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Diffusion of fashion trend information: a study on fashion image mining from various sources

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Abstract

The advancement in the internet and mobile technologies has substantially altered information diffusion in modern society, creating a diverse environment for generating and sharing various forms of information. Specifically, the emergence of new information sources, such as influencers and online communities, has significantly influenced the formation of consumer opinion. We highlight the changes that have occurred in the diffusion of fashion trend information. To do this, we conducted data mining, which involved three main steps: data preprocessing, specifically converting image data (including images from the 2022 F/W season runway collection, fashion influencer outfits, and best items from online fashion retailers) into textual data; data mining analysis (quantitative analysis); and data post-processing. As a result, we found that even items with low or no appearance on the runway held significance in the best item data or fashion influencer outfits. Specifically, the best items on online fashion retailers, reflecting popular fashion trends, had greater similarity to fashion influencer outfits. However, similarities in silhouette attributes were found among runway collections, fashion influencer outfits, and best items data. This study holds great significance because it focuses on fashion items genuinely consumed by the mainstream consumers rather than only focusing on the four major runway collections. Furthermore, these findings offer valuable insights for merchandising and trend forecasting, emphasizing the importance of selectively utilizing fashion trend information in the planning of fashion products.

Keywords: Fashion trend analysis, Data mining, Fashion image mining, Fashion influencer, Social contagion theory

Introduction

In fashion business, it is important to acquire various trend information for planning new products for the upcoming season. Until the early 2010s, the fastest way to access fashion trend information was by participating in the four major fashion weeks or large-scale international exhibitions (Pinchera & Rinallo, 2021). However, the online landscape and social media boom has enhanced the accessibility of real-time fashion information online. Even runway shows, which once had an exclusive audience, are accessible through live streaming to mass consumers (Pinchera & Rinallo, 2021). Furthermore, fashion information is generated and disseminated through various sources on the online channel, leading to the emergence of a new information source such as fashion influencers. Now, fashion influencers play a crucial role as opinion leaders in spreading information on social media platforms (Wang & Lee, 2021). These changes have generated a shift in the dissemination of fashion trend information.

Traditionally, fashion brands follow a hierarchy, and the dominant theory is that fashion trends trickle down from top- to low-tier brands (Furukawa et al., 2019; Sproles, 1981). However, in today's society, the advancement of information and communication technology and widespread social media use have enabled rapid and large-scale information dissemination. Additionally, the influence of opinion leaders (i.e., fashion influencers) on the trend information diffusion process has significantly increased. Despite the increasing diversification of sources for trend information, previous studies have focused on only one source of information and solely relied on one theory to understand the diffusion of fashion trends (Chakraborty et al., 2020; Choi et al., 2021). Therefore, this study aims to examine the dissemination flow of fashion trend by analyzing the relationships among various sources, high-end runway collections, fashion influencer outfits, and trending items on online fashion retailers.

Meanwhile, with the advancements in data analysis techniques, the fashion industry strives to mitigate the risks of intuition-based decision-making and to generate fashion trend reports by exploring and applying big data. However, previous studies have collected text-based data (i.e., consumer social data, and fashion trend reports) to analyze trends over a specified time frame (Li & Leonas, 2022; Pan et al., 2024). Though text-based analyses have been valuable, images offer a richer source of information by conveying visual data. However, research utilizing image data is less prevalent compared with studies based on textual data. Some studies have analyzed fashion trends for specific seasons based on images but faced limitations due to the reduced accuracy of image datasets (Shi et al., 2021). To fill the research gaps, the purposes of this study are investigate the diffusion of fashion trend information, quantitatively analyzing the relationships among fashion trend sources—runway collection images from the 2022 F/W season, outfits worn by fashion influencers, and best-selling items on online fashion retailers. Specifically, this study was conducted using a large dataset of images, with high accuracy.

This study provides the following theoretical and managerial contributions. First, this study's findings contribute to an increased understanding of fashion trend diffusion emerging from the combination of various factors, which assist in predicting upcoming season trends in fashion. Furthermore, the findings of this study offer insight for fashion merchandisers in using trend information for planning upcoming season products. Finally, it provides guidance for brands on how to manage and leverage fashion image data effectively.

Literature Review

Diffusion of fashion trend information in contemporary society

With the advancement of information and communication technology, runway collection, as well as various trend information, are disseminated to mass consumers through online platforms and social media. Various sources of information, including fashion influencers, contribute to the spreading the fashion trend information to the mass consumers. Therefore, in the literature review sections, we reviewed the traditional trickle-down theory, which serves as a fundamental framework for explaining the process of fashion trend diffusion, emphasizing the importance of runway collections. Additionally, we reviewed previous studies on the social contagion theory, which explains the phenomena of information diffusion in modern society, especially emphasizing the crucial role of influencers.

