

User Experience in Personalized E-Commerce: A Configurational Approach

Full Paper

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Abstract

The present work aims to identify the interrelations among trust, privacy, emotions and experience in order to predict high purchase intentions, when using personalized services in the area of e-commerce. Building on complexity theory we present a conceptual model followed by research propositions. Our propositions are empirically validated through a fuzzy-set qualitative comparative analysis (fsQCA) on 182 customers with experience in personalized online shopping. The results indicate five configurations of trust, privacy, emotions, and experience that explain high purchase intentions. The importance of trust and happiness should be noted since they are both present most frequently as core factors. The study has both theoretical and practical implications towards the development of new emotion-centric theories and the design and provision of personalized services.

Keywords

Personalization, emotions, online shopping, fuzzy-set qualitative comparative analysis, fsQCA.

Introduction

User experience in e-commerce environments has been widely studied in the past, and many strategies have been applied in order to attract and retain customers. Such strategies include the implementation of personalized services as an attempt to influence users' behavior (Ho and Bodoff 2014), which may be influenced by their attitude towards the service, the seller, or even the medium. The attitudes and evaluations of individuals may be affected by cognitive factors (Ho and Bodoff 2014), trust and privacy (Liu et al. 2005), emotions (Beaudry and Pinsonneault 2010; Hibbeln et al. 2016), and experience (Chiu et al. 2009). Previous studies contribute by examining the role of trust towards the online vendor, privacy, and emotions when taking into account the role of personalized and user-centric services in an online context (Bleier and Eisenbeiss 2015; Li et al. 2014; Pappas et al. 2013; Pappas et al. 2016).

Thus, it is clear that when using personalized services or receiving customized recommendations, customers' behavior is influenced by their trust towards the online vendor, their privacy concerns, their emotions towards the service as well as their previous experience. It is clear that multiple ways exist in which the aforementioned factors may interact with each other, but further work is needed to understand how such interplays may offer a deeper understanding on online behavior, and how they may lead to high purchase intentions. The majority of the work in this area examines main effects among the various antecedents and employs symmetric tests, such as structural equation modelling (SEM) and multiple regression analysis (MRA) to measure their impact on behavior [e.g., (Ho and Bodoff 2014; Pappas et al. 2014)]. Regression based models (RBMs) build on variance theories, which suggest that a predictor variable must be both necessary and sufficient condition in order to achieve the desired outcome (El Sawy et al. 2010; Liu et al. 2015). However, focusing on symmetric and net effects may be misleading, since such effects do not apply to all cases in the dataset, thus the relationship between two variables is very unlikely to be of symmetrical form (Ragin 2008; Woodside 2014); hence, more work is needed towards this direction.

This research posits that there are synergies amongst trust towards the online vendor, privacy, emotions, and experience which ultimately influence users' behavior when using personalized services in the online shopping context. In detail, it is theorized that there is not one single, optimal, configuration (i.e., set of conditions) of such values. Instead, multiple and equally effective configurations of causal individual adoption factors may exist, which may include different combinations of adoption perceptions (i.e. combinations of high and low perceptions). Therefore, this study extends the literature by exploring the role personalized e-commerce mechanisms through the lens of users' sense of trust, privacy, emotions and experience. In this paper, unless otherwise mentioned, "trust" refers to customers' trust issues towards the online vendor when using personalized online services. The study aims to answer the following research question:

R.Q.: What is the interplay between trust, privacy, emotions, and experience in explaining high purchase intentions?

Identifying the interplay among the aforementioned constructs should help managers and practitioners to specify detailed patterns of factors that stimulate online shopping behaviour, and help them create and offer better targeted personalized services with increased quality. To this end, we bridge complexity theory with configurational analysis, and implement a fuzzy-set qualitative comparative analysis (fsQCA)(Ragin 2008) in order to identify configurations leading to high purchase intentions. FsQCA has received increased attention during the last years in various fields since, when applied together with complexity theory it allows researchers to gain a deeper understanding of the phenomenon under scrutiny (Ordanini et al. 2013; Pappas et al. 2016; Woodside 2014). In the following section we first present the theoretical grounding of this study and articulate the research propositions. Section 3 describes the research methodology, and section 4 presents the research findings. Finally, section 5 concludes the paper with a discussion of the findings as well as theoretical and practical implications of this research.

