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Determining Your 'Fashion Identity' in Fashion Recommender Systems and Issues Surrounding the Right to Privacy

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Abstract

Algorithmic personalisation in the fashion domain illustrates the illusion of reality. This paper offers an outlook on the implications of artificial intelligence (AI) techniques on autonomy and informational privacy focusing on recommender engines in fashion e-commerce. Fashion recommender systems support the optimisation of social processes that are based on implementing *'fashion narratives'* on style and emotional attributes on clothing in the algorithmic process.

Whilst fashion recommender systems illustrate incomplete semblance of individual behaviour, it bases the operation on the responsiveness of individual behaviour, impacting an individual's autonomy. In this respect, algorithmic processes engage in a process of interactive value creation based on the creation of an imaginary that affects the individual's subjective experience of self, and a person's identification of the self in a social context. We need a deeper understanding of conditions that shape an individual's expression of inter-personal values regarding fashion recommender systems. An analysis of the so-called 'right to explanation' in the General Data Protection Regulation reveals that solving issues of interpretability and explainability in fashion recommender systems offers a starting point to assess the parameters of informational privacy in algorithmic personalisation systems.

Keywords: Fashion Recommender Systems, Informational Privacy, Autonomy.

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1. Introduction

Artificial Intelligence (AI) is transforming *'fashion'*. From recommender engines to virtual-dressing rooms, wearable technology, and, robotics, we see the application of AI and machine learning algorithms to automate human tasks as well as optimise human efforts in the fashion domain (Thomassey S, Zeng X, 2018; Ramirez R, 2018).

Machine learning is a field encompassing a series of computational methods, such as converting speech into text, interpreting visual information, or, predicting future events from historical interactions to deal with data- rich environments and improve performance over time (Luce L, 2019; Russel S, Norvig P, 2010). Focusing on fashion recommender systems, this paper intends to investigate the relationship between algorithmic personalisation and an individual's social and personal understanding of *'fashion'* considering the right to informational privacy and autonomy.

Fashion recommender systems illustrate an incomplete semblance of individual behaviour. Advances in computer vision and neural networks incorporate 'fashion narratives' on style and emotional attributes on clothing to analyse user-item interactions (Lin Y et al, 2019). These advances in algorithmic personalisation systems do not reflect the complexity of an individual's personality including the meaning of *'fashion'* that is shaped by the everyday experiences of clothing. Accordingly, fashion recommender systems, whilst not demonstrating the individual's negotiation of the social and personal aspect of *'fashion'*, model the responsiveness of individual behaviour to fashion narratives.

These characteristics regarding fashion recommender systems highlight that algorithmic systems not only require the capacity to identify patterns in data and learn from experience, but also, to compose complex models about human behaviour. This statement is judged against the concept of *'nudges'* developed by Thaler and Sunstein (2008) as a tool to address irrationality in human decision-making and direct the individual towards a preferred choice architecture.

The concept of 'nudges' suggests that individual choices need to be organised and translated into actionable options promoting individual wellbeing (Thaler RH, Sunstein CR, 2008; Tversky A, Kahneman D, 1974). An often- cited example regarding the Thaler and Sunstein's understanding of *'nudges'* as a tool of *'liberal paternalism'* to shape user choice is the organisation of food options in a cafeteria, whereby the healthy food items would be placed in a front row and the unhealthy options in the back row (Thaler RH, Sunstein CR, 2008, pp. 1-6). An individual would be *'nudged'* to choose the healthier options, based on the organisation of the food options by the *'choice architect'* (Thaler RH, Sunstein CR, 2008, pp. 1-6). In doing so, the choice architect including the nudges endorses *'soft paternalism'* in that weak choices are not blocked off but that the environment offers the parameters to act self-consciously for good choices (Thaler RH, Sunstein CR, 2008, p. 5; Thaler RH, Sunstein CR, 2003a).

Furthermore, principles of navigability and defaults shape the conditions of a *'nudge'* to direct users within an informational choice architecture (Sunstein CR, 2015, p.512). Fashion recommender systems, in contrast, utilise the notion of passive nudges, which builds on user responsiveness and unconscious associations with *'fashion identity'*.' Algorithmic personalisation systems in fashion, whilst maintaining the parameters of Thaler and Sunstein's understanding of informational nudges, intend to give a holistic outlook on individual behaviour and shape the conditions of individual decision-making.

We need an enhanced understanding of the impact of fashion recommender systems on the conditions exercising autonomy. In this respect, recommender systems in the fashion domain may generate behavioural insights that may *'nudge'* users into a preferred choice architecture (Yeung K, 2017), having an impact on an individual's autonomy. Referring to the concept of *'hypernudging'* (Yeung K, 2017), fashion recommender systems add another dimension to the issues of autonomy. This creates an imaginary which limits the gaze through which an individual interprets his or her understanding of *'fashion'* and place the complexity of identity-building into a broader imaginary of pre-defined norms and values. Therefore, fashion recommender systems raise issues under informational privacy, which necessitate a deeper understanding of conditions that shape the expression of inter-personal values.

Interpretability and explainability of the algorithmic process could illustrate the first step in ensuring an individual's control over aspects of identity-building. There are inherent challenges to ensure transparency in fashion recommender systems. One consideration is that attentional models for ensuring interpretability for neural networks do not guarantee explainability of the algorithmic process. That being said, focusing on the so-called *'right to explanation'* in the General Data Protection Regulation, we need a clearer account of the parameters of the right to privacy regulating the impact of fashion recommender systems. Therefore, this paper suggests that a right to explanation needs to focus on the comprehensibility of algorithmic decisions regarding the system's functionality to close the gap between issues of interpretability and explainability in fashion recommender systems.

