User experience in personalized online shopping: a fuzzy-set analysis

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Abstract

Purpose

In the complex environments of online personalization multiple factors have been considered to explain consumers' online behaviour, but largely without considering the role of specific configurations of variables, and how they may affect consumer behaviour. This study shows how trust towards online vendors, privacy, emotions, and experience combine to predict consumers' purchase intentions.

Design/methodology/approach

Building on complexity theory we present a conceptual model followed by research propositions. Our propositions are empirically validated through configurational analysis, employing fuzzy-set qualitative comparative analysis (fsQCA) on 182 customers with experience in personalized online shopping. Predictive validity analysis is also performed.

Findings

Five solutions of trust, privacy, emotions, and experience increase intention to purchase, and six solutions inhibit it. The findings verify the importance of trust and happiness in successful personalized online shopping. Their absence inhibits purchase intentions. Also, high experience may help to overcome low trust or negative emotions, while low experience requires the combination of high trust and happiness. None of the examined factors are indispensable to explain purchase intentions.

Research limitations/implications

The study employs fsQCA, differentiating from traditional studies in the area that use variance-based methods, and identifies multiple solutions explaining the same outcome. The proposed approach contributes to theory development in the field.

Practical implications

The multiple solutions lead to new ways on how companies may approach their customers, as each one covers a specific part of the sample, adding to the fact that in personalized marketing there is not one single optimal solution explaining customer purchase intentions

Originality/value

This study contributes by (1) extending existing knowledge on how trust, privacy, emotions and experience combine to increase or mitigate intention to purchase, towards the development of new emotion-centric theories and the design and provision of personalized services; and (2) presenting a step-by-step methodological approach for how to apply fsQCA in e-commerce studies.

Keywords

consumer behaviour, e-commerce, emotions, experience, fuzzy-set qualitative comparative analysis, fsQCA, online shopping, personalization, privacy, trust

Received 29 October 2017
Revised 7 February 2018
Accepted 16 April 2018

European Journal of Marketing
DOI: 10.1108/EJM-10-2017-0707

Introduction

With the advancement of digital platforms online shopping environments are evolving as well, and they are able to offer consumers more options in the purchase process, providing them with better services and products. Indeed, personalization strategies can be employed to influence consumers' behaviour and increase their loyalty both offline (Melewar et al., 2017) and online (Ho and Bodoff, 2014; Pappas et al., 2016), while at the same time they may indicate a company's commitment to offer value to its customers (Adobe, 2015). By 2020, 4 billion people are expected to be online, suggesting that addressing customers' needs will be more important than ever (IDC, 2015), while developing new or improved business strategies and models. Personalization can change consumers' behaviour, and reduce acquisition costs, while increasing revenues, and marketing efficiency (Ariker et al., 2015). However, marketing practice requires further advancement as it is not at the same level as current technical capabilities (Adobe, 2015).

Cognitive and affective factors (Ho and Bodoff, 2014; Pappas et al., 2017b), trust and privacy (Lee and Rha, 2016), and experience (Pappas et al., 2014b) may affect consumers' attitudes and evaluations in online shopping. As marketers use interactive technologies to modify consumers' behaviour (Kaptein and Eckles, 2012), they develop strategies that build on logical arguments, make emotional appeals, or request input or feedback from and for them (Pappas et al., 2017b). Recent studies in personalization have identified the critical role of trust towards the online vendor, privacy, and emotions (Bleier and Eisenbeiss, 2015; Pappas et al., 2016). When using personalized services or receiving customized recommendations, the personalization-privacy paradox may occur (Baek, 2014; Xu et al., 2011), based on which consumers have to make a choice between personalization benefits and privacy risks. In such cases, recent studies show that trust, emotions, and previous purchase experience (Lee and Rha, 2016; Pappas et al., 2017b), are sometimes key factors that can influence consumers' behavioural intentions. Although trust is a multidimensional construct, here, unless otherwise mentioned, we take the point of view of the consumer, thus "trust" refers to consumers' trust perceptions towards the online vendor when using personalized online services and refers to continuing trust rather than initial trust (Gefen et al., 2003). Also, emotions are defined as how happy, anxious, sad, or angry consumers feel (Ekman, 1992a; Ekman, 1992b), which are considered among the basic emotions, clearly distinguished from each other, and have been found to be effective in explaining how people perform and behave with computers (Kay and Loverock, 2008). Therefore, since these factors are critical for successful personalized online shopping and they may interact with each other in multiple ways, they may be studied together to better assess their effects on customers' purchase intentions.

Most studies in the area examine main effects among the various antecedents and employ symmetric tests, such as structural equation modelling (SEM) and multiple regression analysis (MRA) to measure their impact on behaviour [e.g., (Ho and Bodoff, 2014; Pappas et al., 2014a)]. Such solutions may represent a large part of a sample, but there still remains a part of the sample that is not explained by the single best solution identified by regression based models (RBMs). RBMs build on variance theories, suggesting that a predictor needs to be both necessary and sufficient condition to achieve the desired outcome. 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 rather unlikely to be of symmetrical form (Ragin, 2008; Woodside, 2014). For instance, high trust may be sufficient in explaining high purchase intentions, while when trust is low, purchase intentions may still be high, suggesting that trust is not a necessary condition. Indeed, consumers are influenced by different factors when using a technology, an online service, or making online purchases (Pappas et al., 2016), thus a different approach is needed to capture these complexities and the combinations of factors that explain purchase intentions

To address this gap in the literature, this research is based on complexity theory and configuration theory to identify the different causal patterns of factors influencing purchase intentions in personalized online shopping (Lewin, 1999; Woodside, 2017). These theories build on the principle of equifinality, which suggests that multiple complex configurations of the same conditions can explain the same outcome (Woodside, 2014), and on causal asymmetry, which suggests that the causes explaining the presence of an outcome, are likely to be different from those explaining the absence or negation of the same outcome (Ragin, 2008). Thus, the following research question is framed:

RQ: *What configurations of trust, privacy, emotions, and experience explain high and low/medium purchase intentions?*

The research question is addressed by performing configurational analysis and employing fuzzy-set qualitative comparative analysis (fsQCA) (Ragin, 2008). FsQCA provides multiple solutions that explain an outcome, thus showing how trust, privacy, emotions, and experience combine to explain purchase behaviour in personalized online shopping. Employing fsQCA with complexity and configuration theories has been proven suitable for theory building (Fiss, 2011; Woodside, 2014), as it can identify the complex relations among variables. The findings present multiple, distinct, and equally effective combinations of trust, privacy, emotions, and experience, which explain intention to purchase in personalized online shopping. Five solutions are presented that lead to high intentions to purchase in personalized online shopping environments, and six solutions that inhibit purchase intentions. None of the factors is necessary or sufficient in explaining purchase intentions on its own, instead it is their combinations that can lead to high intention to purchase, while avoiding low/medium purchase intentions.

