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FÁBIO VERRUCK

EFFECTS OF RECOMMENDATIONS ON DECISION EFFORT FOR CONSUMERS' CHOICE

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EFFECTS OF RECOMMENDATIONS ON DECISION EFFORT FOR CONSUMERS' CHOICE

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Supervisor: Prof. Dr. Walter Meucci Nique

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Tese de Doutorado apresentada ao Programa de Pós-Graduação em Administração da Universidade Federal do Rio Grande do Sul, como requisito parcial para a obtenção do grau de Doutor em Administração.

BANCA EXAMINADORA

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Prof. Dr. José Afonso Mazzon / FEA - USP

____

Prof. Dr. Norberto Hoppen - Unisinos

____

Prof. Dr. Vinícius Andrade Brei - PPGA - UFRGS

____

Orientador Prof. Dr. Walter Meucci Nique - PPGA - UFRGS

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For Raquel and Stella

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There is nothing harder and, yet,
nothing more rewarding
than making the right decision.

RESUMO EXPANDIDO

Sistemas inteligentes têm sido usados no comércio eletrônico como ferramentas de personalização. Eles são destinados a criar ofertas individualizadas de produtos, recomendações direcionadas e até mesmo modificar o design do website para atender a características específicas de usuários. Tais possibilidades de personalização têm o intuito de facilitar o processo de tomada de decisão, melhorar a navegação e fornecer aos usuários da Internet uma sensação de contato social e de individualização em suas atividades online. A presente tese é o resultado de uma pesquisa experimental destinada a testar os efeitos, ao longo do tempo, de recomendações geradas por meio de métodos implícitos de elicitação de preferências. Para isso, foi criado um website experimental, no qual 189 participantes completaram um série de cinco tarefas de compras com um intervalo de uma semana entre cada tarefa. Os resultados foram analisados a partir da técnica do modelo das trajetórias latentes. Foi possível identificar, a partir disso, que recomendações não têm um efeito significativo no esforço para tomada de decisão nas interações iniciais, mas depois da segunda interação, há uma influência observável da presença de recomendações no tempo utilizado para a tomada de decisão. Em média, tempo para a tomada de decisão foi 21,4% menor para sujeitos no grupo teste quando comparados com o grupo controle. Procurando desvendar os mecanismos através dos quais as recomendações geram a redução no esforço para a tomada de decisão ao longo do tempo, uma análise de moderação foi realizada, incluindo-se como variáveis o envolvimento com a tarefa de compras e a familiaridade com o website, medida a partir do número de interações de compras. Com base nisso, considerou-se que o modelo mais adequado para testar a interação da presença de recomendações geradas por métodos implícitos de elicitação das preferências no website seria analisá-la como um moderador da relação entre envolvimento com a tarefa de compras e esforço para a tomada de decisão. Foi possível observar que em uma análise incluindo envolvimento com a tarefa, presença/ausência de recomendações e familiaridade com o website estas variáveis interagiram entre si em um modelo de moderação moderada, capaz de explicar 40,25% da variância na variável dependente. Este efeito moderador, entretanto, somente demonstrou ser significativo depois da terceira compra simulada. Adicionalmente, os resultados indicaram que a aceitação da recomendação não estava relacionada com a redução no esforço para a tomada de decisão, o que levou à conclusão de que recomendações podem não estar influenciando as escolhas dos consumidores diretamente, mas sendo usadas como pontos de referência que fornecem parâmetros para a tomada de decisão. Isso foi também verificado ao analisar a variância nas escolhas de compras entre os sujeitos que executaram compras com recomendações e os sujeitos no grupo de controle. Os resultados sugerem que as recomendações podem fornecer auxílio importante para a redução do esforço do consumidor na tomada de decisão, mas sua influência se torna efetiva apenas depois que os consumidores estão familiarizados com o website. As companhias de e-comerce podem se beneficiar com tais informações adaptando a maneira com a qual gerenciam e apresentam recomendações aos seus vistantes.

Palavras-chave: recomendação, comércio eletrônico, tomada de decisão, esforço do consumidor.

