework for exploring brand fandom dynamics. This study selected two home appliance brands in South Korea as case studies. In South Korea, consumers tend to search for and discuss brand-related information in online communities before purchasing home appliances. These communities include home appliance, interior design, and parenting communities. We selected 374 online communities frequently visited by electrical appliance consumers.

The dataset was collected using a crawling process. We then performed data interpretation, cleansing, and text data pre-processing. Data cleansing was divided into two steps: in the first step, the noisy data from advertisements were removed, and in the second step, the noisy data from pricing inquiries were removed. Therefore, only content that represents the consumers' perception of the brand was retained. Since most consumer posts in this dataset were written in paragraphs and sentences, the data were classified using a morpheme analyzer to extract nouns and adjust for further analysis.

After initial data processing, the dataset consisted of words with different lexical properties. Therefore, it was necessary to classify the words into several categories for further analysis. The concept of brand personality has been used to distinguish consumer categories. Brand personality, as a critical element of brand identity, identifies consumers' different feelings and emotions toward the functions of the brand. Aaker [46] defines brand personality as "a set of human characteristics reminiscent of a specific brand" and develops a brand personality scale to evaluate the essential tendencies of the brand based on personality traits. After the dataset was coded and classified by brand personality, we defined fandom categories.

3.2 Defining Fandom Categories

We applied a 2×2 matrix to differentiate between general consumer groups and brand fandom. The axes of the 2×2 matrix are dual: the horizontal axis represents the owner and the vertical axis represents the fan. If a customer positively evaluates a product or service in a post, they are defined as a fan; otherwise, they are a non-fan. If a customer makes a payment or leaves a purchase review in a posting, they are defined as an owner. Otherwise, they are non-owners. Therefore, the dataset was classified into four quadrants: "Fan and Owner," "Fan but non-Owner," "non-Fan and non-Owner," and "non-Fan but Owner." "Fan and Owner" indicates a brand fandom. "Fan but non-Owner," "non-Fan and non-Owner," and "non-Fan but Owner" indicate general consumer groups. Next, the consumer clusters in these four quadrants were analyzed using social network analysis.

Social network analysis, proposed by Harrison White from Harvard University in the 1960s, is a general method for exploring digital fandoms in consumer clusters [47]. It can analyze the relationship between consumer posts on social networks and cluster them into different categories based on nodes and links. The network structure is subject to changes in node settings. The tool used in this study to perform social network analysis was Network Navigator, which is provided by Microsoft Power BI software (https://github.com/Microsoft/PowerBI-visuals-NetworkNavigator). Community names represent source nodes. Therefore, the dataset was divided into clusters depending on brand personality. We consider these clusters as collective consumers. The collective consumers in the "Fan and Owner" group are considered brand fandom.

3.3 Generating Fandom Dynamics

This stage aims to generate fandom dynamics using process-mining techniques. Process mining is a series of processes that analyzes the event log occurring in an information system to derive a process model and locate meaningful information [35]. An event log used in process mining consists of an event representing a specific activity, a timestamp where the activity occurs, and a case that binds the event [34]. Using event log data, the process-mining model can generate a dynamic of information in chronological order. This study uses process mining to generate collective consumer dynamics from online posting data. The dynamic of the collective consumer "Fan and Owner" group represents brand fandom dynamic.

3.4 Analyzing Fandom Dynamics

According to the function of process mining, it is possible to analyze collective consumer dynamics in chronological order. Based on the process mining results from the previous stages, the collective consumer dynamics of the four groups were analyzed in detail. In particular, we focused on the process mining result of the "Fan and Owner" group to understand the dynamics of the most loyal fandom group.

