



UNIVERSITY OF AMSTERDAM

Media Studies

Bachelor's Thesis

Media and Information

Group 14

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**Weapons of mass consumption:** fast fashion web stores and consumer  
exploitation practices

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May 27, 2022

10,684 words

## **Abstract**

The digitalisation of consumption has enabled fast fashion web stores to provide end-users with an optimised shopping experience at the cost of their privacy and agency. As these web stores manipulate users' online shopping practices, website visitors are constantly subjected to data-driven strategies. While end-users may be satisfied with their improved shopping experience, the goal of user satisfaction mainly acts under the fast-fashion companies' economic interests. This research observes Shein, Boohoo and Fashion Nova, three major fast fashion companies, to analyse how they drive consumption via UX design and algorithmic surveillance. This research looks at how fast fashion web stores manipulate their users' information and behaviour for their company's profit. It also suggests that by collecting, analysing and repurposing user data, web stores exploit personal information to impel their users to keep consuming via these websites. While data is capitalised upon, digital strategies such as malicious uses of web design are imperative for assessing website performance. As each data flow and data point are surveilled, user free will is constantly hindered by information and power differentials governed by fast fashion platforms. This paper has both technological and ethical goals. While the technological goals underscore the data-driven strategies, the ethical goals shed light on their impact on user free will and the environment.

## **Keywords**

Data exploitation; fast fashion; UX design; dark participation; free will; surveillance capitalism; big data; user practices

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## **Weapons of mass consumption: online fast-fashion stores and consumer exploitation practices**

### **1. Introduction**

Sarah (23) is planning on buying a new outfit for a party this weekend. After a few Google searches, an online fashion brand appears on her browser, guaranteeing her the most fashionable clothes for the best price available. On the website's homepage, she clicks on the 'party' category, sorts the price in ascending order and begins to scroll. Within a couple of minutes, she finds three discounted items for her event: a dress, a shoulder bag and a pair of shoes. Before checking out, a website pop-up shows a flash sale in the makeup and skincare section. Sarah picks out four more items, heads towards check out, and uses a discount code provided to her by the website itself. She has bought her ideal outfit and other makeup products for a highly discounted price, all in under one hour. She is satisfied with her shopping experience and awaits her order, which will arrive just in time for her party.

However, unbeknownst to Sarah, this ideal shopping experience has been catered to a generic category of end-user who fits her consumer description. Sarah is not completely aligned with the online brand, nor does her preference for it result from the range of its stylish products. The agency and privacy of online consumers, such as Sarah, have been hindered without their knowledge. Online shopping platforms are data-intensive industries which thrive on processes of data-driven product offerings, data gathering and analysis of their end-users, which feed these 'preferences' back into them. These web stores extract data from their users and encourage consumption on an interface level to provide them with this supposed ideal shopping experience. While these web stores convey an illusion of free will, shopping online nevertheless is carefully choreographed by data-hungry algorithms. With modern data-driven strategies, online stores take advantage of their consumers by predicting and shaping their shopping experience towards increased consumption for their economic benefits.



## 1.1. Background

Exploitation can be defined as making use of something in order to gain an advantage from it. While industries generally rely on their consumers to buy products, platform companies rely on the ability to extract user data to exploit it. Vili Lehdonvirta (2012) defines the 'digitalisation of consumption' as the way information society interacts with consumer society in a broad range of processes. Indeed, the shift to a digital shopping environment has complexified shopping practices by integrating data- and algorithmic-driven strategies to encourage consumption.

With this digitalisation of consumption, the traditional shopping site of the physical retail store has been replaced with many other forms of online retailing. Digital consumers are subjected to new controlled shopping environments in which platform interfaces guide the user experience in order to maximise conversion rates (Lehdonvirta, 2012). In E-commerce, conversion rates are popular metrics that display to what extent an online store effectively converts user prospects into customers (Ekholm, 2020). The datafication of consumption has given many companies much control over their end-users' behaviour through controlled data accumulation and analysis processes. The data-driven mechanisms have led these industries to prioritise data accumulation as a new way of doing business and governance (Sadowski, 2019). In that sense, the free will of end-users is threatened by the datafied processes led by digital platforms and web stores. As data becomes a valuable source of information, data is understood and extracted as a form of capital. Then, these industries also manipulate the shopping habits of the users that have generated that data in the first place.

This research focuses on the exploitative practices brought about by the exclusively digital environment of fast-fashion stores. Their exploitative practices inhibit users, such as Sarah, from maintaining their free will while shopping via web stores. The shift to a datafied form of retail consumption has transformed how companies approach business practices and predict consumer behaviour. This research only concerns fast-fashion web stores as they are particularly responsible for causing much environmental harm with their contribution to the exponential increase of fast fashion consumption. This research responds to the following question: **How do fast-fashion stores exploit their end-users' data and behaviour to improve their businesses?**

## 1.2 Case study

The following fast-fashion stores serve as the primary sources of the research: [Shein](#), [Boohoo](#), and [Fashion Nova](#) to conduct this research. This decision involves three aspects: demographic, valuation and business model.

The main commonality shared by these three brands is their online business model. The fashion brands Shein, Boohoo, and Fashion Nova, are purely present through a digital interface. Therefore, data-driven practices are more significant for the brands mentioned above since their business model is entirely catered to platform logics and data-driven strategies toward increasing consumption. For example, other fast-fashion brands such as H&M or Inditex (Zara) have web stores but also own many physical branches worldwide. According to H&M's corporate website, in 2021, there were 4,801 of its stores present in several countries (H&M Group, 2021). Therefore, while it is possible to buy products from these stores digitally, their manufacturing models mostly rely on their physical shops.

Second, these stores all have a similar consumer target of women aged 14-25. The fast-fashion brands produce clothing and certain beauty products explicitly advertised to teenage girls and young adult women. Indeed, while scrolling through these fast-fashion platforms, it is apparent that nearly all apparel and accessory products are displayed and advertised with female models. For example, on Shein, Boohoo and Fashion Nova, there are significantly more products and sizes to choose from when shopping in the women's section.

Third, these three brands are highly valued and recognised on a global scale. Shein, the Chinese fashion startup, is known as China's most valuable private business. In August 2020, it had a market valuation of  $\approx$  €13 billion, which has now doubled to as much as  $\approx$  €25 billion (CNN Business, 2021). Moreover, Fashion Nova's market value is estimated at  $\approx$  €1.3 billion (Forbes, 2022). It was also the most googled fashion brand in the United States in 2018, beating luxury brands such as Dior and Gucci (Google Trends, 2018). According to Boohoo Group PLC, boohoo's market value is currently at  $\approx$  €1.4 billion, with a total revenue of  $\approx$  €2.4 billion (Ycharts, accessed 2022).

### 1.3 Relevance

An important aspect which motivates this research is the impact of fast fashion on the environment in recent years. The environmental effect of fast fashion has been considerable and ubiquitous. For instance, the industry generates eight to ten per cent of annual global CO<sub>2</sub> emissions. It annually produces 92 million tonnes worth of textile waste and is responsible for around 35% (190,000 tonnes per year) of oceanic primary microplastic pollution (Niinimäki et al., 2020). This rising impact can be seen as a direct consequence of data-driven production strategies facilitating production practices.

Today's fast fashion industry has generated a shopping experience which thrives on instant gratification and a constant expectation of finding new products on the store's production line. It places users in a loop of product consumption as it feeds on their previously generated data. The current fast fashion market is highly competitive, and there is a continuous exigency to produce new and fresh products (Bhardwaj et al., 2010). Fast fashion stores manufacture clothing and accessories with a shorter life cycle which encourages consumers to visit these stores on a regular — almost weekly — basis. Global consumption of fast fashion has risen to an average of 62 million tonnes of apparel per year and is estimated to reach 102 million tonnes by 2030 (Niinimäki et al., 2020).

My approach to online fast fashion stores helps highlight their reliance on data extraction and analysis, as they have become normative methods in maintaining user interest and market demand at an all-time high (Bhardwaj et al., 2010). The production decisions of fast-fashion stores are pushing the industry to produce items in an unsustainable way. These web stores are able to speed up production processes because it relies on algorithms to identify which items are in trend at any given moment and does not need to ship any of these items to a physical branch. This massive production and consumption cycle relies heavily on the data extraction and behavioural exploitation of end-users who shop in these stores. Additionally, fashion trends change regularly on fast-fashion websites. For instance, Shein has new items in stock every day. As fast-fashion companies rely on exploiting user data, fashion trends appear as dynamic and ever-changing cycles. These companies must keep up with competition which eventually drives the entire industry to keep producing in this way.

Moreover, the global impact of fast fashion has sparked many people to discuss the topic online in recent years.<sup>1</sup> On youtube, fast fashion is part of popular discourse. Many videos that

shed light on the controversial topic garner thousands of views, likes and comments from other users. Indeed, the negative aspects of fast fashion are emphasised in popular online discourse with discussions about its environmental impact and addictive shopping model. For instance, popular videos such as [Why No One Wins the Fast Fashion Debate](#) (Deschanel, 2021) discuss fast fashion's pros and cons. On the one hand, it seems to cater to those with lower incomes thanks to its exceedingly low prices. However, it also lays the ground for obsessive shopping habits due to its facilitated and encouraged consumption mode.

