When does personalization work on social media? a posteriori segmentation of consumers

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Abstract

The aim of this research is to find a segment of consumers of fashion products based on their personal visions of personalization of shoppable ads on mobile social media. To meet this objective, three operational objectives are defined. First, a theoretical model is evaluated based on the stimulus-organism-response framework (S–O–R). This examines, with a PLS-SEM approach, how the stimulation of personalization will affect consumers' internal cognitive state (perceived usefulness) and consequently generates a behavioral response (intention to buy). Second, we look for fashion consumer segments based on their perception of personalization through prediction-oriented segmentation (PLS-POS). Third, the segments are explained based on three constructs that were considered important in fashion consumption through mobile social networks: purchase intention, concern for privacy, and perception of trend. The inclusion of personalization and the perception of usefulness of advertisements can greatly help the intention to purchase clothing to be understood. The application of a posterior segmentation helps to better understand the different types of users exposed to shoppable ads on mobile social networks and their relationship with the purchase intention, concern for privacy and trend. While the measures and scales were tested in a context of mobile clothing trade, the methodology can be applied to other types of products or services.

Keywords Advertising · Social commerce · Personalization · Privacy concern · Mobile social media

1 Introduction

Social media platforms aim to become the "shopping centers" of tomorrow through the development of social commerce tools [16]. Social commerce offers social media users the opportunity to generate commercial transactions, but the efforts of both platforms and advertisers have not been enough to attract consumers [26]. Despite these expectations,

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eMarketer [18] shows that buyers are not filling social media to buy. However, social platforms play an important role in the pre-purchase stages as a search and influence tool. For consumers who have adopted shoppable ads, fashion and clothing are the main product category that users buy in social commerce on social media [17]. Fashion is deeply related to social commerce, where consumers participate, review, and co-create fashion brands [52].

With the aim of selling, one of the formats that social media platforms have experienced are "shoppable ads". This format is presented as personalized advertisements that the user sees while scrolling through their social network, and which are characterized by "buy buttons" from where they can share and buy products directly [16]. Social media ads differ from traditional ads primarily because advertising content extends to the people at whom the ad is directed [38].This is why social networks provide highly relevant targeting technical companies based on demographic, geographic and psychographic information provided by users in their profiles [31].

The personalization of commercial offers is based on the idea that customers have preferences that marketers can reveal when developing a learning relationship with customers [9]. Due to this uniqueness of online shopping channels, an interesting controversy has arisen about the way in which market segmentation should be carried out. Advocates of personalized and one-on-one marketing argue that it is possible to take segmentation logic to the extreme, achieving and targeting "segments of one" [61]. We know that consumers may consider personalized ads useful, but they may regard the use of more confidential information inappropriate [10].

From the development of social media and mobile devices, it is necessary to understand what features fashion buyers have in this new environment [8]. The literature review shows that there are not many works that address the segmentation of online shoppers, and it has focused on physical stores, mainly with a priori segmentation methodologies [36]. We found that this constitutes an important gap in the online segmentation literature, especially since the theory has stressed the importance of personalization in creating consumer profiles. The questions that guide our work are: When faced with a personalized shoppable ad, what does the consumer, personalization or utility of the advertisement value most? Are there different profiles of users who buy fashion products in social networks?

In summary, the main objective of this research is to find a segment of consumers of fashion products based on their personal visions of personalization of shoppable ads on mobile social media. To meet this objective, three operational objectives are defined. First, a theoretical model is evaluated based on the stimulus-organism-response framework (S–O–R) [44]. This examines, with a PLS-SEM approach, how the stimulation of personalization will affect consumers' internal cognitive state (perceived usefulness) and consequently generates a behavioral response (intention to buy). Second, applications of structural equation modeling are generally based on the assumption that the data being analyzed come from a single population, so that a single global model represents all observations. Heterogeneous perceptions and evaluations of products and services form the basis of the concept of market segmentation [49]. This is why we look for fashion consumer segments based on their perception of personalization through prediction-oriented segmentation (POS). Third, the segments are explained based on three constructs that were considered important in fashion consumption through mobile social networks: purchase intention, concern for privacy, and perception of trend.

This work contributes to the literature in a number of ways. First, when evaluating shoppable ads on mobile devices in the context of the use of social networks for commercial transactions (Yahia et al. [68]; [26, 34]). Second, by delving into the field of personalized

ads [1, 9, 10]. Third, this study is based on the fashion industry, affected and transformed by technologies [52]. Finally, the study was applied in an emerging market where there is a tendency towards social commerce, based mainly on mobile devices or tablets [22].

The article is structured as follows. Firstly, a review of the literature on social commerce and social media ads, personalization, perceived usefulness, and consumer segmentation is presented. Next, the methodology is put forward. Graphics are provided on the processes necessary to develop the PLS-SEM and PLS-POS analysis. The results of the analyses performed are provided. The article concludes with the discussion of the results, implications and suggestions for future research.