Trickle-down theory

Trickle-down theory described that fashion trends adopted by the upper class are imitated by lower class consumers (Furukawa et al., 2019; Mohr et al., 2022; Zhao et al., 2024). Though this theory started to explain how a new trend adopted by the "upper class" was imitated by succeeding "lower class", it was still valid to explain the spread of fashion trends in modern society. High-end brands exhibited their new products during four major fashion weeks every season and it played a significant role in creating new fashion trends that spread from the high-end market to mass volume markets (Furukawa et al., 2019). Like this context, a significant amount of previous studies explained the influence of high-end brands` runway shows of the four major fashion weeks based on the trickle-down theory referenced in analyzing and predicting fashion trends (Zhao et al., 2024).

Social contagion theory

The social contagion theory, which explains the rapid and large-scale diffusion of information in contemporary society, posits that the role of individuals in the early stages of information dissemination is crucial (Goldenberg et al., 2009; Liang, 2021; Marin et al., 2020). During the initial phases of information diffusion, success relies on adopters' extensive connections or tightly interconnected relationships (Agarwal et al., 2019; Goldenberg et al., 2009; Jegham & Bouzaabia, 2022).

The importance of high-end brands' runway collections in fashion trends is undeniable. However, with advancements in information and communication technology, social media allows anyone to become an information creator (Lang & Armstrong, 2018; Lyons, 2018; McQuarrie et al., 2013), and fashion influencers serve as opinion leaders providing fashion information to consumers (Chapple & Cownie, 2017; Tiwari et al., 2024). People are connected through online social networks, which facilitates the rapid spread of information.

Fashion trends and retailing

The success of fashion brands depends on selling products that are adopted by the mass consumers during a particular period (Jackson & Shaw, 2017). To achieve this, fashion brands often reference various trend information such as runway collections of high-end brands, successful items from past seasons, or fashion influencers` outfit (Jackson & Shaw, 2017). Thus, in this section, we reviewed previous research related with various sources of fashion trend information: runway collections of high-end brands, fashion influencers and popular items on online fashion retailers.

Runway collection of high-end brands

According to trickle-down theory, fashion brands can be categorized into a hierarchy comprising high-end, diffusion, bridge, and mass-market brands based on price and quality (Jang et al., 2022a, 2022b). Positioned at the top of this hierarchy, high-end fashion brands unveil new collections during the four major fashion weeks (Corona & Godart, 2010). These collections serve as the foundation for fashion trend reports published by trend forecasting agencies, such as the Worth Global Style Network (WGSN). Then, low-tier fashion brands use fashion trend reports to plan their products (Choi et al., 2023; Yang & Kim, 2019). However, the emergence of fast fashion in the early 2010s has diminished the influence of runway fashion shows (Pinchera & Rinallo, 2021). Fast fashion brands, such as ZARA and H&M, cater to rapidly changing consumer needs and release products frequently, not adhering to traditional seasonal cycles (Shi et al., 2021), suggesting that runway collections of high-end brands are no longer at the center of fashion trends.

Fashion influencers

Before the concept of ’fashion influencers’ emerged, up until the early 2010s, the general consumer actively adopted the fashion styles of traditional celebrities, which were conveyed through mainstream media such as fashion magazines and television. However, the dissemination of celebrity fashion to the general consumer required several intermediate channels, and it was not easy for them to quickly adopt fashion trend information in practice (Chapple & Cownie, 2017). However, with the activation of social media in the 2010s, information spread rapidly and on a large scale. According to the social contagion theory, in such information diffusion processes, the role of initial information adopters is crucial, as the general consumer gained immediate access to diverse information through ’fashion influencers’ who were similar to themselves (Agarwal et al., 2019). Thus, the way of disseminating fashion trend information has changed with the emergence of new information sources.

Popular items on online fashion retailers

The “dominant” fashion trend of a season is the fashion style that consumers adopt (Crane, 1997). Specifically, for fashion to be successful, the public must embrace it (Kim, 2013). Thus, the popular items (or items categorized as “best items” on the platform) are those that attract consumers’ attention and mirror prevailing fashion trends among the consumer group. Online shopping platforms possess data on product sales, quantities sold, product views, and consumer purchase behavior. Based on these data, they can select and manage the best items (Musinsa, 2023; Wconcept, 2022). Thus, the best items online are not only products with high sales but also outcomes encompassing various types of information. They serve as indicators of major trends during a specific period.