This research is relevant to the field of media and information because the current discourse on the fast fashion market is incomplete. Indeed, there is a gap in the literature on the industry about the consumer-driven aspect of fast fashion business models, which leaves it an under-researched subject. It forgets the important role of data- and algorithmic-driven practices in shaping consumer behaviour on online shopping platforms. Fast-fashion web stores are dependent on these digital strategies to produce their products and maintain user retention at a maximum. However, this highly efficient business model substantially impacts the environment and consumer behaviour. It relies on these digital strategies to keep production and consumption rates to a maximum. Thus, this research aims to shed more light on the link between data exploitation and environmental degradation.

## **2. Literature Review: Theoretical framework and literature**

### **2.1 Datafication and digitalisation of consumption**

Coined by Kenneth Cukier and Victor Mayer-Schöenberger (2013), datafication is defined as the idea that many aspects of social life are now understood through data-driven mechanisms and have been transformed into new forms of datafied value. However, other, more elaborate conceptualisations of datafication have been built upon this initial definition. Helen Kennedy, Thomas Poell and Jose van Dijck (2015) understand datafication not only as the process of collecting and analysing data but also as the process of 'feeding such data back to users, enabling them to orient themselves in the world.' (p. 1). This definition questions the relationship between data and users regarding user agency online and the power relations that complicate these datafied processes even further. Kennedy et al. (2015) understand user agency in the context of datafied practices as a 'complex and multifaceted concept' (p. 6) because it involves a range of distinct users along with different contexts. Users acquire different levels of agency depending on their interactions with and their knowledge of data structures and collection practices. For instance, a cyber hacker and an everyday (ordinary) user generally have distinct 'interpretations and applications of technological systems' (Smith et al., 2001). These different interpretations largely affect the online experiences of each user in which the extent of their knowledge of data practices shapes their digital interactions. Unfortunately, those visiting fast fashion web stores mainly consist of 'everyday users' with the sole intention to buy new products.

Moreover, online shopping infrastructures take place in a purely datafied environment thanks to the digitalisation of consumption (Lehdonvirta, 2012). Thus, it becomes easier to mediate a user's shopping experience and, in doing so, influence user behaviour. The ability of fast fashion web stores to manipulate user behaviour has a deep impact on their free will. In the context of online platforms, Patrick Waelbroeck (2018) defines free will as 'the possibility to make choices in a neutral "information environment"' (p. 3). Therefore, if end-users can only make optimal economic decisions in information-neutral spaces, fast fashion web stores inhibit them from doing so as a result of their data-driven strategies. Free will on digital platforms is generally obstructed by filtered information and algorithmically-generated recommendations. Indeed, the shift to a digitised form of consumerism has played an important role in constructing user preference.

## 2.2 Participatory culture on fast-fashion platforms

While there is a gap in the academic literature on fast-fashion platforms, my approach makes use of many concepts to theorise the data-driven strategies of these web stores. With Henry Jenkins' (2015) theory on participatory culture, my research connects interface strategies and participatory culture on fast-fashion platforms. These strategies encompass visible website design choices and affordances, which encourage participatory practices through active user contributions on these websites.

Jenkins defines participatory culture as a 'culture with relatively low barriers to artistic expression and social engagement, [...] one in which members believe their contributions matter, and feel some degree of social connection with one another' (2015). Participatory culture has been widely incorporated into many digital platforms with the emergence of Web 2.0, also known as the participatory or social web. Web 2.0 refers to a specific trend of World Wide Web technologies — one which heavily incorporates user-generated content, facilitated use of web technologies and interoperability (the ability to exchange and make use of data). Web 2.0 emphasises user creativity, information sharing, collaboration and overall improved functionality of web technologies. Mirko Tobias Schäfer (2008) discusses user activities within the structures of the participatory web 2.0. He builds on Jenkins' definition of participatory culture by highlighting it as a 'community-based activity which is determined by a high degree of social interaction and mutual understanding among its participants' (p. 148). Schäfer distinguishes explicit and implicit user participation in web 2.0 technologies. The former can be defined as a conscious activity in which users actively engage in participatory practices as they seek freedom from cultural industries. For example, direct participation on fast-fashion platforms consists of users uploading reviews on purchased products, which other users actively read and make judgements. However, the latter form of user participation in Web 2.0 concerns the implicit aspects of digital participatory cultures in which user participation is covert as they are guided by software architecture and interface design. These implicit features, such as clicks and views, facilitate user interactions but are also beneficial for digital platforms as they can gather useful data from their users, such as preferences and product performance rates. For example, as users interact with products on fast-fashion websites, algorithms can extract this information and identify which products are popular and in demand. In this way, fast-fashion platforms are able

to keep up with fashion trends and maintain user interest via implicit and explicit forms of user participation.

Moreover, user agency is thwarted by the participatory practices encouraged by fast-fashion platforms because the companies rely on forms of participation geared towards data extraction rather than user empowerment. While these two options can be implemented together, the latter one is never a priority within these web stores. With Thorsten Quandt's (2018) theory of dark participation, this research discusses online user engagement as an exploitative aspect of the participatory web. Quandt (2018) understands dark participation as the 'evil flip side of citizen engagement' (p. 37), which challenges the idea of participatory culture as a utopian concept. He theorises the idea of dark participation in terms of its ethical and political implications. Additionally, he highlights the negative and destructive participatory effects brought by different forms of user contributions to news-making processes. These contributions by users to the participatory web concern online activities such as misinformation, cyberbullying and trolling. In Quandt's theory, users are considered 'dark participators' (p. 41) as they actively manipulate and spread hate across platforms. His research highlights the negative aspect of user participation on fast-fashion platforms through his theory. However, my analysis does not consider that consumers who engage in participatory practices are dark participators. Instead, it emphasises the significant role of fast fashion companies that encourage user participation on their platforms. In this context, I consider fast-fashion platforms to be 'dark promoters' of participatory culture on their platforms. They advertise participatory activities as beneficial for online consumers, while in reality, these motivations are driven by data-surveillance mechanisms. As fast-fashion brands rely on digital technologies, they retain the ability to gather better predictions and maintain user interest, which ultimately leads to more consumption of fast-fashion products.

Other interface-level theories have criticised this form of dark promotion and its incorporation into UX Design (User Experience Design). Collin M. Gray et al. (2018) discuss malicious uses of web design, in which certain interface elements only benefit the web companies and not the user. They use the term 'dark patterns' to explain the 'instances where designers use their knowledge of human behaviour [...] and the desires of end-users to implement deceptive functionality that is not in the user's best interest' (p. 1). The theory acknowledges the manipulative techniques, criticises their supposed aims and discusses the ethical implications of putting these UX elements in place. These 'dark patterns' reflect the interface-level strategies in

which a company's interest is valued higher than the user's. In the context of fast-fashion stores, these 'dark patterns' are implemented to gain user retention for company profit rather than benefiting user experience — even though they market it as such. With Gray et al.'s (2018) interface design theory, this research analyses interface design elements on fast fashion homepages and product detail pages and discusses their implications. It studies the purpose of these affordances and how they are used to manipulate user behaviour on these websites.



### **2.3 Tracking user behaviour on fast-fashion platforms**

The digital form of consumerism has significantly transformed the structure of the fast-fashion market and how businesses perceive their consumers. The role of data has become central to the way fast fashion companies approach marketing strategies. Jathan Sadowski (2019) discusses the concept of data as a form of capital. His theory understands the ways in which data generates value, the importance of data-gathering processes and the incentives that motivate modern companies to conduct these data-driven strategies. Data is considered the new driving logic which influences user behaviour. It constructs and orders the world as it establishes a context in which data accumulation is central to contemporary market practices (Sadowski, 2019). Moreover, data as capital creates a new dimension of control in which those who know it and have access to it can exercise power over it. Companies that track and analyse user data gain insights into their behaviour through their digital footprints, in which users are considered merely as data bodies (digital user-profiles compiled from their online participation). These data bodies are categorised into different types of users who are then targeted with advertisements matching their preferences. With this information, user behaviour prediction becomes facilitated and, therefore, valuable. This notion of 'data-driven capitalism' addressed how data is collected, circulated and treated as a form of capital. By treating it as a form of capital, data systems become muddled with relations of inequity, extraction and exploitation between users and companies (Sadowski, 2019).

Kennedy et al. (2015) highlight the importance of user agency in the context of the citizens or 'everyday users', for they are not necessarily conscious of what happens with their data and the subsequent effects it has on them. Users are not always aware of which information is being collected about them and how this data may be employed for other purposes. These datafied processes that lie beyond user interactions are not necessarily transparent either. Often, user data is shared with third-party services, which are later accessed and analysed without users' explicit consent (Puglisi et al., 2017).