Background

The implementation of personalization in online environments may lead to better services for their users (Komiak and Benbasat 2006). Online personalization is built on users' personal preferences, which are used to achieve a custom tailored communication. Such communication may influence customers' behavior when shopping online and it is important to examine its role in the context of e-commerce (Ho and Bodoff 2014; Pappas et al. 2016). We are based on the theory of reasoned action (TRA) (Fishbein and Ajzen 1977) which is a well-established theory examining user behavior in the context of e-commerce and personalized services (Komiak and Benbasat 2006). The theory suggests that attitude toward a certain behavior involves users' belief that the particular behavior will lead to certain outcomes and the users' evaluation of those outcomes. In their trust-based model Komiak and Benbasat (2006) build on TRA and examine cognitive and emotional factors when using recommendation agents for personalization, and their effects on users' attitude and behavior. Thus, TRA provides a proper theoretical grounding for this study, in order to examine how trust and emotions combine with privacy concerns and experience in order to explain high purchase intentions. Nonetheless, we should note the goal of this study is not to examine how the aforementioned factors influence purchase behavior, but how their presence or absence may explain purchase behavior.

Trust and privacy on personalized online shopping

Trust and privacy have been identified as critical factors in online shopping (Hongyoun Hahn and Kim 2009; Li et al. 2014) and personalized online services (Bleier and Eisenbeiss 2015). Trust is highly related with customers' previous experiences from purchasing online (Chiu et al. 2009), thus, it is expected that positive experience will increase ones trust towards the retailer and the service, while a negative experience will have the opposite effect. Although trust is important for all customers, no matter how experienced they are (Gefen et al. 2008), it may positively influence customers' affective qualities, but at the same time, trust may not have an effect on their behavior intentions (Chen and Chou 2012). On the other hand, privacy concerns may have a negative effect on customers' affective qualities, however, the use of personalized services may decrease these privacy concerns (Li et al. 2014), indicating that a positive influence on behavior may occur. In any case since personalized services are based on private information, online retailers should aim at developing trust as well as decreasing privacy concerns for their customers.

The role of trust and privacy in influencing behavioral intentions on personalized online shopping fits well with the framework of belief-attitude-intention as suggested by the TRA. High level of trust towards the online vendor means that customers believe that the offered services will be objective, truthful, and well-customized based on their personal needs. Customers' with such beliefs are more likely to rely on personalized services to make a purchase. On the other hand, high levels of privacy towards personalized services mean that customers are skeptical towards sharing their private data because they feel that their online behavior is monitored. Consequently, customers with high privacy beliefs are less likely to purchase online due to personalized services. It is evident that customers develop both trust and privacy beliefs, hence these aspects should be studied together in order to fully comprehend possible combinations between them capable of explaining their behavior. Furthermore, it is critical to incorporate the role of emotions in the process, since they may have equivocal effects on customers' affective perceptions. Past studies have highlighted the importance of examining emotions, which have been found to significantly influence online shopping behavior (Pappas et al. 2016).

The role of emotions on personalized online shopping

The attempt to engage customers in online shopping involves the interplay of multiple factors. The factors are able to influence their behavior, thus creating a positive or negative experience for them. As customers' experience in online shopping increases, they also start to seek affective qualities (Bridges and Florsheim 2008). Research in the area of e-commerce and personalized services has identified the importance of affective qualities and emotions as an antecedent of customers' purchase intentions (Koo and Ju 2010; Pappas et al. 2016). The importance of emotions is highlighted by the fact that on certain occasions (e.g., the absence of clear information) an individual will make a decision based on his or her emotions (DeSteno et al. 2004). Previous studies have examined the relationship among the different types of emotions and behavior (Koo and Ju 2010; Pappas et al. 2014), however, the majority of the studies choose specific emotions and take a unidimensional approach (Pappas et al. 2016). Here, we take a multidimensional approach by including a wide range of emotions which covers the basic mental states a person may feel (Kay and Loverock 2008).