Meanwhile, popular cues such as “best” are widely used in shopping environments and can be considered cues of consumer interest in products (Wu & Lee, 2016). Cues such as “best items” serve as heuristics for consumers to infer product quality in online settings and significantly influence consumer purchases (Agarwal et al., 2019; Wu & Lee, 2016). They also reflect consumer behavior driven by the desire to avoid falling behind trends in a rapidly changing modern society (Choi et al., 2021). Consequently, "best items" on online fashion retailers are information sources that provide consumers with insights into "dominant" fashion trends.

Quantitative approach to fashion trend analysis

A quantitative approach to fashion trends is useful for investigating specific patterns by quantifying the frequency of fashion-specific attribute values in large volumes of fashion trend information. Furthermore, there is an advantage in quantifying various factors that may influence the diffusion of fashion trends (Getman et al., 2021; Zhao et al., 2024). To process data in a specific field, it is essential to define 'attributes' and their corresponding 'attribute values' based on the domain knowledge of that field. 'Attribute value' is a term with specific characteristics, and the attribute represents the characteristics of the values.

The field of fashion places significant importance on images. However, academic research lacks studies that quantitatively transform fashion images into data for trend analysis. Analyzing a vast amount of fashion images requires the conversion of image data into text, necessitating prior learning for computers to recognize and tag attribute values associated with the images (Gu et al., 2020; Klostermann et al., 2018). Specifically, to enhance research accuracy, a large dataset tagged with fashion-specific attribute values is required. However, constructing an image dataset based on a consistent classification system poses significant challenges (Seo & Shin, 2018). While Shi et al. (2021) utilized fashion images for trend analysis, it faced limitations due to the lower accuracy of the dataset used. Therefore, this study aims to construct a high accuracy image dataset to quantitatively investigate the diffusion of fashion trends.

Study objective and research questions

This study explores the diffusion of fashion trend information by analyzing relationships among images from various sources, including high-end runway collections, fashion influencer outfits, and best items on online fashion retailers. These relationships are analyzed based on item and silhouette attributes. More specifically, this study addresses the following research questions:

[RQ 1] Investigate the distribution of item attribute values for the 2022 F/W season, focusing on the images of runway collections, fashion influencer outfits, and best items on online fashion retailers.

[RQ 2] Investigate the distribution of item and silhouette attribute values for the 2022 F/W season using association analysis, focusing on images from runway collections, fashion influencer outfits, and best items on online fashion retailers.

[RQ 3] Investigate the effect of fashion influencers' outfits during the 2022 F/W season on the formation of best-selling items on online fashion retailers.

Methods

Data collection

We collected images of the runway collections of the 2022 F/W season, outfits worn by Korean fashion influencers, and best items on Korean online fashion retailers. Because of the time difference between the release of runway collections and when they are adopted and worn by fashion influencers and consumers, we considered the following three datasets for analyzing the diffusion of fashion trend information. Furthermore, considering the substantial impact of Korean television programs on the increased interest in K-Fashion industries (Jang et al., 2021; Kim & Choo, 2023) and the active global engagement of consumers with K-fashion (Xu et al., 2016), we deemed it necessary to investigate Korean influencers and fashion platforms.

Collecting images of the runway collection of high-end brands

First, we collected WGSN's trend reports for the 2022 pre-fall and F/W seasons. A total 17 reports for the pre-fall season and 40 reports for the F/W season, published between January and April 2022, were collected. Next, for both seasons, we extracted the fashion brands mentioned in the trend reports through text mining. WGSN is recognized as the world's largest fashion trend information company and a global fashion trend research institution (Dubreuil & Lu, 2020; Shi et al., 2021). Therefore, it is considered a suitable source of information for analyzing fashion trends appearing in runway collections for specific seasons. Subsequently, we collected lookbooks or runway collection images of the nine most frequently mentioned brands in each season's trend reports. As this study focused only on women's fashion, men's clothing was excluded. Table 1 presents the selected brands, frequency of their mention, and number of images used.

Collecting images of the outfits of fashion influencers

Before collecting the images, we selected the fashion influencers. We asked 43 female Instagram users aged between 20 and 30 years to provide a list of their favorite Korean fashion influencers. We obtained 243 influencer accounts, among which we selected 9 accounts with the highest number of followers and collected their posts from August 2022 to February 2023 (Table 2). All selected Korean fashion influencers had a follower count exceeding 50 K (where K represents thousand). They actively participated in various events organized by global fashion brands and collaborated with several Korean fashion brands. In other words, these influencers not only engaged in partnerships with