2 Literature review

2.1 Social commerce and social media ads

Social commerce is a new form of electronic commerce through social networks that allows customers to actively participate in the marketing and sale of products in online markets [15]. It involves a variety of commercial activities that can help consumers in pre-product evaluation, purchasing decisions and post-purchase behaviors (Lin et al. [41]. The main attributes of social commerce are social network technologies, interactions in communities and commercial activities [39], representing an economy of recommendation which combines advertising, sales promotion and direct marketing [46].

Social networking services offer the opportunity to carry out commercial transactions traditionally attributed to electronic commerce [26]. Despite this, the rapid growth of social networks has made it difficult to understand the functioning of different social media platforms to carry out commercial tactics [68]. So the incorporation of functionalities in social network applications that allow commercial transactions is an emerging area in social commerce. In this context, social media applications have begun to use shoppable ads. These are characterized by the use of the "Buy" button in ads that appear while the user scrolls through the application and allows them to make purchases directly [34, 37], These functionalities are especially relevant for two main reasons. First, people consider social media applications as an important part of their daily lives and are more likely to move their interactions to social platforms (e.g., Facebook, Instagram, LinkedIn and Twitter) [2], so the exponential increase in the use of social networks has made them the most important advertising media [31]. Second, social media advertising differs from conventional advertising in the way that the advertising content spreads among the people at whom it is targeted [38] through personalized ads.

2.2 Stimulus-Organism-Response (S–O–R)

The theoretical basis of the stimulus-organism-response framework (S–O–R) is related to environmental psychology proposed by Mehrabian and Russell [44]. This affirms that a stimulus of the environment affects the individual's cognitive and affective responses, which in turn lead to a behavior [30]. This framework suggests that stimuli are antecedents which affect the emotional states of consumers (organism), whose response influences the purchase results [48].

The S-O-R theory has been used to investigate online shopping results. Chen and Yao [14] combined the requirements of the e-commerce structure and the S–O–R paradigm

to study impulse buying behavior in mobile auction platforms. Gao and Bai [21] studied the impact of atmospheric signals (such as personalization) of tourism websites as stimuli of the intention to purchase, validating the relations with the S–O–R framework in online tourism. Islam and Rahman [29] used the S–O–R theory to investigate the motivations of users to generate engagement with brand communities in social networks. The framework was used to show how the characteristics of the online community influence consumer engagement and, consequently, loyalty to the brand. Also, recently the framework has been used to study the behavior of product recommendation in social networks Zhang et al. [69]. The use of the S–O–R model is appropriate for this study for two reasons. First, our review of the literature suggests that there are previous studies that apply this framework in contexts of online shopping, social networks and mobile devices, so it is a suitable theory for this study. Second, given the critical roles of technological environments and virtual experiences in influencing customer behavior in social commerce, the S–O–R model provides a parsimonious and structured way to examine the effects of technological characteristics, such as environmental stimuli in virtual customer experiences Zhang et al. [70].

In the case of this study, the stimulus is the perceived personalization of the advertisement, the reason being that consumers are exposed to the situational stimulus in the use of mobile social networks. The organism refers to the emotional and cognitive state of the users, including their opinions, experiences and evaluations, and their factor selected in this study is the perceived usefulness. Finally, the response is the purchase intention. Based on this theory, we develop our research model.

2.3 Personalization

Personalization refers to a customer-oriented marketing strategy that aims to deliver the right content to the right person at the right time to maximize immediate and future business opportunities [59]. Zhang et al. [70] point out that personalization strategies in social commerce mainly focus on providing an online customer with personalized content based on their needs, preferences, profiles, previous interactions and social networks. Personalization involves collecting, analyzing and leveraging consumers' private information beyond their original transaction purpose [9]. The ability to incorporate past user behaviors allows online businesses to customize services more accurately, with advantages for both companies and their customers [1]. The personalization of an ad reflects an individual's interests and preferences, so that with a greater depth of personalization the content will be more relevant and more useful [9]. Therefore, personalization is expected to have a positive effect on the perceived usefulness. In addition, personalization has an effect on behavioral intentions in the context of online ads [9] and electronic commerce [67]. The following hypotheses are proposed:

H1: The perceived personalization of shoppable ads on mobile social networks has a direct and positive effect on the purchase intention.
H2: The perceived personalization of shoppable ads on mobile social networks has a direct and positive effect on the perceived usefulness.

2.4 Perceived usefulness

The perceived usefulness is one of the main variables which explains the intention of behavior regarding a new technology, and has been used as a stimulus in the S–O-R framework to explain the intention to click on personalized ads [9]. Consumers consider

personalized ads useful for making their purchase decisions [9]. The empirical results show that the perceived usefulness is one of the most important predictors of intention. This relationship has been evaluated in the context of the use of social networks for commercial transactions [26], mobile ads [4] and social media ads (C. A. [40]. The following hypothesis is proposed.

H3: The perceived usefulness of shoppable ads on mobile social networks has a direct and positive effect on the purchase intention.

