FEDERAL STATE EDUCATIONAL INSTITUTION
OF HIGHER EDUCATION
NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Saint Petersburg School of Economics and Management

Polovnikova Anna, Pidkova Anastasiia, Syropyatov Vladimir

THE SEMANTIC BRAND SCORE: EVIDENCE FROM FASHION RETAIL INDUSTRY

Master's thesis

In the field 38.04.02 'Management'
Educational programme 'MANAGEMENT AND ANALYTICS FOR BUSINESS'

Supervisor
Position, degree
E. A. Antipov

Consultant
Position, degree
Initials last name

Saint Petersburg 2021

Abstract

Co-creation of the brand is an extensively studied concept that still lacks the diversity of methodological approaches. This research paper examines the Semantic Brand Score in the fashion retail industry to illustrate the core role of the fashion magazines in the creation of the fashion brands value and the role of text data in measuring brand importance communicated by these fashion magazines. The Semantic Brand Score is used alongside the Semantic Network Analysis to process 2018-2020 articles collected from the two categories of publishers: established magazines and independent magazines. A total of 35,091 observations have been collected for this purpose. Seven dimensions are examined within the final dataset - title, author, text, date, source, type. 15 fashion brands in 3 categories have been analyzed: luxury, high-street, sportswear. It has been revealed that for both types of magazines, luxury brands get the highest cumulative relative SBS score. Additionally, a thorough analysis has shown that luxury brands gain more attention from fashion magazines than other brands. However, it cannot be concluded that brand importance is closely related to the sentiment of the content produced by co-creators.

Content

Introduction

Brand management is a common practice in any industry, including fashion retail, where brand building and promotional activities are the key instruments for reaching brand prosperity. Fashion retail companies generate and spend their resources to build stronger brands, and it is not always explicit that the owners of the companies are not the only contributors to brand equity.

If we take a closer look at the brand equity building, we will discover that it is defined as an 'added value' and can be viewed from different perspectives (firm perspective, consumer perspective, trade perspective) (Aaker, 2009). This instantly makes us think about the variety of stakeholders involved in the value generation process of a single brand. In earlier studies, it has been clearly stated that all stakeholders and not only consumers and marketers are being researched by contemporary scholars (Hatch & Schultz, 2010). Hence, we can conclude that to build a strong foundation for further research it is essential to map all possible co-creators and build the more sophisticated classifications atop.

The motivation behind the current master thesis can be expressed with 3 main research questions.

1. *Who are the main co-creators of a fashion retail bran*d?

Once a brand has defined its co-creators, it is logical to assume that the brand will attempt to manage its co-creators effectively. That is, to maintain strong brand equity from all perspectives in the world of big data, it is essential to be aware of what value is communicated by the brand co-creators. Is it as bearable as it sounds? Huge volumes of different types of data related to the brands are generated every second, and brand equity is constantly at risk. Thus, we have come to our second, and by far the most important research question:

2. *How to measure the contribution of co-creators into a fashion retail brand equity?*

A thorough literature analysis has demonstrated that all concepts included in this paper have been studied previously, however, the following research gap has been identified: the contribution of fashion magazines in the brand value co-creation process is not clarified yet as well as the approaches to measure brand importance in the established and independent fashion magazines.

Finally, to make sure that the separate research of the co-creators' contribution into a fashion retail brand is supposed to produce different results, we define our last research question:

3. *Is there a difference in co-creators' contribution to a fashion retail brand equity?*

The following list of objectives has been designed:

- To pick fashion retail brands of interest for further analysis
- To collect a sample of fashion retail brands' co-creators of interest for further analysis
- To collect text data generated by the chosen co-creators of the fashion retail brands
- To apply Semantic Brand Score Measurement to the collected text data
- To apply Semantic Network Analysis to the collected text data
- To demonstrate and interpret the results obtained and provide sufficient feedback on further research and managerial application of the current approach.

This study is an attempt to illustrate the Semantic Brand Score measurement and Semantic Network Analysis as the tools to measure brand equity in the fashion retail industry. The purpose of the master thesis is to examine fashion brands' importance communicated by the fashion magazines using semantic brand score methodology. Both researchers and brand managers may benefit from the research procedure description and research results presentation.

The introduction part is followed by 5 master thesis components:

1. An extensive literature review.
2. Research methodology and conceptualization.
3. Results presentation.
4. Discussion of acquired results.
5. Conclusion covering further research suggestions and managerial application.

The thesis consists of 68 pages in the thesis (without appendices) and refers to 73 cited sources.

1. Literature review

The research questions stated in this paper predefined the keywords that were utilized for the literature review, e.g. semantic analysis, semantic brand score, brand importance, brand equity, co-creation, social network analysis, brand management. These keywords and other terms that will be frequently used in the current paper were summarized in Table 1.

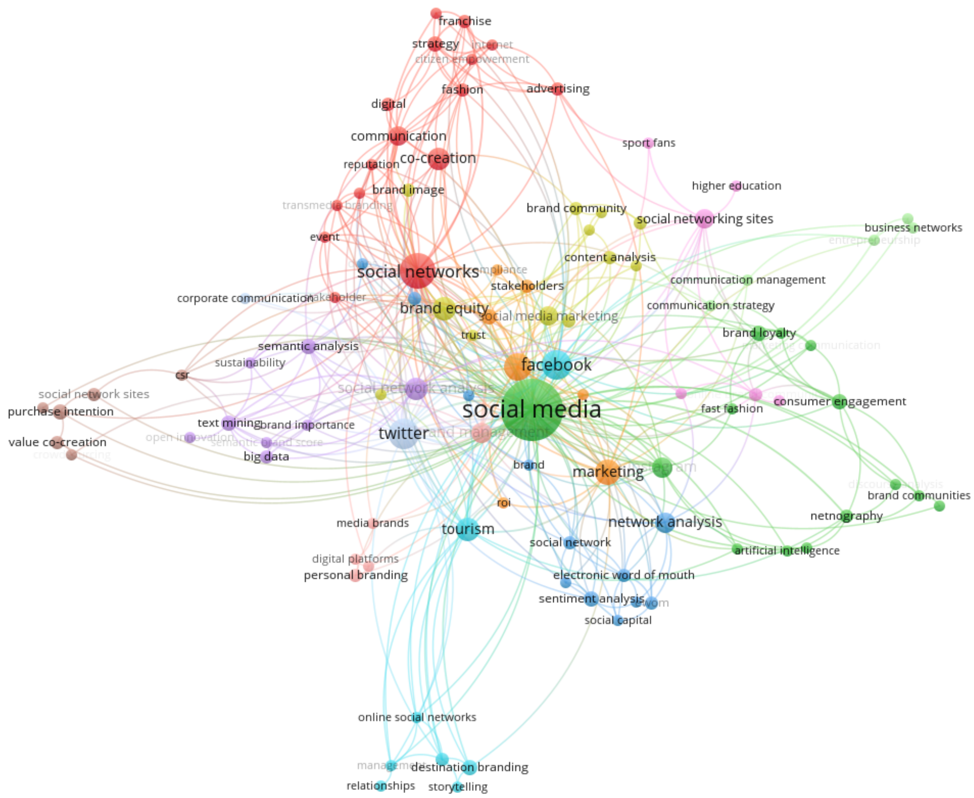
Table 1. Working definitions

Term	**Author, year**	**Definition**
Semantic analysis	Doerfel, 1998	The identification of relationships between words in the text, based on their meaningful combinations, instead of the frequency of their co-occurrence
Semantic brand score	Fronzetti Colladone, 2018	The extensive methodology that can be used to measure the importance of a brand using big data technologies
Prevalence	Fronzetti Colladone, 2018	The relative frequency of a particular word mentions in the text
Connectivity	Fronzetti Colladone, 2018	The variety of words that co-occur with a specific word or brand
Diversity	Fronzetti Colladone, 2018	The frequency of a word occurrence between all other word pairs
Brand equity	Keller, 1993	The set of marketing effects that differentiate the performance of branded products from the one that does not possess the concrete brand name
Brand value co-creation	Prahalad & Ramaswamy, 2004	The process of building brand value by multiple stakeholders
Social network analysis	Serrat, 2017	The type of network analysis that is designed to reveal connections between nodes and identify potential insights regarding these nodes

Web of Science repository was utilized to collect the papers with the aforementioned keywords, from the retrieved set of the publication the networks were built with the help of Vosviewer software to construct and visualize bibliometric and keywords networks.

The network of the author`s keywords for the most recent 188 publications related to the topic of the master thesis is depicted in Fig. 1. From the network, we can see that the biggest nodes are “social media”, “social network”, “Facebook” and “Twitter”, which can be explained by numerous researches of electronic word-of-mouth (Guerreiro & Loureiro, 2020) and social media engagement (Alarcón & Segarra-Saavedra, 2020).

Figure 1. Network of author`s keywords



“Value co-creation” node is strongly linked to the “social media” and “purchase intention”, which predefines the gap between other co-creators that are not directly represented in social media channels.

In the process of literature review, 73 papers were thoroughly studied. Their distribution by theme, year, and research design is presented in Figure 2.

Based on the network of the most cited authors for the period of 2010-2021 in the keywords related to the data analysis approaches chosen (Fig. 3) we can see that the most central node is Trevor Darrell, who is one of the most influential researchers of the semantic segmentation (Girschik, et al., 2021). Noticeably, there is one clear spider web of citation between two authors Yunchao Wei (Wei, et al., 2017) and Ming-Ming Cheng (Yang, et al., 2017) without any strong linking to the big component, this could be explained by the dedication of their works to computer vision. Overall, in the case of building a country's network of citations, we can see that China and the USA are the leaders in the field of popular works on semantic analysis.

Figure 2. Literature review distribution

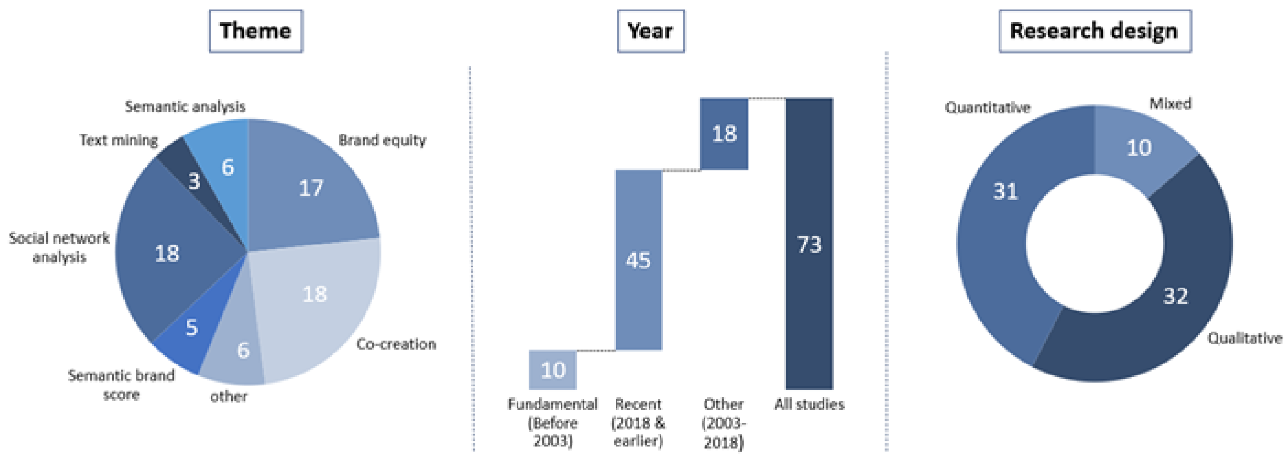
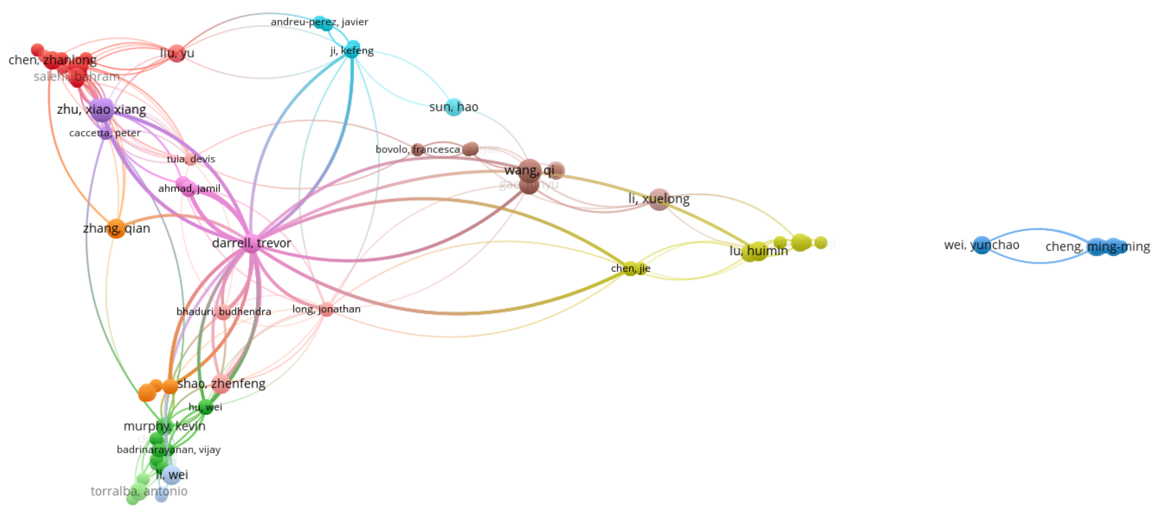


Figure 3. Network of the citations among the most referred works in the social network area



A lot of related publications were focused on computer vision, which is beyond the scope of this paper and cannot be utilized directly in the assessment of the brand importance.

Overall, after studying the statistical data of the related publication, the focus shift towards electronic word-of-mouth research based on social media data and division of the network analysis into computer vision fields and all other applications of this analysis were defined.

1.1 Co-creation branding studies.

Conceptually co-creation was aroused to oppose the paradigm of "company think" way of product establishment (Prahalad & Ramaswamy, 2004). The fundamental paper by Prahalad & Ramaswamy (2004) discussed in detail and reinforced with examples such concepts as co-creation of value and 4 building blocks of co-creation (DART):

- dialogue;
- access;
- risk assessment;
- transparency.

The results of the study showed a strong positive relationship between investments in co-creation and brand value growth. These results were the impetus for the concept to attract a lot of attention and move it outside the initial study area. The concept became actively used in the areas of marketing and consequently branding. Numerous recent brand value co-creation studies are built based on this concept (Khajeheian & Ebrahimi, 2020; Cheung et al., 2020; Tajvidi et al., 2018; etc.).

The scope of brand co-creation is not limited to a specific industry, as brands exist in all industries. For instance, González-Mansilla, Berenguer-Contri & Serra-Cantallops (2019) studied the impact of co-creators such as consumers on brand equity formation in the hotel industry. These authors once again confirmed a direct positive connection between brand equity and the satisfaction of customers.

Iglesias et al. (2020) considered the co-creation of brand identity among business-to-business (B2B) corporate brands and concluded that B2B brand identity creation is a process that involves the interaction of several internal and external co-creators in communicating, internalizing, contesting, and elucidating performances.

Although the scope of application of brand co-creation is quite vast, however, the choice of researchers most often falls only on consumers as the subject of research despite the variety of other co-creators, e.g. Merz, Zarantonello & Grappi (2018), Kamboj et al. (2018), France et al. (2018), Foroudi et al. (2019). The process of co-creation involves a much larger number of stakeholders who simultaneously participate in the brand's value creation. In other words, the study of brand co-creation is currently at an initial stage and has a fairly large potential for investigation, in particular, the contribution of other than consumer stakeholders to the procedure of brand equity co-creation (Hatch & Schultz, 2010).

1.2 Brand importance and brand equity studies.

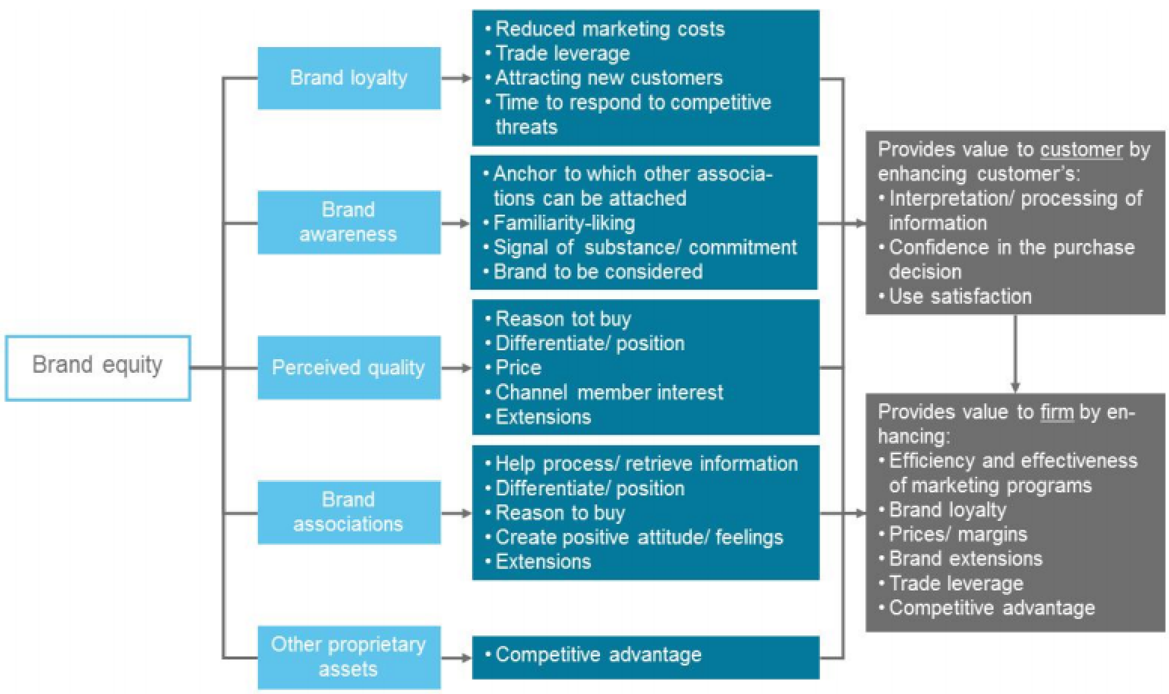
Much of the recent brand studies have focused on identifying and measuring the value and importance of the brand (Keller & Brexendorf, 2019; Foroudi et al., 2018; Seo & Park, 2018, etc.).