Table 1 Selected High-End Brands and the Number of Images Collected

2022 Pre-fall			2022 F/W		
Brand	**Frequency**	**Number of images**	**Brand**	**Frequency**	**Number of images**
Jil Sander	45	51	Jil Sander	12	60
Stella McCartney	31	35	Louis Vuitton	12	47
MSGM	23	28	Stella McCartney	12	42
Burberry	20	37	Miu Miu	11	48
Dsquared2	20	66	Prada	10	54
Tory Burch	20	23	Versace	10	59
Ulla Johnson	20	33	Chloé	8	38
Versace	18	28	Dior	8	83
Chloé	17	17	Diesel	7	41
Total	318		Total	472	

'Frequency' refers to the number of times the brand was mentioned in the collected trend reports. 'Number of images' indicates the count of images of the brand's runway collection

Table 2 Selected fashion influencer accounts and the number of posts collected

Account	Number of followers	Number of collected images	Number of collected fashion images
01	147 k	100,9	167
02	118 k	159	30
03	87.9 k	359	46
04	82.8 k	139	17
05	73.9 k	840	207
06	67.6 k	541	69
07	57 k	91	17
08	54.1 k	160,4	219
09	50.9 k	186	57
Total		492,8	829

K denotes thousand

diverse fashion entities but also wielded influence over Korean fashion consumers (Kim, 2021). We selected posts from August 2022 because runway collections of the 2022 F/W season were released in the market at that time. Among the collected images, we shortlisted only those in which the influencer's outfit was visible. If an influencer posted the same outfit multiple times, only one representative photo was used for analysis.

Collecting images of the best items on online fashion retailers

We collected representative images (i.e., thumbnails) of the top 20 weekly best items, which are the popular items in women's clothing, from two of Korea's largest online fashion retailers: Musinsa (www.musinsa.com) and W Concept (www.wconcept.co.kr). As this study focused on the 2022 F/W season, we used the images collected between September 1, 2022, and February 27, 2023. In cases requiring additional analysis, we selectively utilized data that fell within the required timeframe.

Selecting an image classification system and preprocessing image data

We converted image data into textual data by defining item and silhouette attributes based on the "fashion dictionary" (Jang et al., 2022a), also known as a fashion thesaurus and taxonomy. The "fashion dictionary" is a classification system that primarily focuses on key attributes commonly used to describe the characteristics of fashion products (e.g., item, silhouette, style, detail, pattern and print, color, and material) and encompasses 1,956 representative terms. Table 3 presents some examples of the attribute values of the items and silhouettes included in the fashion corpus dictionary.

Initially, we employed a commercial AI-based clothing image-tagging program (Omnious tagging AI) that is widely used in Korea to tag item and silhouette attribute values of clothing products in the images. The AI solution used in this study has an accuracy of 95%. Then, we reviewed and modified the attribute values tagged by the AI program. Although the AI solution demonstrates high accuracy, it failed to recognize the accurate item & silhouette attribute values when the top (including outerwear) and bottom were coordinated in the same color. In such cases, the researcher modified the tagged values. Finally, another researcher with more than a decade of experience in fashion design reviewed the process (Table 4).

Table 3 Examples of Item and Silhouette Attribute Values

Attribute	Value
Item	balmacaan coat, bomber jacket, cape, cardigan, double-breasted jacket, denim jacket, blouson, double-breasted coat, duffle coat, fur coat, leather jacket, long puffer, mustang jacket, puffer, shearling coat, sherpa, short puffer, single-breasted coat, single-breasted jacket, trench coat, tweed jacket, varsity jacket, vest, zip-up hoodie, etc
Silhouette	- Lenghth: short, midi, half, long, maxi - Sleeve length: sleeveless, short sleeve, three-quarter sleeve, long sleeve - Fit: oversize fit, regular-fit, skinny-fit, slim-fit - Neckline/collar: lip-collar, mock-neck, notched lapel, napoleon lapel, reefer-collar, round-neck, etc - Sleeve shape: straight sleeve, raglan sleeve, puff sleeve, etc - Shoulder type: angular shoulder, drop shoulder, etc - Shape: A-line, hourglass shape, straight shape, etc

Table 4 Examples of Image Tagging

Attribute	Value	
Item	Outwear	Leather jacket
Silhouette	Outwear length	Midi
	Sleeve length	Long sleeve
	Fit	Oversize fit
	Neckline/collar	Reefer-collar
	Sleeve shape	Straight sleeve
	Shoulder type	Angular shoulder
	Shape	Straight shape

This image was created using generative AI (Bing Image Creator), based on the original image

Data analysis

After completing all data preprocessing, we conducted data mining based on the knowledge discovery process shown in Fig. 1. To analysis the preprocessed data, the Pandas library in Python was used to analyze the frequency of attribute values. To calculate the mean absolute error (MAE) values, we used both SPSS 25.0 and Python programs. For association rule analysis, we used the MLxtend library in Python. After that, researchers interpreted the data qualitatively, which is a part of data postprocessing.