2.5 Trendiness and privacy concern

Since fashion is a very dynamic business, it must necessarily be innovative: collections must be launched at least twice a year, and personalized ads must be delivered to customers according to their preferences. In this context, the task of brands is complex, particularly in areas of activity where customer preferences change rapidly, as is the case in the fashion industry [11]. Personalization has an important influence on consumers and they consider personalized ads useful [10]. But, despite the benefits of personalization, highly personalized ads raise concerns about user privacy in mobile device ad contexts [33], web ads [9], and in social media ads [31]. This increased concern about privacy is explained by the fact that users consider that companies capture their information and use it for marketing purposes [31]. Therefore, customers are more likely to ignore social media ads if they perceive a degree of concern for privacy [31]. Despite the possible loss of privacy, users with a greater concern for privacy tend to value greater perceived usefulness in order to justify the social media's continued use [28]. In their study on the impact of privacy concerns on social networks, Tan et al. [60] discovered that the effect of perceived usefulness on behavioral intent is stronger for the group with the greatest concern for privacy. Privacy is a challenging topic on social networking sites and working on trust-building plans can help companies develop a new brand. [62].

2.6 Consumer segmentation

The research body related to segmentation for shoppable ads on mobile social networks is presented in two lines. First the segmentation of fashion consumer profiles, and second the segmentation of consumers in online markets.

Within the research in the fashion industry, consumer segmentation studies focus on elements such as consumer behavior, purchase intention, and fashion innovation. According to this, the literature indicates various approaches and classifications of buyers of fashion products. Based on fashion innovation, Workman and Studak [65] point out that dividing fashion consumers into four groups (innovative communicators, innovators, opinion leaders, followers) can help understand how emerging adult consumers use fashion and appearance to establish an individual or group identity. In a segmentation study of fashion consumers in Portugal, Cardoso et al. [12] outlined three types of consumers: Enthusiastic consumers, who buy clothes frequently, are very involved, innovative and express themselves through fashion,Moderate consumers, who are somewhat innovative and buy clothes with a moderate frequency, but do not especially wear clothes to express themselves; Apathetic consumers, who are not involved with fashion, do not give importance to brands and rarely buy clothes, but especially value the functional aspects of clothing, such as quality, comfort and price. In a study on the women's clothing market in the USA, Shim and Bickle

[54] described three fashion lifestyle segments: symbolic / instrumental users, who are younger, innovative, fashion conscious and represent a higher social class,Practical / conservative users, who are more oriented toward comfort and function than toward fashion or appearance and are not likely to enjoy shopping; and apathetic users, who tend to sponsor discount stores. From this body of research, the groups emerged and presented relatively similar characteristics, even if the categories were labeled with different names.

The literature suggests that online shoppers have different behaviors than those who use traditional means of purchase [13]. For example, Maignan and Lukas [42] indicated that consumer behavior should be studied according to the multiple views of the Internet of consumers (as a source of information, media, place of consumption and social system). Online shopping has the potential to eliminate almost all human interaction from transactions, reducing virtually all relationships between buyers and sellers [47]. Only through an understanding of the different customer segments can marketing professionals develop strategies and tactics to attract and maintain these customers [32]. Barnes et al. [5] studied online consumers according to a set of psychographic, cultural and buying behavior factors. Their analysis revealed three segments: those who doubt risks, open-minded online shoppers and reserved information seekers. In a study on the segmentation of personalized ads on Facebook, Tran [61] identified three market segments that include ad lovers, ad setters and ad enemies.

The present study seeks to unite both lines when studying fashion consumers in online markets. Previous studies focus on making a priori segmentations from the previous literature or comparing behaviors between different generations. This research uses a method of segmentation afterward, when analyzing the heterogeneity of consumers through a segmentation of latent classes, based on a structural model called segmentation, oriented to the prediction of partial least squares. That is, this method implies the grouping of consumers, not to do with a certain variable, but on the basis of their behavior toward the model as a whole that we have proposed based on S–O–R.

3 Methodology

3.1 Sampling and pre–test

The data was collected through a survey between the months of June and August of 2018 in Chile. The survey was aimed at users with experience in the use of social media on mobile devices, specifically in the mobile application of Facebook. It was decided that Facebook is the most appropriate platform for three reasons. First, Facebook continues to be the most popular social media around the world [56]; Chile is the third largest market in the world for Facebook in terms of the reach percentage of visitors [55]; the mobile application of Facebook has been a pioneer in the introduction of features for commercial transactions in social media [23]. In addition, it is important to note that social commerce is a trend in emerging countries and is mainly based on post-desktop factors such as mobile devices or tablets [22]. Finally, it should be noted that according to the report on access, use and Internet users in Chile, the main use of electronic commerce is to buy fashion and clothes [57].

A sampling of quotas based on age and sex ranges was used to select the participants. These quotas were selected according to the profile of Smartphone users in Chile [57]. The surveys were done in personal interviews by professional surveyors. To eliminate possible ambiguities in the questionnaire, a pilot test was applied to 40 users of social media on

mobile devices. After making minor changes in the instrument, face-to-face surveys were carried out. The exclusion of invalid surveys provided a final sample of 486 users of social media on mobile devices. 58.8% were women. The average age was 30 years. The majority had secondary education or university studies (18.9% and 65.6%, respectively), and 84.3% had made at least one purchase through the Internet during the last year. On the other hand, we have controlled Common Method Bias according to the recommendations of the previous literature [35], resulting in VIF levels below the limit of 0.3.