The contribution of this paper in the literature is twofold. First, we extend the literature in e-commerce and marketing by exploring the role personalized mechanisms through the lens of consumers' sense of trust, privacy, emotions, and experience as we examine their combined effects on purchase intentions. Second, we employ fsQCA, an innovative methodology for data analysis, which offers a deeper insight on the data, and is an alternative and complementary method to traditional variance-based approaches. Identifying the interplay among the aforementioned constructs can help managers and practitioners to specify detailed patterns of factors that stimulate online shopping behaviour, and help them create and offer better personalized services with increased quality.

The paper is organized as follows. In Section 2, the theoretical background on complexity and configuration theories, and the antecedents of purchase behaviour in personalized online shopping, followed by a discussion on the conceptual model and research propositions. Section 3 describes the research methodology, and provides details on fsQCA and how it is implemented and Section 4 presents the empirical results. Finally, Section 5 discusses the findings highlighting theoretical, methodological, and practical implications, along with limitations and avenues for future research.

Theoretical Background

Complexity theory and configuration theory

E-commerce and marketing studies aim to offer an understanding of the interaction between companies and their customers, and to achieve this, research should capture the complexity of everyday practices as they are enacted and change over time (Woodside, 2017). Despite this complexity, symmetric and variance-based data analysis techniques remain dominant in the area. Complexity, inherent in many natural phenomena, underpins how emergent and dynamic systems and processes interact in order to influence an outcome (Urry, 2005). There have been high hopes for this body of work: "Complexity theory is destined to be the dominant scientific trend … This revolutionary technique can explain any kind of complex system – multinational corporations, or mass extinctions, or ecosystems such as rainforests, or human consciousness" (Lewin, 1999). The key insight is that to capture, understand, and explain complex phenomena, current approaches of variance-based techniques are not enough.

Theory of complexity and configuration theory both have inherent the principle of equifinality (Von Bertalanffy, 1968), which states that more than one possible complex configurations of antecedent conditions may lead to the same outcome. Configuration theory is also based on the principle of causal asymmetry, which states that a cause that leads to a presence of an outcome, may as well be different from the cause that leads to the absence or negation (i.e., not present) of the same outcome (Ragin, 2008). In other words, the presence of a factor may lead to a certain outcome, but the absence or negation of the same factor may not lead to the absence or negation of that outcome. Also, a variable can be insufficient on its own for an outcome to occur, but at the same time it can be necessary for the same outcome (Pappas et al., 2017a; Woodside, 2017). When the relationship between two variables (e.g., X, Y) is complex, the presence of one (i.e., X) may lead to the presence of the other (i.e., Y), indicating sufficiency. However, variable Y may also be present even when variable X is not present, indicating that presence of X is sufficient but unnecessary condition for Y to occur. Also, when additional variables exist, variable X may be necessary but insufficient for Y to occur. Finally, variable X may lead to a desired outcome Y only when a third variable (e.g., Z) is present (or not present). Thus, various combinations may exist that lead to a desired or observed outcome. These combinations are called *configurations* in fsQCA. A configuration is a specific set of causal variables, on which the synergetic nature among them may lead to an outcome of interest. To identify such configurations fuzzy set qualitative comparative analysis (fsQCA) is employed (Ragin, 2008).

Trust, privacy, and previous experience on personalized online shopping

Trust and privacy play a central part in online services and have a key role in most economic and social transactions [e.g.(Hahn and Kim, 2009; Riquelme and Román, 2014)], as well as in personalized online services (Bleier and Eisenbeiss, 2015; Lee and Rha, 2016). Trust in online commerce comprises of four aspects, that is disposition to trust, institution-based trust, trusting beliefs, and trusting intentions (McKnight et al., 2002). Here focus is on the relation of the customer with the company, thus trust refers to customers' issues and beliefs towards an online vendor that will act according to customers' benefit when using personalized online services. Trust was measured using non-equivalent items of perceived competence, integrity, and benevolence, used in online services research (Ray et al., 2011). Trusting intentions refer to a person's intention to engage in trust-related behaviours with a specific company, they are not included in this study since they are equated by the behaviour of exhibiting purchase intentions (Awad and Ragowsky, 2008), with potentially a low distinction between trusting intentions and intention to purchase. Since trust is influenced by customers' previous experiences from purchasing online (Gefen et al., 2008), positive experience may increase ones trust towards the retailer and the service, with a negative experience having the opposite effect. High trust likely is a contributing condition to high intention, but for some of those cases exhibiting high trust is unlikely to be sufficient by itself to consistently indicate high intention. Trust is important for all customers, regardless of their level of experience (Gefen et al., 2008), and it may positively influence customers' affective qualities, but at the same time, it may not have an effect on their behavioural intentions (Chen and Chou, 2012). On the other hand, privacy concerns may influence negatively customers' affective qualities or increase their negative emotions (Pappas et al., 2013), however, the use of personalized services may decrease these privacy concerns, as the customer will be able to control the information he or she shares with the company, indicating that a positive influence on behaviour may occur.

High level of trust towards the online vendor means that customers believe that the offered services will be honest, and truthful based on their personal needs (Ray et al., 2011), making them more likely to rely on personalized services to make a purchase. On the other hand, customers who desire increased transparency, thus having high levels of privacy, are less likely to accept online profiling for personalization (Awad and Krishnan, 2006), reducing the possibility to purchase online through personalized services. As customers develop both trust and privacy beliefs (Chellappa and Sin, 2005), we propose these aspects to be studied together to fully comprehend possible combinations between them capable of explaining their behaviour. The personalization-privacy paradox remains a critical issue in influencing consumers' behaviour (Lee and Rha, 2016), although consumers that are concerned about their privacy seem not to take any protective measures (Baek, 2014). Thus, a different approach can be employed to gain a better understanding of the complex relation among trust, privacy, and personalization in forming consumers' behavioural intentions.

The role of emotions on personalized online shopping

Research in the area of online shopping and personalized services identifies the importance of affective qualities and emotions as antecedents of consumers' purchase intentions (Christodoulides et al., 2013; Pappas et al., 2016). Indeed, as consumers become more experienced in online shopping, they tend to seek affective qualities as well (Bridges and Florsheim, 2008). The importance of emotions is highlighted by the fact that on certain occasions (e.g., the absence of clear information) individuals will make a decision based on their emotions (Pappas et al., 2017b), as they are expected to take decisions that make them happy and avoid unhappiness. Furthermore, emotions can be formulated based on specific scenarios (e.g., when receiving personalized messages), creating anticipated emotions, and they can influence consumers' action or inaction in various ways (Bagozzi et al., 2016), thus revealing their inherent complexity. Previous studies have examined the relationship among the different types of emotions and behaviour

(Fang et al., 2016; Pappas et al., 2014a), however, the majority of the studies focus on specific emotions and take a rather unidimensional approach (Pappas et al., 2016).

In general, there are at least four categories of emotions, considered as the basic emotions one may feel (Ekman, 1992a; Ekman, 1992b). They have been found to be effective for examining user behaviour when using computers and software (Kay and Loverock, 2008). Here, emotions describe how a consumer feels while using or receiving personalized services. Happiness refers to the degree of satisfaction, excitement or curiosity someone feels, while anxiety to how anxious, helpless, nervous or insecure one feels. Sadness refers to how disheartened or dispirited one feels, while anger describes how irritated, frustrated or angry a person feels. Although emotions are correlated (Chang et al., 2014) their relation is not symmetric (Pappas et al., 2016), instead it is complex, 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 (Pappas et al., 2014a; Pappas et al., 2016). Based on how these emotions combine, customers' behaviour 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. Therefore, to capture emotions' complexity a different approach is needed, as they are a multidimensional concept comprising diverse characteristics.