2. Fashion recommender systems and the relationship to an individual's fashion identity

Fashion recommender systems illustrate an incomplete semblance of individual behaviour. These illustrate a filtering engine that analyses customer behaviour and recommends products suitable to the user (Luce L, 2019). Recommender systems in the fashion domain, commonly exhibiting a hybrid approach, are applied in personalised style recommendations as well as size and fitting recommendations and can be implemented on e-commerce websites, mobile applications, or illustrate a subscription-based service (Luce L, 2019, p. 12; Landia N, 2018, Marr B, 2018).

In this respect, recommender systems use machine learning algorithms or predictive analytics for personalised product recommendations and style advice, using the collection of explicit and implicit data for the analysis of user-item interactions as well as public perception of style or current trends (Landia N, 2018; Xin Thia K, 2020). Nevertheless, implementing personalisation algorithms in fashion recommender systems conflicts with an individual's understanding of the social and personal understanding of *'fashion.'* Accordingly, personalised algorithmic models in fashion, whilst not reflecting an individual's aspects of personality, model the responsiveness of human behaviour to fashion narratives derived from user-item interactions.

2.1 Fashion recommender systems and the relationship between product and user attributes

Algorithmic personalisation in fashion recommender systems illustrates an area of predictive analytics (Luce L, 2019, p. 12). Predictive analytics is defined as a series of computational models that intend to identify future behaviour, based on the analysis of past events (Spencer SB, 2015, p. 630). Predictive analytics can be applied in recommender systems to filter out items an individual would not purchase (Luce L, 2019). In this respect, fashion recommender systems can be found on e-commerce websites, as well as form the basis of subscription-based service (Luce L, 2019, Landia N, 2018, Marr B, 2018).

For example, the *'Style Seek'* is an online fashion recommender system that identifies a user's 'Style DNA' using questionnaires including a selection of images for curated individual recommendations (Guan C et al, 2016, p. 857). Also, the method employed by *'Zalando'* which uses a model that trains neural networks on a set of images, predicting attributes on colour, silhouette, and inferring customer style preferences (Bracher C, Heinz S, Vollgraf R, 2016). These considerations highlight that recommender systems in fashion focus on algorithmic personalisation systems that learn user-item interactions, as well as the emotional attributes of clothing for curated style advice (Guan C et al, 2016; Qing YX, 2014).

Another important aspect regarding recommender engines in the fashion domain concerns the modelling of *'fashion narratives'* regarding user-item interactions. Fashion narratives illustrate shared parameters on garment texture, colour themes, style knowledge on outfit composition, as well as the descriptors on an individual's style or wearing occasion (Lin Y et al, 2019). Regarding this, significant advances in computer vision for image processing and neural networks for the learning of product attributes allow for the analysis of fashion narratives.

Computer vision is a method that picks up the visual features of images showing fashion products, such as colour combinations, texture, and shape (Halan D, 2018; Fernandez-Lopez D, Cabido R et al, 2014). Advances in image processing concern the use of neural networks, whereby a popular method is Convolutional Neural Networks (CNN) for image classification tasks (Schindler A et al, 2017). This CNN methodology, dealing with visual representations in product features, including non-linear relationships between visual features, is normally employed in a factorisation model (Kang, Fang, Wang et al 2017).

Matrix factorisation algorithms in recommender systems in fashion infer rating patterns to characterize items and users as vectors of factors (Cardoso A, Dalolio F, Vargas S, 2018; Taghavi M, et al, 2018, p. 328). Thus, fashion recommender systems using a CNN methodology consist of two embedding layers, whereby the product and user attributes are interpreted in a high-dimensional vector space (Cardoso A, Daolio F, Vargas S, 2018).

Accordingly, personalised recommendations are determined by the space on user-item interactions as well as product attributes (Daolio F, 2018).

It is important to identify how algorithmic models in recommender engines interact with the user. The notion of transparency in the General Data Protection Regulation (GDPR) implies that individuals should be informed about the data processing activities of their personal data, which implies the predictive power of algorithms in recommender engines (Article 5 (1) (a), Recital 60 GDPR; Brkan M, 2019, p. 171).

However, the question is how to ensure the adequate enforcement of transparency regarding the individual's control of personal data in practice. Matrix factorisation algorithms act based on latent features, whereby a collaborative filtering approach can behave like *'black boxes making it difficult to provide a justification for the recommendation process'* (Taghavi M, et al, 2018, p. 327; see also, Luo S 2018; de Laat P, 2018). Indeed, with the pervasiveness of algorithms in the user's daily life, such as user interaction with *'fashion'* in algorithmic personalisation system, the meaning of *'identity'* becomes increasingly data-driven. Therefore, we need to identify the significance of *'fashion'* in recommender engines to define the contours of individual preferences and free choice to express aspects pertaining to the self.

2.2 The meaning of 'fashion' in recommender systems in the fashion domain

How do the advances in computational models and techniques capture the nuances of *'fashion'* and aspects of an individual's personality? It is argued that 'fashion' and appearance can be used to predict an individual's personality (Ferrier M, 2018). This argument suggests that an individual's appearance may be suggestive of a person's personality traits (Ferrier M, 2018; Lake K, 2018). Predictive analytics work with fashion narratives, which may incorporate the inherent values in *'dress'* constitutive of social and cultural meaning, such as codes of appearance, forms of behaviour, and consumption habits. Nevertheless, predictive analytics in fashion recommender systems are a form of semblance of individual behaviour that is inferred from the interpretation of fashion narratives.

Algorithmic constructions, including the building of profiles, rely on the correlations within datasets which are established through the match between user attributes and inferred attributes from other profiles (Amoore L, 2013; De Vries K, 2010). Machine learning algorithms intend to arrive on a *'set of assumptions'* that allows generating an individual profile (Bygrave LA, 2001, p. 17). Focusing on fashion recommender systems, assumptions on individual behaviour are generated based on shared characteristics regarding fashion narratives on cut, size, fit, colour style including notions of personal identification, such as height, age, as well as a person's click or browsing behaviour.