ABSTRACT

Intelligent systems have been used in electronic commerce for the purpose of personalization. They are intended to tailor product offers, recommendations and even the whole website design to specific users needs and characteristics. Such personalization features are supposed to facilitate decision making process, make internet browsing easier and give the Internet users a sense of social feeling and individualization in their online activity. The present dissertation thesis is the result of an experimental research addressed to test the effects, over time, of recommendations generated by implicit elicitation methods. For that, an experimental website was created, where 189 participants completed a series of five purchase tasks with an interval of one week between each task. Results indicated that recommendations do not have a significant effect on decision effort during initial interactions, but after the second interaction, there is an observable effect of recommendations on time to make a decision. On average, time to make a decision was 21.4% lower for subjects in a test group when compared to the control group. The presence of recommendations generated by implicit elicitation methods at the website was also tested as a moderator of the relationship between involvement with the purchase task and decision effort. It was possible to observe that an analysis considering involvement with the task, presence/absence of recommendations and familiarity with the website these variables interacted in a moderated moderation model capable of explaining 40.25% of the variance of the dependent variable. This moderating effect, however, proved to be significant only after the third purchase took place. Additionally, results demonstrated that recommendation acceptance was not related to effort reduction, what led to the conclusion that recommendations may not be influencing consumers' choices, but being used as frames of reference that provide parameters for decision making. That was also verified by looking at the variance in the purchase choices between people who executed purchases with recommendations when compared to the control group. Results suggest that recommendations can be important aids to reduce consumer effort, but their influence will only be effective after consumers are familiarized with the website. E-commerce companies can benefit from such information by adapting the way they manage and present recommendations to their visitors.

Key words: recommendations, e-commerce, decision making, consumer effort.

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SUMMARY

1 INTRODUCTION

While making a purchase, consumers tend to be attracted to more choice, but then experience difficulty due to the negative psychological consequences associated with choosing from such a large set (Schwartz, 2004). Since consumers try to reduce the cognitive effort spent to make a decision (Aljukhadar, Senecal, Daoust, 2012; Tversky & Shafir, 1992; Bettman, Luce, Payne, 1989), it is possible to find evidences to support the existence of negative relations between effort and satisfaction with the purchase (Oliver & Swan, 1989). However, although this is true for individual efforts, consumers generally appreciate other party's efforts trying to help them (Bechwati & Xia, 2003; Mohr & Bitner, 1995). In this sense, recommendations can affect consumers' decision-making processes by altering the amount of effort demanded in order to make a purchase decision (Xiao & Benbasat, 2007).

Once they give advices based on previously specified user preferences, recommendation agents[1] have the potential to reduce information overload and search complexity but at the same time improve decision accuracy (Shani & Gunawardana, 2011; Xiao & Benbasat, 2007). Recommendations, therefore, can influence not only the way users make decisions while searching for product alternatives, but also which, among all available options, they will consider. In particular, "recommendations cause consumers to rely less on the utility difference between a newly inspected product and the best previously encountered one, to make broader comparisons among the set of inspected products" (Dellaert & Häubl, 2012, p. 285).

Despite the benefits recommendations can bring to consumers, there is still a long way to run in order to improve the prediction algorithms used to anticipate consumers preferences as well as to better understand the behavioral responses they trigger (Urban *et al.*, 2013). Even though recommender systems may be able to learn, the process through which they generate the recommendations needs a set of previously developed knowledge to elaborate the rules they should be based on. Therefore, the association rules used to filter user information for posterior classification depend on the development of theories capable of better understanding

[1] Following Xiao & Benbasat (2007) approach, the labels recommendation agents (the terminology adopted in this research), recommender systems, recommendation systems, shopping agents and comparison shopping agents will be used interchangeably.

what features should be considered in order to generate recommendations. Such investigation could improve the recommendation agent effectiveness by creating a broader set of variables to consider before deciding what, how and when to recommend.

In this context, two major issues arise with a need for further investigation. The first one is related to developing forecasting techniques capable of predicting the characteristics and needs of consumers online with more accuracy. The second is intended to understand the consequences (and effectiveness) of the interferences caused by such systems in consumer behavior, considering well-known constructs in consumer behavior, such as attitude, trust and persuasion.

Based on the previous assumptions, the aim of this research is to propose a scientific investigation destined to address some of the knowledge gaps in such a recent and prominent field of study. For this, the following chapters will introduce the research question and objectives, as well as a brief theoretical review of recent findings in the field. From it, research hypotheses will be derived and, based on them, a method of experimental study intended to test whether these hypotheses are confirmed in an empirical investigation.