In the earliest fundamental scientific research, brand equity was positioned as the "added value" of the product (Jones, 1986; Leuthesser, 1988). This additional value is created precisely as a result of proper communication with the client. The current paper will consider online fashion journals as one of the main media of the fashion industry brands communication with the client.

Another early reference to brand equity was done by Keller (1993). The author studied the brand equity concept using aspects of brand image and brand awareness. In the paper, customer-based brand equity was demonstrated as a set of marketing effects that differentiate the performance of branded products from the one that does not possess the established brand name (Keller, 1993).

Aaker (2009) defined brand equity as the combination of assets and responsibilities related to a brand name (Fig. 4).

Figure 4. Brand Equity model of Aaker (Aaker, 2009)



Also, this author noted the importance of changes in the brand name or logo and their negative effect on the brand value, coming up to the nihilation of brand value.

However, even without name changes brand equity itself is very sensitive and can add value to the product, as well as diminish it (Aaker, 2009). Thus, for stakeholders, especially in the fashion industry, it is highly important to granularly create and manage brand equity.

A further study by Keller (2003) examined the process of creation, evaluation, and management of strong brand equity. Moreover, he identified the way marketing actions might influence customer thoughts and emotions that subsequently impact purchasing decisions. The author proposes two complementary methods of brand equity assessment:

- Direct method - measuring the brand knowledge influence on customer reaction on marketing activities.
- Indirect method - detecting and monitoring customers’ brand knowledge frameworks (Keller, 2003).

In a comprehensive study of brand equity Aaker (1996) identified universal brand equity measures that were supposed to be independent of product or industry factors. Following the definition of the main criteria that the measurements should meet, the author summarized them into five exhausting categories:

1. Brand awareness.
2. Customer loyalty.
3. Perceived quality (leadership).
4. Associations or differentiation.
5. Market position (Aaker, 1996).

Initially, for customers analysis survey data was utilized. Currently, due to the intensive development of the Internet and big data technologies, social media data has become the most ubiquitous for studying consumer behaviour. This is due to the following features of social media:

- big amount of data;
- the wide availability of sources;
- statistical sufficiency;
- reliability and validity.

Generally, the most popular types of social media content used by researchers were customer reviews, blog posts, comments, etc.

The majority of the studies considered brand equity from the consumer's point of view, as they were one of the major stakeholders in the fashion industry (Colicev, Malshe, & Pauwels, 2018; Algharabat et al., 2020; Hoang et al., 2019). Current paper authors agree with the importance of the consumer's role in the formation of brand equity, at the same time authors support the position that other stakeholders might play an important role as well (Fronzetti Colladon, 2018).

Besides, Keller (2016) examined the way of how the concept of brand equity had developed since his first paper was written in 1993, as well as considered a potential future research gap in regards to the progress of digital technologies. In his paper, the author defined the term “brand tracking” as the combination of techniques and patterns which companies use for getting a deeper brand perception. Keller indicated successful brand tracking as one of the main directions for future research. He also emphasized that for effective brand management, it was necessary to understand how not only customers but all other related stakeholders interacted with the brand (Keller, 2016).

Taking into account that the consumers’ influence on brand equity was quite extensively covered by existing studies, this paper selected fashion magazines as important stakeholders of the fashion industry. The influence of magazines on brand equity is ambiguous and poorly studied by data scientists.

Moreover, Keller (2016) described the necessity of finding new methods that go beyond regular data collection methods (surveys, focus groups, etc.) to obtain brand and customer insights. He also asked further researchers such questions as “What makes brand stories or narratives convincing?” and “How might they influence brand equity?”. That once again reinforced the relevance of the current thesis, since authors shifted the perspective from consumers to other stakeholders.

1.3 Implications of co-creation studies in fashion.

The application of the brand co-creation concept in the fashion industry is not widely studied nowadays (Thomas, Brooks & McGouran, 2020).

Most of the researchers mentioned only the following brand stakeholders: company, marketers, consumers & “others”, e.g. Hatch & Schultz (2010); Merz, He & Vargo (2009); Christodoulides (2008). However, none of the studies specified all the brand co-creators who establish brand equity. In the current paper, the authors attempted to define the main stakeholders of the brand equity co-creation process in the fashion industry.

Consequently, there was a lack of literature that investigates the influence of different stakeholders on brand importance. Most of the fashion industry studies dealing with the concept of co-creation, as well as in other industries, were aimed at considering and analyzing the impact of only one stakeholder - the customer.

For instance, Choi, Ko & Kim (2016) analyzed the process of value brand co-creation in the luxury fashion market segment. Utilizing in-depth interviews as a data collection method, authors identified the attitude and responses of the Chanel brand consumers within digital marketing value co-creation. As a result of the analysis, a structural chain of relationships was formed:

1. Co-creation experience impacts consumer value.
2. Consumer value impacts brand importance.
3. Finally, brand importance impacts purchase decision (Choi, Ko & Kim, 2016).

In the managerial application part of the study, the authors recommended marketers to pay more attention to empirical and sentimental aspects in the process of interaction between brand and consumer.

Herrando, Jimenez-Martinez, & Martín-de Hoyos (2016) claimed that participation in brand co-creation enabled consumers to sense their importance through perceiving themselves as a part of the organization and consequently stimulated the establishment of both financial and social brand value.

In recent studies, high attention was concentrated on the aspiration of consumers to participate in the brand co-creation process.

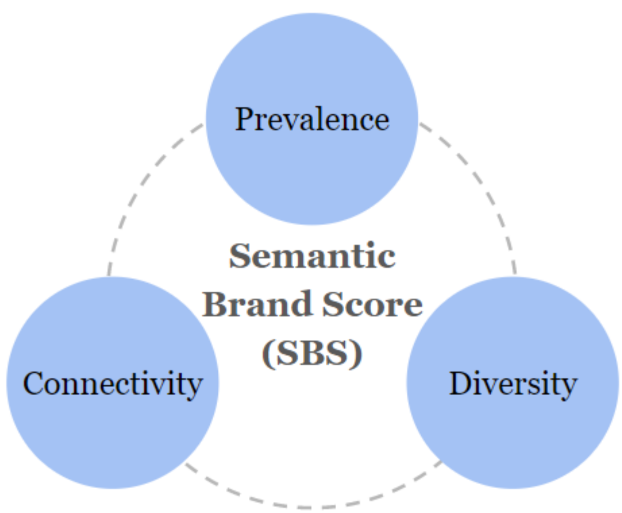
Thomas, Brooks & McGouran (2020), studied the online fashion retail industry from the perspective of activities occurring on e-commerce platforms that contributed to the co-creation of brand value growth. As a result of the paper, the authors identified a list of value co-creation activities with different emotional and informational levels of involvement. Another interesting finding was introduced for the first time in literature where they identified the correlation between fashion industry engagement and readiness to take part in fashion brand value co-creation on the e-commerce platform (Thomas, Brooks & McGouran, 2020). Cheung et al., (2020) also studied the issue of consumer engagement in brand co-creation and found that mentioning positive referrals on social media platforms stimulates customers to participate in the co-creation process and to proceed with brand purchasing.

In the current study, fashion retail branding was chosen as the industry for the application of the co-creation concept because of insufficient knowledge of this study area. Online fashion and lifestyle magazines as the main media of communication between fashion brands and customers, were considered as co-creator. Their importance as one of the main online fashion communication channels as well proves the crucial role of this co-creator in the process of brand equity co-creation.

1.4 Semantic brand score to measure brand importance.

The semantic brand score hereinafter referred to as SBS, is an extensive methodology that can be used to measure the importance of a brand using big data technologies. Conceptually, this approach is based on the fundamental brand equity models (Keller, 1993; Wood, 2000). The SBS indicator itself is a resulting measure that combines the three scales of prevalence, diversity and connectivity (Fig. 5).

Figure 5. Dimensions of semantic brand score



The prevalence shows the relative mentioning of a particular word in the text. This measure is partly related to measuring brand awareness (Aaker, 1996). The rarer the word occurs in the text, the lower the indicator of prevalence is. Applicable to a brand, the frequency of brand mentions on the social media platform may indicate its relevance, the degree of popularity, and awareness of this particular platform audience about this brand. Gustafson & Chabes (2007) claims that brand awareness is the core attribute to help differentiate the product on the market, which is highly important for building brand equity.

Diversity, the second aspect of SBS, indicates a variety of the words which co-occur with a brand. The higher heterogeneity of words co-occurring with a brand the richer discourse the brand receives (Fronzetti Colladon, 2018). Regarding a theoretical background of diversity dimension, it is relatively connected to lexical diversity (McCarthy & Jarvis, 2010) and word co-occurrence constructs (Evert, 2005). This indicator does not directly depend on brand prevalence, i.e. brands that have high prevalence might be mentioned in the text with only a small number of identical words, thereby limiting the brand to a specific context or focus, and vice versa. Mühlbacher, et al. (2016) with the example of the sports shoe category, demonstrated that the variety of brand associations had a strong relationship with brand strength.

The third component of SBS, connectivity, specifies the frequency of a word occurrence between all other word pairs. This aspect of SBS does not overlap with diversity and prevalence, i.e brand might appear in text frequently and co-occur with a big variety of words but stays mostly out of the general discussion. The concept of connectivity is based on the social analysis metric - betweenness centrality (Wasserman & Faust, 1994). Several studies utilized the connectivity of a brand name in online semantic networks to determine brand popularity (Watanbe, Kim & Park, 2021; Wang, 2019, Lin & Himelboim, 2019).

The combination of the three dimensions described above enables SBS to obtain a complete visual picture of the brand importance, to conduct an assessment of the market potential and to compare these parameters by absolute units on different platforms as well as compare brands among themselves.

As SBS is based on a text data analysis, this framework applies to any textual data. The scope of its application is not limited to brands or industry, the only restriction is the type of data used for the analysis.

Most of the researchers that applied the semantic brand score framework are quite recent, including Fronzetti Colladone (2018). These authors have focused on identifying and evaluating the brand importance in different spheres e.g. Fronzetti Colladon, Grippa & Innarella (2020) studied the relationships between brand importance and growth of visitors in five European Museums. Their analysis was based on secondary data of 2.8 mln forum posts for the past ten years. Applying Naive Bayes and regression modelling, a positive correlation between SBS metrics and the number of museum visitors was discovered, which indirectly supported the relevance of using this metric in other areas. An important insight from this paper was that the completeness and quantity of reviews were usually more important for museum visitors than their positive content, which was confirmed by the use of sentiment analysis in conjunction with SBS. The work proved the sentiment of the comments was not necessarily correlated with the volatility of museum visitors, which supported the previous studies of Filieri et al. (2018).

Fronzetti Colladon (2020) also applied SBS to the elections. In his paper, based on data from 35,000 online news articles, the author provided a forecast for three different voting systems in Italy. This study is significant for current research according to the identification of SBS patterns on articles data:

- SBS could be calculated on a daily, monthly or yearly basis.
- The optimal way of SBS measurement is every week. As well as the optimal lead time of the forecast is one weak period. In this period, SBS outperformed voting polls results.
- As fewer voting variants are, the more accurate are predictions. The most precise results model showed in the vote with two potential options.
- 30% of the article's text is significant enough to conduct the analysis. A substantial part of internet users read only the beginning of an article (Nielsen, 2008).

In their next paper, Grippa & Fronzetti Colladon (2020), presented an online model for calculating the SBS indicator from any textual data and demonstrated its effectiveness by predicting the distribution of votes among candidates in the US election 2020. As a result, SBS received more accurate figures on the distribution of votes than polls in four electoral events.

The flexibility of this methodology is highly sufficient. In the current paper, the authors propose to utilize it, to assess fashion brand importance in independent and established magazines, as well as to identify insights for magazines' management, brand owners, and other fashion industry stakeholders.

1.5 Semantic analysis in the fashion industry.

Nowadays big data is widely used by companies in every area of human activity, from food retail to the healthcare industry. In the fashion industry, which historically relies on perception and creative thinking, big data usage is actively applied as well. Fashion retail brands such as Zara, Burberry, LVMH, Swarovski, H&M, Lesara, ASOS, Adidas, Hugo Boss, Macy's, Montblanc, Tory Burch, GAP and Ralph Lauren are already successfully using advanced analytics to gain a competitive edge in the marketplace (Sirimal Silva Hassani & Øivind Madsen, 2019).

One of the most common and universal ways to work with big data is represented by text mining. Much of the existing literature, focused on the search of insights from textual data, apply text mining techniques. Gan et al. (2017) by utilizing text mining, identified and arranged in ascending influence level 5 main attributes that impact the restaurant rating. Kim & Chun (2019) used text mining techniques to determine the most developed and under-developed sides of the three-car models.

Similarly, like in other spheres, text mining is applied in the fashion industry. In the study of Choi and Lee (2020) text mining and sentiment analysis of the reviews on Disney collaborated products was conducted. Using tools such as Python, Textom, and NodeXL reviews data was collected and studied. This work is interesting in terms of the managerial application of textual analysis results. By generating the semantic network and consulting sentiment analysis authors derived crucial knowledge of the target audience of the product, the main factors influencing the purchase decision, and the most frequent problems faced by consumers. Thus, this research distinguished how much useful information for enhancing the stakeholder's engagement, the textual data might contain and how it can be applied for a customer-centric business approach.

Text mining is a generalized concept that comprises a variety of text mining techniques. One of these techniques is semantic analysis. Generally, semantic text analysis, here and after referred to as STA, is the identification of relationships between words in the text, based on their meaningful combinations, instead of the frequency of their co-occurrence (Doerfel, 1998). STA transforms text into a network of words that are logically connected, i.e. the selected words (concepts) are represented by the nodes, and the semantic dependency between them is demonstrated by the edge connecting these nodes. However, in the case of data analysis of social media platforms, the precise detection of the logical relationship between words has several difficulties, for instance, data might be complicated to interpret, contain words and abbreviations that are not presented in the software, possess incorrect capitalization and improperly perceived symbols, etc. Nevertheless, to circumvent these limitations, text normalization techniques have been developed (Desai & Narvekar, 2015).

Regarding the application of semantic analysis in the field of fashion retail, much of the recent literature study clothes' design elements, based on semantic linkage (An & Park, 2018; Martinsson & Mogren, 2019; Hou et al., 2019). An & Park (2018) analyzed a one-year dataset consisting of 38,225 blog posts, utilizing semantic networks, in conjunction with other text mining techniques to obtain several niche insights, such as linking men's striped shirts design elements with evaluation characteristics (e.g. style – trendy, casual, etc.; fit – wide, slim, etc; colour – bright, pale, etc.).

In their next work, An & Park (2020), considered the wider topic of fashion trends forecasting, using as an example one apparel item, a jacket. As in the previous study, text mining and semantic network analysis were selected for research design. Authors collected 29,436 blog posts that contained the following words "jacket" and "fashion collection". They conducted time-series clusterization to distinguish seasonal trends and used semantic network analysis to determine recent seasons' prevalent trends in correlation with their design features (e.g. styles, fabric, colour, etc.). The major result of this paper yielded in developing a methodology of performing fast consumer-driven real-time trends analysis. According to An & Park (2020), nowadays regulation over the fashion industry is transferring from the brand owners to customers.

In the current study, authors are going apply semantic analysis to investigate the impact of other fashion retail sector stakeholders, in particular how fashion magazine articles impact the fashion retail industry, i.e. specifically their influence on brand equity, as well as how brand owners can manage this impact to bring extra value to the brand equity.

1.6 Social network analysis in the fashion industry.

Nowadays the amount of data generated by social media platforms is increasing exponentially. Online social media has grown into a valuable resource for digitalized, relevant, and constantly renewable data (Blazquez & Domenech, 2017). Although, the development of modern tools for data analysis makes it possible to distinguish valuable information among big data volumes and provide useful insights into specific problems. One of such tools is social network analysis, hereinafter referred to as SNA. Initially, the scope of its usage was limited only to sociology. The first mention of social networks was found in Barnes (1954), that considered the social interaction between people and described the social network as a complex of points which represent individual people (groups), connected by lines that visualize the fact of interaction between these people (groups) (Barnes, 1954). Over more than 60 years, the concept of social networks has outgrown the framework of one science and became to be used in scientific papers more frequently, covering a wider range of disciplines from economics to data analysis. Generally, the modern definition of the social network's concept is not strongly different from the definition formulated by Barnes: social networks are frameworks consisting of nodes connected by links on a certain basis (Can & Alatas, 2019).

The social network analysis is a type of network analysis that is designed to reveal connections between nodes and identify potential insights related to these nodes (Serrat, 2017). Nominally, the more links are connected to the node, the higher the influence of this node is. However, after thorough consideration, this metric is more complex and consists of degree, betweenness, and closeness centrality indicators (Freeman, 1978). Nowadays SNA successfully complements regular statistical data analysis techniques and represents the main method for analyzing social networks in various fields (Tabassum, et al., 2018). For instance, Valeri &

Baggio (2020) highlighted the potential application of SNA in the tourism sphere, intending to develop a tourism system in Italy. Sun, et al. (2020) applied SNA to the ecology, in particular, to investigate the transfer of carbon emission between China provinces. Kondakci, Bedenlier & Zawacki-Richter (2018) used social network analysis in the education domain, to identify patterns of global student mobility.

Nevertheless, like any other tool, online social network analysis has its problems and limitations. To exhibit these problems, Can & Alatas (2019) executed significant literature research of 450 papers. The authors did not only assemble and clarify 21 online social network problems but also provided methods on how to solve them moreover characterized those problems based on the relevant studies performed in the area.

In the current paper, the application of SNA will be considered in the fashion industry There are only a few recent studies that applied SNA in this field. One of these few papers was written by Zhao & Min (2020). With help of Python and Gelphi authors collected, visualized and analyzed data from more than 10,000 Twitter account posts. Posts were selected by specific hashtags and were collected in 3 different periods: a week before, during, and after the Paris fashion week, in order to observe changes in Twitter users' discussions in time perspective. The result of the SNA application, in this case, was a visualization of a dynamic network of nodes (hashtags) for The Paris fashion week, identification of the most influential hashtags, and obtaining valuable insights for fashion industry stakeholders. One of such insights, for instance, was the most meaningful celebrity of Paris fashion week, Olivia Palermo, for brands this insight would be valuable due to the fact that hashtagging high-profile celebrities could raise the number of post views and enhance the engagement with the consumer (Zhao & Min, 2020). Researchers presented a comprehensive and detailed discussion of the applicability of text mining and SNA in the fashion industry, as well as demonstrated its potential value to the fashion industry stakeholders, therefore this extensive research of Twitter data is highly important to the current study.