Conceptual Model

The importance of personalized online shopping increases together with the need for better targeted services and products, making it essential to improve our understanding of consumers' behaviour. Recent work in online commerce employs variance based methods to build integrative models including trust, privacy, emotions and experience, which have been found to influence behaviour in different ways (Pappas et al., 2014a; Pappas et al., 2014b; Riquelme and Román, 2014). When consumers have to make a choice between the benefits of personalization and privacy risks (Baek, 2014; Xu et al., 2011), high trust (Lee and Rha, 2016) or positive emotions may influence their behavioural intentions. However, following the previous discussion, additional work is needed to improve our understanding of the role of trust, privacy, emotions and experience and their interrelations in explaining intention to purchase in the complex environment of online commerce.

We explain intention to purchase by identifying configurations of causally related sets of factors, and posit that a synergy exists among trust, privacy, emotions, and experience in explaining intention to purchase. Indeed, there is not one unique, optimal, configuration of such values. Instead, multiple and equally effective configurations of causal conditions exist, which may include different combinations of the examined factors. Depending on how they combine they may or may not explain customers' high and low/medium intention to purchase. *High* intention to purchase means that the condition (i.e., intention to purchase) is present, and *low/medium* intention to purchase means that the condition is not present, thus its negation is computed. The negation means that we examine non-high intention to purchase (i.e., low/medium intention to purchase). This approach allows the identification of asymmetrical relations among the examined factors and the outcome.

The negation of a condition is also referred in the literature as the absence of a condition, and the two terms have been used interchangeably based on how the absence is computed (Fiss, 2011; Pappas et al., 2017a; Ragin, 2008). For example, if the condition is high behavioural intention, the term "negation" refers to non-high behavioural intention, and the term "absence" refers to high behavioural intentions not being present, thus in both cases to low/medium behavioural intentions. Furthermore, the term "absence" has been used to show when the condition is irrelevant in a configuration that predicts a high or low outcome condition (Nagy et al., 2017; Woodside, 2017). To describe the same situation the term "do not care" has been also introduced (Fiss, 2011), and adopted by various studies [e.g., (Pappas et al., 2017a; Pappas et al., 2016)] indicating, in both cases, that a condition has a subordinate role in the solution and can either be present or not, without influencing the outcome. Here the term negation is preferred as it is more accurate since the method computes the presence of a condition or its opposite (i.e., negation).

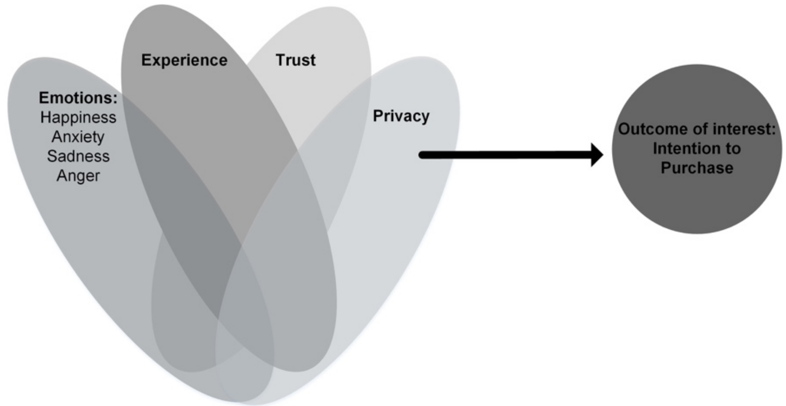


Figure 1 Venn diagram illustrating the conceptual model explaining intention to purchase

To conceptualize these asymmetric relations, we propose a theoretical model (Figure 1) illustrating, on the left, the four antecedents, their intersections, and, on the right, the outcome of interest (i.e., intention to purchase). The overlapped areas represent possible combinations among constructs, that is, areas that one construct may co-exist with the rest (e.g., customers either high in trust and privacy, or high in happiness and experience can have high intention to purchase). To identify such patterns of factors in a complex system as personalized online services, formulating hypotheses, common in variance based methods that are framed as correlational expressions, does not allow for a holistic approach that will lead to the identification of multiple solutions. In configuration theory approaches research propositions are formulated as causal recipes to capture the different combinations among factors, and theoretically specify which should be present or absent from the causal recipe (Fiss, 2007; Ragin, 2008).

Based on the principle of *equifinality* a result may be equally explained by alternative sets of causal conditions (Fiss, 2007; Woodside, 2014). Also, relations among factors (i.e., causes) are complex and depending on how they combine, both high and low conditions of a certain factor may explain high scores of an outcome. Trust, privacy, emotions, and experience are important causal conditions for understanding consumers purchase behaviour (Bleier and Eisenbeiss, 2015; Pappas et al., 2016), thus they may interact with each other in various configurations, and as consumers' perceptions vary, they may consider different sets of attributes before proceeding to an online purchase. Furthermore, mixed emotions have been found to mediate the effect of product related or personal factors on consumers intention to purchase (Penz and Hogg, 2011), while only positive emotions (and not negative ones) may mediate the effect of personalization on purchase intentions (Pappas et al., 2014a). Thus, no single configuration of trust, privacy, emotions, and experience can explain intention to purchase, but alternative configurations of these factors are likely to occur. For instance, customers who trust an online retailer are likely to make an online purchase even with high privacy concerns. Also, if customers feel happy and excited about a purchase, they are more likely to complete a purchase even with low trust. Similarly, trusting the retailer may help to overcome negative emotions, which could be the outcome of an unsatisfactory previous experience, thus increasing their purchase intentions. Therefore, adoption of personalized services occurs through the combination and co-alignment of multiple variables - here, trust, privacy, emotions, experience - with no specific form of co-alignment available as an *a priori* benchmark. Configurations include multiple combinations explaining the same outcome, leading to the following propositions.