The question of user free will within user-data relations brings to light the impact of data extraction practices on user agency online. Shoshana Zuboff (2015) explains how 'big data' has allowed platform companies to acquire massive amounts of information from user interactions with these platforms. Big data consists of complex data sets that are too large for traditional data processing softwares. This extensive volume of information aids these platforms in exercising

more control over their users without them necessarily being aware of it. The power asymmetries between users and platform companies largely result from the existence of big data and its re-application to end-users. These companies seek to analyse and categorise them (Zuboff, 2015). Through Zuboff's theories of data surveillance and data capitalism, this research discusses the notion of user privacy in the context of fast-fashion websites along with their third-party trackers. She defines surveillance capitalism as a 'deeply intentional and highly consequential new logic of accumulation' (Zuboff, 2015). This is important in the context of fast-fashion stores because it identifies the new processes of gathering and marketing information on consumers, enabled by the datafication of the retail experience. This paper uses the idea of surveillance capitalism to criticise the phenomenon of fast-fashion stores gathering and exploiting consumer data for profit gain. It also sees that the rise of datafication has transformed how fashion markets treat their consumers due to these new digital strategies of data collection and consumer participatory culture.

Additionally, fast-fashion web stores aim to facilitate their consumers' shopping experience by exploiting their data with data-gathering services such as site analytics and web trackers. Digital tools such as cookies and web analytics enable these online stores to understand their audiences better. However, other digital tools, such as recommendation algorithms, play a significant role in the content suggested to users on these fast-fashion web stores. This personalisation of content facilitates the decision-making processes of online shoppers as it guides them through the endless range of product offerings (Khusainova, 2020). It provides users with a customised array of store products to navigate the wide range of product choices. Recent research by Accenture (2021), a consultancy, shows that around 40% of consumers have exited a web store due to having too many options.

Furthermore, Tarleton Gillespie (2014) studies the role of algorithmic structures in terms of what information these algorithms gather and how they affect social life. While the general definition considers it a mathematical set of rules and procedures, Gillespie recognises the political ramifications of allowing algorithms to create new information structures. His theories encompass the political importance of the algorithmic assessment of information which 'represents a particular knowledge logic' (Gillespie, 2014). Gillespie's theories allow this research to clarify the public relevance of fast-fashion algorithms and the political implications of how data is collected and for what reasons. This paper touches upon three of the six concepts in

Gillespie's theory to study the public relevance of algorithms. These include 'cycles of anticipation, production of calculated publics and evaluation of relevance' (p. 168). In the first place, 'cycles of anticipation' refer to the fact that algorithm providers attempt to predict user behaviour based on previous activities on a website but also that these predictions can have certain motivations behind them. Websites aim to anticipate user activities through these algorithms, which gather knowledge about them. Algorithms can make recommendations to users based on their past activities in order to provide them with a personalised shopping experience. Recommender algorithms make estimations on what is considered relevant to a given user through processes of collaborative filtering or content-based filtering. In a retail environment, collaborative filtering algorithms recommend items to users based on past recorded interactions between other users and an item. It recommends a product by identifying other users with similar tastes and which products are popular among them. However, content-based recommendations focus on user characteristics and match them to content accordingly. Certain algorithms solely rely on user information and discard any contributions from other users (Isinkaye et al., 2015). Other algorithms also estimate the extent to which other users are similar to each other to recommend certain products for these user groups.

This point brings this paper to the second aspect of Gillespie's theory on the public relevance of algorithms — the 'production of calculated publics'. Indeed, algorithms traffic in calculated publics that have been produced by themselves (Gillespie, 2014). For example, algorithms gather information about users, such as location, age range, and gender. They may use this information to recommend popular products within that group to other users who fit the same consumer description. When recommended products via messages like 'others who liked this also bought', it shows that there is knowledge of what type of user is on the website and their estimated preferences. Lastly, Gillespie's theory of 'evaluation of relevance' addresses how algorithms determine what is considered relevant or not. In this theory, the criteria of relevance are not acknowledged by users and yet continue to have an impact on their behaviour. In fast-fashion web stores, trending products result from algorithmic calculations of user activity that are considered high in the public interest (Gillespie, 2016). These algorithms estimate trends by combining some measure of each item's popularity, novelty, and timeliness.

## **2.4 Motivations and expectations**

My research highlights aspects of the online fast fashion industry that have yet to be discussed in academic research. Much of the current literature focuses on the industry's environmental aspects, the evolution of its market structure, and consumer behaviour in the fast fashion industry. This paper also aims to shed light on how the digitalisation of fast fashion stores has led to the loss of user agency and free will on E-commerce platforms. This research focuses on the use of interface strategies and third-party trackers to modify consumers' shopping experiences, either through interface design choices or web tracking. My research focuses on the digitalisation of clothing consumption which relies on data-driven strategies that facilitate end-users to consume at an increasing rate. While popular discourse rightfully focuses on the environmental impact of fast fashion, this research focuses on the digital tools that allow for fast fashion to exist in the first place. This analysis approaches this digital consumption mode via its impacts on user agency and, consequently, user free will.

My analysis aims to systematise popular knowledge on the industry's market strategies in data-gathering and analysis and data-driven consumerism. It also aims to narrow the gap between academic research and popular discourse on online fast fashion brands by focusing on the data-intensive nature of the digital market. The current discussion on fast fashion has been highly prevalent in popular knowledge on platforms such as TikTok and YouTube. It has gained much popularity with younger generations like Gen Z, thanks to its trendy and cheap clothing (Bhardwaj et al., 2010).

### **3. Methods**

My analysis consists of observing three major fast fashion companies and analysing their web stores on both a front- and back-end level. The corpus consists of three stores: Shein, Boohoo and Fashion Nova. Each of these brands sells apparel, accessories and other fashion products, and they each have an exclusively online presence and a target audience of young women.

My research is concerned with studying front-end and back-end strategies that drive consumer exploitation on these three online fast-fashion platforms. For this reason, the research method is twofold, based on the particular end of the platform being analysed. The front-end research follows a comparative interface analysis of the three web stores. These are strategies visible to the user as they are present on the web store's interface. However, the back-end research consists of a network analysis since it involves the presence of trackers on these web stores, which are invisible to the 'everyday user'.

For both research methods, the interface and network analysis focus on the homepage and a product detail page from each web store — this results in a total of six web pages. This research looks at these two pages because they act as a gateway for users into these web stores, depending on a user's search query. When users search for a particular fast-fashion brand, the homepage acts as the digital entryway into a particular web store. The homepage of each fast fashion store is the main starting point for each user's online shopping experience with a brand. However, when users search for a product online, they access these web stores based on that particular product. For instance, when searching 'blue skirt' on Google, end-users are met with a list of product photos for that specific type of product. Users do not enter via the homepage when clicking on a product via Google search. Rather, they access the product page showing the details of that particular blue skirt. Therefore, this research focuses on a randomly selected product web page from each website since it can also be the entry point of an end-user onto a brand's website.

### **3.1 Front-end analysis**

Through a comparative interface analysis of Shein, Boohoo, and Fashion Nova, this research addresses the front-end strategies which aim to exploit user behaviour. The analysis is similar to an interface analysis but differs as it is conducted on all three platforms. The comparison looks at each website's homepage and a randomly selected product from each store and compares the shared elements present on these pages. These consist of web design choices and features that encourage users to continue shopping, such as pop-ups, flashy information boxes and countdowns. My research observes how these web elements structurally facilitate and entertain the processes of consumption. It also provides an explanation of how a platform's interface can produce routinised forms of user interactions (Raessens et al., 2009) as it critically addresses the relationship between a platform interface and how it shapes user shopping habits.

### **3.2 Back-end analysis**

Web tracking is the practice of gathering, storing and sharing data on website visitors by website administrators and third-party services. These trackers establish data flows between websites and third parties, such as recording user visits, extracting different types of user data and measuring ad effectiveness (Bounegru, 2019). My network analysis of these three fast-fashion stores includes researching their web trackers to study their back-end strategies. It follows the 'Track the Trackers' method, using the media research tool [Thunderbeam-Lightbeam](#), a Firefox browser extension. Thunderbeam-Lightbeam collects browser data and records the trackers present on a web page. Ultimately, the 'Track the Trackers' method is a technique which allows internet users to identify which trackers are actively tracking them via their browsers. The tracker network graph of these three fast fashion web stores allows the researcher to discern the number of trackers present and find what they aim to do on these websites.

The research uses Gephi to visualise the network of third-party trackers shared by these three fast-fashion stores. Gephi is a visualisation software which can display networks in different ways, depending on what one wants to address within the network. Similar to the comparative interface analysis, this method looks for these trackers on each homepage of the fast-fashion web stores and a randomly selected product from each store. Based on the findings, this research observes the site analytics and advertising trackers to identify which third-party partners are present on these websites, the type of information they gather about end-users and

what they aim to do with this information. This selection is relevant for this research because it observes trackers that allow for personalised recommendations and user-data extraction on fast-fashion websites. My research also uses Rawgraphs, a data visualisation tool, to visualise the type of trackers present on Shein, Boohoo and Fashion Nova. Additionally, I analyse the type of trackers, the information they gather and how their providers describe them. By visiting several providers' websites, this research highlights how the trackers utilise data-driven processes to aid these fast fashion web stores in extracting user information and optimising website performance.