The present study divides emotions in four categories which have been found to be effective when examining online services: *happiness*, *anxiety*, *sadness*, *anger* (Kay and Loverock 2008). These emotions describe how a person feels while using or receiving personalized services. Happiness is defined as the degree of satisfaction, excitement or curiosity someone feels, while anxiety describes how anxious, helpless, nervous or insecure one feels. Next, sadness indicates if a customer feels disheartened or dispirited. Finally, anger refers to how irritated, frustrated or angry a person feels. Customers' may experience various emotions of different valence at the same time (e.g., excited and nervous) for different reasons, such as trying a new service or product. Emotions are correlated (Chang et al. 2014) but their relation is not symmetric (Pappas et al. 2016), thus the presence of one does not guarantee or exclude the presence of another. Shopping online has been proven to induce various emotions to customers at the same time (Koo and Ju 2010; Pappas et al. 2014; Pappas et al. 2016). Based on how these emotions combine, customers' behavior is likely to differ. In detail, happiness will most likely increase intention to shop online, while anger or anxiety may create second thoughts towards a purchase.

Research propositions

Following the studies described above, scholars in the area of e-commerce should study adoption of personalized services by examining together the factors of trust, privacy, emotions and experience which have been found to influence behavior with various ways (Beaudry and Pinsonneault 2010; Pappas et al. 2014). Nonetheless, the present analysis proposes that an interaction between these factors exists. This makes it unclear whether we can assume that a particular factor may dominate adoption behaviour and, more importantly, whether there are combinations of these factors that better explain purchase intentions. Towards this direction, we posit that the synergetic nature between them creates a complex, multidimensional phenomenon, in which the configuration of the adoption drivers is more important than the individual drivers. Following this line of reasoning and building on complexity theory, a conceptual framework is proposed in order to explain and better understand users' intention to purchase online when using personalized services. Figure 1 depicts the proposed model.

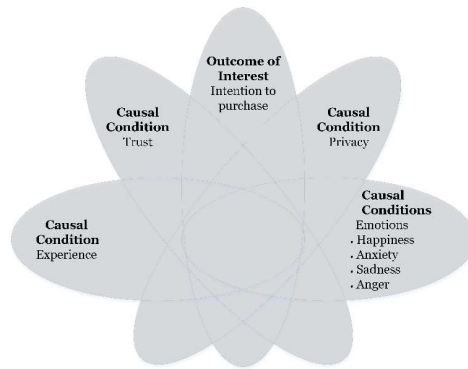


Figure 1. Venn diagram illustrating the conceptual model

The proposed framework is based on the principle of *equifinality* (Fiss 2011; Woodside 2014). The principle of equifinality suggests that the outcome of interest can be explained equally by alternative sets of causal conditions that combine in sufficient configurations for the outcome. This means that adoption of personalized services occurs through the combination and co-alignment of multiple variables - in our case, trust, privacy, emotions, experience - with no specific form of co-alignment available as an *a priori* benchmark. Instead, high intention to purchase may be achieved through different combinations of the causal factors. Hence, configurations include multiple combinations explaining the same outcome, leading to following research proposition:

Proposition 1. *No single best configuration of customers' trust, privacy, emotions, and experience leads to high intention to purchase; instead, multiple, equally effective configurations of causal factors exist, which commonly lead to high usage intentions.*

Complexity theory proposes the concept of *causal asymmetry* (Woodside 2014). Causal asymmetry suggests that different values of the same causal condition (i.e., high and low levels of a factor) may appear in the combinations that explain online shopping behaviour, depending on how this causal condition combines with the rest of the causal conditions. For example, a customer with low perceptions of trust and high perceptions of privacy may present high intention to purchase, if (a) s/he is highly experienced with personalized services and has gained the ability to overcome such issues, or (b) s/he is low experienced but feels very happy about a great offer included in the personalized message. Consequently, the presence or absence of experience and happiness may lead customers with different perceptions towards the same outcome. Based, on the above, we formulate the following research proposition:

Proposition 2. *Single causal conditions may be present or absent within configurations for customers' high intention to purchase, depending on how they combine with other causal conditions.*