However, it is important to note that the meaning of *'fashion'* including its social and cultural connotations is an abstract entity that is subject to the ambivalences of conformity and individuality (Entwistle J, 2000, p. 16; Simmel G, 1971, p. 131). Entwistle (2000) describes the connection between *'fashion'* and *'identity'* as a form of management of behaviour and source for differentiation, within social circles and enforcing *'codes of appearance'*, such as certain dress codes at workplaces or an environment that requires the respect of cultural conventions. A key point of the practice of *'fashion'* concerns the symbolism of dress used to communicate with others, ensuring that individual behaviour aligns to particular social encounters, such as a formal gathering as well as the *'implicit judgement'* of strangers (Sproles G, 1979, p. 156; Entwistle J, 2000, p. 17). It is argued that fashion is a product of an individual's management of appearance and perception (Kaiser SB, 1990, pp.7-8). It represents and shapes social identities, pertaining to every-day interactions, including an individual's engagement in different social roles (Aaker JL, 1991).

Based on these considerations that fashion is both the subject of external pressure and internal negotiation of appearance and perception, there is an important limitation of fashion recommender systems to capture the nuances of it in relation to individual understanding. Algorithms operate on *'pre-defined conceptual spaces'* (Boden M, 1998, p. 353), acting on pre-defined variables on product attributes. Fashion recommender systems can only operate considering the clothing attributes and rules of style that are incorporated into inferred preferences. For instance, in the *'Style Check'* application in the discontinued *'Amazon Echo Look'*, it has been argued that the function seems to prefer *'all-black over grey looks'* (Chayka K, 2018).

Just as *'fashion'* has an ambiguous meaning, notions describing a specific look, such as an *'elegant'* or *'casual'* style differ within a social or cultural context. Thus, the *'Style Check'* application would normally not tell the individual why a certain outfit looks better (Chayka K, 2018). Fashion recommender systems, relying on a certain pre-defined criterion, do not contain a measurement that may causally connect the reliance of the pre-defined criteria regarding an individual's social understanding of *'fashion.'*

Moreover, fashion recommender systems do not capture individual responses for the formation of social values, such as the influence of feelings or memories in the development of an individual's personal aspect of fashion. A fashion recommender system can incorporate so-called emotional attributes attached to the meaning of apparel profiles, such as *'elegant, sporty, casual'* as well as entail attributes regarding the stimuli of clothing, such as *'warmness, loudness, and softness'* (Cheng CI, Liu DSM, 2008).

It is posited that algorithmic personalisation systems can incorporate *'user subjectivity'* into the recommendation process, such as evaluating user sensations including impressions on colours or garment texture (Tokumaru M, Muranaka N, Imanishi S, 2004; Guan C et al, 2016, p. 866). These factors constrain our understanding of *'fashion'* that is measured against factors of objective identification, and which is evaluated based on the explicit and implicit tracking of personal data. Tangentially, so-called *'context-aware'* recommender systems also produce similar situations. For example, a context-aware recommender system, incorporating contextual information about a specific entity, such as recommending a *'winter coat'* based on the user's location is focused on the user's immediate habits, rather than aspects that form an individual's personality including the ambivalences regarding the social aspect of fashion (Lamche B, Rödl Y, Hauptmann C, 2015). Therefore, it can be said that fashion recommender systems can simulate aspects of individual behaviour, rather than representing an individual's personality.

To answer the question of whether fashion recommender systems capture the nuances of *'fashion'* and *'identity'*, the answer suggests that algorithmic personalisation systems can model social behaviour. Fashion recommender systems, incorporating pre-existing ideals of fashion narratives, can help to understand an individual's configuration of the social aspect of fashion, such as investigating existing social norms, preferences, and, outfit composition standards pertaining to appearance management. Advances in predictive algorithms, computer vision, and neural networks, can learn from multiple layers and non-linear relationships in user-item interactions.

However, it is important to note that pre-existing values reflected in user preferences are likely to not exceed the conceptual boundaries that resemble individuals with similar tastes and habits regarding visually similar items and not all individual preferences are predictable. Fashion recommender systems do not accurately reflect an individual's perception concerning the management of appearance, such as affective responses or desires that have an impact on the individual's formation regarding his or her understanding of *'fashion'*.

The answer on the meaning of *'fashion'* in recommender engines is relevant to deal with questions of transparency regarding the algorithmic decision-making process. Whilst a recommender engine has strong predictive power, the matrix factorisation technique will *'only define how much a user is aligned to a set of latent features'* (Luo S 2018), rather than the user's perception of aspects pertaining to his or her fashion identity. The finding that fashion recommender systems intend to act on the social aspects of fashion to predict personal preferences suggests that a user is constrained by default options which are based on his or her user attributes. Thus, it can be said that without any legal safeguards maintaining the transparency of the algorithmic process, the algorithmic personalisation systems in the fashion domain effectively risk undermining the user's participatory nature to maintain and shape the disclosure of the social and personal of the individual's fashion identity. This point will be more closely analysed in section 4 focusing on the so-called right to explanation regarding the GDPR.

The consideration mentioned above form the basis for the discussion on the impact of fashion recommender systems on autonomy and informational privacy. Important developments are advances in computer vision methods and neural networks for the detection of product attributes in unstructured data. These are used to discern the individual's preferences and match with shared parameters or fashion narratives concerning user-item interactions. Studying the meaning of *'fashion'* is a complex field and requires an in-depth understanding of the social, cultural, and personal aspects of an individual's appearance management and perception (Davis F 1992; Kaiser SB, 1990).

Fashion recommender systems constrain our understanding of *'fashion'* to notions of objective identification, whereby aspects of an individual's personality are inferred from the user's explicit and implicit data input. This finding, suggesting that fashion recommender systems build on incomplete narratives on individual behaviour, shows that algorithmic models intend to model the user responsiveness of individual behaviour to fashion narratives within the algorithmic process. This is opposed to gathering data on an individual's negotiation of the social and personal aspect of *'fashion'* within a social context. Therefore, the next question is whether the modelling of a social and personal target in fashion narratives impacts an individual's autonomy and informational privacy.