Results

First, we examined which item appeared most frequently in the data of the runway collection, fashion influencer outfits, and best items (Table 5). Outerwear appeared most frequently in all three datasets. Moreover, the fashion industry considers the revenue of the F/W season crucial, with outwear notably boosting the revenue during the F/W

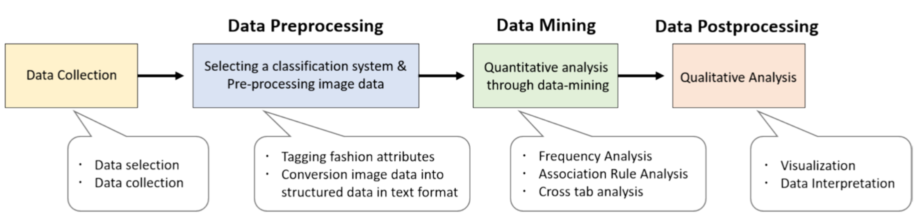

Fig. 1 Research Procedure Based on the Knowledge Discovery Process of Data Mining (Tan et al., 2020. p. 4)

Table 5 Composition of items in each dataset

	Runway Frequency (%)	Fashion influencers Frequency (%)	Best items Frequency (%)
Dress	236 (20.2%)	42 (4.78%)	17 (4.3%)
Top	173 (14.8%)	215 (24.46%)	85 (21.4%)
Skirt	190 (16.2%)	98 (11.15%)	3 (0.8%)
Outwear	397 (34.0%)	286 (32.54%)	267 (67.1%)
Pants	163 (13.9%)	196 (22.30%)	25 (6.3%)
Overalls/jumpsuit	10 (0.9%)	42 (4.78%)	1 (0.3%)
Total	1169 (100%)	879 (100%)	398 (100%)

'Runway' refers to collections from high-end brands, 'influencers' refers to influencers' outfits, and 'best items' indicates the popular items listed on the online fashion retailer

season (Cho, 2024; Ryu, 2022). Therefore, we focused our analysis on outerwear, which constituted the largest portion of the F/W season data.

Distribution of item attribute values in the runway collection, fashion influencer outfits, and best item datasets

We extracted the attribute values of outerwear and their appearance frequency and percentage from the runway collections, fashion influencer outfits, and best items datasets. Table 6 presents the results. Using SPSS 25.0, we performed a chi-square test and determined that the appearance frequency of the extracted attribute values differed significantly among the three datasets ($p = 0.000$).

Runway collections intend to showcase various products and styles, leading to the emergence of diverse item attributes. Thus, runway collections typically include a more diverse range of items than those in fashion influencers' outfits and best items on online fashion retailers. Though general consumers are exposed to these various products and styles, they tend to focus on certain item attributes. Specifically, certain item attribute values (vests, capes, and bomber jackets) were unique to runway collections, while others (short puffers, tweed jackets, varsity jackets, and duffle coats) rarely appeared in runway collections but appeared relatively frequently in fashion influencer outfits or best items.

We examined the similarity between item attribute values in the runway collection, influencer outfits, and best item datasets by calculating the MAE. MAE refers to the mean of all absolute errors; here, error means to the difference between the predicted and actual values. MAE is commonly used in machine learning to evaluate prediction accuracy, where smaller MAE values suggest a closer resemblance between predicted and actual data (Willmott et al., 2005). In this study, we assumed the frequency of item values in the runway data and fashion influencer data as predicted values, and the frequency of values in the best item data as actual values. We then calculated the MAE values between runway collections and best items, and between fashion influencers and best items, in order to compare the similarity between datasets. Using SPSS 25.0, we standardized the appearance frequency of the attribute values of outerwear items and computed the MAE values. The MAE was 1.01 between the best item data and runway data and 0.48 between the best item data and influencer outfits data. From these results,