Another research was conducted by Yu, Moore & Chapman (2020a) to explore the novel fashion technology, direct-to-garment printing, here and after referred to as DTG printing. During the analysis, the authors applied novel techniques, such as social network analysis to indicate the applicability of these techniques for visualization, analysis and obtaining insights in the fashion retail sphere. As in the previous study, the platform for data mining was Tweeter. By

Using Cremson Hexagon analytical software, tweets connected to DTG were collected for over three years, then cleaned with Python and transformed into a matrix view, that was finally visualized into a social network. The results were giving stakeholders valuable insights to assess the competitiveness of the DTG sector, e.g. the main category of clothing for DTG technology, dominant approaches to clothing decorating, market niches that drive the growth of DTG in the fashion industry. In the next paper (Yu, Moore & Chapman, 2020b) the authors decided to proceed with their research, however, used more narrow frameworks and concentrated only on four DTG technology terms. The data set had also been decreased to one year time period and comprised 3,000 tweets. Researchers determined both independent indicators for each of the 4 technologies and interrelated between several technologies. Despite the niche nature of the research results, it distinctly indicates the effectiveness of SNA usage in the fashion industry.

Similarly, the SNA of Twitter data was used by Blas, Brigato & Sedita (2019). Authors collected data for apparel brands, with more than 100,000 followers and then implemented SNA to assess the connection between each of the brands and the following perceptual concepts: fashion and eco-friendliness. Thus, researchers identified the difference in the correlation of fashion and eco-friendliness of the brands between luxury and mass-market segments.

In the fashion industry, SNA can be conducted not only with social network data but also with other data e.g., articles. For instance, Choi & Lee (2020) utilized text mining to collect data on scientific articles published in Scopus and KCI from 2009 to 2019 on the topic of ethical fashion and then with SNA tracked general trends of ethical fashion studies in Korea over a defined period

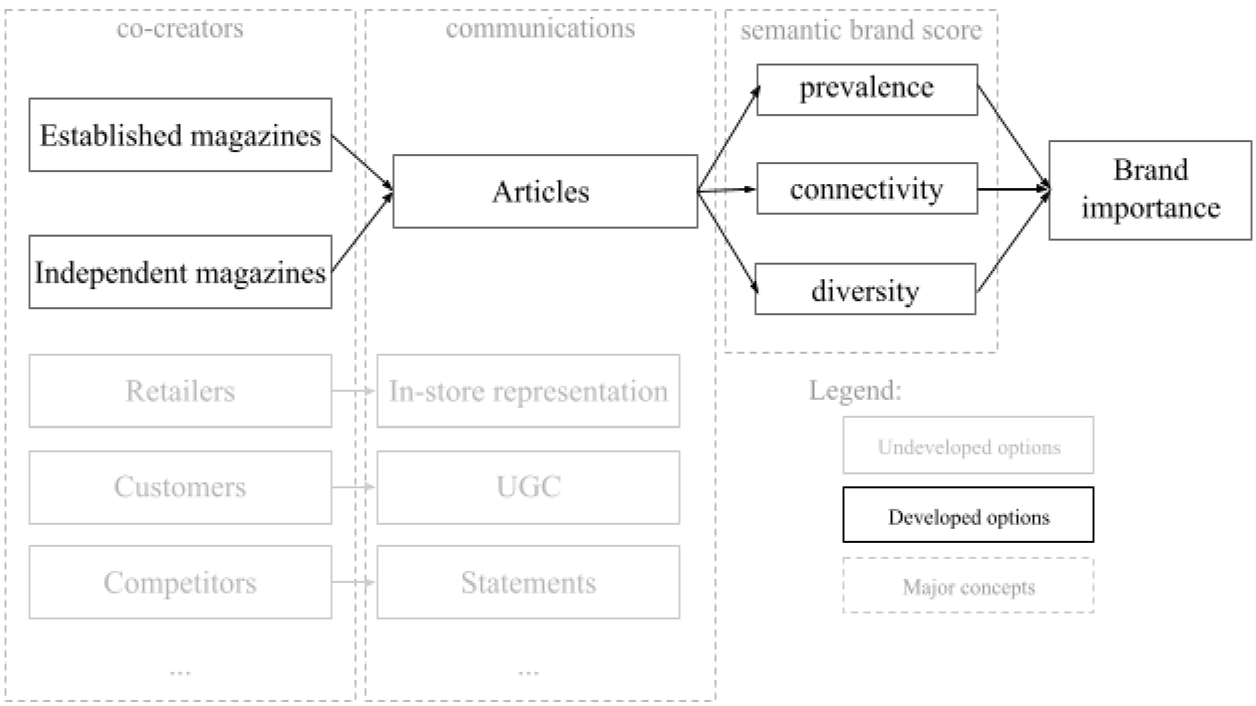
It may be concluded that SNA is a fairly recent tool in the fashion industry, and despite the proven effectiveness of its applicability, its utilization is not strongly widespread at the moment. Thus, its application in the current paper on the fashion magazines articles supports the novelty and relevance of the study.

2. Research design and methodology

2.1 Methodology.

The methodology of the research could be visualized with a conceptual model that links main concepts and shows the direction of the relationships between them (Fig. 6).

Figure 6. Conceptual model



Co-creators is the enactment of joint creation on interactive system environments including agency engagements and structuring organizations (Ramaswamy et al., 2018). This term`s new connotation broadens the list of co-creators, which goes beyond the initial introduction of customers as co-creators by Payne et al. (2008). The new approach enlarged the span to all the agencies (human and institutions), that participate both online and offline in engagement with the brand, product, etc. The evolution of the term was predominantly driven by the growth of digitized environments where co-creators could engage and provide justification to the object of the process.

Magazines comply with all of the features of the co-creators, as they are present both online and offline, go beyond only just one platform of the website, but also present on social media. Moreover, that interaction of the customers can be held on platforms that are created by the magazines, which makes them the agency's drivers.

Communication is the main way of the co-creator to generate value, in our particular case we have selected official website articles of well established and recently created (since 1999) independent fashion and lifestyle magazines.

Semantic brand score methodology was described in the previous section, but it is mainly an approach on how to assess the next concept in question, brand importance.

Based on the conceptual model, we have identified the data needed and the type of analysis that should be done to determine the differences in the brand importances between established and independent magazines and state the following hypothesis:

H1: Fashion magazines' contribution to brand importance is not the same for the same brands.

H2: Luxury brands gain more attention from fashion magazines than other brands.

H3: Brand importance is closely related to the sentiment of the content produced by co-creators.

2.2 Data collection.

The data collection part of the research was performed from February 12 to March 4, 2021, with the help of data scraping techniques.

We have divided co-creators into two parts based on their origin and historical background:

1. Established publishers.
2. Independent publishers.

Established or legacy publishers, the ones that were mainly connected to the global mass media company Conde Nast and were founded in the 19th - 20th centuries. These magazines were established originally as printed fashion or lifestyle magazines.

The second part is dedicated to the recently founded independent and indie fashion magazines, that were created mostly for digital media consumption and occasionally supported by physical versions of the journal. These independent journals started publishing issues in the 21st century and have more narrowed down audiences.

For the thesis paper, we have extracted the data only related to the fashion industry, disregarding other categories covered by publishers, e.g. celebrity news, beauty sections, etc., by utilizing tags or scraping fashion-related categories (fashion shows, runways, style, fashion news, etc.) of the websites.

Data were collected from January 1, 2017, to March 1, 2021, from official websites of the magazines, accessing only free content. The result of data collection is depicted in Table 2.

Table 2. Data collection results

Website	Year founded	Dataset, # observations	Dataset size, MB
Established publishers:			
Harper’s Bazaar	1867	605	1.4
Vogue (USA)	1892	2,270	5.1
Women's Wear Daily	1910	4,462	16.3
Vanity Fair	1913	8,704	25.9
W Magazine	1972	4,756	18.9
Independent publishers:			
Fashion United	1999	7,320	20.6
Fashionista	2007	2,745	11.8
The Glass Magazine	2009	2,277	4.7
Now Fashion	2010	1,048	4.8
Fab UK Magazine	2016	904	2.5
Total		**35,091**	**112**

Individual datasets for each of the magazines were merged for the simplicity of the analysis, the final dataset presented in Figure 7.

Figure 7. Head of the initial dataset

	title	author	text	date	link	magazine	type_dummy	type
0	Abigail Breslin Defends Her Friend Tiffany Trump	Hilary Weaver	After Abigail Breslin posted a photo of hersel...	19.01.2017	https://www.vanityfair.com/style/2017/01/abiga...	vanity_fair	0	established
1	A Good Girl Is in the House of Herrera: Karlie...	Sunhee Grinnell	Last night an iconic fashion house Carolina ...	13.01.2017	https://www.vanityfair.com/style/2017/01/a-goo...	vanity_fair	0	established
2	Amal Clooney Was Honored for Her Continued Fig...	Hilary Weaver	Amal Clooney has been hard at work representin...	18.01.2017	https://www.vanityfair.com/style/2017/01/amal-...	vanity_fair	0	established
3	Angelina Jolie's First Major Job After Split f...	Kenzie Bryant	Guerlain Parfumeur announced on Monday that An...	23.01.2017	https://www.vanityfair.com/style/2017/01/angel...	vanity_fair	0	established
4	President Obama's Tribute to Michelle Brought ...	Kenzie Bryant	President Barack Obama dedicated several minut...	11.01.2017	https://www.vanityfair.com/style/2017/01/barac...	vanity_fair	0	established
...	...	...	...	...	...	...	...	...
35086	Rohmir's autumn /winter collection hopped from...	NaN	EL CASTILLO SECRETO – A magic JourneyThe luxur...	10.03.2017	https://fabukmagazine.com/rohmirs-autumn-winte...	fab_uk	1	independent
35087	Marina Qureshi Spring Summer 2017 Collection	NaN	Marina Qureshi Spring Summer 2017 Collection F...	05.02.2017	https://fabukmagazine.com/marina-qureshi-sprin...	fab_uk	1	independent
35088	Celebrity Beauty Looks	NaN	By Kitty NoofahPhotographer Rene Connage-Dura...	08.01.2017	https://fabukmagazine.com/celebrity-beauty-looks/	fab_uk	1	independent
35089	FASHION International	NaN	AUTUMN WINTER 2016February 2016 see s the fift...	28.02.2016	https://fabukmagazine.com/fashion-international/	fab_uk	1	independent
35090	ISABELLA QUEEN luxury Italian leather accessories	NaN	Founded in 2014 ISABELLA QUEEN is a British-b...	26.02.2016	https://fabukmagazine.com/isabella-queen-luxur...	fab_uk	1	independent

35091 rows × 8 columns

The initial dataset consisted of seven dimensions:

- title - the title of the article,
- author - Name of the article`s author, if applicable,
- text - textual content of the article,
- date - date, when an article was published,
- source - URL of the article to easily access it if needed,
- type - a respective category of the magazine: established=0 or independent=1.

Five dimensions consist of textual data (strings), date dimension was unified in ISO 8601 format and type_dummy is a dummy variable. Further data preparation for SBS analysis is described in the following section.

In Table 3 the operationalized concepts are illustrated. For the co-creation concept, the fashion magazines have been picked as the major marketing stakeholders generating value for the fashion retail brands. The magazine variable identifies the name of the publisher in the analysis. The communication concept is expressed with the text variable standing for the fashion articles' text content.

Table 3. Operationalization

Concept	Variable	Indicator
Co-creator	magazine	Name of the source magazine
Communication	text	Text of the parsed article
Prevalence	$PR'(g_i)$	The relative mentioning of a particular word in the text (a measure of brand awareness)
Connectivity	$CO'(g_i)$	The frequency of a word occurrence between all other word pairs (betweenness centrality)
Diversity	$DI'(g_i)$	A variety of the words which co-occur with a brand (normalized degree centrality of a node)
Brand Importance (Brand Equity)	$SBS(g_i)$	The extensive methodology that can be used to measure the importance of a brand using big data technologies

Brand Equity is measured by the semantic brand score itself with the 3 main components: prevalence, connectivity, and diversity. Though the semantic brand score is not automatically translated into the brand equity score of a brand, it is still related to the brand equity concept and can be used in this context (Fronzetti Colladon 2018).

All data scraping code was written in Python 3 with help of Jupyter Notebook and the number of libraries used: newspaper, pandas, requests, urllib, BeautifulSoup, Colorama, DateTime. We applied multiple tools for data scraping concerning differences in the magazine's website structure.

For sections with pages numbered we used loops to shuffle through all the pages and extracted data manually with a selection of the appropriate HTML tags from the page source code or by applying newspaper library.

For websites with infinite scroll and not directly accessible pages without API keys, we used the code to find all internal and external links mentioned. Only after that, all the links were cleaned based on the handlers of the URL or additional data on the category to which the page belongs and publish dates.

Overall, the data scraping detailed code with comments for each of the cases can be found in our repository Github[1].

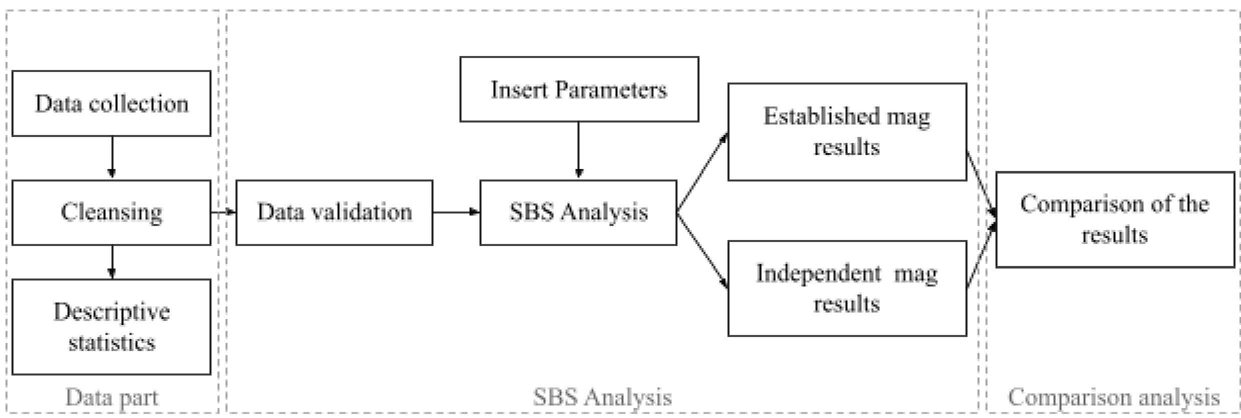
[1] Link to Github repository: https://github.com/AnastasiiaPi/fashion-articles-analytics/blob/main/data-collection

2.3 Data analysis design.

To conduct extensive analysis and test stated hypothesis, the data analysis part will consist of the multiple logical steps (Fig. 8):

1. Descriptive statistics
2. Semantic network analysis
3. Analysis of the semantic brand score
4. Comparison analysis

Figure 8. Analysis flow



Descriptive statistics will be done in the Jupyter Notebook environment for easier access to the visualization materials on the basis of Python 3. The main libraries that will be imported are the ones for data cleaning, preparation and visualization purposes, e.g. numPy, Pandas, SciKit learn, SeaBorn, MatPlotLib and StatsModel. The goal of the descriptive statistic is to assess the dataset and to derive main facts about it: mean, a median, standard deviation of the core metrics and to see the dynamics of the publications with breakdown into magazines' types and publishers.

The network analysis and Semantic Brand Score parts were conducted with the help of Python 3 and GraphTool inside the SBS Brand Intelligence App introduced by Andrea Fronzetti

Colladon and Francesca Grippa (2020). Sentiment analysis of the textual data of fashion articles was done with Natural Language Toolkit (NLTK) library inside the same app.

SBS score was calculated by the app with following formulas for separate dimensions (1-3) and then summing up Z-scores of the each dimension (4) to get the final SBS-score (Fronzetti Colladon, 2018):

$$PR'(g_i) = \frac{f(g_i)}{\Sigma W} \quad (1)$$

Where, PR'(gi) - prevalence score

$f(g_i)$ - overall term frequency

ΣW - Total number of words in the text

$$DI'(g_i) = \frac{d(g_i)}{n-1} \quad (2)$$

Where, DI'*(g_i)* - Diversity score

$d(g_i)$ - degree of the node (brand)

n- total number of nodes is the work

$$CO'(g_i) = \sum_{j<k} \frac{d_{jk}(g_i)}{d_{jk}} / \frac{(n-1)(n-2)}{2}$$

(3)

Where, CO'*(g_i) - connectivity score*

d_{jk} - number of the shortest path between the nodes in the network

$d_{jk}(g_i)$ - number of shortest paths between the nodes, that go through g_i

$\frac{(n-1)(n-2)}{2}$ - total number of node pairs, excluding g_i. Used to normalize the score

$$SBS(g_i) = \frac{PR(g_i) - \overline{PR}}{\sigma(PR)} + \frac{DI(g_i) - \overline{DI}}{\sigma(DI)} + \frac{CO(g_i) - \overline{CO}}{\sigma(CO)} \quad (4)$$

Where, $PR(g_i)$, $DI(g_i)$, $CO(g_i)$ - score of the each dimension

$\overline{PR}$, $\overline{DI}$, $\overline{CO}$- mean dimension scores of all the brands in the dataset

$\sigma(PR)$, $\sigma(DI)$, $\sigma(CO)$ - standard deviation of each dimension

For the purpose of this study, relative SBS values to the whole data set of one type of magazine were compared, as skewness and big variance of the brands related data may interfere with the results.

The data cleansing process took place and was aligned with all data requirements of the data analysis tool. In terms of undergoing the data validation step in the app, the following steps were taken:

1. Only text and date columns were kept
2. The date column was transformed into the following Python format ' %m/%d/%Y'
3. Text columns were cleaned from punctuation symbols, such as colons, semicolons, commas, quotation marks, etc.
4. The time frame of the data was restricted to 2018-2020, as the app sets file size limits of 50 MB.

After that, the Comma-separated values (.csv) format file with URF-8 encoding went through the validation part before the analysis successfully, the program has found zero rows with errors.

The whole SBS analysis was conducted for 3 consecutive years (2018-2020) with the frequency of score calculation of 2 months. Minimal occurrence of the words threshold was set on 5. As was mentioned previously, the best period for SBS calculation is 1 week, as the dataset is extensive and the variety of brands is big, the whole analysis was conducted with SBS calculated every 2nd month. Although, weekly analysis was conducted for three months in the period (January - March 2020). The selection of these particular months is reasoned by the peak activity of the fashion industry during the Fashion Weeks' events.

In terms of the brand short-listed for the analysis, the most popular ones were selected to ensure that chosen magazines are aware and write about those brands. One of the main criteria for selection was the uniqueness of the brand spelling, it should be written in one word without any symbols, e.g. not like H&M, or if having 2 words, one of them should be unique, e.g. Calvin Klein, where Calvin is quite a unique word and also part of the My Calvin's campaign, that is related to the researched brand.