3. Autonomy and interactive value creation through persuasion in fashion recommender systems

The value of data in its inevitable reductionist terms are indicators, not only for the perception of an environment but illustrates a reflection of reality (Hildebrandt, M 2019a, pp.95-96). Machine learning algorithms, using correlations and patterns within datasets, can make predictions on an individual level, identifying the responsiveness of a particular individual with specific personality traits or values, to a persuasive technique (Risdon C, 2017). As noted above, the extent algorithms resemble an individual behaviour is primarily a question regarding the association between product attributes and user profiles including the tracking and evaluation of user-item interactions. However, predictive analytics, as well as behavioural insights generated from data models fulfil another vital role, which is to translate knowledge into actionable knowledge on behaviour (Hildebrandt M, Koops JB, 2010, p. 431; Hildebrandt M, 2015). This, in turn, is a question of interactive value creation. In addition to the design of the algorithms, as well as the individual's interaction with fashion recommender systems, a personalisation strategy aims to improve behaviour-based outcomes, such as directing users to follow product choices and having a positive experience engaging with an e-commerce platform or subscription-based service in fashion. Thus, personalisation algorithms in the fashion domain require two important tasks, which are to *'augment a person's rational self and to control a person's irrational self'* (Risdon C, 2017).

3.1 Systematic interventions into individual behaviour

Focusing on the impact of algorithmic personalisation systems on perception, a systematic intervention into individual behaviour can affect an individual's autonomy, based on questionable persuasion or in some instances, coercion (Milano S, Taddeo M, Floridi L, 2020, p. 6). For instance, several reports indicate that Facebook's model to employ algorithms to analyse user information and activity for targeted advertising has been used for *'voter profiling'*, as well as *'emotion manipulation'* (Privacy International 2020; Machkovech S, 2017). Accordingly, an algorithm can direct advertisers to show specific content in moments when a person needs a *'confidence boost'* or to manipulate the shown content when an individual feels *'anxious'* or *'stressed'* (Machkovech S, 2017; Sax M, Helberger N, Bol N, 2018). Hence, a systematic intervention into individual behaviour is deceptive, when it is an act that aims to exploit an individual's vulnerabilities, such as responding to an individual's negative body image. Accordingly, this type of profiling exploits an individual's psychological *'weak points'* and amplifies an individual's cognitive bias to an extent that behavioural targeting including deception exacerbates an individual's implicit assumptions about a social, cultural, or political target (Spencer SB, 2015).

Persuasive profiling strategies, in contrast, illustrate a *'noncoercive attempt to change attitudes or behaviour'* (Fogg BJ, Cueller G, Danielson D, 2007, p.110). Wearable technology that is based on the tracking of biometric information, as well as environmental factors, is intended to encourage a user for a *'healthier'* lifestyle (Metz 2015). According to Thaler and Sunstein (2008, p. 6) this aspect of persuasion, acting as a reinforcement of the user's desires, is described as *'nudging'*, being *'any aspect of choice architecture that predictably alters people's behaviour without forbidding any options or significantly changing their economic incentives'*. For instance, the *'SUPA Sports Bra'*, which is an example of smart clothing in fashion and gives an insight into the wearer's exercise habits, does not force a person to change calorie consumption, but *'nudges'* the user to optimise the training process (Charara, 2017). According to these considerations, persuasive profiling technologies may be permissible, when their structure is *'purely informative'*, encouraging users in their informed decisions (Susser D, Roessler B, Nissenbaum H, 2019, p. 6).

Nevertheless, Thaler's and Sunstein's conception of *'nudge'* including *'soft paternalism'* to influence individual behaviour, can have an impact on an individual's autonomy (Wang Y, Pedro GL et al, 2013). Nys and Engelen (2017, p. 203) highlight that persuasive profiling may effectively *'alter an individual's decisions'* to the extent that it imposes the nudger's own goals on the individual. One example, which indicates that a person can be influenced in their reflective preference, is when an individual, engaging with a virtual try-on application to search for a new lipstick for a night out with friends, will ultimately end up buying make-up, based on the recommendation that these products will help to correct the person's skin blemishes. Blumenthal-Barby, Hadley, Burroughs (2012, p. 5) argue that persuasive profiling is considered to manipulate individual behaviour when it effectively undermines a person's freedom of choice, by exploiting an individual's reflection of the irrational self or directing choices in a way that are not observable to the user. It is that conception of autonomy, based on the ability of informed choice, which is undermined by profiling technologies.

These considerations, suggesting the algorithms' subtle interventions into an individual's free choice, indicate that an individual's autonomy is framed against the expression of agency and choice that is free from hidden influence (Susser D, Rössler B, Nissenbaum H 2019, p. 4). As suggested by Raz (1986, p. 204) *'the autonomous person's life is marked not only by what it is but also by what it might have been and by the way it became what it is.'* An individual's decision-making process is framed against the own rationality to exercise choice based on the existence of a *'variety of acceptable options'* including the social context allowing to build and create opportunities to act autonomously (Raz J, 1986, p. 205; Fredman S, 2008, p. 18). Subtle and hidden influences distract from my capacity and process to reach my own decisions. Accordingly, persuasive profiling and *'nudging'* are manipulative when it affects an individual's independence from the systematic intervention and agency of free choice (Varshney LR, 2020).