## 4. Findings

### 4.1 Comparative interface analysis

Fast fashion web stores use many web elements in their strategy, which push users to buy these products. These interface strategies instil feelings of urgency, facilitate user shopping experiences, and transform online shopping into a form of entertainment. While these strategies concern interface affordances and design choices, they play an important role in shaping user shopping habits.

#### 4.1.1 Producing urgency via interface design

On an interface level, users encounter many nudges that push them to consume an increasing number of products. Since users can be leveraged to perform certain actions on these websites, UX designers use that knowledge by incorporating nudges (or 'dark patterns') which influence how users shop on digital platforms. For instance, each product on these three websites has a 'Quick add/view' option. This affordance enables users to place them in their digital shopping cart immediately. Consequently, this shortens the path of putting items in one's cart by avoiding the visit to the individual product page. Though, many other front-end strategies on these web stores involve interface design and how it aims to create urgency in website visitors. In this context, urgency refers to the fact that these fast-fashion companies leverage user weaknesses against them by instilling the idea that they must urgently buy an item on these web stores. For instance, Shein's homepage contains many enticing elements that persuade users to consume discounted store products rapidly before being out of stock. These elements can be seen on the homepage's sale section, where the displayed products are either fast-selling or soon-to-be out-of-stock items.

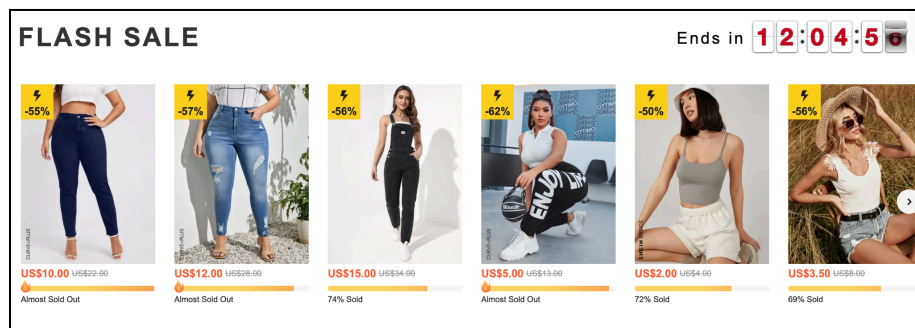


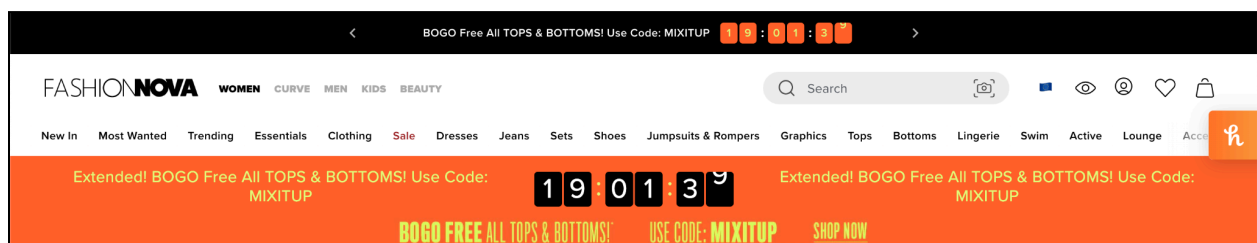
Fig. 1: Shein website. Flash sale section.



**Figure 1** consists of a screenshot of the 'Flash Sale' category on the homepage of Shein's website. In this section alone, various web components instil feelings of urgency within end-users to consume their discounted products. These include sale countdowns, yellow flash boxes, and each item's purchasing rate. This countdown at the top of the 'Flash Sale' section catches users' attention more easily and promotes their immediate consumption. It also shows the time left to buy these products in real-time before the 'Flash Sale' ends.

Moreover, each product shown on the 'Flash Sale' carousel has a yellow flash box on the top left corner which indicates the discount percentage of each item. It alerts users with the bold yellow colour and flash symbol that these products are being sold at a better price. On top of this, a bar shows the current availability at the bottom of each of these discounted Shein products. Though, in order to make estimations about items' availability, Shein must gather and compare user purchasing data about which items are being majorly consumed. For instance, when items start to reach their minimum stock availability, Shein inserts the following text: 'Almost sold out'. Without gathering data on which items users buy and then feeding that information back into the website for new users, this digital strategy would not be possible.

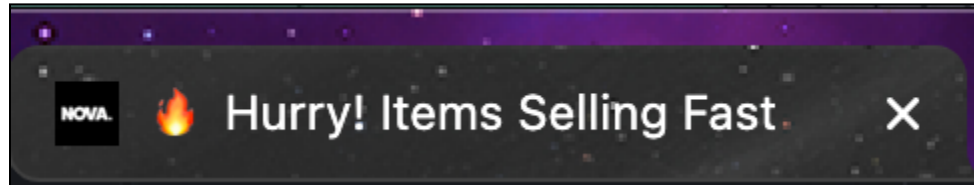
Contrastingly, Fashion Nova's homepage does not have any 'Flash sale' section but still follows similar interface strategies to encourage users to buy discounted products. **Figure 2** shows the first view of what users encounter on the Fashion Nova homepage. At the top of the page, there is a carousel banner of product offers and a countdown for their current (during this research) sales on top and bottom items. This countdown occurs in real-time and appears twice on the Fashion Nova's homepage: top of the page and under the menu bar.



**Fig. 2: Fashion Nova website. Top of the homepage (gif).**

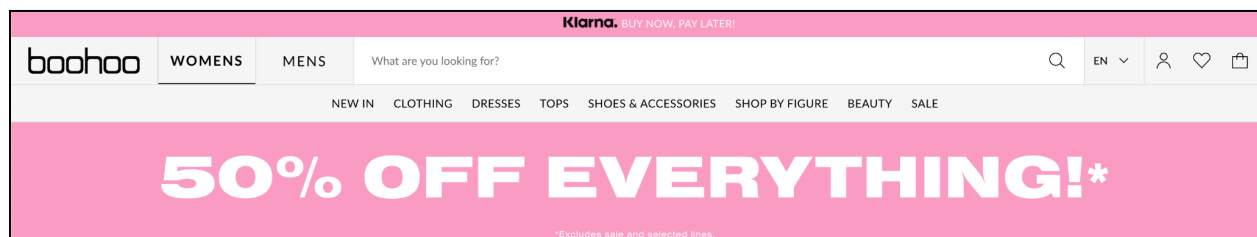
Additionally, Fashion Nova instils feelings of urgency into its users when they are not present on the website itself. When users open Fashion Nova's homepage and switch to a different tab, the domain name changes between the website's name and a notification. **Figure 3** shows what happens when users leave the Fashion Nova website. A flickering message appears,

shifting from the brand's name to a notification saying: 'Hurry! Items Selling Fast' with a fire emoji. This notification alerts users to return to the Fashion Nova homepage by catching their attention through its dynamic domain name.



**Fig. 3: Fashion Nova website. Domain name notification.**

The comparative analysis shows that Boohoo's interface design does not contain as many web elements that produce urgency in its users as on Shein and Fashion Nova. However, Boohoo relies on displaying promotions and offers at the top of the homepage. By emphasising its deals and offers, Boohoo can engender a feeling of anticipation to consume in its users. Upon entering the Boohoo website, the message '50% OFF EVERYTHING' appears in big, bold letters, as seen in **Figure 4**. This message follows users as they scroll through the homepage in the form of a banner, without including the exceedingly smaller text 'Excludes sale and selected lines' displayed under the first message.



**Fig. 4: Boohoo website. Top of the homepage (gif).**

The comparative analysis demonstrates that all three websites have various interface design strategies which promote urgency in their users. While Shein and Fashion Nova mainly rely on dynamic elements, flash boxes and countdowns, Boohoo uses banner carousels and bold texts to urge their users towards consumption.

#### 4.1.2 Facilitating the shopping experience via personalisation

The shift to a digital form of shopping has simplified the shopping experience for many users. In comparison to traditional shops, web stores are more accessible as they are not subject to any closing hours or limited by staff availability. This facilitation is not limited to the fast fashion industry. Thanks to their digitised environment, many E-commerce platforms can cater to users at any time, place, and even personal preference. For example, users who shop online can manually personalise their search results by sorting categories such as product size, price range, rating, colour, or material.

Moreover, fast-fashion web stores implement general user-personalisation settings yet also provide ways to shop which are specific to clothes consumption. For instance, website menu headings such as 'shop by style' or 'shop by occasion' are widely present on fast-fashion web stores. While these categories may facilitate a user's shopping experience, these classifications

SHOP BY TREND	SHOP BY STYLE
Crochet	Y2K
Floral Print	Street
Graphic	Chic
Cut Out	Comfy
Bustier	Preppy
Bright Color	
Tribal Inspired	SHOP BY OCCASION
Oversized	Vacation
Prom	Party
Feminine Glam	Sporty
Cottagecore	Night out
	Wedding
MUSIC FESTIVAL	Office

provide new and various ways to incentivise users to consume clothes. **Figure 5** shows the 'Trends' menu selection on Shein's website, where users can shop by trend, style or occasion. The former category, 'shop by trend', displays a range of categories that classify fast-fashion products according to the trend to which they belong. For example, products with an oversized fit are all sectioned into the 'Oversized' trending category. Indeed, users looking for particular designs can easily find them through these ready-made categories.