Methodology

Sampling

To explore our propositions a survey based research approach was followed. As such, a custom built survey instrument was developed, comprising of questions on background information of respondents and on the identified constructs. A snowball sampling methodology was used to attract respondents. The target sample included experienced individuals in personalized online shopping. The respondents were presented with a few examples of personalization in online shopping and were asked to answer based on their personal evaluations and perceptions. We aimed at about 600 online shoppers, out of which 215 responded. From the respondents, 182 had previous experience with personalized online shopping which represent the final sample of this study which was retained for further analysis. The sample composed of 54% males and 46% females, with the vast majority (59%) being under 30 years old. The rest (24%) were between 30 and 39 years old, and 17% were 40 years old or older. Regarding their education, the sample consisted almost equally of postgraduates (44%) and university graduates (42%). The rest (14%) had a high school degree or less. Finally, in terms of experience all the respondents had made at least one purchase in the past six months with personalized services, with a mean value of 13.3 (S.D. 29.3).

Measures

In the survey respondents were presented with questions on their demographic characteristics, followed by questions on the constructs as identified in the literature review section. Table 1 presents the definitions of the adopted constructs and their source in the literature. In all cases, except experience, 7-point Likert scales (1 Not at all - 7 Very Much) were used to measure the variables.

Construct	Definition	Source
Trust	Customers' trust issues towards the online vendor when using personalized online services.	(Pappas et al. 2013)
Privacy	Customers' privacy concerns when using personalized online services.	(Pappas et al. 2013)
Emotions	Measuring customers' happiness, anxiety, sadness, anger when using personalized services.	(Kay and Loverock 2008)
Intention to purchase	Customers' intention to purchase online when using personalized services.	(Pappas et al. 2016)
Experience	Customers' number of online purchases the past six months based on personalized services.	

Table 1. Constructs definition

Reliability and validity

In terms of reliability, the Cronbach alpha indicator showed that all constructs present high internal consistency. Regarding validity, all item loadings were above the threshold of 0.7 (available upon request). Further, all average variance extracted (AVE) values exceeded the minimum threshold of 0.5, and the square root AVE for all construct were greater than their respective correlations (Table 2).

Construct	Mean	SD	CR	AVE	Construct							
					1	2	3	4	5	6	7	
1. Trust	3.18	1.4	0.86	0.61	0.78							
2. Privacy	5.35	1.63	0.91	0.77	-0.15	0.88						
3. Happiness	3.84	1.46	0.71	0.55	0.41	-0.12	0.74					
4. Anxiety	2.97	1.44	0.81	0.52	-0.06	0.21	0.04	0.72				
5. Sadness	2.68	1.43	0.77	0.63	-0.04	0.19	-0.08	0.55	0.79			
6. Anger	2.62	1.54	0.75	0.59	-0.04	0.24	-0.12	0.58	0.68	0.77		
7. Intention to purchase	4.06	1.66	0.9	0.74	0.41	-0.2	0.6	-0.12	-0.17	-0.24	0.86	

Note: Diagonal elements (in bold) are the square root of the average variance extracted (AVE). Off-diagonal elements are the correlations among constructs (all correlations higher than 0.1 are significant, $p < 0.01$). For discriminant validity, diagonal elements should be larger than off-diagonal elements.

Table 2. Descriptive statistics and correlations of latent variables

Next, multicollinearity (O'Brien 2007) was examined along with the possibility of common method bias by utilizing the Harman's single factor test (Podsakoff et al. 2003). The variance inflation factor (VIF) for each variable was below the value of 3, indicating that multicollinearity is not an issue. The results suggest that common method bias is not a problem, since the first factor did not account for the majority of the variance and no single factor occurred from the factor analysis. Several fit indices of the research model were also examined. The chi-square statistic, the comparative fit index (CFI), and root mean square error

of approximation (RMSEA) served as indices to assess the overall measurement model fit. All values were within the recommended range. Specifically, χ^2/df : 1.65, CFI: 0.95 and RMSEA: 0.06.