'Nudges' within fashion recommender systems allow persuasion that relates to an individual's characteristics or a particular social environment. For instance, a fashion recommender system analysing the user-item interactions may identify that a user has a specific interest in floral motives, suggesting only outfits that fit the item variables of a 'playful' style. Here, what matches the recommendations are not based on the individual's

considered judgment that floral motives are a better reflection of her or his youthful look, but on the ubiquitous manifestations to identify an individual's psychological mechanism to desire floral motives over other unrecognised or unfamiliar alternatives. Accordingly, fashion recommender systems may have an impact on an individual's autonomy when the intervention intends to manipulate user incentives and responsiveness regarding aspects pertaining to the self, rather than preserving an individual's agency and choice.

These considerations indicate that we need a better grasp of the influence of passive nudges on the conditions exercising autonomy in fashion recommender systems. We need to identify how the hidden and non-coercive nature of 'nudges' in the context of fashion recommender systems affects the conditions to exercise independence in decision-making.

3.2 Fashion recommender systems and interactive value creation

The systematic intervention into an individual's autonomy is argued to be exacerbated with persuasion profiling that exhibits *'hypernudging'* (Yeung K, 2017). According to Karen Yeung, hypernudging *'are extremely powerful and potent due to their networked, continuously updated, dynamic and pervasive nature'* (Yeung K, 2017, p. 118). Yeung (2017, pp. 121-122), contrary to Thaler and Sunstein's conception of 'static nudges', emphasises that the personalised algorithmic process constantly adapts its recommendations relative to the user's implicit feedback, such as location, changing preferences, and attitudes. This way, hypernudges operate in a complex way, because the systematic interventions operate as a form of a performative change of values, that is both invisible for the observer and pre-emptive regarding the formation of an individual's perception (Yeung K 2017, p. 122).

Hypernudges add another dimension to the issues of independence and free choice regarding an individual's autonomy. On the one hand, personalised algorithmic systems rest on the *'dynamic adjustment'* in the recommendation process, based on the constant construction of knowledge on the user's profile, the data feedback that re-defines the choice architecture (Yeung K, 2017, p. 131). Further, hypernudges add to the process of objectification of identity-building, treating an individual as a subject constituted and shaped by an information infrastructure (Yeung K, 2017, p.129). That said, hypernudges enhance the process to structure the environment as well as the situated subject within the nudger's choice architecture (Yeung 2017, 129-130). Accordingly, Sax, Helberger, Bol (2018, 109, p. 115) suggest that hypernudges have an impact on an individual's authentic self, including the autonomy to decide which 'values, desires, and goals' inform a person's actions and lifestyle.

Fashion recommender systems and their persuasive strategy equally exhibit an impact on an individual's autonomy including appearance perception. According to the individual's personal understanding of *'fashion'*, unconscious associations are the *'gaze'* through which pre-existing social values are looked at. Hypernudges in fashion recommender systems can make use of several variables within clothing attributes that can shape an individual's associations for appearance perception, based on the user's emotions, self-perception, motives, as well as the perception of others (Johnson K, Lennon SL, Rudd N, 2014; Slepian ML et al, 2015). These inherent social associations with the nature of *'fashion'*, being responsible for the relationship between the self and the environment and shaping the personalised algorithmic output, constrain an individual's options for reflective choice, leading to a process of alienated subjectivity. The notion of *'fashion'* and clothing a social stimulus for impression formation, attitudes, and beliefs, is presented within the algorithmic constraints that shape an individual's authenticity.

Yet, fashion recommender systems and persuasion add another dimension to the impact of autonomy and authenticity noted above, based on the interpretation of the gaps and effects of an individual's personal understanding of *'fashion'*. When I started the analysis of whether recommender systems can resemble an individual's understanding of *'fashion'*, I underlined that algorithmic personalisation systems constrain our understanding of identity as one of objective identification, whereby the subject is described by virtue of pre-existing values. These pre-existing values illustrate the parameters to evaluate user profiles, that are used to predict user preferences of clothing style, and preferences. Accordingly, a fashion recommender system may engage in a process of dispositional attribution, whereby an individual might choose a fashion style that will increase his or her body image, such as referring to the variables on aesthetics to maintain an *'hour-glass'* figure. Moreover, a fashion recommender system may impact the process of situational attributions, based on the social connotations of dress that shape an individual's embodied experience of the body and self, such as the recommendation of a *'provocative dress'* that seems to be suitable for a *'confident personality.'* Hence, fashion recommender systems seem to interpret the gaps of the personal aspect of *'fashion'* as a given reality, rather than a process of interaction that allows an individual to define and explore his or her understanding of 'fashion' and *'self'*.

In other words, fashion recommender systems inherently limit the gaze through which an individual interprets his or her understanding of *'fashion'* and place the complexity of identity-building into a broader imaginary of pre-defined norms and values. For example, Oobah Butler, a journalist who pretended to be a designer at the Paris Fashion Week in 2017 and selling a brand as the design of Giorgio Pevani (Butler O, 2017; Tseëlon E, 2018, p. 4). The imaginary created by Oobah Butler effectively corresponded and created a certain attitude, which is that of an idealised fashion designer from the elite, wearing expensive outfits that exhibit an haute couture design (Tseëlon E, 2018, p. 4). Fashion recommender systems equally exhibit an imaginary of norms and values through the creation of dispositional and situational attributions. The perceiver, engaging with fashion recommender systems that work with social associations with clothing and situational causes, is less concerned with the unique specifications of the object but rather, the broader imagery that seemingly reflects the person's attitude.

It follows that the degree of persuasion in fashion recommender systems is one of interactive value creation, that places the notions of identity building based on a networked environment, rather than with reference to self. Fashion recommender systems inevitably affect an individual's association process regarding the inference of self, based on the creation of an imagery that has an impact on the individual's subjective experience of his or her presence within a social context, as well as a person's understanding of the self and the body. The individual's lack of autonomy is not only witnessed in the lack of control the actions and formation of desires but in the process to associate appearance perception with appearance management. That said, fashion recommender systems have an impact on the content of consciousness, which undermine an individual to identify the roots of unconscious thought. These considerations indicate that fashion recommender systems have an impact on an individual's autonomy which not only pertains to appearance perception including the formation of desires but the conscious experience to create the associations for the inference of self.