**Fig. 5: Shein website. 'Trends' menu selection.**

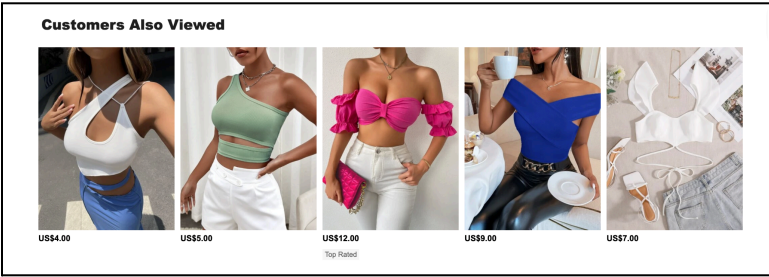
However, on Boohoo's website, occasion wear and shopping by body type is noticeably more detailed. Boohoo's 'Occasion wear' menu selection has over 20 category options for different event styles, such as weddings, prom dances, and even baby showers. Boohoo also facilitates the shopping experience by providing various categories for different body figures (see

**Figure 6).** Each type of body figure has its extensive classifications for all clothing types provided by Boohoo.

PLUS SIZE & CURVE	PETITE	TALL	MATERNITY
View All	View All	View All	View All
Plus Size New In	Petite Dresses	Tall Dresses	Maternity Coats
Plus Size Dresses	Petite Joggers	Tall Tops	Maternity Hoodies & Sweatshirts
Plus Size Tops	Petite Hoodies & Sweatshirts	Tall Knitwear	Maternity Dresses
Plus Size T-Shirts	Petite Tops	Tall Coats & Jackets	Maternity Tops
Plus Size Shorts	Petite Swimwear	Tall Jeans	Maternity Knitwear
Plus Size Tracksuits	Petite Knitwear	Tall Bottoms	Maternity Jeans
Plus Size Gym Wear	Petite Playsuits & Jumpsuits	Tall Joggers	Maternity Jumpsuits
Plus Size Coats & Jackets	Petite Jeans	Tall Hoodies & Sweatshirts	Maternity Loungewear
Plus Size Knitwear	Petite Coats & Jackets	Tall Playsuits & Jumpsuits	Maternity Leggings
Plus Size Trousers	Petite Trousers	Tall Bodysuits	Maternity Skirts
Plus Size Accessories	Petite Shorts	Tall Skirts	Maternity Trousers
Plus Size Swimwear	Petite Skirts	Tall Shorts	Maternity Swimwear
Plus Size Hoodies & Sweatshirts	Petite Nightwear	Tall Nightwear	Maternity Lingerie
Plus Size Loungewear	Petite Tracksuits	Tall Swimwear	Maternity Bras

**Fig. 6: Boohoo website. 'Shop by figure' menu selection.**

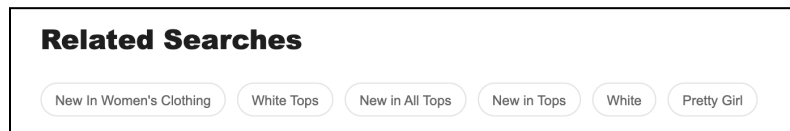
Additionally, users encounter several features that rely on algorithmic filtering or recommendations on these fast-fashion web stores — mainly on product detail pages. Upon clicking a [random product](#) on Shein's website, a carousel of pictures appear along with the product's details and reviews. However, below these elements, a section entitled 'Customers Also Viewed' is exhibited to the user with 15 other Shein products (see **Figure 7**). This section is an example of Shein's collaborative filtering on individual product pages. In this context, the algorithmic filtering method displays products viewed by other Shein users who viewed the randomly chosen product of that page. In this way, users who view any product are immediately led to other items viewed by similar types of users.



**Fig. 7: Shein product page. The first five displayed items from the 'Customers Also Viewed' section.**

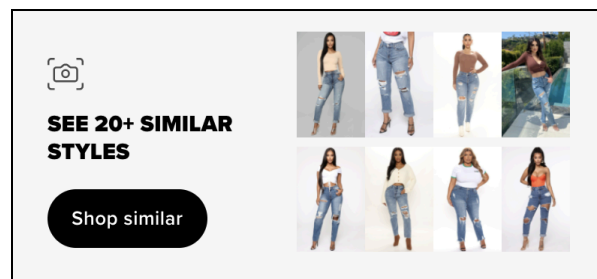
After this section, a 'Related Searches' heading appears at the bottom of the product page, separated by a Shein advertisement (see **Figure 8**). While this does not show users individual

products, it leads them to other search queries related to the randomly chosen product. These recommendations derive from Shein's algorithmic suggestions, which calculate the extent to which a search term is related to another based on previous user search queries. By clicking on any of these affordances, users are then redirected to a page exhibiting a page of product results concerning a particular search query.



**Fig. 8: Shein product page. Related Searches.**

On Fashion Nova's website, the [product page](#) provides users with an affordance similar to the technology of Google Lens, a photo-based search engine (See **Figure 9**). Upon clicking, users can scroll through a stream of similar products and select their size and price preference. With this tool, users can search for and find other products that resemble the main product rather quickly. This facilitates the shopping experience by providing users with different ways to discover similar products offered on the website.



**Fig. 9: Fashion Nova website. Affordance entitled 'See similar styles'.**

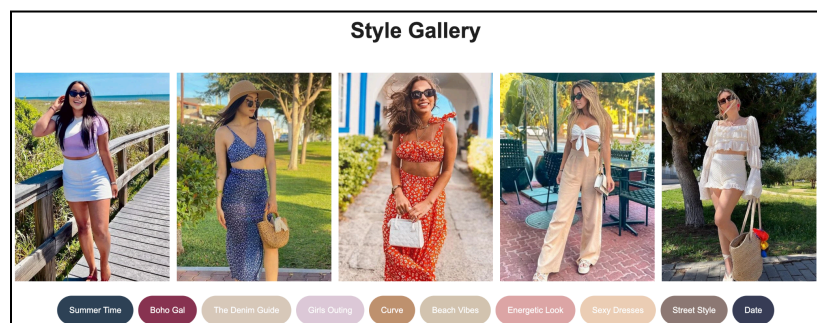
Furthermore, the comparative analysis shows that product recommendation occurs more on Shein and Fashion Nova than on Boohoo. Users only see one heading entitled 'Complete the look' on the bottom right of the [product's detail page](#) on the latter's website. It only displays two sections, 'Shoes and accessories' and 'New season', redirecting them back to the website to any selected categories. In contrast, users encounter more personalised results on Shein's website with collaborative-filtering recommendation techniques and image-searching technology on Fashion Nova's website.

### 4.1.3 Online shopping as a form of entertainment

Fast-fashion web stores nudge users towards consumption through elements of urgency and a facilitated shopping experience. These web stores also implement aspects of the entertainment industry through gamified elements and social media logics. Shein and Fashion Nova's homepages have pop-up messages that notify users about current sales and discount codes. For instance, on Shein, the option to sign up for their newsletter occurs in the form of pop-ups. Users must first click on the notice 'GET US\$3 OFF' to sign up for the Shein newsletter. While Boohoo's website doesn't flash users with these messages, these web stores market their Email newsletters through the strategy that users may find additional offers when purchasing. At the bottom of Fashion Nova and Boohoo's homepage, a message explicitly offers discounts upon signing up for their newsletter.

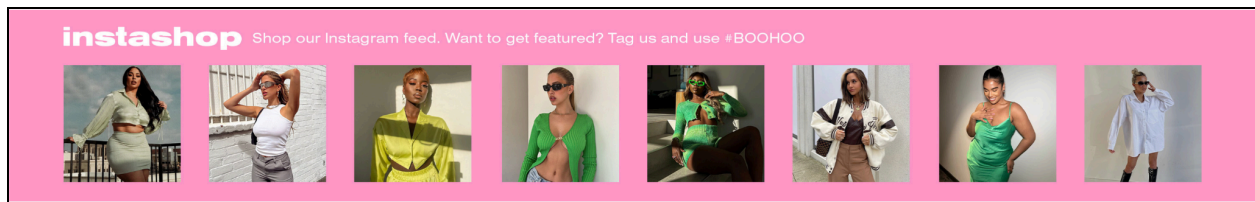
Additionally, Shein offers a point system for their users, in which they can collect points in return for buying the brand's products and posting pictures on the website. With this loyalty programme, users obtain 100 points after verifying their email and earn one point for each US Dollar they spend on the website. These accumulated points allow users to buy other products at a lower price. Besides shopping, users can gain five points by posting pictures of themselves wearing Shein's products on the website and may earn 50 points if their picture is chosen as a feature post by Shein's editorial team.