The final list of 15 brands (Table 4) was divided into 3 categories: luxury, high-street and sportswear. Fifteen brands' sample is broad enough for the analysis to be representable. This division was made to later get a more aggregated view on the brand’s importance with different positioning and price-points. Reliability of the brands’ selection and division can be supported by a recent Sustainability Index study by a reputable fashion magazine (Kent, 2021), where they used the same division, but analysed the holding companies.

Table 4. Categorization of studied brands

Category	**Luxury**	**High-street**	**Sportswear**
Brands	Hermès	Bershka	Adidas
	Gucci	Zara	Nike
	Balenciaga	Levi’s	Puma
	Dior	Uniqlo	Supreme
	Calvin Klein	Gap	Under Armour

Overall, the analysis design is straightforward and includes data collection, preparation, analysis in the SBS BI App and further comparison of the retrieved results between different types of co-creators.

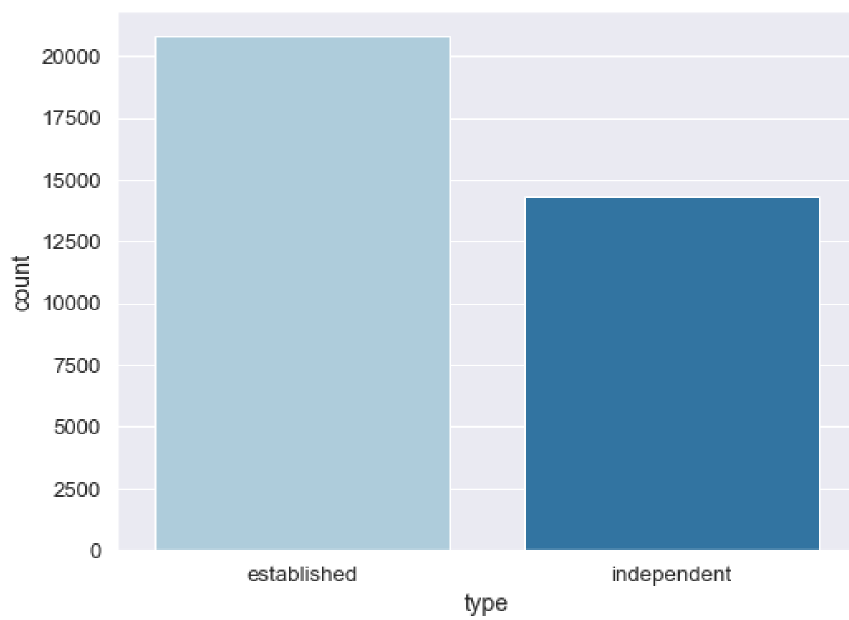
3. Results and findings

3.1 Descriptive statistics.

Descriptive statistics was focused on the dynamics and categorical analysis of the different types of magazines. To examine yearly dynamics the time period of 2017 - 2020 was chosen, 2021 data was only available for January - March, which will not be reflected correctly when considering yearly dynamics, but it would be used for monthly breakdown.

In Fig. 9 the count plot of the publications is presented with the breakdown by the magazine type.

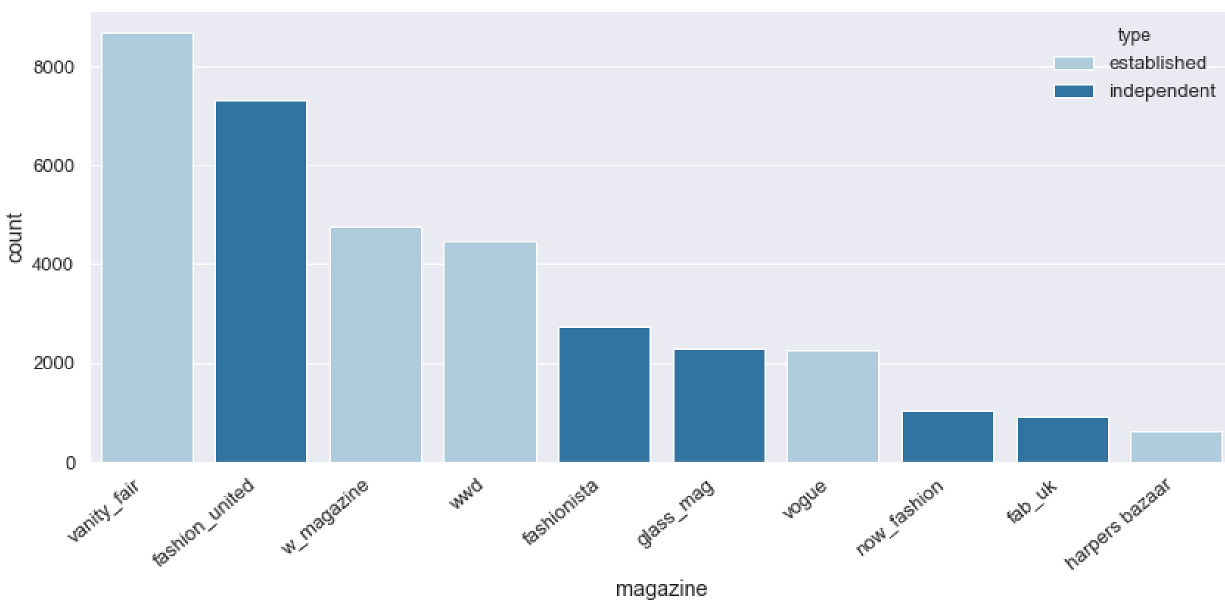
Figure 9. Breakdown of the dataset by magazine types



Established magazines occupy 59.8% (19,675) of the total observations, whereas independent magazines comprise only 40.2% (13,243) of the cleared and validated dataset. The discrepancy between the number of observations could be explained by the resources and sizes of audiences of the established magazine, which are more extensive than the ones of independent magazines. The skewness of the data did not intervene in the results of the SBS analysis, as datasets of different magazine types were analyzed separately and relative score metrics were calculated and considered for further analysis.

Based on Fig. 10 data, Vanity Fair magazine was the leading one in terms of the publications for the period of 2017-2020. This publisher was closely followed by the digital magazine Fashion United. Consecutive 2 positions were taken by the established magazines that contributed to the asymmetry of the dataset. The majority of the independent magazines were located in the rear end of the plot.

Figure 10. Breakdown of the observations by the magazines and types

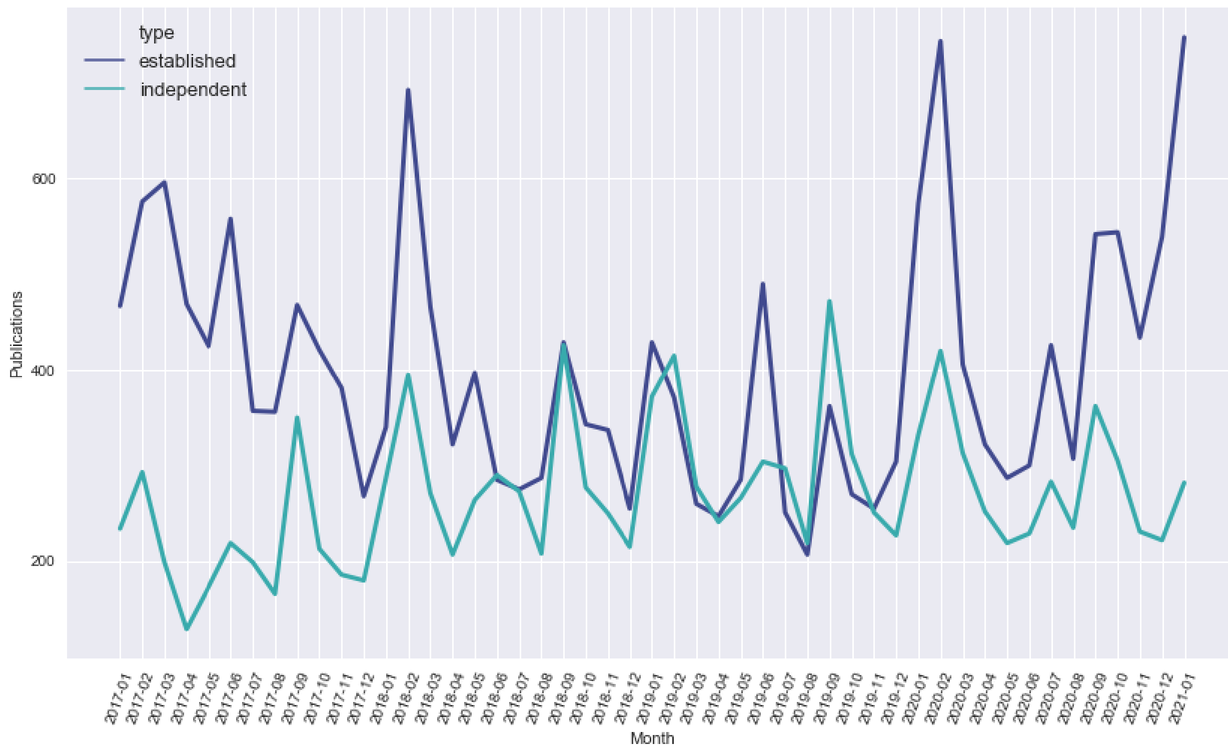


Based on the yearly number of publications, in 2020 an increase of 19.5% occurred (Table 5). To understand the nature of the increase, monthly dynamics of publications were studied, including the month of January 2021. (Fig. 11).

Table 5. The yearly dynamic of total publications

Year	2017	2018	2019	2020
Publications, pcs.	7,883	7,792	7,385	8,828

Figure 11. The monthly dynamic of number of publications

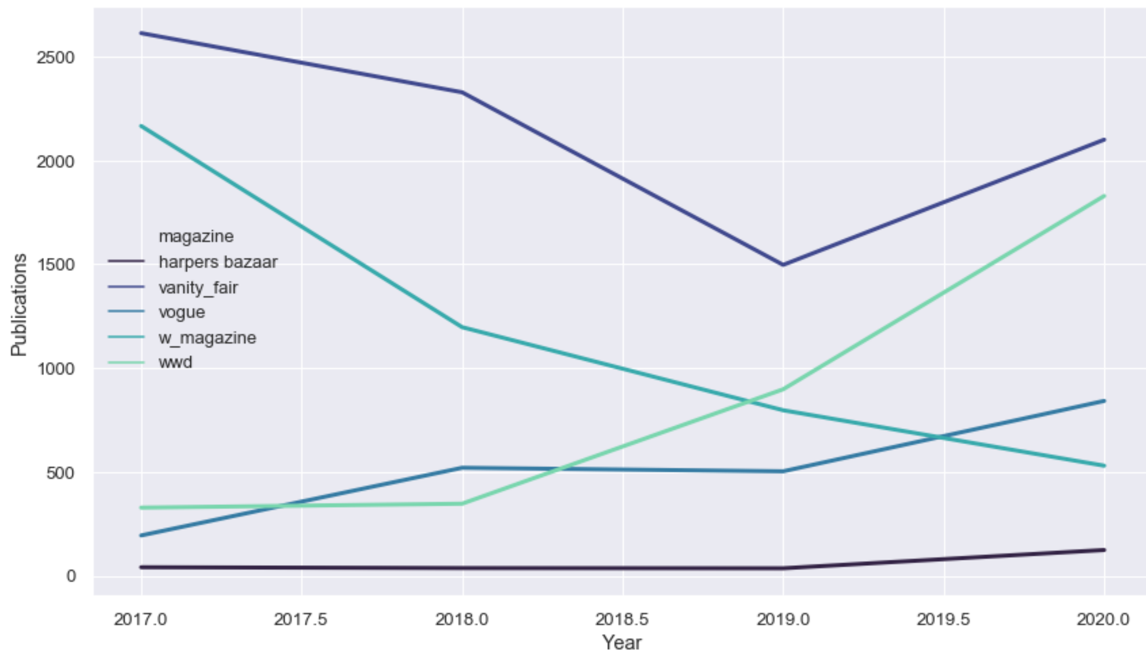


From Fig. 11 we could see the monthly changes in publications among different types of magazines fluctuated dramatically throughout the years. Two visible peaks took place in February 2018 and 2020, distinguishable that not in 2019. The fashion industry month of February is dedicated to the Fashion weeks in four major “fashion capitals”. Other big Fashion Week events are usually held in September, where an increase in publication was apparent compared to the previous month, but not as striking as the one in February.

Regarding the differences in publications among magazine types, we could see that before the second half of 2018, established magazines were producing significantly more content. Content production amount equated for the second half of 2019. Since the end of 2019 and in 2020 the difference between different magazine types has started to increase. January 2021’s spread of the results was strikingly bigger than the initial gap in the January of 2017.

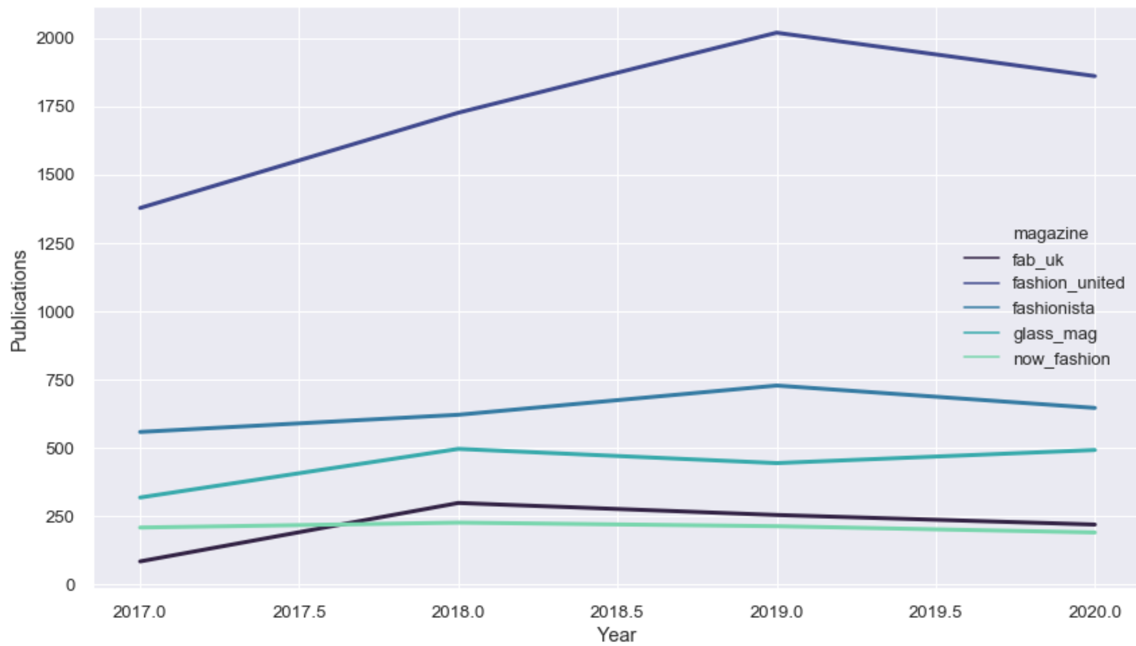
Yearly dynamics of the established magazine (Fig. 12) could be utilized to explain the big splurge of the publication of this type of magazines. Four out of five magazines increased the number of posted articles. The biggest positive change was seen by Women's Wear Daily (wwd) magazine.

Figure 12. The yearly dynamic of the established magazines' publications



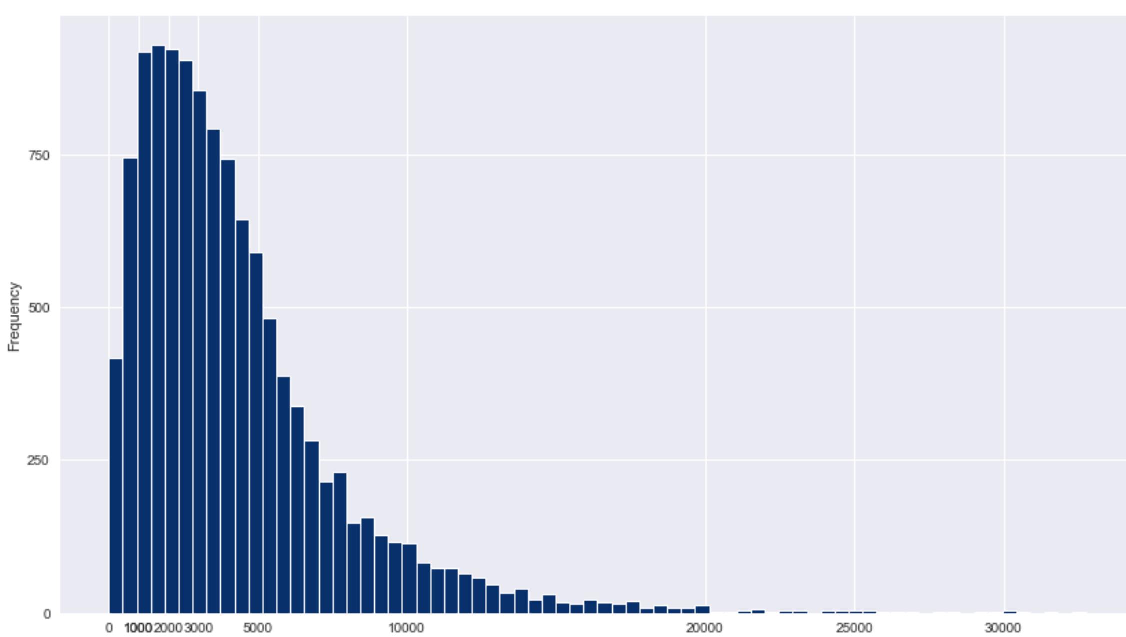
On the other hand dynamics of independent magazines (Fig. 13) was not positive, contrary, all, but Glass Magazine had a decrease in the number of publications. Noticeably, that Now Fashion magazine had a constant number of publications across all 3 years. Data from this magazine was collected from only one section, "Magazine". This could be regarded as an explanation for the adherence to the same number of publications.

Figure 13. The yearly dynamic of the independent magazines' publications



The distribution plot of the characters count (Fig. 14) was right-skewed signifying that articles were mostly less than 5,000 characters, 800 in words or approximately 1.5 pages. This format is applicable for articles online.

Figure 14. Distribution plot of characters count



The average number of characters in the articles was 2,974 that occupies less than 1 page. This could be reinforced by the magazines writing about the fashion industry, which appears to have a much more visual domain.

In Table 6 we could observe a small difference in the characters count among different types of magazines. For example, independent magazines were more close to the global average of that dataset. On average, the mean and median of established magazines was only 9.4% higher.