Data analysis

fsQCA

The study applies fuzzy-set Qualitative Comparative Analysis (fsQCA) using fs/QCA 2.5 (Ragin and Davey 2014). FsQCA identifies patterns of elements, between independent and dependent variables, that lead to an outcome and goes a step further from the analyses of variance, correlations and multiple regression models (Woodside 2014). A variable that affects the outcome in only small subset of cases can not be identified by the regression analysis (Liu et al. 2015). Applying fsQCA may complement and extend the findings from RBMs. The benefits of fsQCA mainly occur from the limitations of RBMs (El Sawy et al. 2010; Liu et al. 2015; Pappas et al. 2016; Woodside 2014). Finally, fsQCA may be more robust than RBMs mainly as it is not sensitive to outliers. In detail, employing fsQCA to analyze the data, the sample is divided into multiple subsets, thus creating multiple combinations of configurations. In effect, the outliers will not have influence all solutions (i.e., configurations) but only on specific ones. To this end, every configuration represents only a subset of the sample, hence the representativeness of the sample is not able to affect all the configurations (Fiss 2011; Liu et al. 2015). FsQCA offers two types of configurations, which include necessary and sufficient conditions. Such configurations may be marked by their presence, their absence, or a “do not care” condition. The necessary and the sufficient conditions create a distinction among core and peripheral elements. Core elements are those with a strong causal condition with the outcome, peripheral elements are the ones with a weaker one (Fiss, 2011).

As a first step in fsQCA, the outcome and the independent measures need to be defined. Next, all measures need to be calibrated into fuzzy sets with values ranging from 0 to 1, which defines their level of membership (Ragin 2008). Data calibration may be performed either with a direct or an indirect method. In the direct method, the researcher chooses three qualitative breakpoints (i.e., thresholds). These represent a full set membership threshold value (fuzzy score = 0.95), a full non-membership value (fuzzy score = 0.05), and the crossover point (fuzzy score = 0.50). In the indirect method, the measurements require rescaling based on qualitative assessments. The researcher may choose either method depending on both the data and the underlying theory (Liu et al. 2015; Ragin 2008). The direct method of setting three values that correspond to full-set membership, full-set non-membership and intermediate-set membership is recommended (Ragin 2008). The calibration here is done by following the procedure employed by Ordanini et al. (2013) and Pappas et al. (2016). With this calibration method, the three qualitative anchors for the calibration, are based on the survey scale (7-point Likert). The full membership threshold is fixed at the value of 6; the full non-membership threshold is fixed at the value of 2; and, the crossover point was fixed at the value of 4. The values of every variable are calibrated based on a linear function to fit into the three aforementioned thresholds. The calibration is performed using the “Calibrate” function by setting the three thresholds.

Following the calibration, the fsQCA algorithm is applied to produce a truth table of 2^k rows, with k representing the number of outcome predictors, and each row representing each possible combination. For every combination, the minimum membership value is calculated; that is, the degree to which every case supports the specific combination. fsQCA uses the threshold of 0.5 to identify the combinations that are acceptably supported by the cases. Thus, all combinations that are not supported by at least one case with membership over the threshold of 0.5 are automatically removed from further analysis. Finally, the truth table needs to be sorted out based on frequency and consistency (Ragin 2008). Frequency describes the number of observations for each possible combination. Consistency refers to “the degree to which cases correspond to the set-theoretic relationships expressed in a solution” (Fiss 2011). A frequency cut-off point needs to be set, to make sure that a minimum number of empirical observations is obtained for the assessment of subset relationships. For small and medium-sized samples, a cut-off point of 1 is appropriate, but for large samples (e.g., over 150 cases), the cut-off point should be set higher, and may be set at 3 (Fiss 2011; Ragin 2008). Thus, the minimum acceptable observation frequency is set at three. Also, a consistency cut-off point should be set. A low consistency threshold would lead to the identification of more necessary conditions, and would reduce type II errors (i.e., false negatives), however it would increase type I errors (i.e., false positives) (Dul 2016). Hence, we set a relatively high consistency threshold at $>.85$; not too high but higher than the recommended value of 0.75 (Ragin 2006).