While Fashion Nova and Boohoo do not offer any loyalty programmes, they all — including Shein — integrate a social media logic through website features and affordances. Indeed, user-generated content is widely present on these websites. These web stores enable users to submit pictures of themselves wearing products from the brand, through which others can scroll and find its product details. On Shein, this 'Style Gallery' appears at the bottom of the homepage (see **Figure 10**) and product pages — only on which users have uploaded their pictures. Users can also select certain style categories on the 'Style Gallery' to search for particular products worn by other users.



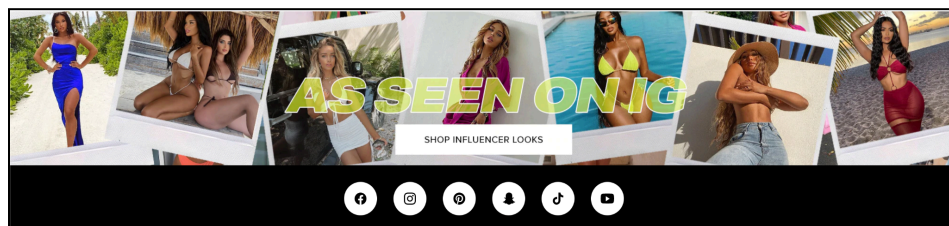
**Fig. 10:** Shein website. 'Style Gallery'.

Boohoo's 'Instashop' section explicitly advertises itself as Boohoo's Instagram feed. It encourages users to submit their pictures via the hashtag #BOOHOO. On this section of the homepage, Boohoo displays eight user pictures (**Figure 11**). Upon clicking one, users are redirected to a feed of uploaded pictures with products purchased from Boohoo. Moreover, the layout of these user-uploaded pictures is similar to an Instagram feed, with three pictures on each row. By clicking on a user-uploaded picture, other users can find the details of an item bought from Boohoo.



**Fig. 11: Boohoo website. Boohoo Instashop.**

Finally, on Fashion Nova's website, user-generated content is displayed on both its homepage and on the product details page. On the former website page, there are two types of user-uploaded pictures: influencers and ordinary users. It distinguishes between 'Influencer looks' and 'Looks from the "gram"' (in reference to Instagram). **Figure 12** shows that the former section contains several social media features and affordances. At the bottom of this section, there are six buttons linking to Fashion Nova's social media platforms (ex: Facebook, Instagram, Tiktok). In addition, Fashion Nova markets these product pictures with frames similar to an Instagram post. Lastly, the web store includes user-uploaded pictures on product pages in a section entitled 'Seen on Instagram' under the product's details. With this affordance, users can scroll through images showing what the product looks like on different body types and how it matches with other pieces of clothing. Thanks to this, users observe products via user-uploaded pictures, similar to a social media feed logic.



**Fig. 12: Fashion Nova website. 'Influencer looks' section.**



## 4.2 Network analysis

In order to infer that fast-fashion stores exploit their users' data, there must be evidence that fast fashion web stores rely on data-gathering practices and back-end infrastructures to help them obtain this type of information. This network analysis demonstrates how fast fashion web stores utilise trackers to monitor and understand their users and online behaviour.

### 4.2.1 Trackers on Fast-fashion web stores

With the extension tool Thunderbeam-Lightbeam, the network analysis seeks to find the trackers present on all three fast fashion web stores via their homepage and on a product details page. After downloading the [CSV file](#), Gephi, a software for network visualisation, presents the tracker network encompassing Shein, Boohoo and Fashion Nova's web stores by visualising the findings with a network graph (**Figure 13**). The graph's properties are made up of nodes (main entities) and edges (connections between these entities).

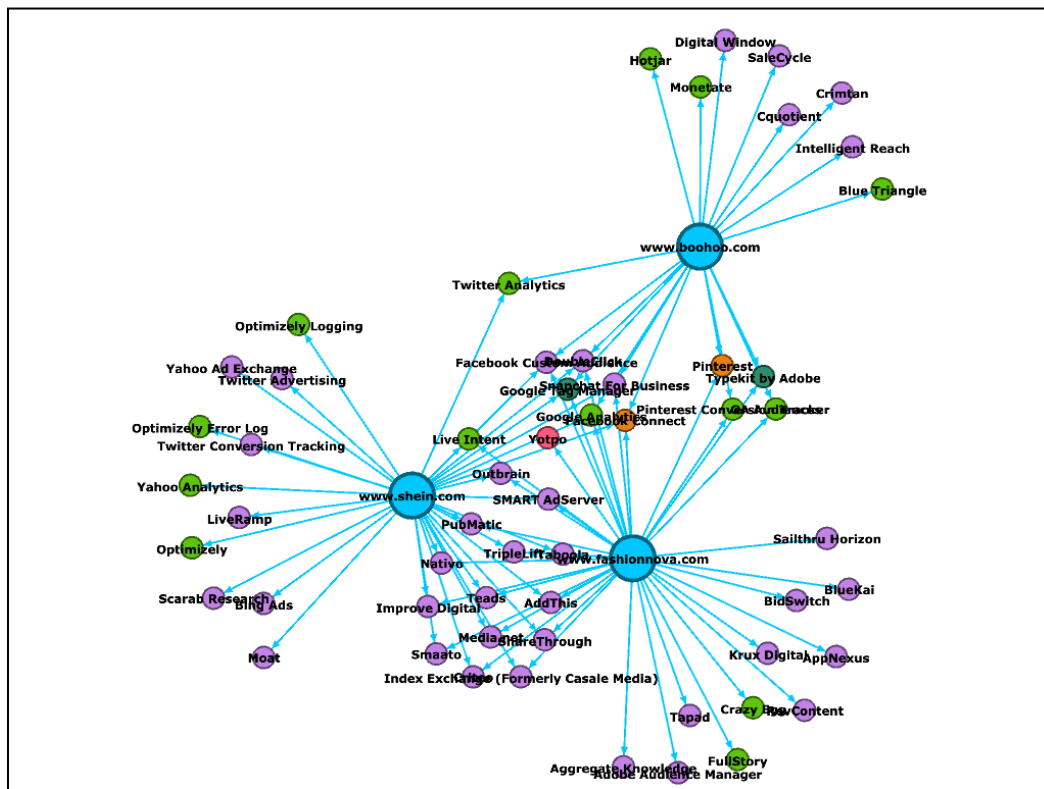


Fig. 13: Network analysis results. Trackers present on Shein, Boohoo, and Fashion Nova. Via Gephi.



**Figure 13** shows the visualised representation of the tracker network research in Gephi's layout 'Yifan Hu'. Each blue-coloured node represents a fast fashion web store, and each edge between the nodes displays the links between the trackers, thus meaning their presence on these web stores. In terms of tracker types, the majority (63,33%) belong to advertising companies (in purple), 23,33% are concerned with site analytics (in green), and 3,33% make up the social media trackers (in orange). The rest involve tracker types categorised as 'source', 'essential' and 'comments'. There are 89 edges present in this graph, thus meaning that there are 89 unique and shared trackers in this network. With 57 trackers, 33 are present on Shein, 37 on Fashion Nova and 19 on Boohoo.

Moreover, 45,6% of these trackers (26 in total) have more than one connection between these web stores. Therefore, almost half of the trackers present in this graph are networked into another website. This means that users who shop on one website will most likely be cross-tracked by third-party trackers present on other fast-fashion web stores. The surveillance of tracking infrastructures on Shein, Fashion Nova, and Boohoo show that these websites monitor their users and aim to understand their behaviours via site analytics and advertising profiles. Indeed, end-users leave tracks each time they visit a website. As they scroll through style galleries and click on product details, their website interactions are recorded and analysed. These web stores track their data flows, which are then used to monitor the performance of their products and estimate user preferences. For instance, trackers collect data by monitoring end-users' keystrokes, browsing habits, the length of time they look at a product, and other personal user data such as IP addresses and via which device their website was accessed. As this clickstream data is gathered, it is also being analysed. For example, trackers profile users into different categories based on their data to provide them with personalised recommendations and targeted advertisements.

#### 4.2.2 Tracker purposes on fast fashion web stores

This analysis uses Rawgraphs, a data visualisation software, to display the different categories of trackers present on the fast fashion web stores. With the CSV file (compiled with Thunderbeam-Lightbeam), Rawgraphs enables this data to be mapped and visualised in different ways with multiple chart options and customisable settings. **Figure 14** shows an alluvial diagram made with the software, which represents each tracker category on the right (type) and their prevalence on Boohoo, Shein, and Fashion Nova on the left (source). It shows that site analytics and advertising trackers are the most pervasive categories of trackers on these websites.