3.2 Measurement scales

The questionnaire that we have designed to capture data has three blocks. These blocks are presented from the most general to the most specific. The first deals with demographic questions of the people such as age, sex, etc. (Table 1). The second block gathers the people's characteristics concerning their privacy and the perception of trend of the products. The third addresses people's relationship with shoppable ads.

Specifically, the measures for the constructs in this study were taken from the existing literature and adapted to the context of shoppable advertisements and social commerce. The personalization (PERS) and perception of trend were adapted from Yadav and Rahman's [67] work on perceptions of social media marketing activities in the context of electronic commerce. The measure of perceived usefulness was adapted from the work of Natarajan et al. [45] on the intention of purchase applications on mobile devices. The purchase intention measure was adapted from the work of Shaouf et al. [53] about the intention to purchase in web ads. The measure of privacy concern was adapted from the work of Lin

Table 1 Demographic data

| Item		Frequency	Percentage
Sex	Men	200	41.2
	Women	286	58.8
		486	
Age	18 to 20 years	126	20.6
	21 to 30	308	50.3
	31 to 40	84	13.7
	41 to 50	64	105
	51 to 60	22	3.6
	60 or more	8	1.3
	Total	486	
Experience in internet	Less than a year	7	1.4
	2 to 3 years	9	1.9
	4 to 6 years	58	11.9
	More than 6 years	412	84.8
	Total	486	100
Purchase in internet in the last year	None	122	25.3
	Last than 6	209	43.3
	Between 7 and 12	76	15.7
	More than 12	76	15,7
	Total	486	

Fig. 1 Proposed model
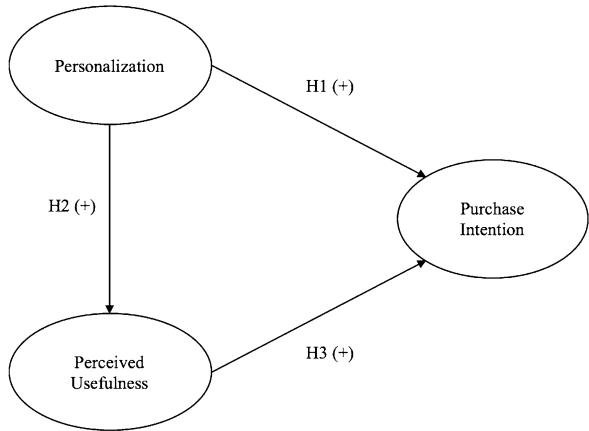
and Kim [40] on user responses to ads on social media. All the scales were measured with items on a 7-point Likert scale, ranging from "totally disagree" to "totally agree", except for sociodemographic and other variables related to purchases on the Internet.

3.3 Statistical tools

The main methodologies and approaches used in the literature are a priori segmentation and segmentation revealed by the consumer. The latter can show the potential segments of a product and provide an understanding of the motives, lifestyles or needs of the segment [58]. When appropriate variables are used, the segments revealed by the consumer directly reflect the responsiveness of the segments to the product [3]. Although the consumers' demographic characteristics may be identical, individual differences in psychographic characteristics may lead to different purchasing processes [64]. This study is based on a posterior segmentation in the importance of the purchase intention, the concern for privacy and the perception of trend to segment consumers of shoppable ads of fashion products on mobile social networks (Fig. 1).

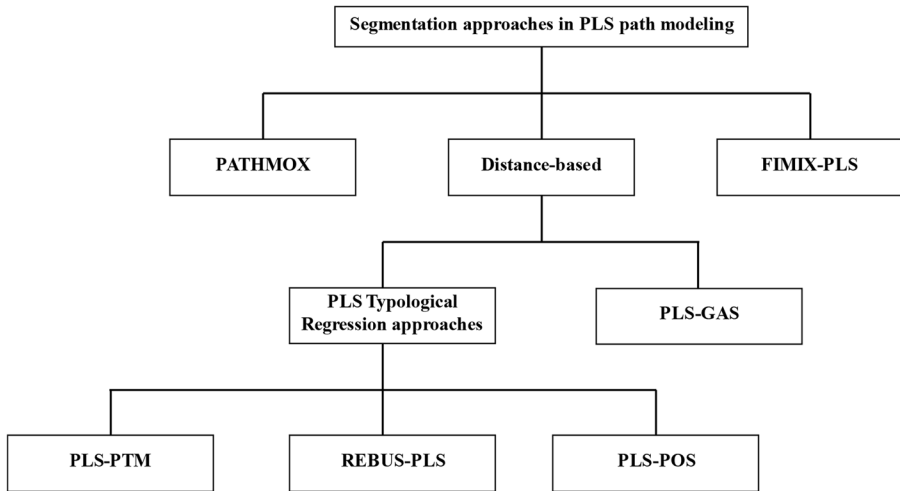**Fig. 2** The basic PLS-SEM algo-rithm (adapted from [51], p. 3)
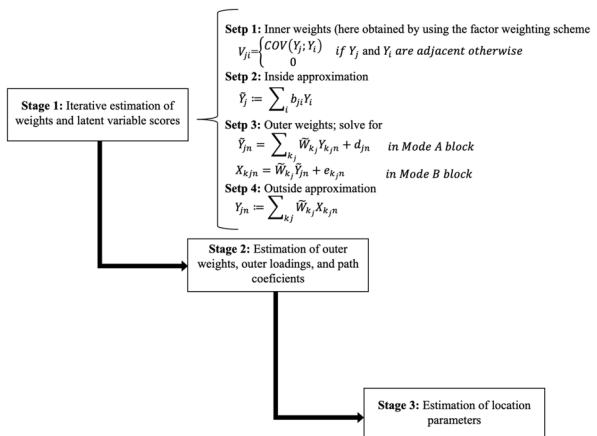
Fig. 3 Segmentation approaches in PLS path modeling (adapted from [49], p. 270)