4. Experimental Verification

4.1 Preparing Data

4.1.1 Data Interpretation

The data collected in this study contained online community posts on two brands. A total of 374 Korean online communities related to home appliances were selected as data sources for this study. Online communities include interior design, family life, and childcare communities. We collected posts that included two brands' names and their products' names. The dataset format is shown in **Table 1**, including the post date, post title, post content, and online community name. Data were collected from January 1, 2021 to May 31, 2021. The dataset consisted of 14,593 posts. Korean language in the analysis results was translated into English using the Papago translation site (https://papago.naver.com/). We anonymized the actual brand names in the data and labeled them as Brand A and Brand B.

Table 1. Online community dataset format

Post date	Post title	Post content	Online community name
5/31/2021	Is the Kimchi refrigerator and Brand A okay?	The place I moved to is empty, so I have to fill it up as soon as possible because I'm worried. Actually, I want to fill the refrigerator's seat with Brand A, but it's a new product. Can you give me some advice if you have a regular refrigerator of Brand A?	Songdo International City Mom
5/17/2021	Product 1 vs. Product 2	Product 1 and Brand A Product 2, which is more common when you search for them? I bought all of them from Brand A, so I'm worried because Product 1 seems to have good performance.	Preparation for Direct Marriage
1/20/2021	How about a dark grey dishwasher with a white sink?	At first, I only thought of Brand B white for the dishwasher but when I went to the store, I was informed that you could buy completely white ones only on the Internet, and there was only an Brand B product. The Brand B product is slightly beige, so I thought it would look yellow in the white sink. Is there anyone who uses it like this? What do you think?	Self-interior My Home

4.1.2 Data Cleansing

Data cleansing was performed by two steps. The first step is to clean up the data related to advertising. We have accumulated experience from our previous work, online community posts containing "advertisements," "experience group," "recruitment," "special price," "finish," and " reservation" are often made by brands for promotional purposes, not by customers. Since we focus on consumer dynamics in this study, we remove posts containing these terms in Excel with a manual search. After this step, 12,912 posts remained.

After the first data cleansing, datasets still included many posts about consumers asking about pricing. Thus, we performed a second data cleansing step to search for posts about consumers' true cognization of the brand. In the second data cleansing step, posts containing the keywords "comparison," "quotation," "question," and "price inquiry" were deleted. Consequently, 6,681 posts were selected for the analysis.

4.1.3 Text Data Pre-processing

This stage aimed to extract keywords from the consumer posts. First, we removed words that were irrelevant to the meaning of the sentences. The "end of words" is often used after nouns in Korean. Since it does not have any meaning, we removed the "end of words," personal pronouns, and temporal pronouns. Second, we extracted nouns from sentences using a morpheme analyzer. As a post's first sentence reflects the post's intention and meaning, the first noun and adjective of the sentences were set as the core keywords. These nouns mainly consisted of product and brand names such as "Kimchi refrigerator," "washing machine," and "cleaner." The adjectives included "kind," "advanced," and "popular." Third, we integrated keywords for a better understanding. The abbreviations were modified to formal names and unified into one form. For instance, the keywords "oven," "microwave," and "microwave oven" were modified to "oven range." The keywords "fryer," "AF," and "A-F" were unified as "air fryer." An example of the text data pre-processing results is shown in **Table 2**.

Table 2. Examples of replacing the consumers' perception with upper and lower brand personality factors

Brand personality (upper)	Brand personality (lower)	Word example
Sincerity	Small-town	Cheap
	Real	Real
	Honest	Honest
	Friendly	Friendly
Excitement	Trendy	Popular
	Unique	Special
	Up-to-date	New
	Contemporary	Modern
Competence	Hard-working	Hard
	Secure	Safe
	Confident	Certain
Sophistication	Upper-class	Expensive
	Glamorous	Gold
	Good-looking	-
	Charming	Pretty
Ruggedness	Western	Overseas
	Tough	Strong
	Rugged	-