Table 6. Descriptive statistics of the characters count

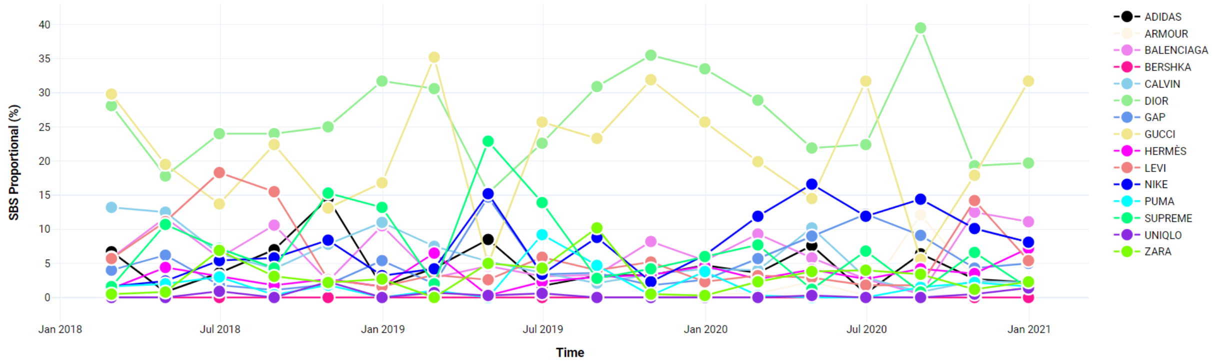
Metric	Established	Independent
count	19,664	13,184
mean	3,029.91	2,890.93
std	2,584.44	2,513.0
min	33	21
25%	1,634.0	1,395.0
50%	2,385.0	2,091.0
75%	3,673.25	3,474.0
max	32,765.0	32,765.0

Results of descriptive statistics showed good general features of the resulting dataset, that could provide better insights to the understanding of the data differences among two types of magazines while assessing brands they participate in co-creation of.

3.2 Established magazines.

Based on the overall dynamics (Fig. 15) of the SBS metrics in established magazines, brands with the highest brand value were Gucci and Dior. Fluctuation of the SBS was drastic for most of the brands, but a quite constant and low score for Bershka, Uniqlo and Puma.

Figure 15. SBS dynamic in established magazines



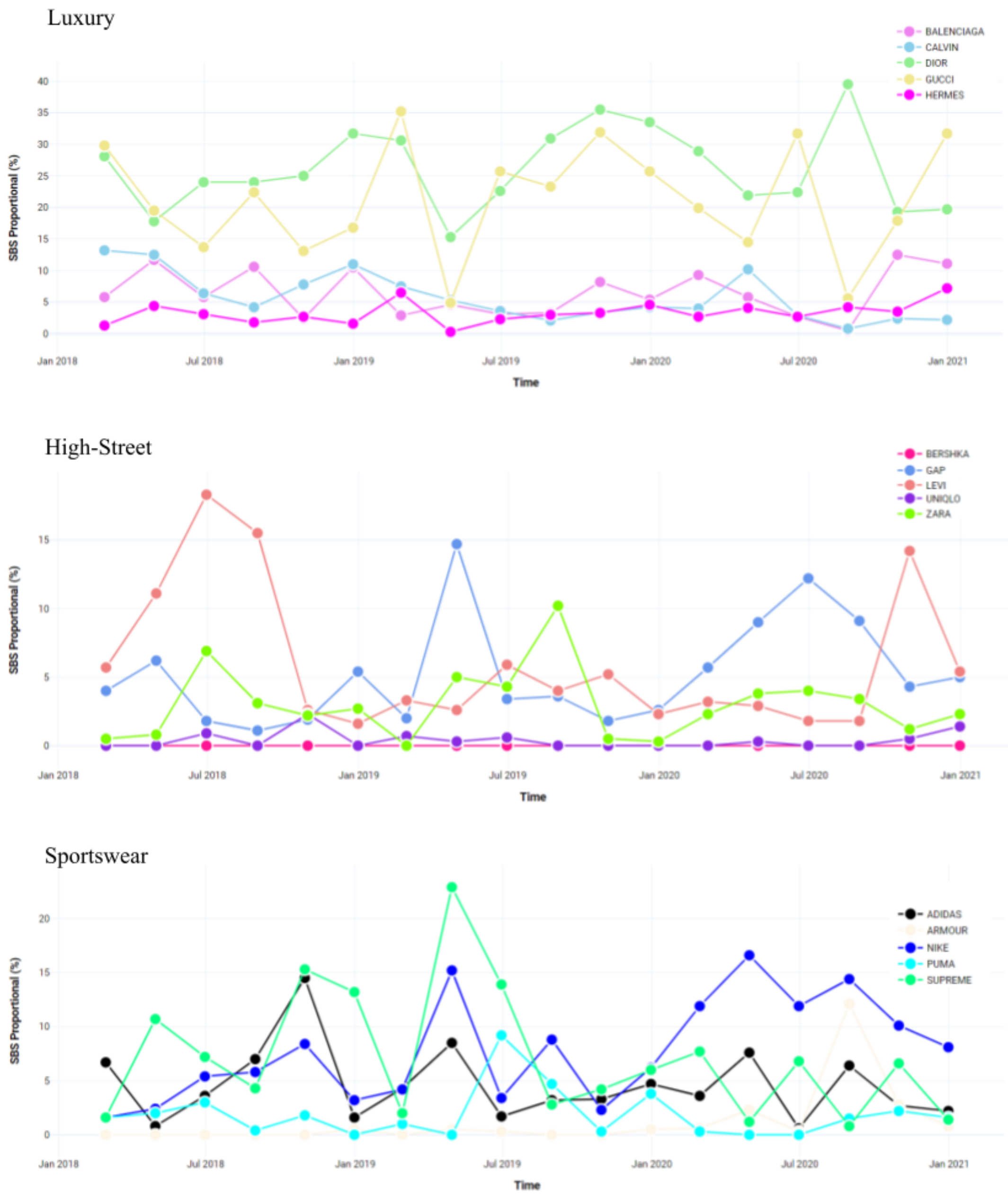
For a deeper understanding of the SBS changes over time, the study of the SBS dynamics was broken down into brands categories (Fig. 16).

Regarding the luxury brands that scored the highest among all the studies brands, dynamics showed that Dior was the only brand that throughout the period had only a relative SBS score higher than 10%. Gucci's score dropped significantly in May 2019 and September 2020. Hermès and Calvin Klein (calvin) had rather stable dynamics. The brand importance of Calvin Klein moved downwards since the beginning of the period with an occasional increase in May 2020. Balenciaga had shown a sudden increase towards the beginning of 2021 after the 6 months slip prior to that.

High-street fashion brands also had no constant leader in terms of SBS score. Drastic fluctuations of the score could be observed, where Levi's (levi), Gap and Zara had rare peaks. The highest peak was attributed to Levi's in July 2018 that was followed by Gap around May 2019 and closed by the peak of Zara in September 2019. The most recent splurge of the high-street brand's SBS occurred in November 2020 for Levi's.

Sport-wear brands also had 2 leaders, that were Supreme and Nike. Supreme's SBS had multiple spikes, which were based on the numerous collaborations this brand had had with other fashion brands. Nike had started to pick up from the second half of 2020 and showed stable positive dynamics till January 2021.

Figure 16. SBS dynamics of established magazines by brands categories



Apparently, the brand importance of Adidas was considerable during 2019, which was shown by SBS going up to 15%. By the end of the studied period, the SBS of Adidas fluctuated below 10%.

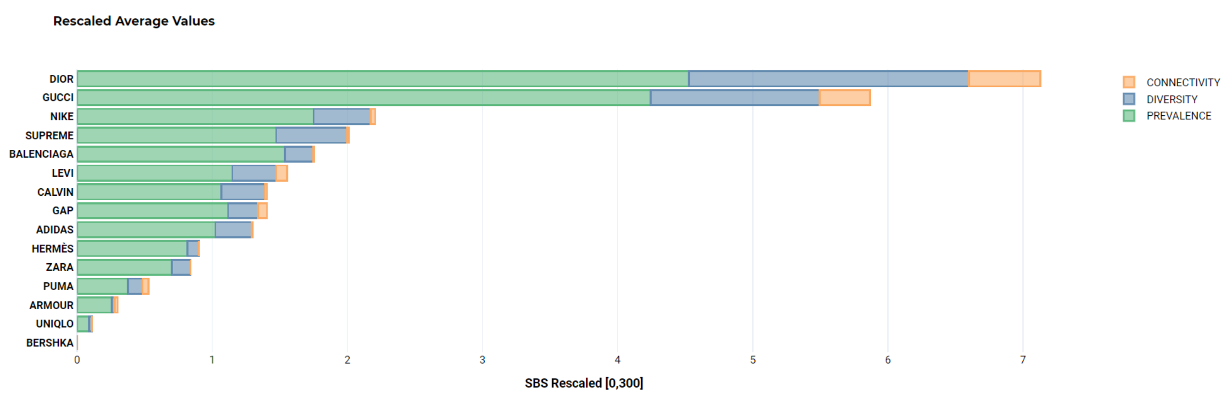
Overall, the scale of the SBS for different brand categories turned out to be unique and skewed in the favour of luxury brands, as for the last point of the dataset in January 2021 total SBS for three categories was the following:

- Luxury - 71,9%
- High-Street - 14,1%
- Sportswear - 14,1%

These numbers could roughly state that luxury brands were the main point of interest for the established fashion magazines and support Hypothesis 2. Sportswear was the next leader predefined by the popularity of the sporty styles. High-street brands had the lowest SBS range, which signified their low brand equity in fashion magazines.

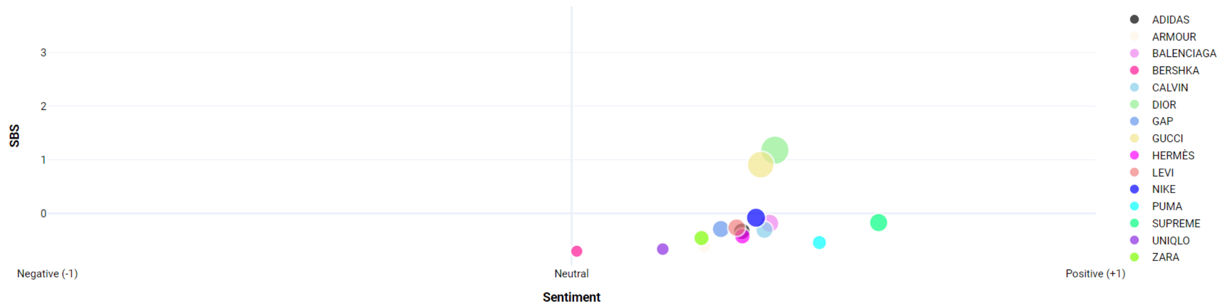
Based on Fig. 17, the high SBS score of the top brands was mainly due to the prevalence and diversity dimensions, which contribution was significantly bigger than others. Connectivity was also high enough for these brands. Overall, the connectivity dimension contributed less to the SBS based on visualized data. The leading role was occupied by the number of mentions of the brands and brand awareness.

Figure 17. Each dimension's contribution to the SBS score of the brands in established magazines



Brand positioning that entails both SBS and sentiment score of the brand also changed throughout the considered period. Average positioning is shown in Fig. 18.

Figure 18. Average positioning of the brands



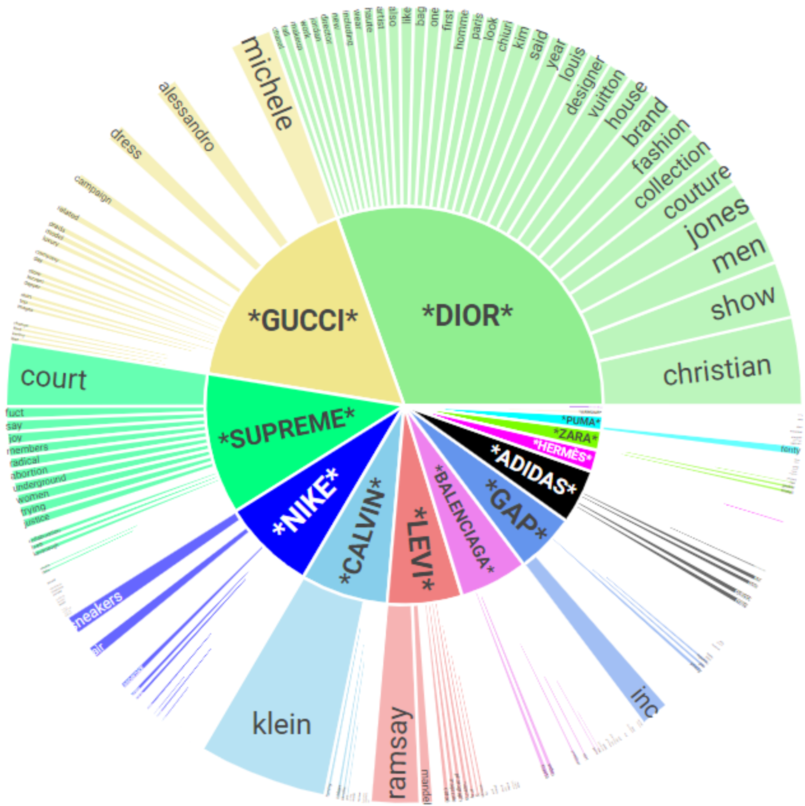
All of the brands had either positive or close to neutral brand positioning, however, during the period following brands had negative positioning:

- Zara in August 2018 and July 2020
- Uniqlo in October 2018
- Hermès in April 2019
- Under Armour in February 2020
- Bershka in December 2020

High-street brands were more frequent ones to have a negative brand positioning, whereas luxury and sportswear brands did not always portray the positive image in the view of fashion magazines.

Among the frequently used words (Fig. 19) with connection to the brands, for all of the brands' trend was to use the full brand name, e.g Christian Dior, Levi Strauss, Gap Inc. The next word association was with regards to putting the name of the designers, e.g. Alessandro Michele of Gucci, Kim Jones of Dior, etc

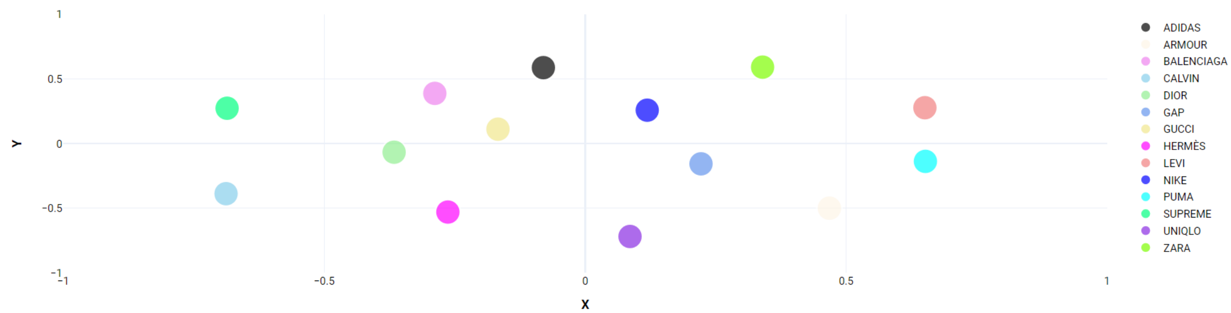
Figure 19. Word associations with the brands in established magazines



A closer look at the brands' word associations revealed that a lot of brands were used together with other brands, which was beyond the scope of this study. For instance (see Appendix 1), Gucci brand name was used with such brands as Prada, North Face, Louis Vuitton, where at that time there were no collaborations, so the reasoning behind this relationship is unclear.

Based on the textual associations the similarity or proximity of brands could be identified (Fig. 20)

Figure 20. Brands similarity within established magazines content

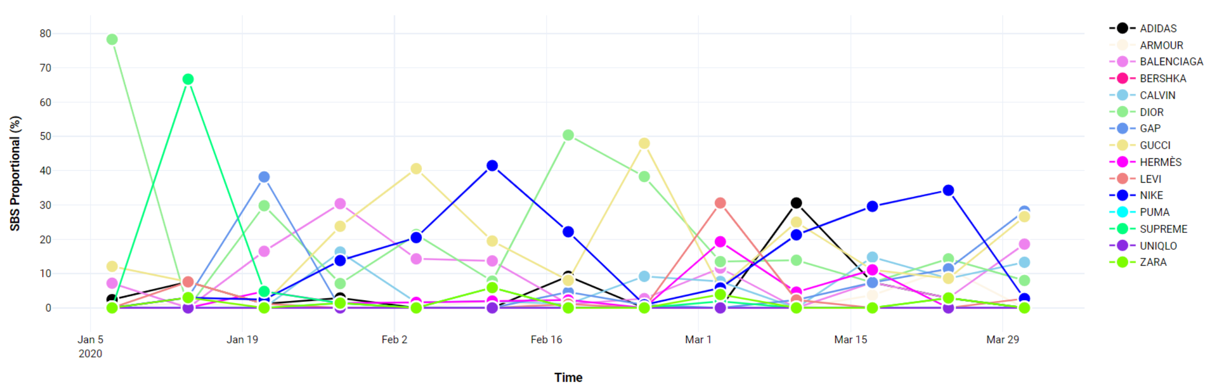


From the graph in Fig. 20 was seen that all luxury category brands were located on the left side of the X-axis and high-street brands were on the opposite side. Sportswear brands were scattered across the graph, where Supreme and Adidas were closer to luxury brands.

As was mentioned in the literature review part, for SBS analysis the most optimal period for calculations is a week. With the purpose to illustrate the feasibility and reliability of the monthly SBS score, 3 months of 2020 (January - March) were chosen to compute weekly SBS, like those one months of increased fashion interest.

From Fig. 21 we can see that SBS changed drastically each week, where spikes were attributed to such brands as Dior, Supreme, Gap, Balenciaga, Gucci, Nike and Adidas.