Proposition 1. *No single configuration of trust, privacy, emotions, and experience is sufficient for explaining high intention to purchase; instead, multiple, equally effective configurations of causal factors exist.*

Based on the principle of causal asymmetry, for an outcome to occur the presence and absence or negation of a causal condition depends on how this condition combines with the other conditions (Fiss, 2011). A predictor may have an asymmetric relation with the outcome, meaning that even if one variable is *insufficient* for the outcome to occur, it is still able to serve as a *necessary* condition for the same outcome (Fiss, 2011; Woodside, 2013). In this case, a necessary condition is a variable that is present, at least to a degree, in every configuration that explains the outcome, making it indispensable to the outcome. Perceptions of trust, privacy, emotions, and experience differ in online environments, and they may influence each other, and by extension consumer behaviour. Also, privacy may act as an antecedent of trust (Riquelme and Román, 2014), which in turn is a well-established antecedent of intention to purchase (Gefen et al., 2008), thus its presence will influence both trust and intention to purchase. For the conditions explaining intention to purchase, it is important to examine how the presence or the negation of privacy will influence the presence or negation of trust, and vice versa. Complex and contradicting results exist also on the influence of positive and negative emotions on intention to purchase (Pappas et al., 2016). Causal asymmetry suggests that the conditions explaining the presence of an outcome, cannot be assumed as mirror pictures (i.e., exact opposite patterns) of conditions explaining the absence or negation of the same outcome (Fiss, 2011). For instance, customers with low trust and high privacy may present high purchase intentions, if (a) they are experienced and have gained the ability to overcome such issues, or (b) they are not experienced but feel happy about an offer included in the personalized message. Consequently, either the presence or negation of experience and happiness may lead customers with different perceptions towards the same outcome. Thus, we formulate the following research proposition:

Proposition 2: *Single conditions of trust, privacy, emotions, and experience can have opposite effects on intention to purchase, depending on how they combine with other conditions to form a solution.*

Proposition 3: *Configurations of trust, privacy, emotions, and experience explain high intention to purchase are no mirror opposites of configurations for its negation (i.e., low/medium intention to purchase).*

Furthermore, building on the above discussion, this study formulates specific testable propositions which include configurations that are expected to hold true for a part (small or large) of the sample. This allows to identify within the sample specific cases, or persons, (who and how many) that will have high or low/medium intentions depending on specific antecedent conditions (if they are high or low/medium).

Proposition 4a: *Customers having high trust, high happiness, and high experience will have high intention to purchase online.*

Proposition 4b: *Customers having high trust, high happiness, and low/medium experience will have high intention to purchase online.*

Proposition 5a: *Customers having low trust, high privacy, and low/medium happiness will have low/medium intention to purchase.*

Proposition 5b: *Customers having low trust, high privacy, and high anxiety, will have low/medium intention to purchase.*

Methodology

Data Collection

To explore the propositions a survey-based research approach was followed. A custom-built questionnaire was developed, comprising of questions on background information of respondents and on the identified constructs using established measurement items as discussed below. 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 [e.g., personalized offers from well-known online retailers through emails or when viewing the homepage while logged in based on personal preferences, previous purchases, search history, etc) 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.

Participants

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 demographic characteristics, followed by questions on the constructs identified in the literature review section. The Appendix presents 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. Experience was defined as the number of online purchases the past six months using personalized services. All items along with descriptive statistics and loadings are presented in the Appendix.

FsQCA

FsQCA was developed through the combination of fuzzy sets and logic principles with Qualitative Comparative Analysis (QCA) (Ragin, 2008), and may take researchers beyond traditional MRAs as it offers the opportunity to identify multiple pathways explaining the same outcome. These pathways (or combinations) of independent variables, can lead to solutions that are not identified by MRAs, as their effect on the outcome exists only for a small number of cases (Woodside, 2014), in contrast to the main effects. The benefits of configurational analysis and fsQCA mainly occur from the limitations of regression-based methods (Liu et al., 2017; Pappas et al., 2016; Woodside, 2013). Regression based methods take a net effect approach in examining the effects among factors of interest and the variables are examined in a competing environment. The covariance among the variables in a model suggests that the presence or negation of one variable influences their effect, both on the other variables and on the expected outcome, adding to the importance of applying configurational analysis, which is based on this notion (Fiss, 2007).

Combinations leading to multiple solutions in fsQCA may include both necessary and sufficient conditions, which may appear as present or negated on a solution. Also, they may be on a situation that they do not play a role on a specific solution, thus they do not appear at all in the solution. First, an analysis of necessity is performed, which will identify if any of the causal conditions is a necessary (i.e., indispensable) condition for the presence or negation of intention to purchase, that is high or low/medium intention to purchase, respectively. Necessity, from a set theory approach, means that a condition is a superset of the outcome (Ragin, 2008), thus for each case in the sample, the fuzzy-set membership score of the outcome is smaller than the fuzzy-set membership score of the causal conditions. For a condition to be necessary, its consistency should exceed the threshold of 0.9 (Schneider and Wagemann, 2010). Consistency is the degree to which the cases in the sample that share a causal condition or configuration agree in displaying the focal outcome (Ragin, 2008).

Data Calibration

A critical step in configurational analysis is the calibration of the data. This means that all factors need to be transformed (i.e., calibrated) into fuzzy sets, with a value range of 0-1 (Ragin, 2008). Data calibration may be either direct or indirect. In the direct method, the researcher chooses three qualitative thresholds, while in the indirect method, the factors need to be calibrated based on qualitative assessments. Either method may be chosen, depending on the data, the underlying theory, and the experience of the researcher (Ragin, 2008). In the direct method, the three qualitative thresholds correspond to full membership, full non-membership and intermediate membership, representing the degree that a case is part of a set (Ragin, 2008). This study follows the direct method for data calibration, and the qualitative thresholds were chosen based on the survey scale (7-point Likert scale) (Ordanini et al., 2014; Pappas et al., 2016). 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. Next, each variable is calibrated following a logistic function to fit into the three aforementioned thresholds, embedded in the fsQCA software.

Obtaining Solutions

Next, fsQCA provides a truth table of 2^k rows, with *k* representing the number of outcome predictors, and each row representing every possible combination. The truth table is sorted based on frequency and consistency (Ragin 2008). Frequency describes the number of observations for each possible combination. To ensure that a minimum number of observations is obtained for the assessment of the relationships, a frequency threshold is set. For samples larger than 150 cases the frequency threshold may be set at 3, while for smaller samples the threshold may be set at 2 (Fiss, 2011; Ragin, 2008). As our sample is 182, the threshold is set at 3, and all combinations with smaller frequency are removed from further analysis. Also, the threshold for consistency is set at the recommended threshold of 0.75 (Ragin, 2008). The combinations (i.e., each row in the truth table) over the consistency threshold are those that fully explain the outcome, which means that for those combinations the outcome variable is set at 1, and for the rest is set at 0. FsQCA computes three sets of solutions (i.e., complex, parsimonious, intermediate) that need to be interpreted by the researcher. The complex solution includes all possible combinations of conditions when traditional logical operations are applied. Next, complex solutions are simplified into parsimonious and intermediate solutions, which are simpler and up for interpretation. The parsimonious solution is a simplified version of the complex solution and presents the most important conditions which cannot be left out from any solution.

Findings

Measurements

A confirmatory factor analysis (CFA) is performed to verify the factor structure of the constructs. For reliability testing, Cronbach alpha and Composite Reliability indicators show acceptable indices of internal consistency as all constructs exceed the cut-off thresholds of 0.70. For validity testing, the average variance extracted (AVE) should be larger than 0.50, the correlation between the variables should not exceed 0.80 points, and the square root of each factor's AVE should be higher than its correlations with the other factors (Fornell and Larcker, 1981). AVE for all constructs ranges between 0.57 and 0.84, all correlations are lower than 0.80, and square root AVEs for all constructs are higher than their correlations (Table 1). Furthermore, multicollinearity is examined along with the potential common method bias, by utilizing the common latent factor technique and the CFA marker variable technique, which are better from other control procedures frequently employed in the literature (e.g., Harman's single factor test) (MacKenzie and Podsakoff, 2012). As the variance inflation factor (VIF) for each factor is lower than 3 multicollinearity is not an issue here (Hair et al., 2006). Common method bias is not a problem, as the variance from the common latent factor technique and the CFA marker variable technique, is .08 and .21, respectively.