In addition to extracting keywords, we distinguished each post based on brand personality. According to brand personality theory, nouns with adjectives can indicate consumers' feelings about brands and products [44]. This study introduced brand personality to replace the perception of home appliances with upper and lower brand personality factors. The five upper factors of the brand personality dimension are Sincerity, Excitement, Competence, Sophistication, and Ruggedness. These five upper factors, include 42 lower factors. We then coded the posts into five brand personality dimensions according to the keywords. For instance, among the comments, "I bought a brand's product and gave reviews because I liked the product" was coded as sincerity. "I heard that built-in refrigerators are in trend these days" was coded as excitement. "The vacuum cleaner has high suction power when it is used on carpets" was coded as competence. "Why is the color of the dishwasher so pretty?" was coded as sophisticated. Moreover, "The water purifier is durable" was coded as ruggedness. An example of the brand personality results is shown in **Table 2**.

Moreover, the fans and owners of the brands were distinguished. Based on the post content, if consumers purchased products, we marked them as "owners." We also marked consumers as fans if they showed a preference for Brands A or B. Finally, because purchase and preference have qualitative properties, quantification was performed to assign values to these domains. In **Table 3**, the owner domain is assigned a value of 1, and non-owner domain are assigned a value of 0. The same process was performed for the fan and non-fan domains.

Table 3. Preparation result of the dataset from unstructured data

Brand	First noun (keywords)	Brand personality (upper)	Brand personality (lower)	Date	Source	Fan	Owner
A	Kimchi Refrigerator	Sophistication	Charming	5/31/2021	Community A	0	0
A	Brand A	Competence	Reliable	5/31/2021	Community B	1	1
A	Brand A	Sincerity	Small-town	5/31/2021	Community C	1	0
B	Electric Dryer	Sophistication	Charming	5/31/2021	Community A	1	0
B	Brand B	Competence	Reliable	5/31/2021	Community D	0	0
A	Department Store	Sincerity	Real	3/1/2021	Community E	0	1
A	Washer	Sophistication	Upper-class	3/1/2021	Community B	0	0
B	Department Store	Excitement	Contemporar y	3/1/2021	Community F	0	0
A	Refrigerator	Competence	Reliable	1/7/2021	Community C	0	0
B	Dishwasher	Sincerity	Real	1/5/2021	Community D	0	0
B	Brand B	Sincerity	Small-town	1/1/2021	Community A	0	1

4.2 Defining Fandom Categories

In this phase, data-set were divided into Brands A and B, and the brand fandom cluster size and the relationship between clusters were confirmed using social network analysis.

First, each brand's data-set were divided into four groups based on whether they purchased the product or liked the brand. "Fan" refers to a consumer who likes the brand, "non-Fan" refers to a consumer who does not like the brand, "Owner" refers to consumers who purchased the brand, and "non-Owner" refers to those who did not purchase the brand. In **Fig. 3**, the four groups are "Fan and Owner," "Fan but non-Owner," "non-Fan and non-Owner," and "non-Fan but Owner." Second, in social network analysis, a network consists of nodes and links connecting nodes. The online community name was mapped to the source node, and the brand personality scale was mapped to the target node. The network was visualized using the Power BI Network Navigator tool.