Having examined the way hypernudging in fashion recommender systems may an individual's autonomy, the next question is to elaborate on the extent persuasive profiling interferes with an individual's informational privacy. Several considerations indicate that an individual's right to informational privacy is impacted by persuasive profiling in recommender systems (Yeung K, 2017; Sax M, Helberger N, Bol N, 2018, p.130; Lanzing M, 2019). Informational privacy is implicated by persuasive profiling technologies as it is powered by surveillance of individual actions and behaviour. One consideration is the large-scale collection of personal information to define the personalised recommendation process and to constantly re-assess an individual's choice architecture beyond the user's conscious observation (Yeung K, 2017; Sax M, Helberger N, Bol N, 2018, p. 130; Lanzing M, 2019). In this respect, the algorithmic personalisation systems implicated another development which is that of a *'new kind'* of power relationship that is dictated by the so-called global players, such as Google or Amazon, as well as other organisations who participate in the ownership of data as a tool for competitive advantage including market control (Zuboff S, 2015; Lanzing M, 2019; Danaher J, 2017; Fuchs C, 2011).

Nevertheless, surveillance is not only an idea entailing the systematic observation and the establishment of power relationships but illustrates an organisational idea to regulate human behaviour (Degli Esposti S, 2014, p. 211). Frank Pasquale's views offer a powerful notion on the use of algorithmic decision-making processes in a wide range of applications that act as *'black boxes'* embodied in sophisticated and opaque machine learning algorithms (Pasquale F, 2015a; Pasquale F, 2018b). These considerations indicate that the line between legitimate and questionable persuasion is increasingly blurred by the operation of personalised algorithmic systems, which is not readily observable by external factors (Pasquale F, 2006, p. 132). That said, it is difficult to assess the parameters for privacy interferences with *'hypernudging'* practices. In other words, do we look at the conditions on the access to information and handling of an individual's personal data that manifest the administration of individual behaviour and personal identification, or do we need a deeper understanding of conditions that shape the expression of inter-personal values?

4. Fashion recommender systems and explainability and transparency according to the GDPR

The impact of fashion recommender systems on autonomy requires a deeper understanding of the models that implicate individual behaviour. Fashion recommender systems build on the responsiveness of individual behaviour considering the fashion narratives that establish the relationship between product and user attributes. An individual's negotiation of the social and personal aspect of *'fashion'* is created with reference to an imaginary that is based on the personalised algorithmic process, rather than with a view to an individual's inference of knowledge to the self.

The individual's creation of attitudes, beliefs, and desires, of *'fashion'* are constrained within the parameters that resemble the approximations of the recommendation process. Recommender systems in fashion, engaging in a process of interactive value creation, raise issues of an individual's informational privacy regarding the control of the personal information including aspects of identity, as well as interventions into the dialectic nature of the social and personal aspect of *'fashion'*.'

An important safeguard of an individual's informational privacy is how an individual's preferences including behaviour are assessed in the algorithmic process (Hildebrandt M, 2015, p. 102). A means by which you could protect an individual's informational privacy culd be to ensure transparency of the personalised algorithmic process. This is argued by Milano, et al (2020, p. 6) where they state that *'explaining how personalised recommendations generated for individual users could be valuable for users to understand why some suggestions are provided by the engine.'*

The notions of explainability and transparency in algorithmic personalisation systems allow users to challenge the accuracy of the algorithmic decision-making process (Sinha R, Swearingen K, 2002). Finally, it is suggested that explainability and transparency should respect an individual's autonomy, protecting users against deceptive practices in algorithmic personalisation systems, and establish a reference point for acceptable nudging and questionable *'hypernudging'* practices.

4.1 Interpretability in fashion recommender systems

There are inherent challenges to incorporate notions of explainability and transparency in fashion recommender systems. Neural networks pose issues of interpretability based on the operation of hidden weights that do not outline how the weights are adjusted and evaluated (McQuillan D, 2018, p. 256). These issues of interpretability underline the challenges to provide explainable decisions (Zhang S et al, 2019). Despite the issues of transparency in fashion recommender systems, attentional models provide for improved interpretability (Zhang S et al, 2019, Tay Y et al, 2018; Sun Y et al, 2020). Current efforts and challenges regarding issues of transparency in fashion recommender systems have to be viewed in light of the so-called 'right to explanation' in the GDPR.

The application of the 'right to explanation' has been extensively criticised regarding its scope regarding the articles 13-15 of the GDPR, including its feasibility in the first place (Articles 13-15 GDPR; Wachter S, Mittelstadt B, Floridi L, 2017; Selbst AD, Powles J, 2017; Mazur J, Henrad K, 2018). Focusing on the nature of fashion recommender systems and the impact on informational privacy, a 'right to explainability' needs provide an account of the system's logic to close the gap between issues of interpretability and explainability.

Current research, acknowledging the challenges of non-interpretability of recommender systems using deep learning, focuses on two important tasks, which are to develop methods that allow users to understand the factors contributing to predictions and to enable practitioners to gain a clearer picture about the inner workings of the model (Zhang S et al 2019, p. 26). A *'neural attentional model'* is argued to solve issues of non-interpretability, based on the mechanism's task to provide implicit feedback on each user-item interaction and inferring the importance of weights within a recommendation (Tay Y et al, 2018; Sun Y et al, 2020, p. 3016).

There is increasing interest to make post-hoc models that are intended to make recommender systems explainable, providing *'user-centred explanations'* (Edwards L, Veale M, 2017, p. 19). For example, matrix factorization methods can be developed in such a way that recommendations are accompanied by an explanation sentence for the suggested item (Zhang Y, Chen X, 2020, p. 8). Similarly, the use of a convolutional neural network approach with an attentional mechanism where the model provides for user/item feature explanations can also be used (Seo S et al, 2017).