Table 1 Descriptive statistics and correlations of latent variables

					Construct						
Construct	**Mean**	**SD**	**CR**	**AVE**	**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.

FsQCA Results

Results from the analysis of necessity are presented in Table 2. For the presence of intention to purchase, consistency values range between 0.26-0.81, for both the presence and negation of the causal conditions. Similarly, for the negation of intention to purchase, consistency values range between 0.26-0.88, for the presence and negation of the causal conditions. Since none of the causal conditions exceeds 0.9 (Schneider and Wagemann, 2010) they cannot be considered necessary for high or low/medium intention to purchase. We proceed with the fuzzy set analysis to identify sufficient combinations of causal conditions that explain intention to purchase intentions and its negation.

Table 2 Analysis of necessity for the presence and negation of intention to purchase

	Intention to purchase		**~Intention to purchase**	
Causal Conditions	**Consistency**	**Coverage**	**Consistency**	**Coverage**
Trust	0.55	0.88	0.31	0.47
~Trust	0.68	0.51	0.82	0.65
Privacy	0.78	0.53	0.88	0.55
~Privacy	0.35	0.76	0.26	0.54
Happiness	0.78	0.87	0.41	0.43
~Happiness	0.49	0.47	0.87	0.79
Anxiety	0.33	0.61	0.42	0.73
~Anxiety	0.81	0.61	0.77	0.52
Sadness	0.28	0.62	0.37	0.77
~Sadness	0.85	0.61	0.81	0.51
Anger	0.26	0.59	0.37	0.79
~Anger	0.85	0.61	0.80	0.51
Experience	0.53	0.57	0.42	0.42
~Experience	0.47	0.46	0.57	0.53

The outcomes of the fuzzy set analysis for intention to purchase are presented in Table 3. Black circles (●) denote the presence of a condition, while crossed-out circles (⊗) indicate its negation. Blank spaces suggest a do not care situation, in which the causal condition may be either present or absent with no influence on the solution. Core elements of a configuration are presented with large circles, peripheral elements with small ones (Pappas et al., 2016). The solution table includes values of set-theoretic consistency for each configuration and for the overall solution, with all values being above threshold (>0.75). Coverage assesses the empirical relevance of a consistent subset (Ragin, 2008). 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 0.70 for high intention to purchase, and 0.79 for low/medium intention to purchase, both suggesting that a substantial proportion of the outcome is covered by the five and six solutions, respectively.

For high intention to purchase, solutions 1a-5a present combinations for which the different factors may be present or absent depending on how they combine with each other. Specifically:

Solution 1a and 2a: Customers have high intention to purchase, when they have high trust or high privacy, and feel happy when using personalized services, while their negative emotions remain at low or medium levels. In both cases, the combination of high trust and happiness for high purchase intentions is an expected finding; however, the combination of high privacy and happiness shows that happy customers are likely to overcome their privacy concerns. This highlights the importance of happiness and positive emotions in personalized online shopping. These solutions explain the purchase intentions of 42% and 52% of the customers, respectively.

Solution 3a: Highly experienced customers who have low trust levels and low privacy concerns, will have high intention to purchase, if their negative emotions are at low levels. In this case, happiness is not important for high purchase intentions. This solution suggests that experienced consumers are likely to feel more capable in proceeding to a purchase even when they do not fully trust an online vendor, if no negative experience has occurred in the past. This solution explains 15% of the customers with high intention to purchase.

Table 3 Configurations leading to high and low/medium intention to purchase

	High intention to purchase						Low/Medium intention to purchase					
Configuration	1a	2a	3a	4a	5a		1b	2b	3b	4b	5b	6b
Trust	●		⊗	●	●				⨂	⨂	⨂	●
Privacy		•	⨂	•	•							●
Emotions												
Happiness	●	●		•	•		⨂					⨂
Anxiety	⨂	⨂	⊗		•						●	
Sadness	⊗	⊗	⊗	⊗	•				●			
Anger	⊗	⊗	⊗	⊗	•			●		●		
Online Shopping Experience												
Purchases in the past six months			●	⊗	•		⨂	⨂			●	
Consistency	0.97	0.91	0.90	0.95	0.92		0.85	0.85	0.87	0.90	0.83	0.82
Raw Coverage	0.42	0.52	0.15	0.19	0.18		0.51	0.21	0.37	0.35	0.16	0.27
Unique Coverage	0.07	0.17	0.05	0.02	0.03		0.24	0.01	0.02	0.01	0.02	0.04
Overall solution consistency	0.91						0.81					
Overall solution coverage	0.70						0.79					

Note: Black circles (●) indicate presence of a condition. Circles with "x" (⊗) indicate its negation. Large circles indicate core conditions; small ones, peripheral conditions. Blank spaces indicate that condition may be either present or absent

Solution 4a: Low experienced customers will have high purchase intentions when they trust the seller and feel happy, but not sad or angry, about using personalized services, even if they have high privacy concerns. Here, trust is the only core condition, thus, it is likely to dominate the other factors. This suggests that for inexperienced customers trusting the online retailer before proceeding to a purchase is a critical factor, as opposed to experienced customers who may have high purchase intentions even with low levels of trust (solution 3a). This solution explains 19% of the sample.

Solution 5a: Finally, high experienced customers who have negative emotions, will have high intention to purchase if they trust the online retailer and are happy to use personalized services, even with high privacy concerns. This is the only solution that presents a combination in which customers have high negative emotions, showing that high intention to purchase can be achieved, on certain occasions, even when customers had a negative experienced. Nonetheless, trust is here the only core condition; thus, it can also be considered as a dominant factor. This solution explains 18% of the customers with high intention to purchase.

Table 3 also presents the solutions for low/medium intention to purchase (Solutions 1b-6b), and shows that solutions explaining low/medium purchase intention are not perfect opposites of solutions explaining high purchase intentions.

Solutions 1b and 2b: Low experienced customers, unhappy or angry with personalized services will not have high intentions to purchase. This is a rather expected finding, as unhappy customers would generally not be expected to proceed to a purchase. Nonetheless, it is interesting that this applies only for inexperienced customers, since solution 5a shows that, on certain occasions, experienced customers could overcome negative emotions and proceed to a purchase. Solution 1b explains the largest part of the cases with low/medium intention to purchase (51%), and solution 2b explains 21% of them.

Solutions 3b, 4b, and 5b: These solutions show that not fully trusting the online retailer is likely to lead to low/medium intention to purchase, but it is insufficient. This is an intuitive finding considering the importance of trust in online shopping. However, this happens when the customer is sad or angry (solutions 3b and 4b), regardless of other factors, with the two solutions explaining almost equal amount of the sample (37% and 35%). Also, this may hold for high experienced customers who get anxious using personalized services (solution 5b). This solution may refer to customers with negative experiences in the past leading to low trust and high anxiety, and explains 16% of the sample.