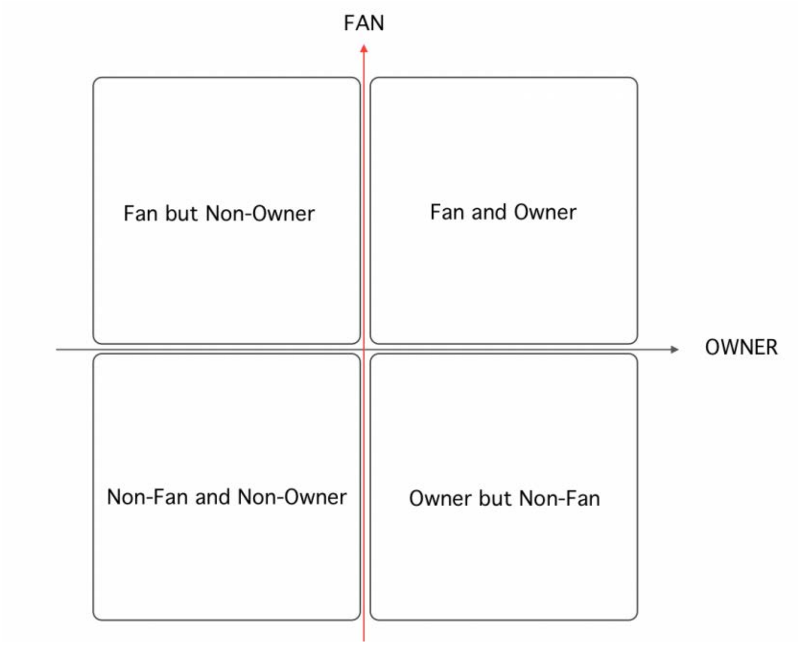

Fig. 3. 2 × 2 matrix of fan and owner.

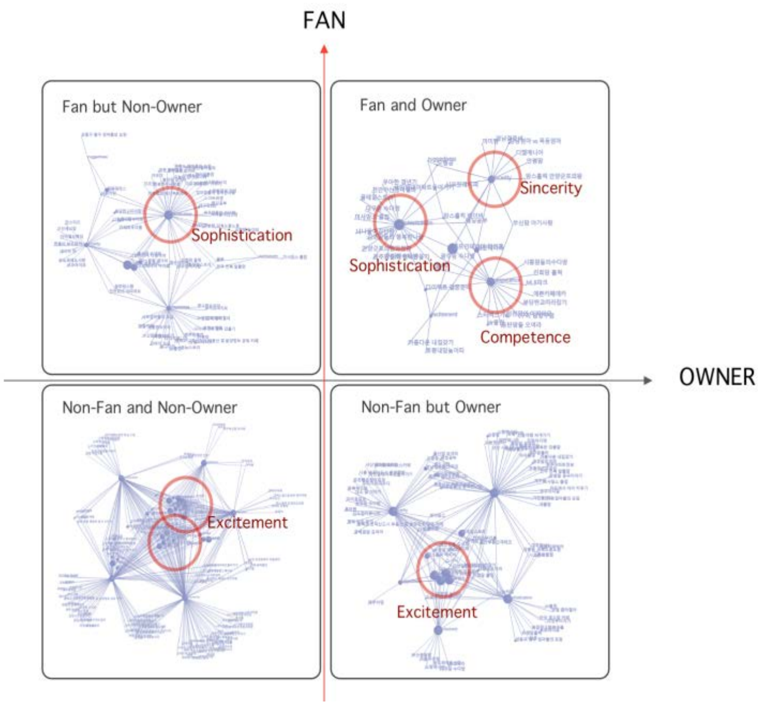

Fig. 4. Fandom categories of Brand A defined by social network analysis (Source nodes mapped by community name and target nodes mapped by the brand personality scale).

4.2.1 Fandom Categories of Brand A

Based on the social network analysis of Brand A, "Fan and Owner" tends toward sophistication, sincerity, and competence, and "Fan but non-Owner" tends toward "sophistication." Additionally, "non-Fan but Owner" and "non-Fan and non-Owner" tend toward "excitement." In conclusion, Brand A's fandom tends toward sophistication, sincerity, and competence, as shown in **Fig. 4**.

4.2.2 Fandom Categories of Brand B

Based on the social network analysis of Brand B, "Fan and Owner" and "Fan but non-Owner" tend toward "sophistication." Additionally, "non-Fan but Owner" and "non-Fan and non-Owner" tend toward "excitement." In conclusion, Brand B's fandom has a sophistication tendency and Brand A's non-fan group has an excitement tendency, as shown in **Fig. 5**.