In the first phase, a structural equations model of structural equations (SEM), specifically partial least squares (PLS) is proposed to test the reliability, validity and the hypotheses presented. Model estimation in PLS-SEM is based on a three-stage approach that belongs to the family of (alternating) least-squares algorithms [43]. Figure 2 illustrates the PLS-SEM algorithm adapted from Sarstedt et al. [51]. PLS-SEM allows researchers to evaluate both causal relationships between indicators / items and causal relationships of latent constructs [24]. The procedures suggested in the previous literature were used to evaluate the measurements and the structural model [19, 27, 66]. The data were analyzed using SmartPLS 3.2.7 software [50].

Most research which uses PLS-SEM analyzes a complete set of data, assuming that the data come from a homogeneous population. However, especially in the consumer
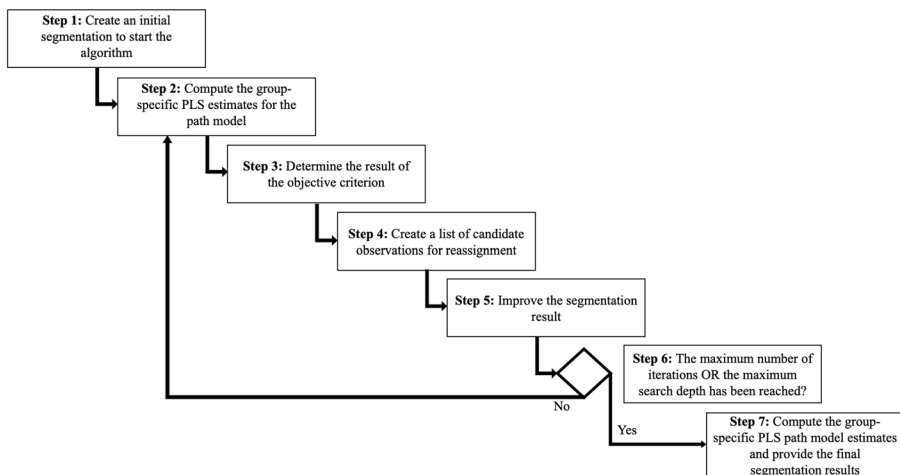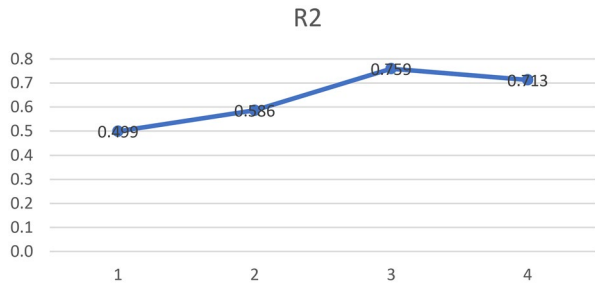

Fig. 4 The PLS-POS algorithm (Adapted from [6], p. A7)

Fig. 5 Average R^2:

area, it is appropriate to consider people's heterogeneity [25]. Figure 3 shows the evolution of segmentation methods. Some of these methodologies have been criticized in the literature for problems with the imposition of distributional assumptions and heterogeneity in the internal and external models of endogenous and exogenous variables [49]. To solve these problems, Becker et al. [7] present the prediction-oriented segmentation method for PLS path modeling (PLS-POS). This methodology has been designed to overcome several problems and limitations of existing PLS segmentation methods [49] (Fig. 4).

Therefore, in phase 2, we identify consumer segments of fashion products through shoppable ads with differentiated behaviors in the model previously analyzed through prediction-oriented segmentation (PLS-POS). This technique allows calculating the parameters and segments of the observations simultaneously [6]. The PLS-POS algorithm introduces three novel features: (1) it uses an explicit PLS-specific objective criterion to form homogeneous groups, (2) it includes a new distance measure that is appropriate for PLS path modeling with both reflective and formative measures and is able to uncover unobserved heterogeneity in formative measures, and (3) it ensures continuous improvement of the objective criterion throughout the iterations of the algorithm (hill-climbing approach). The algorithm of the PLS-POS methodology [6] is shown in Fig. 4.

Then, we seek to explain the characteristics of the resulting segments in the following steps. In phase 3, we compare the differences in the model between the segments using the PLS-multigroup (PLS-MGA) analysis. We analyze the different behaviors of each segment in the model proposed with this technique. Finally, in Step 4, the resulting segments were characterized by analysis of variance (ANOVA) for the variables: purchase intention, concern for privacy and perception of trend.