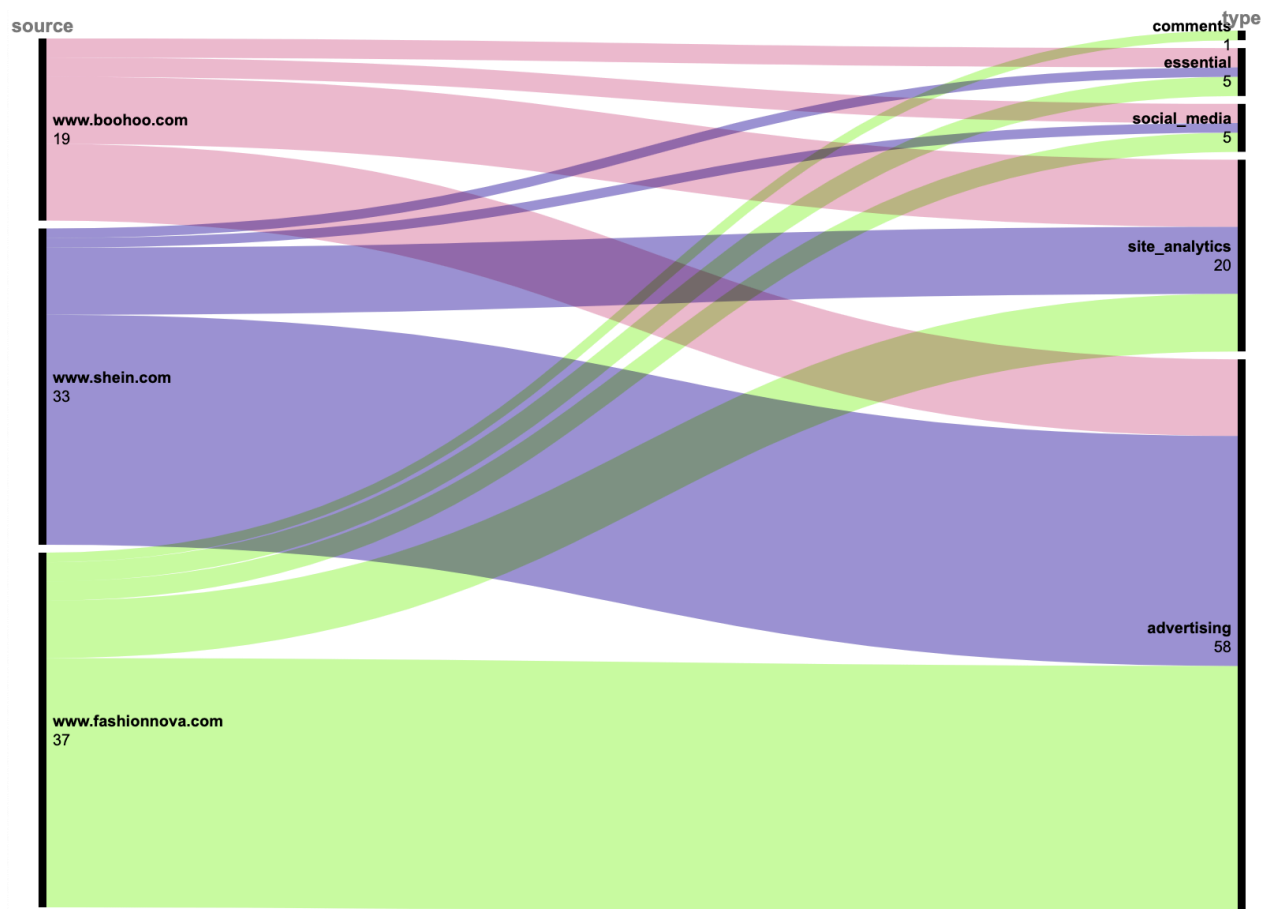


Fig. 14: Alluvial diagram of trackers present on Boohoo, Shein and Fashion Nova. Via Rawgraphs.

This research focuses on advertising and site analytics tracker types since they are the most ubiquitous on these web stores. These particular categories also correspond with my research as they involve gathering user interactions, estimating website performance, and targeting users with personalised services. Certain trackers specialise in in-site recommendations

and advertising, while others focus more on estimating website performance. Indeed, these trackers provide the web stores with gathered data about their end-users' browsing behaviour, user categories, and preferences. For instance, Hotjar, a tracker used by Boohoo, gathers site interactions and determines the website's performance rate. Hotjar's website shows the following slogan: 'Understand how users behave on your site, what they need, and how they feel, fast.' Another tracker, Optimizely, tracks website performance and provides A/B testing on Shein's website. A/B testing is a widely-used method used on e-commerce platforms which tests two versions of a web page, an app or a feature and compares them to each other to determine which version has a better performance rate.

Moreover, trackers such as Blue Triangle collect and assess user data in real-time and provide web stores with performance rates and feedback on improving conversion rates. Real-time monitoring enables fast fashion web stores, such as Boohoo, to continuously gather user data and obtain website performance metrics as the data streams pass through the network. This allows web stores to accurately identify browsing habits and determine user preferences by observing what contributes to positive performance rates, thus building on these results for better performance. Additionally, site analytics trackers observe bounce rates, an important web traffic metric since it acts as the main proxy for assessing website performance. A bounce rate, represented as a percentage, represents the number of website visitors who access a website and leave it without navigating to another web page. For example, if a fast fashion web store has a 25% bounce rate, a quarter of website visitors leave the website without accessing another web page.

Furthermore, advertising trackers on Shein and Fashion Nova, such as LiveIntent, profile users' digital footprints and group them into different audience types. In doing so, LiveIntent uses targeted advertising based on group audience preferences instead of reaching individual users. Other advertising trackers such as Scarab Research offer highly personalised advertisements through machine learning technology. Crunchbase, a business information website, explains that Scarab Research analyses user behaviour to 'generate individually relevant product offers for consumers to make the most of their online experience.' (Scarab Research, 2014). This form of tracker surveillance emphasises the extent to which web stores aim to understand their end-users and use that information to manipulate their shopping habits.

## 5. Discussion

### 5.1 Free will among end-users on fast fashion platforms

The digitalisation of consumption has provided the E-commerce market with ground-breaking benefits thanks to big data analytics and other digital technologies. Web stores have access to a wide array of user data which generate valuable insights to maximise conversion rates and improve website performance. On E-commerce platforms, big data enables companies to track user behaviour and determine the most effective ways to convert one-time customers into repeat buyers (Akter et al., 2016). While fast fashion companies aim to provide users with an optimised shopping experience, their motives aim to maximise their profit and thus turn each end-user into a consumer. In doing so, their marketing strategies have effectively become user data and user behaviour exploitation strategies. Consequently, the systematic monitoring and analysis of user practices and preferences threaten the notion of free will among end-users. I contend that this threat of free will occurs as a three-step process in fast fashion web stores: **extraction, analysis** and **repurposing**. First, users are unaware of which interactions or personal information are extracted from these web stores. Second, it is not explicitly communicated to end-users how their data is analysed and for what purposes. Third, fast fashion platforms are not transparent about how the analysed data is repurposed back into these platforms.

In the first place, fast fashion platforms typically extract user information based on structured and unstructured data (Akter et al., 2016). The former involves demographic data, while the latter focuses more on clickstream data. On the one hand, unstructured data result from data flows from users' computer-mediated interactions. This includes product likes, search queries, browsing patterns, purchases, product clicks, page views, and bounce rates. These trivial interactions consist of 'everyday user' (Smith et al., 2001) behaviour, yet these forms of big data are widely harvested on fast fashion web stores. Zuboff (2015) explains how these big data flows are 'constituted by capturing small data from individuals' computer-mediated actions' (p. 79). Indeed, the surveillance of trackers on fast fashion platforms demonstrates the extent to which data is extracted, aggregated, and analysed for predictive purposes on these web stores. This paper's findings show that the provider websites of these trackers explicitly mention that their tools are designed for improving website performance through data accumulation and analysis.

On the other hand, structured data looks at demographic user information such as metadata which may reveal their location, gender, preferences, device type, and the date they accessed a web store. Akter et al. (2016) consider that both types of user data must be aggregated so that they 'generate meaningful insights to increase conversions' (p. 176) on E-commerce platforms, or as they call 'BDA environments' (Big Data Analytics environments). For example, both structured and unstructured data can be used to sort and profile users into groups of data bodies, which deeply facilitates personalised targeting practices on fast fashion web stores. These data-extraction strategies are informed decisions that contribute to surveillance capitalism (Zuboff, 2015). Data is considered a source of value and capital by E-commerce companies, so data accumulation and analysis will remain ubiquitous within these platforms. Ultimately, these data-driven processes hinder users' free will on fast fashion web stores as their personal information and computer-mediated interactions are exploited for companies' profit.

Furthermore, user data is exploited due to information differentials as users are unaware of how E-commerce companies manipulate their data points. This data exploitation also leads to power differentials between users and those who inspect and analyse their data. Fast fashion platforms possess a new dimension of digital control as they exercise power over their users' data. Indeed, the optimised shopping experience promised by fast-fashion web stores is purely enabled thanks to the extraction and analysis of end-user data, which occurs in real-time on Shein's website, for instance. This form of real-time recommendations highlights the immediacy of Shein's consumer-driven business model. In fact, Shein uses artificial intelligence to identify market trends in real-time since it relies heavily on demand-driven business models. They operate within a consumer-to-manufacturer (C2M) model, providing Shein's manufacturers with real-time feedback on their products (Kamarudin, 2021). Since it relies on a consumer-driven model, Shein's algorithms extract user and website data, such as search queries and product performance, in a real-time manner to constantly adapt to their user's preferences. This ultimately leads to real-time personalisation on Shein as it constantly modifies its advertisements and recommendations based on the constant assessment of user information. The trackers on Shein effectively recognise different user preferences and target them accordingly. This speed and scale of personalisation services and targeted advertisements contribute to the optimised shopping experience that these fast fashion web stores promise. While users may find satisfaction with personalised recommendations on fast fashion stores as it facilitates their shopping experience, it

also inhibits their decision-making abilities. Their data is persistently aggregated and analysed to match them with algorithmically-constructed preferences, creating an inadequate environment for ethical and economic decisions. In this way, users' free will is held back by how fast fashion companies manipulate user data, thus inhibiting them from making their own informed decisions on these platforms.