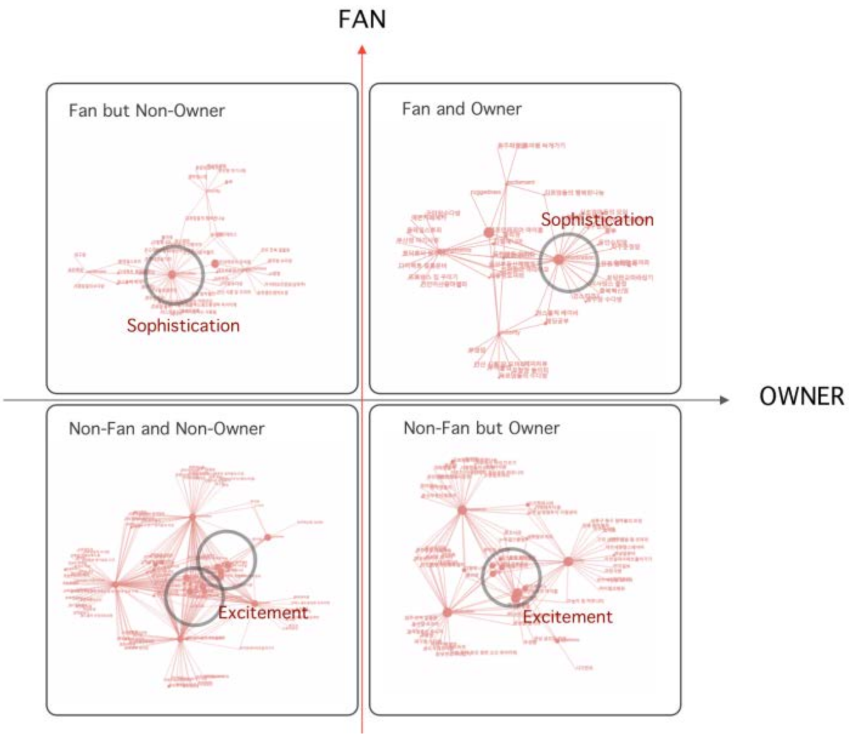

Fig. 5. Fandom categories of Brand B defined by social network analysis (Source nodes mapped by community name and target nodes mapped by the brand personality scale).

Table 4 compares fandom category results for brands A and B. In the fan and owner group, brand A has three fandom categories: sincerity, sophistication, and competence. Brand B has only one fandom category, sophistication. In the remaining three consumer groups, brands A and B have all the same fandom categories. The result of the brands' A and B fandom category comparison indicated the fandom characteristics of brands A and B differ, but the general consumer groups show high consistency.

Table 4. Fandom categories comparison of Brands A and B

Groups	Brand A	Brand B
Fan and Owner	Sincerity Sophistication Competence	Sophistication
Fan but Non-Owner	Sophistication	Sophistication
Non-Fan but Owner	Excitement	Excitement
Non-Fan and Non-Owner	Excitement	Excitement

4.3 Generating Fandom Dynamics

Process mining can be used to explore fandom dynamics in chronological order. We conducted process mining to analyze fandom dynamics using the Power BI software PAFnow tool. The case ID, timestamp, and activity need to be input when conducting process mining in Power BI. The community name was indicated as a case ID, the posting date was indicated as a timestamp, and the online community posting keyword was indicated as an activity. To present the structure of fandom dynamics more clearly, we further divided online community posting keywords into four categories. First, if the posting keyword was Brand A related full name and abbreviation unified as “Brand A.” Second, if the posting keyword was the full name or abbreviation of Company A, it was unified as “Brand A.” Third, brand product words, for instance, refrigerator, dryer, TV, dishwasher, and water purifier, were replaced with “product.” Fourth, the brand personality lower-factor classification detailed in the data preparation phase was used for the remaining posts. Finally, the dynamics of the keywords posted by consumers were presented in a flow chart in chronological order. This flowchart of the “Fan and Owner” groups is known as the fandom dynamics of the collective consumers. We also conducted process mining analysis for the “Fan but non-owner,” “non-Fan and Owner,” and “non-Fan and non-Owner” groups.