However, these approaches of explainability and interpretability suffer from drawbacks. Attention models, being a scheme visualise relational representations of user-item interactions, do not create human- readable explanations, or in other words, these models do not necessarily provide for explainability (Gilpin LH et al, 2018). The work by Lin et al (2020a, p. 1514) which uses user feedback within the neural attention mechanism to generate outfit explanations for recommendations underlines that the model highlights the difficulty to explain why an outfit did not match with the user. Based on these considerations, there is still a gap between the extent of interpretability and providing explainable recommendations to users.

4.2 Fashion recommender systems and the 'right to explanation'

Articles 13-15 of the GDPR are notification duties for the data controller to provide the data subject with information regarding the collection of personal data as well as a data subject's right to access his or her personal information (Articles 13-15 GDPR). Whilst Article 13 outlines the notification duties for data controllers regarding data collection, Article 14 specifies the duties for data collected from a third party (Article 13 GDPR; Article 14 GDPR; Wachter S, Mittelstadt B, Floridi L, 2017, p. 82).

Following these considerations, the data controller has a duty to take appropriate measures meaning that any changes with regard to the content or conditions of privacy notices need to be communicated to the data subject (Flett EL, Harley E, 2018, p. 85). The right to access information in Article 15 and the duty of notification in Articles 13 and 14 of the GDPR may include additional safeguards subject to article 22 of the GDPR (Article 15 GDPR; Articles 13-14 GDPR; Goodman B, Flaxman S, 2017, p. 6). Articles 13(2)(f), 14(2)(g) and 15(1)(h) provide that, when automated decision-making and profiling take place, the data subject can receive 'meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for the data subject' (Article 13(2)(f) GDPR; Article 14(2)(g) GDPR; Article 15(1)(h) GDPR).

Within this context, Wachter, Mittelstadt, Floridi (2017, pp. 78-79) make an important distinction between the duties in articles 13-14 and article 15. They underline that the former includes ex-ante notification about the extent of data processing or automated profiling from the beginning, whereby the latter provision stipulates an ex-post obligation to provide information on a data processing activity, including the decisions that are taken about a particular individual.

Article 22(1) of the GDPR provides that *'the data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her'* (Article 22(1) GDPR). Article 22(3), referring to article 22(2)(a) and 22(2)(b), highlight that a data controller needs to implement suitable safeguards, which may entail a *'right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision'*, in accordance to Recital 71 (Article 22(3) GDPR; Article 22(2)(a) GDPR; Article 22(2)(b) GDPR; Recital 71 GDPR).

Based on these considerations, the existence of automated processing including profiling gives individuals an ex-ante protection to receive information on the system's functionality, as well as an ex-post protection to receive information upon the individual's specific request. However, these provisions led to a series of criticisms. One consideration is that article 22(1) directs to not be subject to *'a decision based solely on automated processing'* which may constrain the provision's scope to a limited number of circumstances (Article 22(1) GDPR; Wachter S, Mittelstadt B, Floridi L, 2017, p. 79).

Fashion recommender systems are semi-automated in that algorithms will evaluate the matching criteria and relative probability a user will choose a style, which sometimes requires manual intervention to fill the gaps or sparse matrix, circumventing the classic problems in collaborative filtering systems ('Stich Fix'). The prohibition of article 22(1) does not apply when there is meaningful human oversight, rather than a token gesture (Article 29 Working Party 2016, p. 21). For instance, it could be argued that a fashion recommender system using a CNN methodology and causing issues of verifiability and interpretability of output could serve as an indicator that significant human oversight over the algorithmic personalisation process cannot be guaranteed. Yet, how much human oversight is meaningful is not sufficiently clarified in the GDPR.

The second consideration is that the decision needs to *'produce legal effects concerning him or her or similarly significantly affects him or her'* (Article 22(1) GDPR). Thus, the GDPR guidance specifies that the decision needs to have an impact on an individual's legal rights or legal status, or it produces an effect that is of an equivalent impact (Article 29 Working Party 2016, 21). It underlines that the extent of data processing seems to be of *'sufficiently great or important to be worthy of attention'* when the activity *'significantly affects the circumstances, behaviour or choices of the individuals concerned'*, when it *'has a prolonged or permanent impact on the data subject'*, or the decision *'leads to the exclusion or discrimination of individuals'* (Article 29 Working Party 2016, 21). The guidance refers to behavioural advertising from a *'mainstream fashion outlet'* may significantly affect the user, depending on the intrusiveness of the profiling process or the expectations of the individual concerned and considering the particular vulnerability of the data subject targeted (Article 29 Working Party 2016, p. 11). That said, advertising or marketing strategies as such do not enter the scope of article 22 (Article 29 Working Party 2016, 11).

However, a dividing line that is based on a simple demographic profile, and a clear discriminatory practice, is not a helpful distinction with regard to fashion recommender systems which work with pre-defined values resembling aspects of an individual's ambivalence of conformity and individuality. This also includes behavioural parameters influencing the individual's personal understanding of *'fashion'* as both aspects have an impact on an individual's individual autonomy. This distinction does not give added value to the relationship between decisions that produce a legal effect on the status of the individual and those algorithmic processes that have a similar influence. Hypernudging practices are not designed by virtue of the vulnerability of a specific individual as such, but their operation amplifies unconscious associations on an individual inference of self. Thus, it is difficult to define the point fashion recommender systems and hypernudging practices produce a prolonged effect on individual behaviour, as it pertains directly how expectations are formed.

Building on the above, there is a lack of clarity regarding the safeguards available in article 22(3) GDPR, which is whether the GDPR introduces the so-called legally binding 'right to explanation' (Article 22(3) GDPR). Recital 71 stipulates that *'in any case, such processing should be subject to suitable safeguards, which should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision*' (Recital 71 GDPR).