Table 6 Frequency and proportion of outerwear attribute values in each dataset

	Runway		Fashion influencers		Best item	
	Frequency	%	Frequency	%	Frequency	%
Single-breasted jacket	74	18.6	42	14.7	20	7.5
Single-breasted coat	41	10.3	11	3.9	13	4.9
Leather jacket	36	9.1	17	5.9	10	3.7
Double-breasted coat	29	7.3	6	2.1	8	3.0
Blouson	18	4.5	23	7.7	13	4.9
Denim jacket	18	4.5	3	1.2	0	0.0
Mustang jacket	17	4.3	8	2.8	5	1.9
Cape	17	4.3	0	0.0	0	0.0
Trench coat	15	3.8	5	1.8	2	0.7
Double-breasted jacket	14	3.5	5	1.8	0	0.0
Bomber jacket	14	3.5	0	0	0	0.0
Fur coat	12	3.0	6	2.1	1	0.4
Tweed jacket	12	3.0	24	8.4	19	7.1
Vest	10	2.5	0	0	0	0.0
Shearling coat	10	2.5	9	3.2	8	3.0
Puffer	5	1.3	8	2.8	15	5.6
Short puffer	3	0.8	29	9.4	48	18.0
Long puffer	3	0.8	1	0.35	7	2.6
Balmacaan coat	2	0.5	17	5.9	20	7.5
Duffle coat	1	0.3	6	2.3	9	3.4
Varsity jacket	0	0.0	8	2.8	7	2.6
Other	44	11.6	58	20.8	62	23.3
Total	397	100.0	286	100.0	267	100.0

Note: 'Runway' refers to collections from high-end brands, 'influencers' refers to influencers' outfits, and 'best items' indicates the popular items listed on the online fashion retailer

it can be inferred that outerwear items featured in the best item data are more similar to those featured in influencer outfits than those in runway collections.

Analysis the distribution of silhouette attribute values in runway collections, fashion influencer outfits, and best item data

For RQ 2, we analyzed the association rules among the runway collection, fashion influencer outfits, and best item datasets. Association rule analysis, commonly known as market basket analysis, is used to discover relations between attribute values within datasets (Tan et al., 2020). An association rule has two parts: an antecedent (if) and a consequent (then), identifying the relationships between the data (Tan et al., 2020). Antecedents and consequents, unlike independent and dependent variables, are not determined by the researcher but are automatically identified by the algorithms used for association analysis in Python. Furthermore, if there are common association rules across datasets, it can be interpreted as indicating similarity between the datasets (Anwar et al., 2012). Typically, support, confidence, and lift value are the measures used for determining association rules.

The threshold values for support and confidence are adjusted according to the data to determine whether significant rules exist. If no rules are found, lower values for support and confidence can be used. Conversely, if rules are found, support and confidence

Table 7 Common association rules in the runway, influencers outfit and best item dataset

Rule	Antecedents	Consequents	Support	Confidence	Lift
1	straight shape, drop shoulder	oversize fit	0.17	0.83	1.61
2	straight shape, oversize fit	midi	0.16	0.54	1.08
3	midi, drop shoulder	oversize fit	0.15	0.81	1.57
4	midi, regular fit	straight shape	0.14	0.72	1.24
5	angular shoulder, regular fit	straight shape	0.14	0.82	1.41

Note: The support, confidence, and lift values are reported based on the data derived from fashion influencers' outfit data. Antecedent (if) refers to the condition that precedes the consequent in an association rule, and consequent (then) refers to the outcome that follows the antecedent in an association rule

Table 8 Common association rules in the runway and influencers dataset

Rule	Antecedents	Consequents	Support	Confidence	Lift
1	Angular shoulder, midi	Straight shape	0.14	0.83	1.43
2	Straight shape, notched lapel	Angular shoulder	0.12	0.85	1.69
3	Angular shoulder, midi	Notched lapel	0.12	0.72	3.76
4	Single-breasted jacket	Midi, angular shoulder	0.12	0.79	4.78
5	Single-breasted jacket, midi	Notched lapel	0.11	0.82	4.27
6	Straight shape, notched lapel	Midi	0.11	0.78	2.92
7	Single-breasted jacket, angular shoulder	Notched lapel	0.10	0.83	4.33

Note: The support, confidence, and lift values are reported based on the data derived from fashion influencers' outfit data; Antecedent (if) refers to the condition that precedes the consequent in an association rule, and consequent (then) refers to the outcome that follows the antecedent in an association rule

values can be increased to discover meaningful rules (Ünvan, 2021). However, when it comes to lift, values less than one generally indicate rules that may have occurred by chance and are considered nonsignificant (Miller, 2014). We extracted association rules for item and silhouette attribute values in each of the three datasets using a minimum support of 0.1 and minimum confidence of 0.5 as thresholds. After removing duplicate rules, 21 rules including three or more attribute values were found in the runway collection data, 13 in the fashion influencer outfit data, and 13 in the best item data (Appendix 1, 2, and 3).

We found five association rules common across all datasets (Table 7). This result shows that similarities were observed among the three datasets, particularly in the combinations of silhouette values. It can be inferred that that similarities exist in the item and silhouette attributes that appear in the runway collection, fashion influencer outfits, and best item datasets. Furthermore, this result suggests that while the types of items (i.e., item values) the mass consumers adopted may resemble those by fashion influencers, silhouette attributes from runway collections garnered attention from both fashion influencers and consumers.