Findings

The outcomes of the fuzzy set analysis for high intention to purchase are presented in Table 3. In detail, black circles (●) denote the presence of a condition, while crossed-out circles (⊗) indicate the absence of it (Fiss 2011). Blank spaces suggest a do not care situation, in which the causal condition may be either present or absent. Core elements of a configuration are presented with large circles, peripheral elements with small ones (Mikalef et al. 2015; Pappas et al. 2016). The solution table includes values of set-theoretic consistency for each configuration as well as for the overall solution, with all values being above threshold (>0.75). Consistency measures the degree to which a subset relation has been approximated, whereas coverage assesses the empirical relevance of a consistent subset (Ragin 2006). The overall solution coverage provides an indication as to what extent high purchase intentions can be determined based on the set of configurations, and is comparable to the R-square value reported in correlational methods. The results indicate an overall solution coverage of .701, which suggests that a substantial proportion of the outcome is covered by the five solutions.

Configuration	Solutions				
	1	2	3	4	5
Trust	●		⊗	●	●
Privacy		●	⊗	●	●
Emotions					
Happiness	●	●		●	●
Anxiety	⊗	⊗	⊗		●
Sadness	⊗	⊗	⊗	⊗	●
Anger	⊗	⊗	⊗	⊗	●
Online Shopping Experience					
Purchases in the past six months			●	⊗	●
Consistency	0.973	0.912	0.899	0.951	0.921
Raw Coverage	0.422	0.522	0.146	0.188	0.176
Unique Coverage	0.066	0.167	0.05	0.017	0.033
Overall solution consistency	0.909				
Overall solution coverage	0.701				
Note: Black circles indicate presence of a condition. Circles with “x” indicate its absence. Large circles indicate core conditions; small ones, peripheral conditions. Blank spaces indicate “don’t care”.					

Table 3. Configurations leading to high purchase intentions

Solution 1-5 presented in the columns of Table 3 indicate combination of elements leading to high online purchase intentions. These solutions reflect combinations of the presence or absence of trust, privacy, emotions, and experience. All factors appear both as core and peripheral conditions in the solutions, suggesting their importance, which varies depending on how one factor is combined with the others. In detail, the combination of trust with happiness, coupled with low anxiety, sadness, and anger, will lead to high purchase intentions regardless of privacy issues and experience (Solution 1). Similarly, high privacy when combined with high happiness, and low anxiety, sadness, and anger, may explain high purchase intentions despite trust issues and experience (Solution 2). Next, the absence of both trust and privacy issues, along with the absence of all negative emotions, leads to high purchase intentions for highly experienced users regardless of how happy they feel (Solution 3). Finally, when both trust and privacy issues are high (i.e., present) and users feel happy about personalized online shopping, high purchase intentions are achieved by either (i) having low experience and not feeling emotions of sadness or anger,

regardless anxiety (Solution 4), or (ii) by having high experience and sustaining all four emotions simultaneously (Solution 5).

Discussion, Implications and Future Work

The present work suggests that in e-commerce, trust, privacy, emotions, and experience combine to form different configurations that can explain online purchase intentions in personalized service settings. In order to identify these configurations a conceptual model is proposed. The findings indicate that multiple recipes exist that explain customers' behavior in online environments. These solutions incorporate different combinations of the causal conditions, confirming as such both research propositions. The results highlight the importance of trust, privacy, and emotions, for the adoption of personalized services in online shopping.

Outcomes also confirm the importance of trust in personalized environments, which when present in a solution, is always as a core factor. Nonetheless, the presence of trust is not enough to lead to high purchase intentions. It is interesting to point out that happiness should be present as well, indicating that customers' not only need to trust the online vendor but they should also feel good about the personalized recommendations they receive. Further, privacy issues are always present as a peripheral factor, which may be explained by the presence of trust or happiness as core factors. This suggests that customers are likely to overcome high privacy concerns when they trust the online vendor or feel happy with the offered services. Curiously enough, when almost all factors are absent then the presence of experience as a core factor may explain high purchase intentions. Highly experienced customers are likely to proceed to a purchase even when their trust levels are low, as long as all negative emotions are low as well. The low privacy in this solution is explained by the fact that customers have increased experience with personalized online shopping, and are thus used to sharing their personal information.