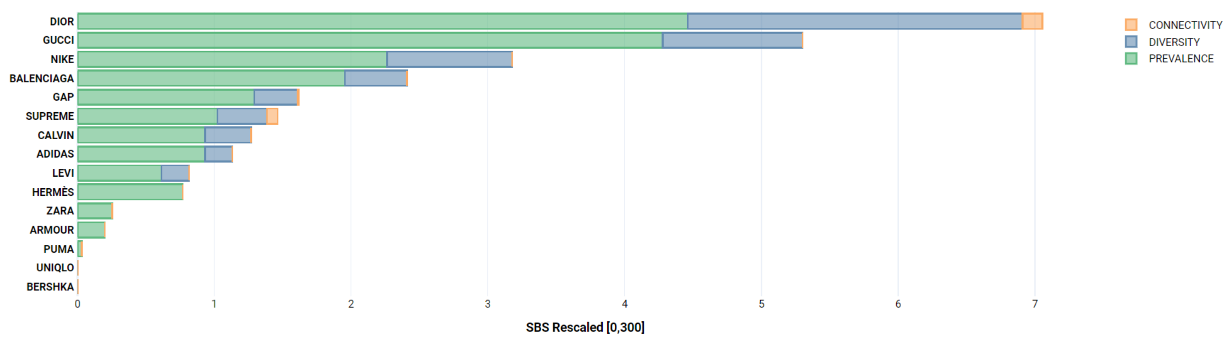
Figure 21. Weekly SBS dynamics of brands in established magazines



Some of the brands, Bershka and Uniqlo, had SBS of zero, which means that there were no mentions of these brands during that period.

Looking at the rating of the brands and contribution of each dimension to the average SBS of 3 months (Fig. 22) Top 3 brands were the same as for the whole period, although the connectivity scores were significantly lower, due to the shortened data sample.

Figure 22. Dimension contribution averaged weekly for established magazines



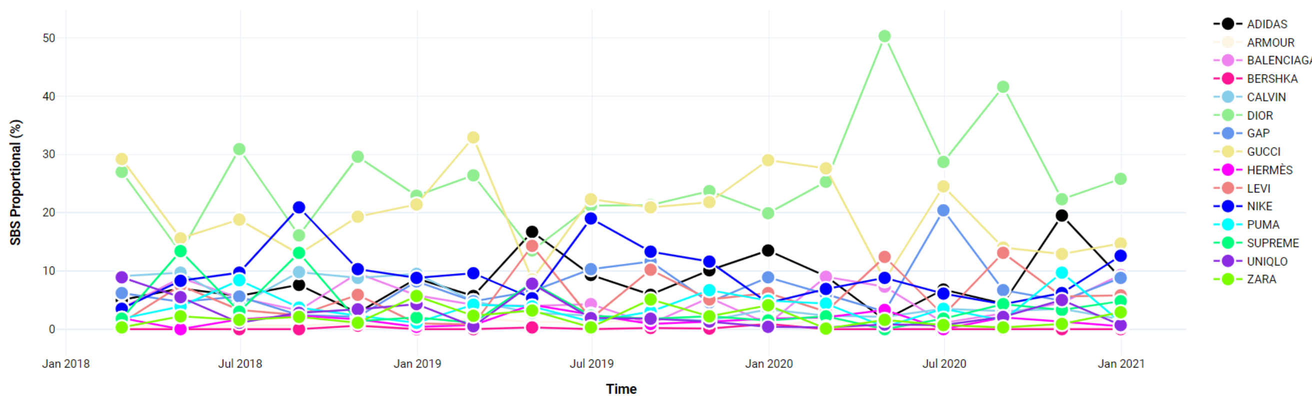
Overall, weekly data was scattered a lot, the general picture of leaders in terms of SBS was kept stable if taking a frequency of 2 months or for 7 days. With the availability of data and numerous brands existing in the fashion industry, not all brands selected for study would be constantly present in fashion magazines articles. Zoomed out view on which we based this work, given a full picture without increased digitalization

In general, SBS analysis of established magazines revealed a lot of insights on separate brands and categories as those were perceived by this type of co-creators.

3.3 Independent magazines.

For independent magazines, the most influential fashion brand among studied ones was Dior (Fig. 23). Although the Gucci brand's scores were higher during the February Fashion season of 2019 and 2020, the rest of the time Dior was the dominant brand.

Figure 23. SBS dynamic in independent magazines

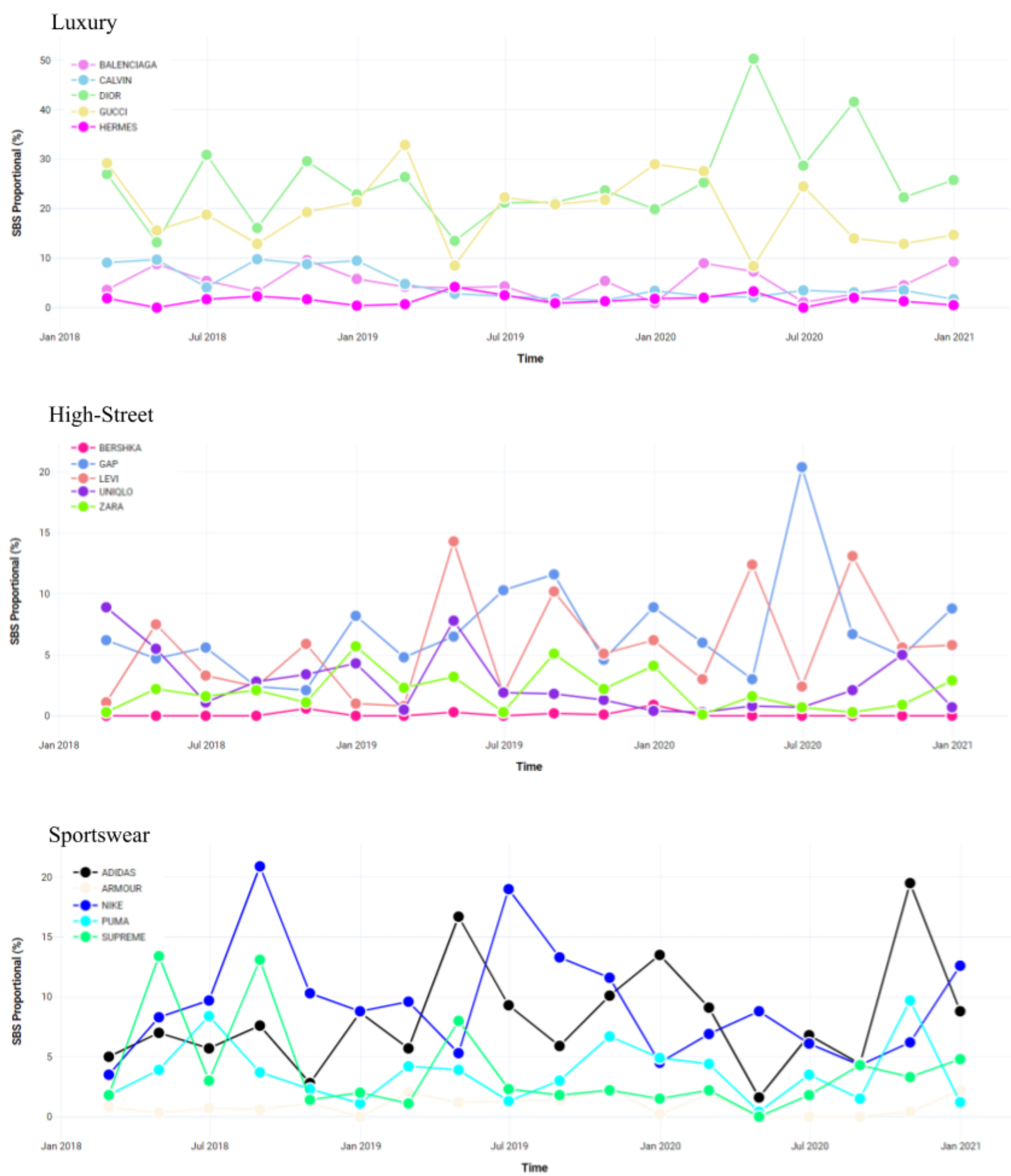


In Fig 24. dynamics for the same period was shown but grouped into brands categories for better visibility.

Luxury brand leaders Dior and Gucci seemed to have the mirrored trend, if Gucci's SBS increased, Dior's decreased and vice versa. Dior was definitely a top brand for independent magazines based on the content of their articles. The rest of the luxury brands fluctuated a lot as well but on the lower level of average SBS. Calvin Klein and Hermès seemed to be evened out by April 2019 around 1-2%, although the gap between 2 brands was considerable at the beginning of the studied period. Hermès's SBS increased and Calvin Klein's decreased in order to almost overlay each other throughout the rest of the period.

High-street brands were headed by Gap, which outperformed Levi's by a small margin, although the latter one had three moderate peaks reaching 14% of relative SBS. Uniqlo could be considered as closer to Top-3 high-street brands, as in general, it scored higher than Zara in multiple periods. Bershka was the most neutral brand with SBS closer to zero throughout the whole period.

Figure 24. SBS dynamics of independent magazines by brands categories



Among sportswear brands, tight competition between the SBS scores of Nike and Adidas could be studied. In general, peaks of Nike SBS occurred in September, whereas the ones of Adidas happened in May or in Winter.

Recently, Puma improved its position towards the end of the studied period and overcame the Supreme's brand importance. On the other hand, Supreme after being the star sportswear brand in 2018 incurred a downward trend. Under Armour fluctuated closer to zero of SBS score.

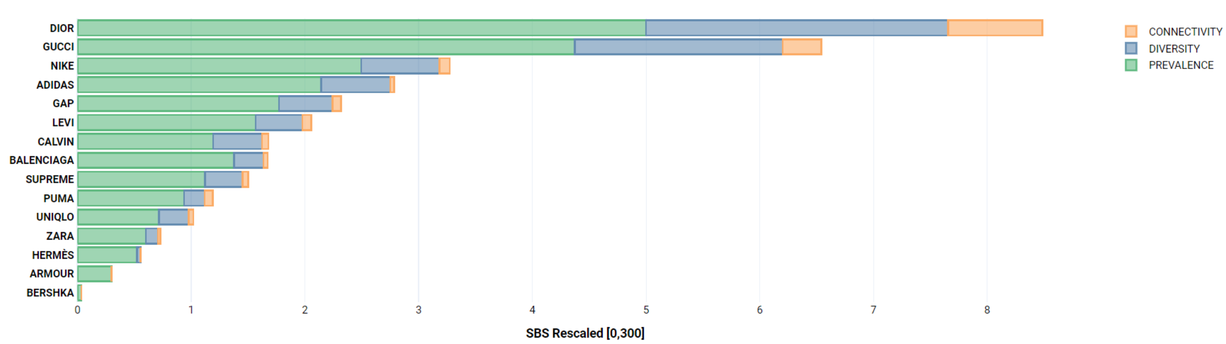
Total SBS of the categories as of January 2021 are:

- Luxury - 52%
- High-street - 18.2%
- Sportswear - 29.6%

In the case of independent magazines, luxury brands occupied almost half of the total brand score. Sportswear took up another big part of the total brand score and was 64% more in relation to the high-street brands' importance. The high number for luxury brands category support Hypothesis 2.

Analysis of the contribution of different dimensions could be seen in Fig. 25 prevalence provides the most of the SBS amount. Diversity played a significant part as well, but once the SBS approached zero, prevalence and connectivity mattered the most. Connectivity decreased almost proportionately as SBS went down.

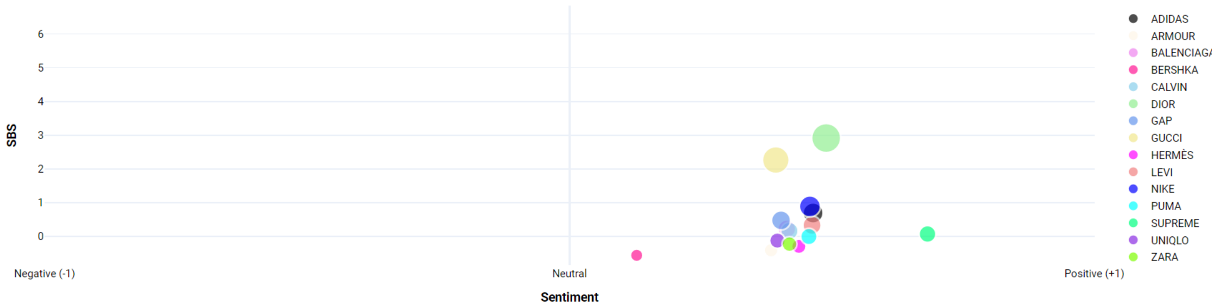
Figure 25. Each dimension contributes to the SBS score of the brands in independent magazines



The positioning of the brands in independent magazines was generous (Fig. 26). On average, all of the brands had positive sentiments. Most of the brands were flocked around the

0.4-0.5 mark of the sentiment axis. The less positive sentiments were channelled towards the Bershka brand from the high-street category. On the contrary, Supreme turned out to be the most positive brand regarding its sentiments (0.68).

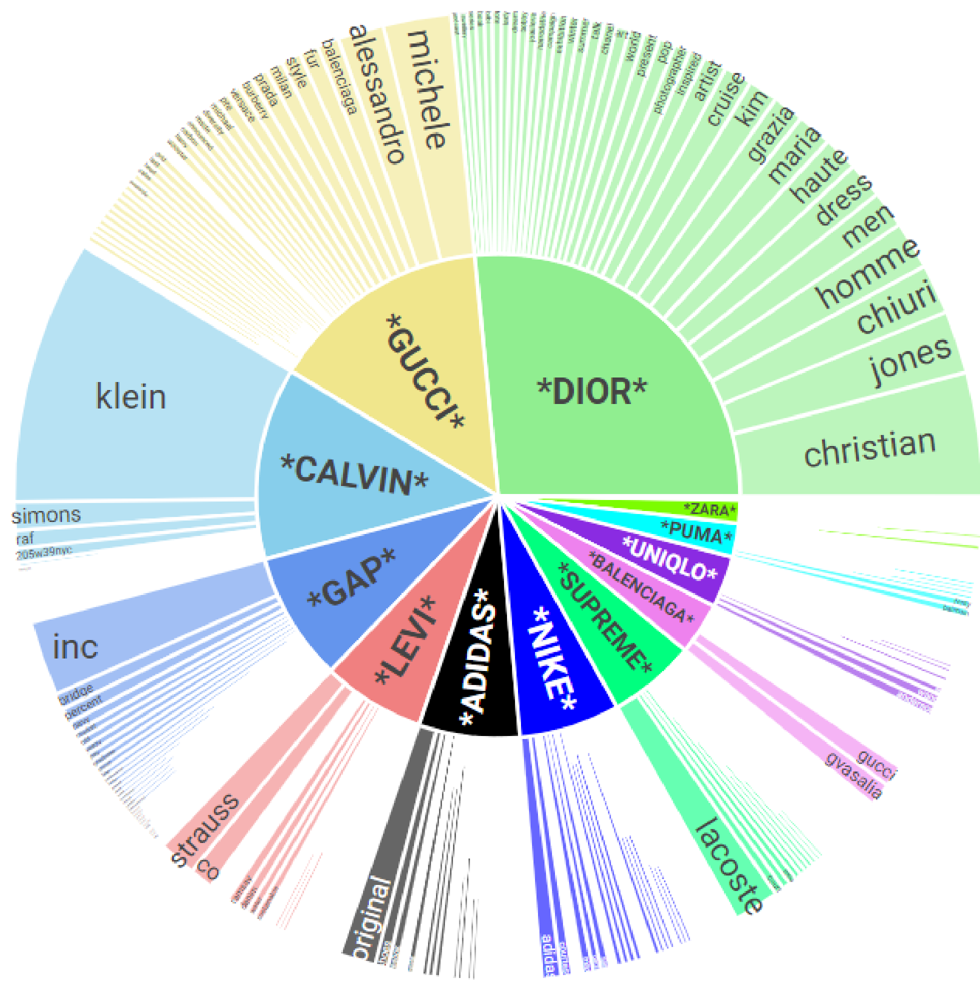
Figure 26. Average positioning of the brands in independent magazines



During the span of 3 years, only one brand had a negative sentiment of -0.172, which was Uniqlo in December 2019. Rest of the period the lowest point was neutral sentiment for Bershka. Record high sentiment was in December 2018 for Under Armour.

Sentiment analysis is closely related to the analysis of the words used together with the brand name (Fig. 27). Self-explanatory, the most frequent phrase was to use with brand names were a full brand name, as they could have multiple words and forms of spelling, additional brand name parts or collections, e.g. Adidas Originals, Calvin Klein, etc. The designer's or creative director's name with concatenation to the brand he or she represents was also encountered frequently in independent magazine's articles, e.g. Demna Gvasalia of Balenciaga, Raf Simons of Calvin Klein.

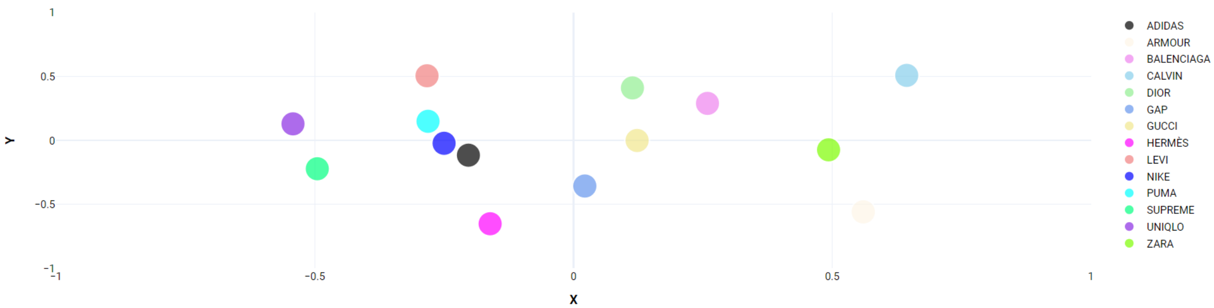
Figure 27. Word associations with the brands in independent magazines



Among different words, in independent magazines articles usage of multiple brand names together was striking. For instance, the Gucci brand was used frequently with the following brands: Prada, Burberry, Versace, Chanel, Armani, Bottega Venetta, Michael Kors; Nike were most of the times mentioned with Adidas; Adidas has a lot of links to Yeezy, Reebok and Prada.

One of the other domains of sentiment analysis usage was brand image similarity (Fig. 28).