Among the association rules extracted from fashion influencer outfits, seven were found to be common between runway collections and fashion influencer outfits (but not best items) (Table 8). These rules primarily pertained to formal jackets and coats. According to WGSN's trend report for the 2022 F/W season, comfortable and oversized styles have continued to be on-trend; however, formal outerwear has also emerged as a major trend. Fashion influencers adopted this trend before the consumers, which explained why silhouette association rules resembling formal outerwear and including single-breasted jackets were extracted with high support from the fashion influencer outfit dataset. In contrast, only one association rule {(short, straight shape), (regular fit)} was found to be common between both the best item and fashion influencer outfit datasets (not runway collections). This rule predominantly corresponds to the silhouette pattern of tweed jackets, which rarely appeared in runway collections but frequently appeared in best items and fashion influencer outfits. This explains why the rule {(short, straight shape), (regular fit)} was extracted from the best item and fashion influencer outfit datasets.

Analysis of the Impact of Fashion Influencers' Outfits on the Formation of Best Items

For RQ 3, we focused on item values that showed an increase in the best item data since 2020. To select continuously increasing item values, we considered the best item values from the 2020 dataset (Appendix 4). Based on the best item data since 2020, we have selected six items that have been consistently increasing: short puffers, balmacaan coats, tweed jackets, duffle coats, varsity jackets, and blousons. To identify the impact of influencers on mainstream consumers during the 2022 F/W season, we believe it is necessary to examine the data from August 2022. Thus, we derived the monthly data of fashion influencer outfits and best items between August 2022 and February 2023 (Table 9) and identified patterns (trends) in the appearance percentage of outerwear attribute values (Fig. 2).

Consequently, the impact of fashion influencers on mainstream consumers can be categorized into two types. First, items that not only highly appeared in fashion influencers` outfit but frequently appeared in best item since 2020 (e.g., short puffers, tweed jackets, and balmacaan coats), implying that these items were trending before the 2022

Table 9 Frequency of outerwear appearances per month

	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Influencer	13	41	42	56	57	34	43
Best item	50	54	46	54	43	36	34

Fig. 2 Changes in the appearance proportion of item values. 'Influencers' refers to influencers' outfits, and 'Best' to best items which means popular items listed on the online fashion retailer

F/W season, were already familiar to consumers through various online communities, platforms, and social media. According to Fig. 2, the graphs of short puffer, tweed jacket, and balmacaan coat indicate that these items initially emerged as popular choices among mainstream consumers. Fashion influencers may not play a role in exposing these products early in the season, but they do 'reinforce' the choice of mainstream consumers. They not only reflect the preferences of the mass consumers in their postings but also reinforce the choices made by mainstream consumers. Second, contrastingly, items frequently appeared in the fashion influencers' outfits but appeared only from 2022 in the best items (e.g., duffle coats, varsity jackets, and blousons), were primarily led by fashion influencers. Fashion influencers played a significant role in promoting items that had relatively limited exposure to mass consumers beforehand. Mass consumers appeared to follow the choices of influencers, as depicted in Fig. 2.

Varsity jackets and duffle coats, in particular, had appeared only in men's runway collections since the 2021 F/W season but were highlighted as key items in trend reports. After they were promoted by fashion influencers, their appearance frequency increased in the best item data. This suggested that, through their re-interpretation of runway collection items and exposure to consumers, fashion influencers contributed toward disseminating these items in mainstream fashion and played a significant role in shaping popular fashion trends for items that were not widely exposed to consumers.

Discussion

This study obtained several insightful results. Regarding RQ 1, this research found little association between the item attribute values appearing in runway collections and those appearing in the best items. This was because various item attribute values did not appear or barely appeared in runway collections but appeared frequently in the best items or fashion influencer outfits. Moreover, we observed that the best items on online fashion retailers were more similar to fashion influencer outfits. However, this research identified that similarities still existed in the silhouette attribute values of outerwear items appearing in runway collections, fashion influencer outfits, and the best items, as identified through RQ2. Finally, regarding RQ3, this research identified that fashion influencer outfits had an impact on the best items listed on online fashion retailers, especially items that had little exposure to consumers in the past. In other words, some items featured in influencers' outfits preceded the best items, indicating that influencers lead the trend. The discussion regarding specific results is as follows.

First, we confirm that the theory of social contagion can be adopted to explain the spread of fashion trends, which posits that successful information dissemination occurs when initial information adopters have many connections with others or when their relationships are close (Goldenberg et al., 2009; Liang, 2021; Marin et al., 2020). In this study, the item attribute values that appeared in fashion influencer outfits, which were based on interactions with consumers on social media and rooted in close relationships, were similar to the item attributes the consumers adopted. Moreover, through RQ 3, we confirm that fashion influencers contribute toward popularizing items that had little exposure to consumers in the past. These findings highlight the importance of initial information adopters, corresponding to the social contagion theory.