4.4 Analyzing Fandom Dynamics

4.4.1 Dynamics of Brand A

The results of Brand A’s dynamics are shown in **Fig. 6**. Among the four groups, the “Fan and Owner” and “Fan but non-Owner” groups are fan groups of Brand A. In the fan groups, the dynamics include the keywords “Brand A” and “Company A” in the end, we highlight it as red color in **Fig. 6**. They represent the fan groups of Brand A, their dynamic consisting of the brand and company name in the final stage.

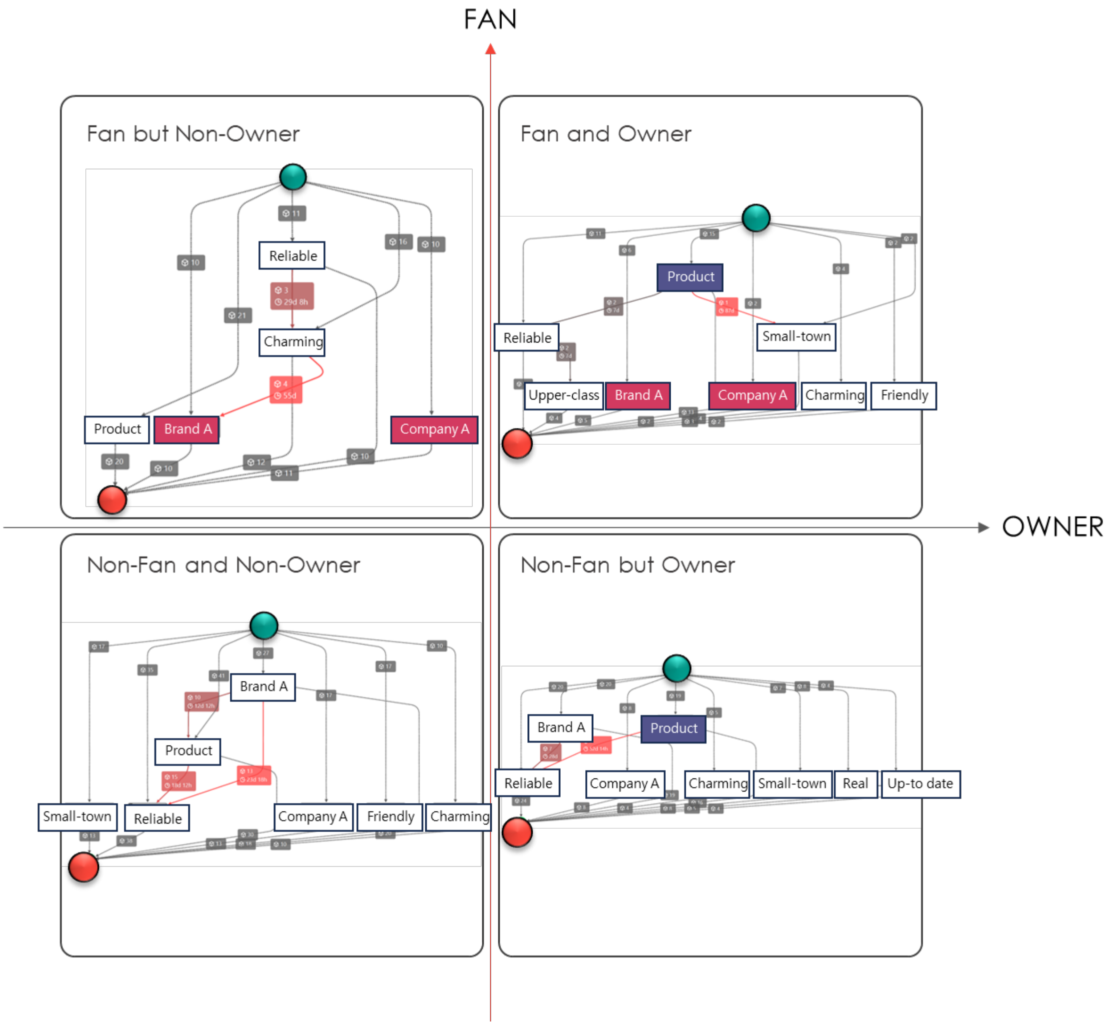

Fig. 6. The fandom dynamics of Brand A analyzed by process mining (The online community name was mapped as the case ID, the review posting date was mapped as the timestamp, and the keywords extracted from the post were mapped as the activity).