Table 2 Path Coefficients

Construct	Global		Seg. 1		Seg. 2		Seg. 3	
	Paths	p-values	Paths	p-values	Paths	p-values	Paths	p-values
PERSPU	0.667	0.000	0.967	0.000	0.923	0.000	0.573	0.000
PERSPI	0.262	0.000	2.601	0.000	1.159	0.000	0.133	0.003
PUPI	0.543	0.000	−1.767	0.000	−0.198	0.000	0.611	0.000

PERS personalization, *PI* Purchasing intention, *PU* Perceived usefulness

Table 3 Variance Explained of the endogenous variables (R^2)

Constructs	Global	Seg. 1	Seg. 2	Seg. 3
PI	0.553	0.994	0.958	0.484
PU	0.445	0.936	0.853	0.328

PI Purchasing intention, *PU* Perceived usefulness

4 Results

First, the reliability and validity of the scales were analyzed following the recommendations of the previous literature [19, 27]. For the proposed variables, the individual reliability of each item is ensured through loads of more than 0.7 in its corresponding latent variable. Second, the reliability of the cyberstructures was analyzed using Cronbach's alpha criteria and the composite reliability. In all the cases, the indicators are greater than 0.7. Additionally, convergent validity is ensured by analyzing the average extracted variance. In the analysis, all the indicators offer levels above the 0.5 score proposed in the literature. Finally, discriminant validity was evaluated in two ways: using the Fornell and Larcker test and employing the heterotrait-monotrait criterion, which together offer levels below 0.9 [27]. In summary, the results of the analysis ensure the validity and reliability of the measurement scales used. Then, a structural analysis was performed. The results are shown in Tables 2 and 3. Additionally, the SRMR indicator was calculated for the entire sample. Standardized Root Mean Square (SRMR) is a measure of the overall fit of the model, especially suitable for PLS. For the proposed model, a value of 0.05 (less than the required 0.08) was obtained, demonstrating that the goodness-of-fit test is appropriate.

As a second step, the PLS-POS technique was applied following the guidelines proposed by [6]. As a result, three user segments were obtained. To determine the optimal number of segments, the criterion of the mean of the explained variance of the proposed model was adopted, see Fig. 5. The size of the segments is shown in Table 4. The three-segment model attains the highest average R2 values.

The evaluation of the structural model for each of the four previously obtained segments was calculated. The values of the path coefficients and the explained variance of the endogenous variables (R2) are shown in Tables 2 and 3. The path coefficients indicate the intensity and the sign of the relationship between the dependent and independent variables. The bootstrapping technique was used to calculate the reliability of the path coefficients in the hypothesized relationships.

Subsequently, in step 3, the PLS-MGA technique was used to compare the differences between the three segments resulting from the PLS-POS analysis (Tables 4 and 5).

Finally, to characterize, variables related to the shoppable ads of fashion brands that present personalization were analyzed: Purchase intention, Privacy Concern and Perception of trend. The ANOVA technique was applied for each of these continuous variables (Table 6). As a result, it was obtained that the proposed variables offer significant directions between segments.

Table 4 Size of segment

Seg. 1	Seg. 2	Seg. 3	Total
20	74	392	486
4%	15%	81%	100%

Table 5 Comparison of models by segment

Construct	Seg. 1 versus Seg. 2			Seg. 1 versus Seg. 3			Seg. 2 versus Seg. 3		
	Dif. Path	PLS-MGA	Parametric Test	Dif. Path	PLS-MGA	Parametric Test	Dif. Path	PLS-MGA	Parametric Test
PERSPU	0.044	0.086	0.350	**2.378**	**0.000**	**0.013**	**0.351**	**0.000**	**0.000**
PERSPI	**1.442**	**0.000**	**0.000**	**2.468**	**0.000**	**0.000**	**1.026**	**0.000**	**0.000**
PUPI	**1.569**	**1.000**	**0.000**	**0.395**	**1.000**	**0.000**	**0.809**	**1.000**	**0.000**

Table 6 Descriptive analysis and ANOVA p-values

Variable	Seg	N	Average	*P*-value
Purchase intention	1	19	–0.45302	0.049
	2	74	0.15305	
	3	388	–0.00700	
	Total	481	0.00000	
Privacy Concern	1	20	–0.54715	0.027
	2	74	0.128901	
	3	385	0.00365	
	Total	379	0.00000	
Perception of trend	1	20	–0.72118	0.004
	2	74	0.04737	
	3	385	0.02836	
	Total	479	0.00000	

5 Discussion

The use of social networks for commercial transactions is an emerging area of social commerce that represents a challenge for both professionals and academics. To address this limitation, the main objective of this research has been successfully achieved: to find a segmentation of consumers of fashion products based on their personal views of the personalization of shoppable ads on mobile social networks.