1.1 Research question and objective

A great part of existing research on recommendations is mainly concerned with finding the best match between consumers and products (Xiao & Benbasat, 2007). Traditionally, recommendation agents deal with applications that consider only two kinds of variables: items and users (Xiao & Benbasat, 2014, 2007). This focus ignores recent findings in behavioral decision research that considers the decision-making process as a contingency of its context (Adomavicius & Tuzhilin, 2011).

System accuracy, thus, is not the only driver of consumer's responses to recommendations (Gershoff, Mukherjee, Mukhopadhyay, 2003; Cooke *et al.*, 2002; McNee, Riedl, Konstan, 2006a). This happens because consumers frequently do not have well defined preferences when they choose among products and services (Häubl & Murray, 2003). Instead, they tend to construct their preferences on the spot when they are prompted either to express an evaluative judgment or to make a decision (Bettman, Luce, Payne, 1998). As a result, preferences are sensitive to the particular way in which a decision problem is formulated and to the mode of response used to express these preferences (Tversky & Kahneman, 1986; Slovic, 1995).

Rana and Jain (2012) have also outlined the role that contextual factors play for consumers' decision processes. They present a need for the development of recommendation agents that could handle the temporal dynamics of users' needs as well as system content and, accordingly, present modified recommendations to users in real-time (Rana & Jain, 2012). Gorgoglione, Panniello and Tuzhilin (2010) found that context-aware recommender systems capable of considering the intent of purchase and customer's mood were more effective in building trust and generating higher sales revenues.

Another understudied contextual factor that could be interfering in consumers' decision process in assisted purchase is the familiarity with the same recommendation agent. Considering the aforementioned, it is possible to suppose that consumers are especially sensitive to the recommendation context at an early stage, but as experience with the website grows, so does the level of trust that the consumer places in the recommendations (Cooke *et al.*, 2002). That is, the dissociation between agent and item evaluations disappears with repeated visits to a specific website, consequently leading to a reduced time spent for decision-making. Recommendation agents, then, should consider previous user experience in order to incrementally adapt and simplify the way preferences are elicited and recommendations are presented to a specific user's reality.

Additionally, a great amount of research so far has been concentrated on analyzing interactions with recommendations generated by explicit elicitation methods. This means that such studies have only considered situations in which consumers clearly stated their preferences before the recommendation was presented. Besides the fact that explicit elicitation methods may be influencing consumer preferences and consequently leading to biased choices (Häubl & Murray, 2003), this focus also disregards current trends in the way recommendations have been applied in websites.

Various types of companies providing products or services on the Internet (i.e., Amazon, Aliexpress, Saraiva, Netflix, Facebook, Youtube) have preferred to apply implicit elicitation methods to generate recommendations. Furthermore, customers of these companies have been characterized for repeated visits to their webpages, what points out to the necessity of understanding consumers' responses to recommendations in a long-term perspective.

Considering the already mentioned conflicting goals consumers seek to fulfill when making a purchase, it becomes even more necessary to investigate how their responses vary after they develop a certain familiarity with the website and its tools.

Current theoretical models intending to reach a comprehensive framework of users' responses to recommendations so far have not considered such longitudinal perspective (i.e., Xiao & Benbasat, 2007, 2014; McNee, Riedl, Konstan, 2006b; Martínez-Lopez, 2010; Simonson, 2005). Empirical investigation, with some rare exceptions (*see* Xiao & Benbasat, 2003), has also failed to consider the effects of product recommendations across time. There is, therefore, an important gap related to understanding the effects of recommendations generated by implicit elicitation methods on decision effort and consumer's choice after the first purchase at the same website.

In order to contribute with the reduction of such gap, this thesis develops and analyzes the results of a longitudinal experiment destined to address the following research question: "what are the effects of recommendations generated by implicit elicitation methods on decision effort after repeated purchases at the same website"?

1.2 Research objectives

In order to answer to the proposed research problem, the objectives of this research were established as follows.

1.2.1 Main objective

Analyze the effects of recommendations generated by implicit elicitation methods on decision effort after repeated purchases at the same website.

1.2.2 Specific objectives

a) Identify product categories for which consumers are more susceptible to recommendations when purchasing online;

b) Conduct a pre-study to generate recommendations based on the purchase tasks proposed for the experimental study;

c) Perform a longitudinal study with a set of purchase tasks to be executed in a simulated ecommerce store;

d) Develop a model that incorporates the effects of recommendations on consumers' choices based on empirical data.