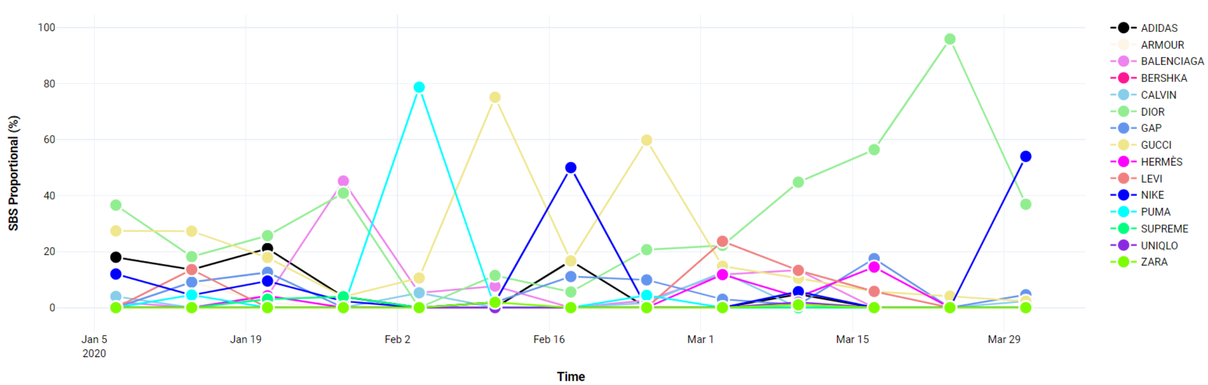
Figure 28. Brands similarity within independent magazines content



Different categories of brands were diffused among each other, no clear division or clusters could be defined. However, sportswear brands, Nike, Puma and Adidas, were located very close to each other. Some sparse triangle-like locations of the luxury brands were formed out of top brands, like Gucci, Dior and Balenciaga. The main point was that Calvin Klein was located much further from the "luxury triangle" than Hermès. Other remote brands included high-street and sportswear brands on both sides of the graph.

To reinforce the validity of the monthly SBS calculations for independent magazines period of January - March 2020 was chosen in order to calculate weekly SBS (Fig. 26).

Figure 29. Weekly dynamics of SBS score in independent magazines

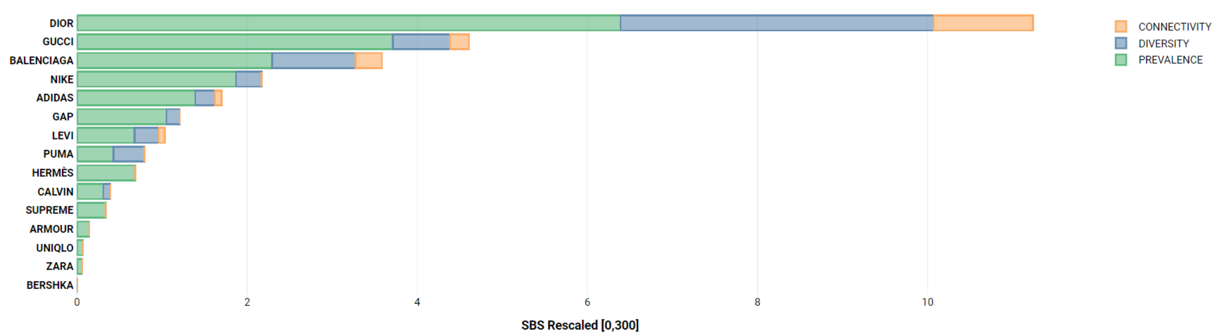


Based on the weekly dynamics (Fig. 29) top-performers during the fashion weeks period were Dior, Gucci, Balenciaga and Nike, which even in enlarged dynamics were the top performers. Gap had decreased the SBS. Other brands fluctuated in lower SBS proportions.

Dior's SBS was getting up to 100% around the week of March 24. During that time almost no other brand from our selection got any disclosure in independent magazines.

According to the dimensions breakdown (Fig. 30), Top 3 brands turned out to be luxury ones. The third place was taken by Balenciaga, high-street brands (Zara and Uniqlo) significantly had the lowest SBS score for this 3 months period.

Figure 30. Dimension contribution averaged weekly for independent magazines



To conclude, independent magazine analysis shed a light on the brands from other perspectives of different types of co-creators. The comparison between the brand importance among two types of creators will be conducted below.

3.4 Comparative analysis of established and independent magazines results.

To assess the scores of dimensions and SBS among two types of co-creators the resulting score percentage data were summed up and scaled to the relative numbers (Table 7). Based on the detailed breakdown for the whole period, we could make the following observations.

Table 7. Comparison table of averages relative dimensions and SBS by brand

	Established magazines					Independent magazines				
Brand	Sent.	PR	DI	CO	SBS	Sent.	PR	DI	CO	SBS
Adidas	0.0671	0.0515	0.0438	0.0100	0.0480	0.0725	0.0888	0.0735	0.0197	0.081588
Armour	0.0522	0.0125	0.0033	0.0169	0.0107	0.0599	0.0124	0.0002	0.0000	0.008816
Balenciaga	0.0780	0.0764	0.0333	0.0098	0.0640	0.0646	0.0574	0.0319	0.0248	0.049576
Bershka	0.0020	0.0000	0.0000	0.0000	0.0000	0.0199	0.0015	0.0000	0.0000	0.001029
Calvin	0.0760	0.0529	0.0549	0.0147	0.0517	0.0654	0.0492	0.0528	0.0323	0.049222
Dior	0.0802	0.2248	0.3475	0.4429	0.2612	0.0764	0.2071	0.3214	0.4803	0.248552
Gap	0.0589	0.0557	0.0376	0.0535	0.0516	0.0630	0.0738	0.0573	0.0415	0.068155
Gucci	0.0746	0.2106	0.2091	0.3081	0.2146	0.0613	0.1811	0.2214	0.1979	0.191718
Hermès	0.0673	0.0406	0.0136	0.0000	0.0329	0.0683	0.0214	0.0038	0.0000	0.016083
Levi’s	0.0650	0.0577	0.0530	0.0689	0.0571	0.0722	0.0647	0.0491	0.0452	0.059925
Nike	0.0727	0.0866	0.0697	0.0272	0.0803	0.0715	0.1030	0.0834	0.0511	0.095629
Puma	0.0977	0.0189	0.0180	0.0386	0.0196	0.0712	0.0388	0.0211	0.0448	0.034821
Supreme	0.1211	0.0728	0.0882	0.0094	0.0734	0.1064	0.0462	0.0400	0.0281	0.043799
Uniqlo	0.0359	0.0044	0.0041	0.0000	0.0041	0.0618	0.0297	0.0317	0.0219	0.02981
Zara	0.0512	0.0346	0.0240	0.0000	0.0308	0.0654	0.0250	0.0124	0.0124	0.021278

Firstly, in terms of sentiment, the values were very close for most of the brands, but among independent magazines, the score was higher for such brands as Bershka, Uniqlo, Zara (more than 20% increment), those were the high-street brands. Sportswear brands Puma and Supreme had a lower relative sentiment score than in established magazines

Prevalence score was also significantly higher for Uniqlo, Puma, Adidas and Gap, which represented high-street and sportswear categories. On the other hand, Hermès, Supreme and Zara were mentioned as half or more times less than in established magazines.

Diversity leaders were once again Uniqlo, Nike and Adidas (see Appendix 1), but the scores were much lower than once from established magazines for brands as Under Armour, Hermès and Supreme, which had the highest price-points among the other brands of the same category.

The connectivity of Uniqlo, Calvin Klein and Adidas were almost twice as high of the brokerage power as among established magazines, but Gucci and Levi's lost 30-40% of the connections to other brands.

From the resulting relative scores of brand categories and after calculating the deltas of them Table 8), on average, scores of the brands in independent magazines 53% were higher than the ones from established publishers. Inspection of the differences in categorical scores shown that independent magazines wrote with the more positive sentiment about high-street and sportswear brands. In general, all dimensions' scores but connectivity were higher for high-street brands. Interestingly, the reverse (all dimensions but connectivity are lower) was true for luxury brands.

Table 8. Difference between independent and established magazines' scores among different categories

Category	Sentiment	PR	DI	CO	SBS
High-street	3.0150	2.4873	2.6882	0.7157	2.5725
Luxury	0.8956	0.7980	0.8372	1.6148	0.8121
Sportswear	0.9640	1.3183	0.9133	1.5955	1.2182
Average	1.6249	1.5345	1.4796	1.3087	1.5343

SBS score on average was also higher for independent magazines, due to the twice as high score for high-street brands (driven by outstanding Uniqlo's performance) and significantly generous SBS for sportswear brands. Looking at Table 9 with T-test results, we can see that indeed, magazines write differently about different brands.

Table 9. T-test results among different magazines types

	Magazines totals	High street	Luxury	Sportswear
F-test	1.101	2.765	0.601	1.283
df	34	27.874	34	34
t-test	2.602	2.447	1.086	1.89
p-value	0.0136	0.021	0.2851	0.0673
CI	$0.015<\mu<0.121$.	$0.004<\mu<0.041$	$-0.016<\mu<0.054$	$-0.002<\mu<0.056$

Based on this comparison data of brands and categories, taking into account the summed up relative SBS for different brand categories in two previous sections with individual magazine type and dimensions breakdown, Hypothesis 1 could be supported based on the fact, that category means are different among magazine types at the α=0.05

Analysing pairwise p-values of the brand categories among different co-creators types, we can see (Table 10), that null-hypothesis of the indifference could be rejected at the α=0.05 significance level.

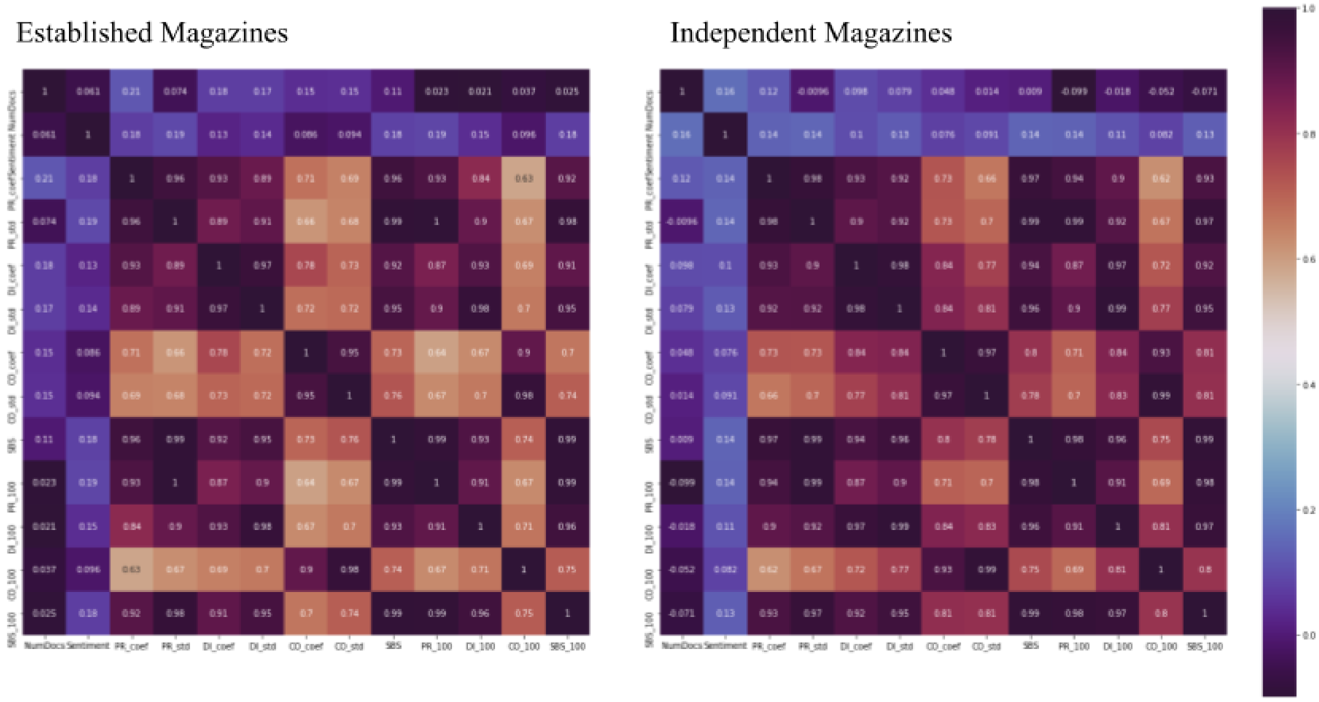
Table 10. P-values of pairwise comparison of brand categories

Co-creator	Independent magazines			Established magazines		
Category	High street	Luxury	Sportswear	High street	Luxury	Sportswear
High street	1	0	0.0359	1	0	0.0303
Luxury	0	1	0	0	1	0
Sportswear	0.0359	0	1	0.0303	0	1

Table 10 contributes to the support of the Hypothesis 2, that indeed, luxury brands have higher brand importance among fashion magazines.

From the correlation plot of all the values (Fig. 28), we could see that the correlation coefficients were high even among the dimensions of prevalence, diversity and connectivity, where the first two dimensions had a correlation coefficient higher than 0.97 in the case of both co-creators. Looking at the connectivity scores it was apparent that in the case of independent magazines, those were more closely related to the movement of other dimensions. Moreover, with independent magazines, sentiment, although its overall connection strength is lowest, was weaker related to all other metrics, especially connectivity.

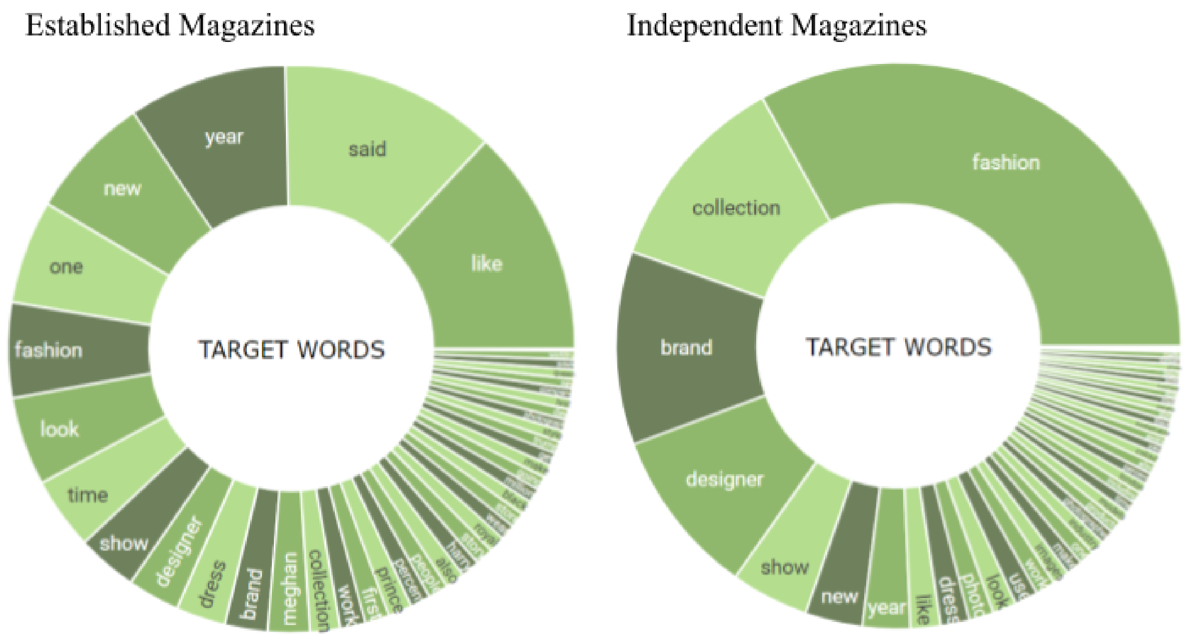
Figure 31. Correlation plot of dimension scores and SBS between different magazines



Based on Fig. 31 we can see that sentiment was not related to the SBS score, as correlation is almost zero for SBS and some minimal value for other SBS dimensions. Hence, Hypothesis 3 could not be supported, as there were no relationships between SBS and sentiment movements.

SBS Brand intelligence App analyzed the potential improvements for the connectivity, i.e. suggested the words to use in concatenation with brands to increase one dimension of the SBS. Suggestions for two types of magazines were shown in Fig. 32. For established magazines, the number of the words was much bigger with fewer weights assigned to each of them, where fashion-related words (e.g. “fashion”, “look”, “show”, “designer”, etc.) were presented only from sixth place. Contrary, for independent magazines all fashion specific words occupied the top-5 of target words suggesting a much bigger share.

Figure 32. Connectivity improvement suggestions for both co-creators



To conclude, the comparison part summed up the results discussed in previous parts. Based on the conducted analysis in current sections and with reinforcement of the individual analysis of different magazines types, Hypothesis 1 and 2 were supported and Hypothesis 3 was not supported.

4. Discussion

4.1 Results interpretation.

In the discussion of the current paper results, we are aiming at giving brief answers to the research questions defined in the introduction part of the research.

- *Who are the main co-creators of a fashion retail brand?*

A thorough literature review allows us to conclude that customers build the most researched brand co-creation group, however, in reality, any stakeholder speaking about the brand can be defined as a co-creator, as well as any classification can be applied to research the co-creators contribution to the brand equity. At least, no obstacles have been discovered in relation to this.

The list of the co-creators in the fashion industry can be expanded to the following one:

- Consumers;
- Marketers;
- Suppliers;
- Producers;
- Retailers;
- Competitors;
- Fashion magazines;
- Collaboration partners;
- Fashion designers & stylists;
- Fashion institutes and design schools;
- Fashion entertainment (e.g. Fashion week);
- Brand ambassadors & Influencers;
- Social media;

- *How to measure the contribution of co-creators into a fashion retail brand equity?*

The semantic brand score methodology has been applied to measure the contribution of the chosen co-creators into brand equity. As long as the brand performance analytics rely significantly on the mentions count and semantics around the brand names, the Semantic Brand Score methodology is believed to be a relevant choice for the research purpose stated at the beginning of the paper.

- *Is there a difference in co-creators' contribution to a fashion retail brand equity?*

The difference in the co-creators contribution to a fashion retail brand equity according to the semantic brand scores obtained seems to be explicitly leading us to the main conclusions of the paper. Among the most explicit differences are the prevailing SBS of the luxury brands in all types of fashion publishers and the tendency of the independent magazines to cover the more straightforward fashion agenda.

The descriptive analysis of the data collected has shown the difference in volumes of writing between established and independent magazines. The assumptions, that the established magazines are more likely supposed to have a large audience and a larger number of articles, are clearly demonstrated with the imbalanced nature of the datasets collected for the same timeline.

The skewness of the SBS towards the luxury and sportswear brands in established and independent fashion magazines may illustrate their sustainability and authority in the fashion industry. Such results can be understood in a way that luxury and sportswear brands more likely set trends, which are later adopted by the high-street brands integrating new trends into the mass market. It is a very common type of content when articles about high-street talk about reproduced looks promoted by the luxury and sportswear brands with the cheaper alternatives that any citizen can afford. Another big part of high-street articles is related to the collaborations of these brands with luxury ones, e.g. Uniqlo and JW Anderson, Jil Sanders, etc., that from the SBS point of view increases the connectivity of the brand. We can also assume that such content only mentions the stores, where the items can be bought, though the article itself focuses on the luxury items, eventually generating a higher luxury brands SBS and emphasizing the importance of these role models in fashion retail. This situation may be further studied, as there is more evidence supporting the phenomenon, such as than the word associations graph has shown how frequently brands are mentioned together.