The first operational objective of this research was to evaluate a theoretical model that includes personalization and perceived usefulness and its effects on the purchase intention with a PLS-SEM approach based on the S–O–R framework. The results of this study show that the proposed model is a useful tool to explain the intention to purchase through shoppable ads in a context of mobile devices and fashion brands. This is demonstrated in the validity and reliability of the scales, in the variance explained and in the adjustment of the structural model. The parsimony of the model should be noted, R2 values show that with few variables it manages to explain a high percentage of the purchase intention. The results indicate that personalization has an impact on the intention to purchase through shoppable advertisements of fashion products on mobile social networks (H1). Personalization implies the degree to which social networks offer customized products or services to meet a customer's preferences [67], so that with greater personalization mobile social network users will have a greater intention to buy fashion products through shoppable ads. It also shows that the personalization of the ads influences the usefulness perceived by users (H2). This result is in line with the previous literature on the importance of personalized ads [9]. The results of this study show that the perceived usefulness plays an important role in the intention of purchase through shoppable ads (H3), as well as in ads on mobile devices [4], mobile shopping applications [45], and commercial transactions in social networks [26].

The second objective of this study sought to identify the profiles of fashion consumers based on their perception of personalization through a prediction-oriented segmentation (POS). According to the PLS-MGA analysis, there are significant differences between the segments in the relationship between the constructs of the proposed model. This result can be explained by their different perceptions about the concern for privacy and the perception of trend. In the case of occasional buyers, social networks are part of their daily lives, and the concern for privacy does not prevent users from using mobile social commerce [28]. In

this sense, if advertisers have to use highly personalized messages, providing a justification that explains how consumer information is relevant to the personalized offer is a way to reduce privacy concerns [63]. When firms do not inform their customers about their data compiling efforts, an ad which contains different personal information can indicate to the customers that the information has been compiled without their consent [1]. Regarding the trend, the literature shows that it is an important element when evaluating products in social commerce (Menon et al., 2016). This is why the idea of buying clothes implies obtaining information on trends and fashion [20]. Finally, from an instrumental point of view, we would like to point out that PLS-POS analysis is suitable for segmentation based on user perceptions in social networks. This tool, which we have described in the methodology, enables us to distinguish different types of consumers based on their different behaviors in the face of a predefined structural equation model (SEM). In general, the results of applying this instrument demonstrate the heterogeneity of behaviors within the sample and identify significant segments of consumers with behaviors far from the general average.

The third objective was to explain the segments based on three constructs that were considered important in fashion consumption through mobile social networks: purchase intention, concern for privacy, and perception of trend. When delivering a data analysis for each of the segments, the variance explained for the purchase intention improves significantly when compared with the results of the global sample. Next, some significant aspects of the results and an explanation for each of the segments found will be discussed.

Segment 1: Techno–shy This is the smallest segment, only 4% of the sample. It has a strong relationship between personalization and the variables perceived usefulness and purchase intention. In addition, this set of users shows a strong and negative relationship between the perceived usefulness and the purchase intention. This implies that this type of consumer tends to value personalization, considering its effect on perceived usefulness but, regardless of the utility, they would not buy fashion products through shoppable ads. This result can be explained by why some consumers resist online shopping, even if they engage in other online activities [3]. This segment is also characterized by a low purchase intent, a low concern for privacy and a low perception of trend. A possible explanation of this group is that it makes them uncomfortable to make purchases through new technologies, so they prefer to check prices and other attributes of products online and go to the point of sale to acquire them. This study shows that this group has a parallel with "apathetic" [12] and with "ad haters" [61], mainly because they are not involved with fashion and personalized ads do not affect their intention to purchase.

Segment 2: Occasional online shoppers This is an intermediate sized segment, representing 15% of the sample. This group of users behaves similarly to segment 1 with respect to the relationships of the proposed model. Unlike the previous group, and as shown in the PLS-MGA analysis, there are significant differences regarding the relationship between the variables related to the purchase intention (PERS and PU). The ANOVA analysis shows that this segment is characterized by a high purchase intention, high concern for privacy and a high perception of trend. This segment is considered more active with respect to the trends shown in the advertisements and in making online purchases, using mobile social networks for social commerce. This behavior can also generate a greater concern for privacy. This group has a similarity with the "moderate" segment [12], and with "ad lovers" [61], as they have a greater intention to behave after seeing a personalized advertisement for fashion products.

Segment 3: Rational Shoppers This segment is the largest group–more than three quarters of the sample belong to it (81%). This segment of users shows strong and positive relationships in all the relationships of the proposed model. According to the results of the ANOVA analysis, this majority group within the sample is characterized by a low purchase intention, an average concern for privacy and an average perception of trend. They are considered the segment below the occasional buyers, less active in making online purchases through social commerce platforms. In addition, the interest of this type of ads as a benchmark for purchases is less important. This segment is similar to "moderate" [12] and "ad setters" [61], due to the fact that in the activity of purchases before fashion advertisements, they are very prudent and do not present impulsive behaviors.

6 Implications

This study has theoretical and managerial implications. For the academy, it has added knowledge for future studies that explore consumer adoption behavior toward the clothing trade through the use of social networks. The inclusion of personalization and the perception of usefulness of advertisements can greatly help the intention to purchase clothing to be understood. The application of a posterior segmentation as PLS-POS allows observing heterogeneity within the sample and helps to better understand the different types of users exposed to shoppable ads on mobile social networks and their relationship with the purchase intention, concern for privacy and trend. While the measures and scales were tested in a context of mobile clothing trade, the methodology can be applied to other types of products or services.