Solution 6b: Customers that trust the online vendor but have high privacy concerns and are not happy with receiving personalized services, will have low/medium intention to purchase. Similar to solution 1b, this suggests that unhappy customers are not expected to have high intention to purchase regardless of other factors. This solution explains the purchase intentions of 27% of the customers. The findings offer support for P1, P2, and P3.

Finally, we test the specific propositions to identify how the defined configurations will lead to high and low/medium intention purchase, and more importantly for which cases and for how many in our sample. This is performed by computing the specific configuration in fsQCA, thus creating a model, and plotting it against the outcome of interest. The process on how to compute the models and plot them is similar to predictive validity (see next section). Details and instructions can be found on Pappas et al. (2017a). In the plots, *"*"* means *and*, *"~"* means *not*, and *"+"* means *or*.

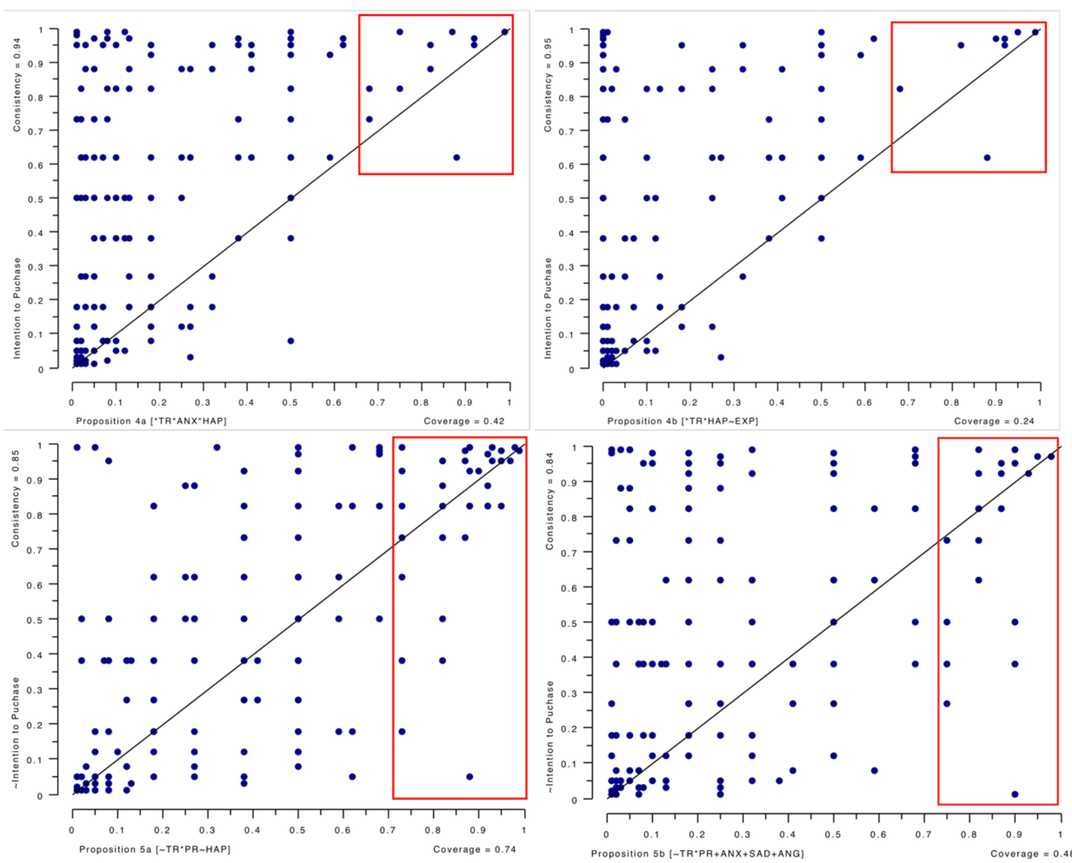


Figure 2 *Fuzzy XY plots for testing propositions 4a,b and 5a,b.*

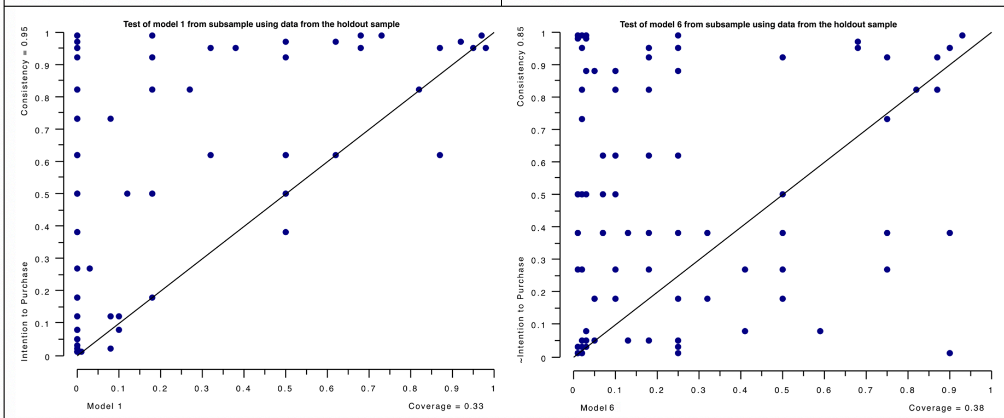
Notes: *Rectangles highlight cases for which the propositions have values over 0.7 but intention to purchase can be either high or low, describing different persons in the sample. TR; Trust, PR; Privacy, HAP; Happiness, ANX; Anxiety, SAD; Sadness, ANG; Anger, EXP; Experience.*

Figure 2 presents the fuzzy XY plots for testing propositions 4a,b and 5a,b with the cases of interest being highlighted. Findings show 11 persons with high trust, anxiety, and happiness (scores over 0.7), out of which only 9 have high intention to purchase (scores over 0.8). Thus, proposition 4a includes only 11 cases, but 9 out of 11 will have high intentions (upper right corner). Similarly, proposition 4b includes 8 cases (persons with high trust, happiness, and low/medium experience), but 7 out of 8 will have high intentions (upper right corner). For the negation of intention to purchase, proposition 5a includes 32 cases (persons with low/medium trust, happiness, and high privacy), but 26 out of 32 will have low/medium purchase intention (upper right corner). Finally, proposition 5b includes 20 cases (persons with low/medium trust, high happiness, and high anxiety or sadness or anger), but 11 out of 20 will have low/medium purchase intention (upper right corner). Propositions 4 and 5 are partially supported, as expected, as they hold true for a (small or large) part of the sample. They do not correspond to a specific solution identified by fsQCA, instead they allow the identification of specific cases, or persons, (who and how many) that will have high or low/medium intentions depending on specific antecedent conditions (if they are high or low/medium). Asymmetric analysis indicates that high scores on the model (i.e., configuration) usually occur for high scores on the outcome condition, making the model useful for the researchers. However, this model does not predict all cases with high scores on the outcome, as other models exist that predict high scores of the same outcome (i.e., the upper left side in the plot). Models with consistency above 0.80 are useful and can serve theory advancement (Woodside, 2017).