Consistent with prior studies (Koo and Ju 2010; Pappas et al. 2014), we confirm the critical role of positive emotions (i.e., happiness) since they are present in almost all solutions. In addition, two conclusions may be drawn from the last solution regarding the role of emotions; (a) when all negative emotions are present, positive emotions should be present as well for high purchase intentions to occur, and (b) when all emotions are present, they are present as peripheral factors suggesting that an interrelation exists among them and they neutralize each other. This finding hints that a deeper understanding of emotions is required. Finally, concerning emotions, we extend previous studies that either choose specific types of emotions (Koo and Ju 2010; Pappas et al. 2013) or choose two generic types of emotions (i.e., positive and negative) (Pappas et al. 2014), by examining four major types of emotions (i.e., happiness, anxiety, sadness, anger) that have been proven to be valid when examining computer related behaviors (Kay and Loverock 2008).

This research has both theoretical and practical implications regarding the online behaviour of customers' as well as the design of personalized services. This study complements extant research in the area of personalized online shopping [e.g., (Ho and Bodoff 2014; Pappas et al. 2014)] by providing an alternative view on the purchase process and how important factors that influence customers' behaviour may combine with each other to predict future intentions. In addition, by employing configurational analysis we are able to include in our results the part of the sample that is not represented by the main effects among the examined constructs. Thus, we offer multiple solutions that cover a larger part of the sample and at the same time show how different levels of trust, privacy, emotions and experience may still lead to high purchase intentions. Researchers may apply the theoretical propositions to other information systems, which involve online services to extend the generalizability of the results. The study empirically demonstrates the synergetic nature of emotions when combined with trust, privacy, and experience. The findings extend previous studies (e.g., Pappas et al. 2016), who identified the important role of emotions, when combined with cognitive factors. The present study also points out the need for the development of emotion-centric theories, which will be able to better explain behaviour in e-commerce environments.

In addition, we offer specific paths which may lead to high purchase intentions when using personalized services; such paths may be used by practitioners to better design these services. In detail, they should employ user-centred designs and strategies on their websites in order to better address user needs, evoke positive emotions, and mitigate the formulation of negative emotions. Retailers may employ a variety of information technology tools to capture perceptions regarding trust, privacy concerns and emotions (e.g.,

text mining of user reviews from confirmed buyers, implementing collaborative filtering and/or sequential pattern analysis of user ratings, session-based recommendations based on users' browsing/navigation history). We add to the fact that retailers should constantly interact with their customers' to capture their preferences (Bui et al. 2012), as well as their emotions which might be mixed based on their experience. It is important for retailers to invest on mechanisms that induce happiness, such as emotional contagion strategies (Pappas et al. 2016), or to capture emotions, for example with mouse clicking patterns (Hibbeln et al. 2016).

This study adopts a different methodological approach from the majority of the studies in the area of e-commerce, which focus on multiple regression analysis and structural equation modeling. Indeed, configurational analysis has only recently received increased attention, in various areas, and has been proven useful in theory building when combined with the theory of complexity and configurational theory (Fiss 2011; Mikalef et al. 2015; Ordanini et al. 2013; Pappas et al. 2016; Woodside 2014). The aim of fsQCA is to identify combinations of various factors that are able to explain a specific outcome. Hence, multiple combinations of independent factors may be identified that explain the same outcome. Also, since the methodology examines combinatorial effects, the influence of every independent factor on the outcome is not quantified (Liu et al. 2015).

As with all empirical studies, there are some limitations. First, the generalization of the findings should be performed with caution, since a snowball sampling method was followed and the sample comprises of only Greek users of personalized services. Also, findings are based on self-reported data. For an interdependent approach, semi-structured interviews and actual usage data may be beneficial. This paper differs from previous studies in the area that focus on net effects among variables, adopts complexity theory and employs fsQCA to better explain intention to purchase based on personalized services. Future studies should take a similar approach to verify our findings, and to extend theory in different contexts.

Conclusion

This study examines combinations of customers' perceptions of trust, privacy, their emotions and experience in an attempt to explain and predict their intention to purchase online based on personalized services. Towards this direction, we employ complexity theory and identify the importance of analyzing complex patterns of predictors and asymmetric relations among the the aforementioned factors. Multiple and complex relationships exist among trust, privacy, emotions, and experience, indicating that different values of these variables may occur simultaneously depending on role of the rest.

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