For the industry, the first implication for fashion apparel companies is that it is observed that globally, and for each segment, the personalization of the ads shows a positive and significant influence on the usefulness of the mobile clothing commerce, and clothing in the purchase intention. This suggests that consumers value clothing ads being related to their tastes and preferences when they browse their mobile social media. Although the literature indicates that highly personalized advertisements may cause privacy concerns, the results show that these concerns are only deeply expressed in a small group of the sample. Having overcome the requirements that the legal regulations and the ethical responsibility of each firm impose, the brands must carefully choose criteria when generating the product offer. The second implication is with respect to the perceived usefulness and the intention to purchase. Although this is highly valued at the level of the global sample, when reviewing each segment, it is distinguished that only the consumers of the largest group (Group 3) show a positive influence, while for Groups 1 and 2 the influence of perceived usefulness has a negative effect. This result shows that not all consumers behave in the same way. For the "techno-shy" and "occasional online shoppers" segments the brands and platforms must work on elements such as the concern for privacy and, as consumers are interested in finding unique styles, brands should try to deliver ads that reflect current trends.

For technology, the results show differences among consumers, so to provide the same solution for all consumers alike may be a mistake. In the face of this, an opportunity is opened to develop specific technologies for each of the proposed segments. With respect to the techno-shy segment, platforms can improve the personalization of the shoppable ads and foster use by improving the usability and trust. An example would be improvements in the shopping process, reducing the steps from the search for information to the product payment, making it simpler and more

direct. For the segment of occasional shoppers, although the techno-shy solution may be a good basis, this must be completed with improvements in the transparency and dissemination of the data privacy policies to reduce their concerns. Apart from providing large texts of data privacy policies, the platforms could make efforts to simplify the shopping terms and conditions, make the payment mechanisms clear and that control suppliers to avoid frauds. With respect to rational buyers, developing predictive technologies which help to anticipate the products' usefulness for this type of consumers appears to be key, taking into account that it is the largest segment. For example, in the case of fashion, to be able to identify people's main morphological characteristics or their likes could be good predictor of the most useful apparel and brands to show as shoppable content. Finally, the platforms must continue going deeply into the characteristics of social commerce, implementing ways of offering products, an example of this being that Instagram has transformed the app into a catalog in December 2020.

7 Limitations and future research lines

The results of this study should be seen in the context of its limitations. First, this research uses data from a country in technological development. The results could vary in a country with high technological development. We propose as a future research line to seek segments in countries with different levels of technological development. In this sense, it would be interesting to repeat the research in other cultural contexts. This work having been done in Chile, a country of Latin culture, the study could be replicated in Anglo-Saxon, European or Asian cultures. Second, the study is applied to only one mobile social network, but it works on multiple platforms. In the future, other purely mobile social networking sites such as Instagram, Pinterest or Snapchat could be evaluated and compared. It would be interesting in future research to delve into the role of the text, images and videos in mobile devices in their relationship with the success of shoppable contents. Third, this study focuses only on fashion brand advertisements, so it is necessary to evaluate other types of brands or products (e.g., sports brands, health, consumer technology, etc.). A research line which is opened is to determine the differences between hedonic products and utilitarian products. We have used a hedonic product -fashion- and it would be interesting to repeat the research with utilitarian products such as banking services or food products. Finally, the evidence indicates that platforms are quickly incorporating social commerce characteristics, providing consumers with new store formats and shoppable ads. So, faced with the incorporation of new functionalities of product shopping in social network platforms, it is necessary to go deeply into the response of consumers.

Appendix 1

Construct	Item	Author
Personalization (PERS)	The Facebook mobile application offers shoppable ads in line with my interests	[67]
	I feel that my needs are satisfied with the shoppable ads in the Facebook mobile application	
	The Facebook mobile application facilitates the search for personalized information	
Perceived usefulness (PU)	Shoppable ads can be useful in my life	
	The use of shoppable ads allows me to make transactions faster	[45]
	The use of shoppable ads will increase my productivity	
	The use of shoppable ads will increase my efficiency	
	Using shoppable ads will allow me to perform shopping tasks faster	
Purchase intention (PI)	After seeing a shoppable ad, I'm interested in buying	[53]
	After seeing a shoppable ad, I want to buy the product that is advertised	
	After seeing a shoppable ad, I'll probably buy the product that is advertised	
Privacy concern (PRIV)	I feel safe about delivering sensitive information in the Facebook mobile app	[40]
	I feel safe about posting personal information on Facebook's mobile application	
	I feel safe about posting personal information in my friend's profile through the Facebook mobile application	
	I feel safe about sending personal information through the messaging services of Facebook's mobile application	
Perception of trend (TREND)	The shoppable ads of fashion brands in the mobile application of Facebook are trendy	[67]
	To use shoppable ads in the mobile application of Facebook is trendy	
	Fashion products are available as shoppable ads in the mobile application of Facebook	

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