However, not all luxury brands have relative high SBS. From analyzed brands, Hermès has the lowest brand score in both established and independent magazines. It can be explained by the lifestyle nature of the brand and the highest price positioning. Not all items of this brand are not freely accessible to purchase and the overall brand image in fashion magazines is niche.

An attempt to interpret the potential to influence brand importance communicated by the fashion magazines can be also made based on the obtained results of the analysis. As long as the frequency of mentions seems to be the main factor contributing to the SBS of the luxury, sportswear and high-street brands, it seems possible to regulate the number of mentions in the fashion magazines through the strategies aimed at this particular metric. As well as the fashion magazines themselves possess this capability to regulate brand importance measured through SBS. Besides, it seems that the researched brands tend to get a positive sentiment from the fashion publishers, which emphasizes the significance of the number of mentions compared to the sentiment. It can be assumed that fashion magazines prefer to adhere to the more neutral or positive sentiment. There can be different reasons behind this, such as that negative sentiment does not exclude the contribution that a magazine makes into the brand performance indicators, and the unnecessary attention to the negative stories about the brand just boosts the popularity of the latter.

The fact that the SBS differs for the brands in established and independent magazines illustrates the potential of the indicator to be used further with the variety of classifications. Besides, the score seems to be a relevant indicator in terms of the common-sense phenomena, such as the higher volumes of writing in established magazines described above. Overall, independent or digital-native magazines tend to be more in favour of high-street and sportswear brands. On the other hand, established magazines do sometimes incline to negatively influence the brand positioning, especially for high-street brands.

While taking a closer look at the differences in co-creators contribution to the brand importance, we have revealed that the smaller the volumes of the publications, the more likely we can come across the more straightforward writing. As it has already been mentioned, the SBS tend to be generally higher in independent magazines, which signifies the bigger focus of the magazines on the fashion retail, whereas established magazines may have more topics on their agenda. This conclusion can be also supported by the presence of more fashion-related words in the independent magazines' articles. Thus, the smaller publisher has a chance to dictate the bigger brand importance.

4.2 Results correspondence to prior studies.

In correspondence to Hatch & Schultz (2010) conclusions, the current study has illustrated that there is a vast potential of the variety of stakeholders to influence brand importance scores. Even with the top-level classification of magazines major differences in their communication of the brands have been revealed.

Brand equity research demonstrates the strongest extent to which these studies are focused on the customer perception of the brand. In this paper, we have attempted to use other than consumer-generated text data and the cumulative metric to measure different dimensions generally believed to be the components of the overall brand equity. In reply to Keller's (2016) suggestions to track a brand for the deeper brand perceptions, we have applied the approach to track the brand importance using the articles' scraping approach. The approach has proved to deliver volumes of data necessary for the representative analysis.

The main contribution of the research is believed to be the addressing of the gap in brand co-creation studies within the fashion industry, particularly the lack of studies devoted to other than customers' role in co-creation of the brand. The paper is also motivated by the fact that social media has become the major platform for retrieving brand data. Though the role of social media is not doubted at this stage, it seems that social media represents the reflection on the brand perception by the customers, rather than the understanding of how this perception has been formed and who has motivated customers to express this perception of the brand.

Conclusion

Overall, research results supported Hypothesis 1 and Hypothesis 2, however, Hypothesis 3 was not supported. In general, different types of magazines have different preferences, e.g. established magazines put more attention on luxury brands, whereas independent magazines favour sportswear and high-street brands compared to established magazines. One more important point is that the content of the article with brand mentioning is not that important as the number of mentionings.

Managerial application.

Brand management is the common set of activities within any marketing department at any company that is concerned about their brand perception. Typically, we can find the following KPIs that allow brands to measure their performance and set goals:

1. Brand awareness KPIs. Here the search volume measurement tools and online mentions count are usually used to track the frequency of mentions, as well as their sentiment.
2. Brand associations and satisfaction with the brand services/products KPIs. A well-known way to measure these is through focus groups or surveys (both qualitative and quantitative).
3. Brand reputation. Here we can meet a widely-used NPS (Net Promoter Score), which can literally show you the possibility that somebody is going to recommend your brand.

From these observations, we can already conclude that components of the SBS score are relevant to the more traditional brand management KPIs. The number of mentions and the sentiment around them is the parts of the SBS score and they can be used by the brand managers as the monthly/annual KPIs. Thus, the decision-making process can be supported by the SBS methodology integration.

Another direction for SBS methodology application is the trend analysis based on the large volumes of textual data. In the current research, we have been using brand names to retrieve Semantic Brand Scores for the particular brand. However, both text data sources and the keywords searched might follow another logic relevant to the different research questions and purposes outside brand management scope (use names of the products, models of the product, designers, etc.).

Limitations.

The research is limited by 2 main factors. Firstly, only 15 brands in 3 categories (luxury, high-street, sportswear) have been analyzed in order to get the SBS from 10 established or independent fashion magazines. The limitation is stated due to the fact that on average a single fashion magazine tends to write about more than 600 fashion brands.

Secondly, the number of fashion magazines (5 established fashion magazines and 5 independent fashion magazines) might not be sufficient enough to demonstrate the power of the SBS measurement on the text data. The more voluminous sample of text data for the more extended timeline could have shown a radically different outcome, as well as the similar one.

Further research.

Further studies are recommended in two directions: further studies of the co-creation of a brand and further Semantic Brand Score application.

As for the co-creation studies, other stakeholders and the brand equity communicated through their channels shall be picked in order to fulfil the area of study. Custom marketing classifications are also proposed to ensure more sufficient managerial application suggestions. It is believed that if the classifications of the co-creators and their sources get clear enough for the brand managers, it will be easier for them to apply the Semantic Brand Score as a long-term brand management performance metric. In Figure 6 of the current paper, the uncovered areas are illustrated. Other co-creators of the brand may include other retailers, customers, competitors, etc.

Further Semantic Brand Score application is proposed to the scholars in terms of extension of the data collection timeline. The same methodology and approach to measure fashion magazines' brand co-creation might be used in further studies with the less limited timeframe and hardware capacities. Moreover, it has been noted during the research that it is still not clear enough, which articles of the fashion magazines are sponsored, and which of them can be considered as part of the content strategy of a particular magazine. Thus, we suggest conducting more substantial research taking into consideration this 'advertising factor' to ensure the cleanliness of the findings. The sponsorship status is more likely retrievable through the specialized labels accompanying the article.

References

Aaker, D. (2009). Aaker's brand equity model. European Institute for Brand Management.

Aaker, D. A. (1996). Measuring brand equity across products and markets. California management review, 38(3).

Aaker, D. A. (2009). Managing brand equity. Simon and Schuster.

Algharabat, R., Rana, N. P., Alalwan, A. A., Baabdullah, A., & Gupta, A. (2020). Investigating the antecedents of customer brand engagement and consumer-based brand equity in social media. Journal of Retailing and Consumer Services, 53.

An, H., & Park, M. (2018). A study on the evaluation of fashion design based on big data text analysis-Focus on semantic network analysis of design elements and emotional terms. Journal of the Korean Society of Clothing and Textiles, 42(3), 428-437.

An, H., & Park, M. (2020). Approaching fashion design trend applications using text mining and semantic network analysis. Fashion and Textiles, 7(1), 1-15.

Barnes, J. A. (1954). Class and committees in a Norwegian island parish. Human relations, 7(1), 39-58.

Blasi, S., Brigato, L., & Sedita, S. R. (2020). Eco-friendliness and fashion perceptual attributes of fashion brands: An analysis of consumers' perceptions based on twitter data mining. Journal of Cleaner Production, 244, 118701.

Blazquez, D., & Domenech, J. (2018). Big Data sources and methods for social and economic analyses. Technological Forecasting and Social Change, 130, 99-113.

Can, U., & Alatas, B. (2019). A new direction in social network analysis: Online social network analysis problems and applications. Physica A: Statistical Mechanics and its Applications, 535, 122372.

Cheung, M. L., Pires, G., Rosenberger, P. J., & De Oliverira, M. J. (2020). Driving consumer–brand engagement and co-creation by brand interactivity. Marketing Intelligence & Planning.

Choi, E., Ko, E., & Kim, A. J. (2016). Explaining and predicting purchase intentions following luxury-fashion brand value co-creation encounters. Journal of Business Research, 69(12), 5827-5832.

Choi, Y. H., & Lee, K. H. (2020). Informatics analysis of consumer reviews for「Frozen 2」fashion collaboration products-Semantic networks and sentiment analysis. The Research Journal of the Costume Culture, 28(2), 265-284.

Christodoulides, G. (2008). Breaking free from the industrial age paradigm of branding. Journal of Brand Management, 15(4), 291-293.

Colicev, A., Malshe, A., & Pauwels, K. (2018). Social media and customer-based brand equity: An empirical investigation in retail industry. Administrative Sciences, 8(3), 55.

Colladon, A. F. (2018). The semantic brand score. Journal of Business Research, 88, 150-160.

Colladon, A. F. (2020). Forecasting election results by studying brand importance in online news. International Journal of Forecasting, 36(2), 414-427.

Colladon, A. F., Grippa, F., & Innarella, R. (2020). Studying the association of online brand importance with museum visitors: An application of the semantic brand score. Tourism Management Perspectives, 33, 100588.

Desai, N., & Narvekar, M. (2015). Normalization of noisy text data. Procedia Computer Science, 45, 127-132.

Doerfel, M. L. (1998). What constitutes semantic network analysis? A comparison of research and methodologies. Connections, 21(2), 16-26.

Evert, S. (2005). The statistics of word cooccurrences: word pairs and collocations.

Filieri, R., Hofacker, C. F., & Alguezaui, S. (2018). What makes information in online consumer reviews diagnostic over time? The role of review relevancy, factuality, currency, source credibility and ranking score. Computers in Human Behavior, 80, 122-131.

Foroudi, P., Jin, Z., Gupta, S., Foroudi, M. M., & Kitchen, P. J. (2018). Perceptional components of brand equity: Configuring the Symmetrical and Asymmetrical Paths to brand loyalty and brand purchase intention. Journal of Business Research, 89, 462-474.

Foroudi, P., Yu, Q., Gupta, S., & Foroudi, M. M. (2019). Enhancing university brand image and reputation through customer value co-creation behaviour. Technological Forecasting and Social Change, 138, 218-227.

France, C., Grace, D., Merrilees, B., & Miller, D. (2018). Customer brand co-creation behavior: conceptualization and empirical validation. Marketing intelligence & planning.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. Social networks, 1(3), 215-239.

Fronzetti Colladon, A. (2018). The Semantic Brand Score. Journal of Business Research, 88, 150–160.

Fronzetti Colladon, A., & Grippa, F. (2020). Brand Intelligence Analytics. In A. Przegalinska, F. Grippa, & P. A. Gloor (Eds.), Digital Transformation of Collaboration (pp. 125-141). Springer Nature Switzerland. https://doi.org/10.1007/978-3-030-48993-9_10

Gan, Q., Ferns, B. H., Yu, Y., & Jin, L. (2017). A text mining and multidimensional sentiment analysis of online restaurant reviews. Journal of Quality Assurance in Hospitality & Tourism, 18(4), 465-492.

González-Mansilla, Ó., Berenguer-Contri, G., & Serra-Cantallops, A. (2019). The impact of value co-creation on hotel brand equity and customer satisfaction. Tourism Management, 75, 51-65.

Grippa, F., & Colladon, A. F. Brand Intelligence Analytics for the 2020 US Democratic Presidential Primaries.

Gustafson, T., & Chabot, B. (2007). Brand awareness. Cornell Maple Bulletin, 105, 1-5.

Hatch, M. J., & Schultz, M. (2010). Toward a theory of brand co-creation with implications for brand governance. Journal of Brand Management, 17(8), 590-604.

Herrando, C., Jiménez-Martínez, J., & Martín-De Hoyos, M. J. (2017). Passion at first sight: how to engage users in social commerce contexts. Electronic Commerce Research, 17(4), 701-720.

Hoang, H. T., Wang, F., Van Ngo, Q., & Chen, M. (2019). Brand equity in social media-based brand community. Marketing Intelligence & Planning.

Hou, M., Wu, L., Chen, E., Li, Z., Zheng, V. W., & Liu, Q. (2019). Explainable fashion recommendation: A semantic attribute region guided approach. arXiv preprint arXiv:1905.12862.

Iglesias, O., Landgraf, P., Ind, N., Markovic, S., & Koporcic, N. (2020). Corporate brand identity co-creation in business-to-business contexts. Industrial Marketing Management, 85, 32-43.

Jones, J. P., & Slater, J. S. (2003). What's in a Name?: Advertising and the Concept of Brands. ME Sharpe.

Kamboj, S., Sarmah, B., Gupta, S., & Dwivedi, Y. (2018). Examining branding co-creation in brand communities on social media: Applying the paradigm of

Stimulus-Organism-Response. International Journal of Information Management, 39, 169-185.

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. Journal of marketing, 57(1), 1-22.

Keller, K. L. (2003). Understanding brands, branding and brand equity. Interactive Marketing, 5(1), 7-20.

Keller, K. L. (2016). Reflections on customer-based brand equity: perspectives, progress, and priorities. AMS review, 6(1), 1-16.

Keller, K. L., & Brexendorf, T. O. (2019). Measuring brand equity. Handbuch Markenführung, 1409-1439.

Kent, S. (2021) Measuring Fashion's Sustainability Gap. Business of Fashion. Retrieved from https://www.businessoffashion.com/reports/sustainability/measuring-fashions-sustainability-gap-download-the-report-now

Khajeheian, D., & Ebrahimi, P. (2020). Media branding and value co-creation: effect of user participation in social media of newsmedia on attitudinal and behavioural loyalty. European Journal of International Management, 14(3), 254-273.

Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. Journal of Business research, 65(10), 1480-1486.

Kim, E. G., & Chun, S. H. (2019). Analyzing online car reviews using text mining. Sustainability, 11(6), 1611.

Kondakci, Y., Bedenlier, S., & Zawacki-Richter, O. (2018). Social network analysis of international student mobility: Uncovering the rise of regional hubs. Higher Education, 75(3), 517-535.

Leuthesser, L. A. (1988). Defining, measuring and managing brand equity: A conference summary. Cambridge, MA: Marketing Science Institute (No. 88-104). Report.

Lin, J. S., & Himelboim, I. (2019). Political brand communities as social network clusters: winning and trailing candidates in the GOP 2016 primary elections. Journal of Political Marketing, 18(1-2), 119-147.

Martinsson, J., & Mogren, O. (2019). Semantic segmentation of fashion images using feature pyramid networks. In Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops.

McCarthy, P. M., & Jarvis, S. (2010). MTLD, vocd-D, and HD-D: A validation study of sophisticated approaches to lexical diversity assessment. Behavior research methods, 42(2), 381-392.

Merz, M. A., He, Y., & Vargo, S. L. (2009). The evolving brand logic: a service-dominant logic perspective. Journal of the Academy of Marketing Science, 37(3), 328-344.

Merz, M. A., Zarantonello, L., & Grappi, S. (2018). How valuable are your customers in the brand value co-creation process? The development of a Customer Co-Creation Value (CCCV) scale. Journal of Business Research, 82, 79-89.

Mühlbacher, H., Raies, K., Grohs, R., & Koll, O. (2016). Drivers of brand strength: Configural paths to strong cognitive brand equity. Journal of Business Research, 69(8), 2774-2780.

Nielsen, J. (2008). How little do users read. Nielsen Norman Group, 5.

Payne, A. F., Storbacka, K., & Frow, P. (2008). Managing the co-creation of value. Journal of the academy of marketing science, 36(1), 83-96.

Prahalad , C . K .and Ramaswamy , V .(2004) The Future of Competition: Co-Creating Unique Value with Customers. Boston, MA: Harvard Business School Press .

Ramaswamy, V., & Ozcan, K. (2018). What is co-creation? An interactional creation framework and its implications for value creation. Journal of Business Research, 84, 196-205.

Seo, E. J., & Park, J. W. (2018). A study on the effects of social media marketing activities on brand equity and customer response in the airline industry. Journal of Air Transport Management, 66, 36-41.

Serrat, O. (2017). Social network analysis. In Knowledge solutions (pp. 39-43). Springer, Singapore.

Silva, E. S., Hassani, H., & Madsen, D. Ø. (2019). Big Data in fashion: transforming the retail sector. Journal of Business Strategy.

Tabassum, S., Pereira, F. S., Fernandes, S., & Gama, J. (2018). Social network analysis: An overview. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(5), e1256.

Tajvidi, M., Richard, M. O., Wang, Y., & Hajli, N. (2018). Brand co-creation through social commerce information sharing: The role of social media. Journal of Business Research.

Thomas, L. J., Brooks, S., & McGouran, C. (2020). Antecedents of value co-creation activities for online fashion brands. Journal of Strategic Marketing, 28(5), 384-398.

Valeri, M., & Baggio, R. (2020). Italian tourism intermediaries: A social network analysis exploration. Current Issues in Tourism, 1-14. Sun, L., Qin, L., Taghizadeh-Hesary, F., Zhang, J., Mohsin, M., & Chaudhry, I. S. (2020). Analyzing carbon emission transfer network structure among provinces in China: new evidence from social network analysis. Environmental Science and Pollution Research, 27(18), 23281-23300.

Wang, H. J. (2019). Green city branding: perceptions of multiple stakeholders. Journal of Product & Brand Management.

Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications.

Watanabe, N. M., Kim, J., & Park, J. (2021). Social network analysis and domestic and international retailers: An investigation of social media networks of cosmetic brands. Journal of Retailing and Consumer Services, 58, 102301.

Wood, L. (2000). Brands and brand equity: definition and management. Management decision.

Yu, Y., Moore, M., & Chapman, L. P. (2020). Social network analysis of an emerging innovation: direct-to-garment printing technology. Journal of Fashion Marketing and Management: An International Journal.

Yu, Y., Moore, M., & Parillo-Chapman, L. (2020, December). Social Media Based, Data-mining Driven Social Network Analysis (SNA) of Printing Technologies in Fashion Industry. In International Textile and Apparel Association Annual Conference Proceedings (Vol. 77, No. 1). Iowa State University Digital Press.

Zhao, L., & Min, C. (2019). The rise of fashion informatics: A case of data-mining-based social network analysis in fashion. Clothing and Textiles Research Journal, 37(2), 87-102.

Word associations for brands

Established Magazines | Independent Magazines