Finally, after extracting and analysing user data, it is fed back into fast fashion platforms to enhance personalisation services and predict user demand via data-driven forecasting. Algorithms on fast fashion platforms are relevant as they aim to understand and predict user preferences and anticipate their future decisions (Gillespie, 2014). Indeed, these algorithms can traffic in the targeted demographic groups or 'calculated publics' that they themselves produce. For instance, users of different targeted demographics (according to fast fashion algorithms) may encounter entirely different results while having the same search query. Thanks to these automated algorithms, fast fashion web stores can evaluate users based on their preferences, group them into targeted demographics, and determine which products are relevant for which users. By constantly observing market trends, algorithms can regulate which products are trending or which items are relevant for different groups of users. They impose their criteria by which they consider which product to suit a type of targeted demographic on fast fashion web stores. For instance, this paper's findings show that fast fashion platforms use recommender systems that rely on collaborative filtering to match users belonging to the same generic category with products relevant to them.

Lastly, thanks to their digital environment, E-commerce platforms are able to mediate users' shopping experience and leverage their weaknesses in order to increase consumption. Fast fashion web stores rely on interface-level strategies such as dark patterns and dark elements to manipulate user behaviour to maintain their direct participation on these platforms. These web stores also target user vulnerabilities through elements of urgency, such as dynamic countdowns and popup notifications. They also facilitate processes of consumption with elements like Quick Add, related searches, and image-searching technologies. These dark patterns implement deceptive functionalities which are not inherently in the user's best interest (Gray et al., 2018). While these elements seem to optimise the user's shopping experience, they also serve economic interests. Features such as user style galleries or Instagram shopping feeds promote active user participation as if it were for the user's benefit. In reality, fast fashion stores use these elements to

estimate product success rates and preserve user engagement on their websites. Though the actual process of users uploading their pictures and reviews to web stores may be beneficial to other users, this form of online participation acts as one of the main drivers of fast fashion consumption. Jenkins' (2015) definition of participatory culture as 'one in which members believe their contributions matter' is capitalised upon by these platforms and thus manipulated according to their economic motives. With this combination of exploiting personal data and implementing dark patterns onto their interface, fast fashion platforms hinder users' free will.

For this reason, my research concludes that fast fashion web stores are dark promoters of online user participation. Dark participation on these platforms reflects the 'evil flip side of citizen engagement' (Quandt, 2018). It is not entirely motivated by the users' well-being but rather to exploit their engagement for lucrative value. While fast fashion consumers can freely decide to participate on these platforms, their free will is disrupted by how these web stores use that information against them. As these platforms are heavily data-laden environments and aim to construct and predict user preferences, they fail to provide users with information-neutral spaces and refrain them from making optimal economic decisions (Waelbroeck, 2018). With numerous personalised recommendations and advertisements, end-user decision-making skills become deeply entangled with algorithmic suggestions. And, as fast fashion web stores prioritise their economic interest and maintain their exploitative practices, they will continue to drive fast fashion consumption to its limits which will therefore have devastating consequences on the environment. The persuasive strategies of fast fashion platforms demonstrate the inevitable link between data-exploitation mechanisms and environmental degradation. However, this can be very well avoided once fast fashion platforms cease prioritising their manipulative practices. Instead of exploiting their information, user data can be employed in alternative and thus more sustainable ways.

## 5.2 Alternatives to fast-fashion data usage

Fast fashion web stores abide by the definition that sees datafication as a phenomenon in which users have a passive position: they simply produce data. In response, fast fashion platforms use this data to govern their consumers and engineer ways to maintain website performance and user engagement. However, according to Kennedy, Poell and van Dijck (2015), datafication also implies that data is fed back to the users to make decisions, enabling them to orient themselves in the world. This understanding shows the potential for data to empower consumers. Though, fast fashion web stores consciously decide not to go down that road. Fast fashion platforms could potentially repurpose user data in more transparent ways to promote more conscious forms of shopping rather than simply aiming to maximise company profit. For instance, these web stores can display data about the selling rates of trending products, informing users about the impact it may have on CO2 emissions throughout its delivery and production processes. Otherwise, data can be used to offer sustainable shopping advice to users at the end of their shopping experience. For example, gathered data about a user's purchasing history can be used to advise them about future purchases while respecting a certain consumption threshold to maintain a sustainable shopping habit. Current data analysis strategies and interface-level manipulation techniques such as dark elements have exponentially increased consumption rates through facilitated and attractive modes of shopping. While these alternatives may contradict the goal of maximising conversion rates and company profit, fast fashion platforms must find more sustainable solutions to their marketing strategies. There are other ways to operate with user data; those methods should serve the user's best interest and not the company's economic motives.



## Conclusion

This paper seeks to understand how fast fashion web stores exploit their end-users' data and behaviour in order to improve their businesses. It acknowledges that the digitalisation and datafication of social life have enabled manipulative practices to pervade within these digital market environments. As fast fashion web stores aim to maximise their conversion rates and thus turn each user into a consumer, they prioritise company profit over their users' best interests. On both front-end and back-end levels, fast fashion web stores operate with digital strategies aiming to manipulate shopping habits and increase user retention on these websites. On the front end, fast fashion web stores implement interface elements such as dark elements and patterns, which aim to promote dark forms of participation on these websites. These interface design choices work towards instilling feelings of urgency within users, facilitating their shopping experiences and keeping them entertained throughout it. On the back end, my research suggests that online retail strategies heavily rely on extracting, analysing and repurposing user data to understand their website visitors and target them accordingly. Fast fashion web stores operate with a multitude of third-party trackers which collect user information and provide feedback on improving website performance. These web stores rely on algorithms such as recommender systems and search engine optimisation to provide users with personalised results. They gather structured user data, such as their demographic information via their metadata but also unstructured data, which results from users' computer-mediated interactions. As each data flow is recorded and each data point is analysed, fast fashion web stores gain control over their users due to their optimised digital systems. This research also acknowledges that there are information and power differentials between fast fashion platforms and the users that visit them. Since these platforms are heavily-laden with tools for data extraction and analysis, they are not considered information-neutral environments. Indeed, users' free will is inhibited on fast fashion platforms as they are unable to make ethically informed decisions because its digital environments are instrumentalised for profit gain rather than for user benefit.

Moreover, this paper highlights the link between data exploitation and environmental degradation. As fast fashion web stores pursue their own economic motivation, they will continue to promote unsustainable shopping practices and rely on their digital strategies to do so. As the fast fashion industry already highly contributes to worldwide CO<sub>2</sub> emissions and 92 million tonnes of annual textile waste, it is important to look for more sustainable ways to

produce and consume fashion products. While this research offers alternative ways to operate with data to promote sustainable shopping habits, it is paramount to conduct further research into how data can be used to foster sustainable online shopping practices rather than to drive consumption. User data can be repurposed towards benefiting personal and environmental interests by being more transparent about the type of data being collected and for what purposes. I invite further research to study how user data can be used to move away from fast fashion toward slow fashion. As fast fashion entails the constant production of new items, slow fashion offers an alternative approach in which the production of an item takes into account all aspects of the supply chain in order to promote more sustainable modes of production. User data can be garnered to slow down fast fashion platforms, which may potentially reshape online shopping practices to meet better, more sustainable goals. If user data and behaviour can be exploited to increase consumption online, this data can equally be used to foster environmentally-friendly shopping habits.

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## Endnotes

1. To measure the popularity of fast fashion in popular discourse, I use the web scraping tool [Youtube Data tools](#) to observe how many Youtube videos have been made on the topic in the last five years. Youtube Data Tools is a web scraper tool which extracts data from the online platform Youtube. It generates a network of relations between videos via the 'Video Network module' option. With the search query 'fast fashion', an iteration of 1 (1 iteration = 50 items) and a timeframe of 2017-01-01 to 2022-01-01, the web scraper tool generates a GDF file consisting of all the related Youtube videos during the last five years.

After importing the [list](#) into Google Sheets and delimiting the values with commas with the list's information, it is evident that the topic of fast fashion has been widely discussed on Youtube between the years 2017 and 2022. About 1,709 Youtube videos concerning fast fashion were made during that time, with around 878,763 total views until April 2022 (during my scrape). Additionally, these videos have received high engagement rates with a total average of 1,641 comments and a total average like count of 20,530 by other Youtube users.