Predictive Validity

This study tests for predictive validity to examine if the model can predict equally well the same dependent variable on a different sample (Pappas et al., 2016; Woodside, 2014). Although testing for predictive validity is not so common in relevant literature, it is critical to be performed because a good fitted model may not always predict the outcome well. To test for predictive validity, first, the sample is divided randomly into a subsample and a holdout sample. The analysis is executed for the subsample, and its findings (Figure 3) are tested against the holdout sample. Both samples need to explain well the outcome variable at a similar level. Details and instructions on how to perform predictive validity can be found on Pappas et al. (2017a). Figure 3 shows that the patterns of complex antecedent conditions are consistent indicators of high and low/medium intention to purchase for the subsample, with overall solution consistency 0.89 and 0.82, respectively. Each solution in Figure 3 represents a model that needs to be plotted against the outcome variable. The findings for testing model 1 against high intention to purchase indicate high consistency (0.95) and coverage (0.33), and for model 6 against low/medium intention to purchase (negation) indicate high consistency (0.85) and coverage (0.38). Predictive tests for all models suggest that the highly consistent models for the subsample have high predictive ability for the holdout sample and vice versa, for high intention to purchase and its negation. All results are available upon request.

Models from Subsample for High Purchase Intention	**Raw Coverage**	**Unique Coverage**	**Consistency**
1. EXP*~SAD*~ANG*~ANX*HAP	0.35	0.21	0.90
2. ~EXP*~SAD*~ANG*HAP*PR	0.31	0.09	0.90
3. EXP*~SAD*~ANG*~ANX*~SAD*~PR	0.16	0.04	0.86
4. ~EXP*~SAD*~ANX*HAP*~TR*PR	0.24	0.01	0.89
5. SAD*ANG*ANX*HAP*TR*PR	0.16	0.06	0.96
Overall Solution Consistency	*0.89*		
Overall Solution Coverage	*0.78*		
Models from Subsample for Low/Medium Purchase Intention (negation)	0.16	0.06	0.96
6. SAD*~TR	0.37	0.03	0.87
7. ~HAP*~EXP	0.51	0.24	0.85
8. ANG*~EXP	0.22	0.01	0.84
9. ~HAP*TR*PR	0.27	0.04	0.82
10. ~TR*ANG	0.36	0.01	0.90
11. ANX~TR*EXP	0.16	0.01	0.83
Overall Solution Consistency	*0.82*		
Overall Solution Coverage	*0.80*		



Note: TR; Trust, PR; Privacy, HAP; Happiness, ANX; Anxiety, SAD; Sadness, ANG; Anger, EXP; Experience

Figure 3 Complex configurations indicating high intention to purchase for subsample

Discussion, Implications and Future Work

The present work proposes that trust, privacy, emotions, and experience combine to form different configurations that can explain online purchase intentions in personalized service settings. Drawing from complexity theory and configuration theory, a conceptual model is developed to identify such configurations (or combinations), which includes four antecedents of online shopping adoption, that is trust, privacy, emotions, experience, and purchase intention as the outcome variable. The findings identify multiple configurations explaining both high and low/medium intention to purchase, and highlight the importance of trust, privacy, emotions, and experience for the adoption of personalized services in online shopping. Trust, happiness and customer experience are key reasons that people continue purchase online while bad service and product experience, which lead to negative emotions or a lack of positive experience overall, are key reasons of people stopping online shopping.

Outcomes confirm the significance of trust in personalized environments (Komiak and Benbasat, 2006; Lee and Rha, 2016), however, its presence is insufficient to lead to high purchase intentions. 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. Indeed, highly experienced customers are likely to proceed to a purchase even with low trust, if negative emotions are also low, suggesting that experience makes them feel confident or in control to purchase from vendors they do not trust (e.g., new online retailer that has no reputation yet). We confirm the critical role of positive emotions (Fang et al., 2016; Pappas et al., 2014a) since they are present in almost all solutions. 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 may neutralize each other.

This study also explains low/medium levels of intention to purchase, showing that the inverted solutions for high intention to purchase cannot be interpreted as explanations for low/medium intention to purchase. Customers with low positive emotions or high negative emotions are unlikely to proceed to a purchase, combined with low experience or low levels of trust. The results add to the significance of emotions in personalized online commerce, since, for example, trusting a company is not enough, if the customer does not feel happy about the offered personalized services. As emotions are an important part of the persuasion process in personalized online shopping (Pappas et al., 2017b), they may enhance reciprocal communication. Finally, the analysis of necessity showed that none of the examined factors are indispensable to explain high or low/medium purchase intentions. This confirms that purchase intentions may be achieved also with the absence or negation of factors that are, in general, considered as critical in predicting consumer behaviour (e.g., trust), thus, verifying the need to examine combinations of these factors to better explain purchase behaviour.

Theoretical and Methodological Implications

The most important contributions of this paper are its methodological implications, as it differs from previous studies in online commerce that employ variance methods, such as regression and structural equation modelling, to examine purchase intentions (Ho and Bodoff, 2014; Pappas et al., 2014a). Such methods formulate hypotheses as correlations expressions, while configuration methods formulate hypotheses as causal recipes, which are more complex and lead to the identification of causal recipes (Fiss, 2007; Ragin, 2008). Different from the traditional hypotheses, here research propositions are formulated which can capture such causal recipes taking a holistic approach of complex, interconnected systems and processes that should be studied together. Thus, this study formulates research propositions and a configuration analysis is performed with the use of the data analysis tool fsQCA to examine the asymmetric relationships among the factors. This methodology has recently received increased attention in marketing and e-business studies (Fang et al., 2016; Foroudi et al., 2016; Pappas et al., 2016), and when applied together with complexity theory and configuration theory, is able to contribute towards the creation of new hypotheses and theories (Fiss, 2007; Woodside, 2014). To this end, we build on complexity theory and configuration theory to propose a conceptual model to predict customers' intention to purchase in personalized online shopping.

This work also extends online consumer behaviour and emotions studies that employ configurational analysis and fsQCA (Fang et al., 2016; Pappas et al., 2016), and goes beyond them by taking a multidimensional approach as it examines four major types of emotions (i.e., happiness, anxiety, sadness, anger), and by performing more analyses and formulating propositions that can capture specific types of consumers within the sample, thus contributing to theory development (Woodside, 2017). An analysis of necessity is conducted to detect if any of the antecedent conditions is indispensable for explaining intention to purchase. It is important to highlight such factors, as they can help in identifying what conditions should be met or avoided, for the presence or the absence of an outcome. Further, predictive validity using subsamples is examined when employing fsQCA, which is critical as a model that fits well to the data may not predict well the outcome. Finally, we identify how many consumers, within the sample, with similar perceptions on trust, privacy, emotions, and experience have different intention to purchase. The results show complex causal patterns among the predictor variables and highlight asymmetric relationships that lead to the same outcome, towards the development of new hypotheses and new models of consumer behaviour.