The "non-Fan but Owner" and "non-Fan and non-Owner" groups are owner groups of Brand A. In the owner groups dynamic, the keyword "product" is shown at the top of the dynamics, we highlight it as red color in **Fig. 6**. In other words, if customers discuss product related topic at the early stage of dynamics, the group is likely to become the owner group.

In addition, the group "Fan and Owner" is the most loyal fandom of Brand A. The results show that the groups who followed Brand A's products at the beginning and followed "Brand A" and "Company A" at the end of the dynamics will most likely become a fandom of Brand A. This result is a metaphor for Brand A. It can guide customers to focus on the brand's products in the early stages of marketing and increase consumers' understanding of the brand and company in the later stages. With this strategy, consumers can become fandoms of Brand A.

4.4.2 Dynamics of Brand B

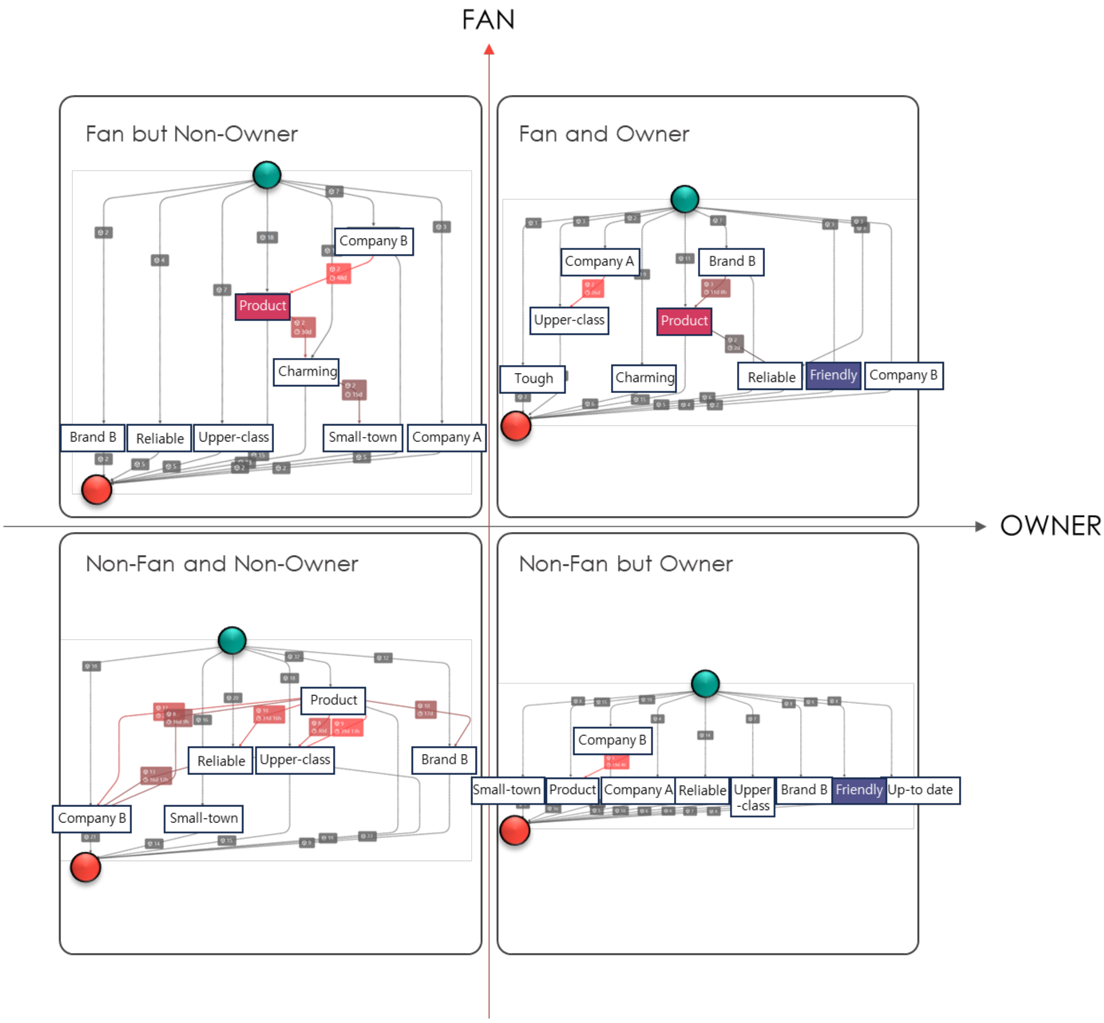

Fig. 7. The fandom dynamics of Brand B analyzed by process mining (The online community name was mapped as the Case ID, the review posting date was mapped as the timestamp, and the keywords extracted from the post were mapped as the activity).

The results of Brand B's dynamics are shown in **Fig. 7**. In the "Fan and Owner" and "Fan but non-Owner" group dynamics, the keyword "product" is in the middle of the dynamics, we highlight it as red color in **Fig. 7**. This indicates that if a brand shows keyword "product" in the middle of group dynamics, the group is likely to become a fan group.

In the "non-Fan but Owner" and "non-Fan and non-Owner" group dynamics, the keyword "friendly" is shown at the bottom of the dynamics, we highlight it as blue color in **Fig. 7**. It indicates that a group containing the "friendly" brand personality at the end of the dynamic was likely to become the brand's owner group.

Additionally, the dynamics of the "Fan and Owner" group dynamics shows "product" in the middle and "friendly" in the end. The result is a metaphor for Brand B. It can guide customers to focus on the brand's products during the middle stages of marketing. In the later stages of marketing, Brand B can lead consumers to develop a "friendly" emotional disposition toward the brand.

In summary, our proposed brand fandom dynamic analysis framework can analyze the fandom dynamics of different brands. In addition, by analyzing the fandom dynamics of brands, we can provide marketing insights related to facilitating brand fandom.