Wachter, Mittelstadt, and Floridi (2017, p. 79), doubt the existence and feasibility of a 'right to explanation', highlighting that Recitals are not a guidance regarding the interpretation of the provisions, and therefore, Articles 22, and, 13-15, of the GDPR, do not seem to mandate an *'explanation'* of the decision reached concerning automated processing. Instead, they postulate that they provide an ex-ante obligation on the 'right to be informed'. However, Selbst and Powles (2017, p. 236) argue that requesting *'meaningful information about the logic involved'* mandates a right to explanation to ensure the effective compliance with Article 22(3) of the GDPR.

It follows that the focus is not on whether the right to explanation is expressly provided in the GDPR, but instead, to assess the feasibility of such a right in the first place (Mazur, Henrad 2018). Malgieri and Comandé (2017, p. 244), argue that an important safeguard for individual would illustrate to inform users *'as much as possible about the existence and the logic involved in such algorithmic decision-making, both as for system functionality and for specific decisions'*.

Yet, this safeguard does not signify full transparency about the algorithmic process. One consideration is that a company has a legitimate interest in ensuring the proprietary information or trade secret regarding the underlying work of the algorithms (Edwards L, Veale M, 2018a; Recital 63 GDPR). Moreover, it is argued that full transparency is not even desirable, in that once individual's comprehend what signs are suggestive for individual behaviour, these signs may lose its predictive value (Kroll, Huey, Barocas et al 2016, 657-

658). Accordingly, a 'right to explanation' is a mechanism that acts as both, an ex-ante, and ex-post, obligation, whereby it defines the scope of an algorithmic process, as well as the consequential implications of these tools on the individual right to privacy.

4.3 Setting the Parameters for Transparency in Fashion Recommender Systems

A 'right to explanation' could operate as an accountability mechanism for the design and implementation of interpretable fashion recommender systems. In practical terms, this means that the GDPR needs to take a clearer stance on the operation algorithmic personalisation systems, which even though not fully automated, do cause issues of transparency as highlighted in light lack of interpretability and explainability in recommender systems.

Indeed, the opinion by the UK Information Commissioner's Office that article 22(1) of the GDPR needs to be interpreted to include processes where there is minimal, but not *'real influence on the outcome of the decision-making process'* (ICO 2017, p. 19; ICO 2018a; Malgieri G, Comandé G, 2017). Similarly, Recital 71, stipulating that *'profiling consists of any form of automated processing of personal data evaluating the personal aspects relating to a natural person'*, including *'personal preferences or interests'*, indicates that there is a legitimate interest to protect individuals from persuasive practices that are manipulative (Malgieri G, Comandé G, 2017; Recital 71 GDPR).

Nevertheless, further efforts to secure an unambiguous interpretation of article 22(1) of the GDPR need to the character of fashion recommender systems and their impact on an individual's autonomy and informational privacy. A 'right to explanation' can not only refer to specific vulnerabilities created by marketing or nudging strategies, but it also needs to be assessed considering the parameters of the right to privacy.

Privacy, being instrumental for the protection of an individual's autonomy, does not only comprises the essential independence from unwarranted intrusions but the conditions that enable an individual the autonomous construction and expression of self (Cohen JE, 2000, pp. 1427-1428). Essentially, a 'right to explanation' needs to assess the contours of the created imaginary of fashion recommender systems. That requires an ex-ante obligation to outline the logic of the algorithmic association processes regarding situational and dispositional attributions in the recommendation process. An ex-post obligation needs to contextualise the rationale of the decision considering the functionality of the decision-making process, which would be an outline of the relevance of *'fashion narratives'* regarding the person's user-item interactions.

As a first step, this requires interpretability of the recommendation process. In this respect, a neural attentional model can help to ensure the interpretability of fashion recommender systems and provide the relevant guidance to fulfil the notification duties considering articles 13(2)(f) and 14(2)(g) of the GDPR (Article 13(2)(f) GDPR; Article 14(2)(g) GDPR). As a second step, attentional neural models need to provide for explainability concerning a decision taken regarding the data subject within article 15(1)(h) of the GDPR (Article 15(1)(h) GDPR). That said, providing comprehensibility in algorithmic decisions regarding the system's functionality intends to close the gap between issues of interpretability and explainability in fashion recommender systems.

Therefore, providing interpretable and explainable decisions in algorithmic processes requires an account of the system's functionality regarding the system's logic and to a certain extent, its general functionality to provide the representations of data on the workings regarding user-item interactions. This way, ensuring transparency of algorithmic processes should enhance an individual's autonomy to understand the parameters of interactive value creation in fashion recommender systems. It is submitted that effective explainability and interpretability of fashion recommender systems will provide an account of an individual's autonomy. This will protect users against manipulative practices in algorithmic personalisation systems, and also, establish the reference point for acceptable nudging and questionable hypernudging practices.

5. Conclusion

This paper gives an outlook on the importance of algorithmic systems in the fashion domain, focusing on advances in AI techniques in recommender systems. Fashion recommender systems, learning from product attributes and evaluating user-item interactions, intend to provide personalised recommendations that fit an individual's preferences, style, size, or shape (Guan C et al, 2016).

Referring to the concept *of 'hypernudging'* (Yeung K, 2017) fashion recommender systems have an impact on an individual's autonomy and informational privacy. Algorithmic personalisation systems generate assumptions on individual behaviour that illustrate an incomplete picture on the meaning of *'fashion'*. Accordingly, fashion recommender systems influence the unconscious associations that generate an imagery on the individual's personal and social understanding of *'fashion'*.

This paper offers a starting point to think about the impact of fashion recommender systems on informational privacy and autonomy, claiming that we need a deeper understanding of conditions that shape the expression of inter-personal values. That being said, closing the gap between issues of interpretability and explainability in fashion recommender systems could illustrate a reference point to set the parameters of informational privacy considering the GDPR.

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