This study complements extant research in personalized online shopping [e.g., (Ho and Bodoff, 2014; Pappas et al., 2014a)] by providing an alternative view on the purchase process and showing how important factors that influence customers' behaviour are able to combine with each other to predict future purchase intentions. The findings are consistent with recent studies that highlight the importance of these factors in online personalization (Bleier and Eisenbeiss, 2015; Lee and Rha, 2016; Salonen and Karjaluoto, 2016), although without examining how different combinations and interrelations of the same factors can better explain intention to purchase (Pappas et al., 2016). This study contributes by providing deeper insight on the role of trust and privacy, and how they combine with emotions and experience to explain intention to purchase. This paves the ground for scholars to revisit models and theories in personalized online commerce, through the identification of new research questions based on the multiple solutions that explain the same outcome.

The findings verify previous studies (e.g., Pappas et al. 2016) on the important role of emotions, when combined with cognitive factors. Previous studies have focused on specific affective factors shaping the relation between customers and online retailers (Christodoulides et al., 2013; Penz and Hogg, 2011), and offer ways on how to take advantage of the massive amount of data available online to cover customers' personalized demands (Xie et al., 2016). However, it is still not clear how customers' emotions can be better explained, or even manipulated, to improve customers' perceptions and by extension the personalized services and products of the future (Pappas et al., 2017b). Positive emotions can be considered when offering or designing personalized services or products, as they may reduce consumers' privacy concerns (Lee and Rha, 2016), thus addressing the personalization privacy paradox. The study empirically demonstrates the synergetic nature of emotions when combined with trust, privacy, and experience. These findings suggest that emotions can be important at different stages of the purchase process (Bagozzi et al., 2016; Pappas et al., 2017b), pointing out the need for the development of emotion-centric theories to better explain consumer behaviour.

Practical and Managerial Implications

This study offers insight to retailers on how to streamline their personalization strategies and business models in online commerce for improved services or products - based on different levels of trust, privacy emotions, and experience - by identifying specific paths which can lead to high purchase intentions. The provided multiple solutions lead to new ways on how companies may approach their customers, as each solution covers a specific part of the sample, adding to the fact that in personalized marketing there is not one single optimal solution explaining customer purchase intentions (Pappas et al., 2016). Retailers may gather clickstream data (i.e., aggregate data on which websites and with what order a customer visited) to improve the knowledge on specific groups of customers through a detailed analysis of their browsing behaviour, to improve the personalization and purchase process (Grant et al., 2010). Since successful personalization is based on the interaction, communication, and engagement between companies and customers (Pappas et al., 2017b; Salonen and Karjaluoto, 2016), clickstream data can offer more insight on how customers behaviour in order to create value. Analysing clickstream data allows retailers to find customers' interests, purchase history, and habits, and pinpoint when and where they started their online journey, that can lead to foresee customer behaviour through predictive modelling. This can help retailers understand why customers visited their website and if and when they visited their competitors, thus creating a potential competitive advantage over them. Such data may be combined with feedback mechanisms to better assess customers' behaviour. For example, the company may ask customers, while they purchase, to rate their interactions with the company (e.g., using a scale) in terms of trust and privacy, or ask how they feel that specific moment, and combine this response with their clicking behaviour to increase value creation and improve the purchase process.

Retailers should constantly interact with their customers' to capture their preferences and emotions which might be mixed based on their experience, thus they may 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). Retailers may employ a variety of information technology tools to capture perceptions regarding trust, privacy concerns, and emotions such as text mining of customer reviews and feedback (Ganu et al., 2013) and developing collaborative filtering or pattern analysis of customer ratings and comments (Choi et al., 2012). The findings could be beneficial for new online retailers, who have not yet developed a strong or well-known brand name, as they offer alternative solutions to increase intention to purchase or avoid reducing it, when for example trust is relatively low due to no previous experience with the specific retailer. Finally, by understanding the difference between the reasons that explain high and low/medium intention to purchase, retailers can identify different types of customers, and, for example, target their competitors' unhappy customers. Even when predictors of intention to purchase are on a similar level, consumers can have different intention to purchase, thus, companies need to invest in building, improving, or redefining their online environments, making one more step towards digital transformation.

Limitations and Suggestions for Future Work

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. Also, findings are based on self-reported data. For an interdepended approach, future studies may combine self-reported data with archival data from retailers that offer personalized services, and extend them with interviews and data from actual purchases, which may provide deeper insight on consumer behaviour. The findings here point towards the need to create models that will identify how trust, privacy, and emotions evolve during the different parts of the purchase process in online shopping. This paper differs from previous studies in the area that focus on net effects among variables, adopts complexity theory and employs configurational analysis to better explain intention to purchase based on personalized services. FsQCA does not identify the unique contribution of every variable for every solution, instead it identifies complex combinations of variables and the amount of the outcome that is explained by these combinations. This study is among the first to employ fsQCA in e-commerce, to advance the field by better understanding the customer through a novel approach. Future studies may take a similar approach to verify our findings, and to extend theory in different contexts of user adoption of IS and IT (Dwivedi et al., 2017a), responding to the need to re-examine and evolve existing popular acceptance models and increase their complexity (e.g., Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology) (Benbasat and Barki, 2007; Dwivedi et al., 2017b; Pappas et al., 2017a) .

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Appendix

Scale items with mean, standard deviation and standardized loading

Construct and scale items	Mean	S.D.	Loading
Trust, CA = .9 *Customers' trust issues and beliefs towards an online vendor that will act according to their benefit when using personalized online services (Awad and Ragowsky, 2008; Pappas et al., 2013)*			
The online vendor can be trusted at all times.	2.99	1.64	0.78
The online vendor can be counted on to do what is right.	3.07	1.6	0.82
The online vendor has high integrity.	3.1	1.51	0.82
The online vendor is competent and knowledgeable.	3.58	1.59	0.69
Privacy, CA = .92 *Customers' privacy concerns when using personalized online services (Pappas et al., 2013)*			
Personalization causes privacy problems because it may keep track of my web behavior.	5.34	1.75	0.93
Personalization causes privacy problems because it may monitor my clicks and browsing records.	5.3	1.77	0.96
Personalization causes privacy problems by exposing my personal information to unknown parties.	5.41	1.73	0.73
Intention to purchase, CA = .94 *Customers' intention to continue purchasing online when using personalized services (Pappas et al., 2016)*			
In the future I intend to continue shopping online based on personalized services.	4.24	1.83	0.89
My general intention to buy online based on personalized services is very high.	3.92	1.86	0.86
I will shop online in the future based on personalized services.	4.00	1.75	0.83
Emotions *Measuring customers' happiness, anxiety, sadness, anger when using personalized services (Kay and Loverock, 2008).* In general, when I purchase based on personalized services I feel:			

	Mean	SD	Loading		Mean	SD	Loading
Happiness, CA = 0.77				Anxiety, CA = 0.84			
Satisfied	4.27	1.75	0.79	Anxious	3.31	1.79	0.74
Excited	3.52	1.75	0.69	Insecure	3.3	1.84	0.7
Curious*	3.73	1.78	0.56	Helpless	2.61	1.70	0.69
				Nervous	2.66	1.67	0.76
Sadness, CA = 0.79				Anger, CA = 0.79			
Disheartened	2.72	1.52	0.69	Irritable*	1.78	1.83	0.52
Dispirited	2.64	1.62	0.89	Frustrated	2.75	1.64	0.79
				Angry	2.48	1.75	0.75

CA; Cronbach alpha, * deleted due to low loading