5. Conclusion

Service research relates to both individual and collective consumers. Brand fandom refers to collective consumers who are deeply attached to a brand. These dynamics indirectly or directly influence brands to change their services, products, or strategies. Owing to the development of information technology, a large amount of consumer data has become available in online communities and social media. Social network analysis and process mining allow brands to explore digital fandom dynamics to better understand brand consumers.

This study proposes a framework for exploring brand fandom dynamics in an online community. This framework consists of four stages: Preparing Data, Defining Fandom Categories, Generating Fandom Dynamics, and Analyzing Fandom Dynamics. The framework was built on social network analysis and process mining, combined with brand personality theory, to explore fandom dynamics. We conducted experiments on two home appliance brands in South Korea to verify our proposed framework. The dataset contained 14,593 posts by consumers in 374 online communities in South Korea. The results of this study show that brand fandom dynamics can be effectively explored through the proposed framework. This indicates that a combination of social network analysis and brand personality theory can identify and classify brand fandom through consumer posts in online communities. Fandom dynamics can be explored in chronological order through process mining techniques. This process demonstrates the potential of consumer-generated textual data in online communities to help brands better understand brand fandom dynamics. The proposed framework provides a digital solution for interdisciplinary research at the intersection of data-driven service design and the quantification of consumer culture.

In future work, this framework should be extended to study consumer data beyond the home appliance domain to test its applicability. Additionally, future studies could consider combining customer research tools for service design. For instance, fandom categories can contribute to the design of customer personas and fandom dynamics can contribute to customer journey mapping. Finally, fandom dynamics include many aspects, and more research needs to be conducted on other aspects.

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