Second, our finding for RQ 2 indicates that silhouette trends from runway collections are reflected in fashion influencer outfits and mainstream fashion trends. As runway collections are revealed approximately six months before the selling season, it can be explained that fashion influencers' outfits and items sold on online fashion retailers are influenced by runway collections. While some exaggeration may exist in the degree of silhouette, we can still infer that the overall silhouette trends will be similar, with overall silhouette attributes stemming from runway collections. These results demonstrate the effectiveness of the trickle-down theory (Zhao et al., 2024), especially in the context of silhouette attributes.

Ultimately, considering our findings for RQs 1, 2, and 3, it can be concluded that the diffusion of fashion trends in modern society cannot be explained solely by one theory, indicating that information is dynamically spreading. Furthermore, considering the abundance of information available online (Silva et al., 2024), retailers and merchandisers need to make an effort to selectively identify the specific trend information to utilize, and the results of this study may be beneficial in this regard. Though there are some arguments that runway collections of high-end brands are no longer at the center of fashion trends (Pinchera & Rinallo, 2021), it is evident that some clothing attributes in the runway collection dataset particularly attracted the mainstream consumers` attention.

Consequently, our results propose how fashion merchandisers can effectively leverage trend information in developing new products and suggest precisely which information to utilize. Item attribute values in the best item dataset were more similar to those appearing in fashion influencer outfits than to the major item attribute values in runway collections. Moreover, for item attribute values that had not been widely exposed to the public, the influence of fashion influencers was considerably strong. In contrast, silhouette trends were influenced by runway collections. While the types of items (item attribute values) appearing in runway collections differed from those appearing in the best items and fashion influencer outfits, the overall form of the silhouette remained similar. However, not all trend information reflected in runway collections is crucial. Thus, fashion brands should selectively incorporate fashion trend information in planning their products.

Conclusions

In the era of social media, where a vast amount of information is distributed, this research provides insights into how fashion merchandisers and designers can efficiently use trend information. The theoretical and managerial contributions, along with suggestions for future research that could address the limitations of this study, are as follows.

Theoretical and managerial contribution

This study explains how fashion trend information diffuses across different attributes of clothing products and makes several important contributions. First, it contributes to the field of fashion trends by examining how fashion trend information spreads, integrating crucial sources of fashion trend data, such as images of runway collections of high-end brands and best-selling items on online fashion retailers. Additionally, it considers an emerging source of fashion trend information: fashion influencers. It provides insights that enable the prediction of upcoming season trends by analyzing the patterns of fashion trend diffusion, considering various factors influencing fashion trend formation. Second, this study holds significance for its methodology. Using data mining techniques, it quantitatively analyzes the spread of fashion trends, eliminating researcher subjectivity and yielding more objective results. Finally, the findings provide concrete insight into the utilization of fashion trend information by fashion merchandisers. They emphasize the importance of selectively using fashion trend information when planning products. More specifically, they confirm the significance of silhouette attributes appearing in runway collections, suggesting their applicability to fashion merchandising.

Limitations and future research

This study had several limitations. First, it focused solely on outerwear. Future studies should explore the diffusion and adoption of trends in other item categories, such as dresses, pants, and skirts. It would be interesting to compare and analyze how trends diffuse across different item categories. Second, it focused on Korean fashion influencers and the best items on online Korean fashion platforms. Although K-fashion exerts global influence, fashion trends can vary by region (Getman et al., 2021), and the degree to which consumers are influenced by fashion influencers or respond sensitively to new fashion trends may differ based on cultural contexts (Kao et al., 2021). Therefore, future studies should comparatively analyze how fashion trends propagate not only in Korea but also where the four major fashion weeks occur. This will provide a broader understanding of trend diffusion. Lastly, there are limitations in that there are various types of fashion influencers but the research proceeded without making such distinctions. In future studies, it would be meaningful to examine the roles of each influencer in the dissemination of fashion trends by further refining the categorization of influencer types.

Abbreviations

WGSN Worth Global Style Network
MAE Mean absolute error

Supplementary Information

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Supplementary Material 1.

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Author contributions

WC designed the study and developed the theoretical framework, and analyzed the data, and wrote the manuscript. YL guided the development of the theoretical background, results, and conclusion, and revised the manuscript. SJ and WC collected data. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and analyzed during the current study are available from the first author on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Competing interests
The authors declare that they have no competing interests.

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