2 THEORETICAL BACKGROUND

When consumers engage in online shopping assisted by recommendation agents (RA), they are simultaneously consumers buying products and users of an information technology artifact (Xiao & Benbasat, 2007). This is why research in recommendation agents follows within the domains of both Information Systems and Consumer Behavior fields of study. The interface between these two academic disciplines regarding recommendation agents lies on their mutual concern in understanding how RA use and characteristics affect consumer decision-making processes and outcomes. This theoretical review will focus in defining and identifying the existing types of recommendation agents and the main theories used to understand how consumers respond to them.

2.1 Recommendation agents: a definition

Recommendation agents are decision aids designed to identify consumer preferences based on previously collected data, in order to present personalized information about the products that better fit their needs (Bodapati, 2008; Wang & Benbasat, 2007; Shih *et al.*, 2002; Resnick & Varian, 1997). Kardan and Ebrahimi (2013) define them as personalized decision support systems capable of predicting the utility of an item for a particular user and suggesting it to her (Kardan & Ebrahimi, 2013). These personalization systems have been applied in the marketplace to help users finding news of their interest (Lu *et al.*, 2012), in banner advertising to adapt messages to different profiles of users (Urban *et al.*, 2013) or to design webpage layouts that match preferences of different groups of users (Hauser *et al.*, 2009).

Considering they are means of personalization, recommendation agents can help consumers to make purchase decisions at a certain point in time by giving them advices tailored specifically to their needs (Shani & Gunawardana, 2011). According to Kardan and Ebrahimi (2013), this personalization process follows three steps: (i) understanding user needs and interests in order to create some sort of user profile, (ii) recommend items and information accordingly, and (iii) evaluate the quality and utility of personalization considering user feedbacks and other related measures.

A typical interaction proceeds as follows: first, user's preferences are elicited (whether directly or indirectly). Based on the collected preference data, the system tries to predict how much the user would appreciate each of the available items in the catalog. Finally, it presents those items that have the highest predicted value to the user. In some recommendation agents this terminates the interaction, in others, users continue to indicate their preferences and receive recommendations continually.

The design of a recommendation agent, then, needs to consider three main factors: (i) inputs, which are related to the way user preferences are elicited; (ii) process, when recommendations are generated; and (iii) outputs, that is, the way recommendations are presented to the user (Ricci, Rokach, Shapira, 2011). Recommendation agents, therefore, can be classified according each one of the mentioned characteristics (input, process and output) and also according to the type of algorithm used to generate the recommendations (RA type). Table 1 shows a summary of different features and classification for each one of these four dimensions.

Table 1 - Different classifications for Recommendation Agents

Factor	**Feature**	**Classification**
RA Type	Filtering method	Collaborative Filtering vs. Content-Filtering vs. Hybrid
	Decision strategy	Compensatory vs. Non-compensatory vs. Hybrid
	Adaptability	Dynamic vs. Static
	Problem resolution capability	Knowledgeable vs. Smart
Input	Preference elicitation method	Implicit vs. Explicit
	Information elicited	Feature-based vs. Needs-based vs. Hybrid
	Communication design	Concrete vs. Abstract
	Consumer participation	Amount of input from consumers about their product related preferences
	Control	Level of user control
	Structural characteristics of the preference elicitation process	Level of topic relevance, level of transparency, amount of effort
Process	Information about search progress	Presence vs. absence of information about search progress
	Response time	High vs. low response time
Output (recommendation content)	Information available about recommended products	Amount of information on recommended products
	Familiarity of the recommended option	Familiar vs. unfamiliar product recommendations
	Explanation	Trace vs. justification vs. strategy
Output (recommendation format)	Ordering procedure	Sorted vs. Non-sorted lists
	Number of recommended products	Single vs. several products recommended
	Navigation and layout	Navigational path to product information and layout of the product information

Source: elaborated by the author based on Xiao and Benbasat (2007) and Yoo and Gretzel (2012)

The next sub-chapters will present more detailed information about the classification criteria proposed in Table 1 and recent findings regarding the differences in the RA design and their impacts on user behavior. The process factor will not be addressed in this theoretical review because their influence in consumer behavior is still uncertain and research on this topic is still inconclusive (Yoo & Gretzel, 2012). Furthermore, recent improvements in the algorithms used to generate recommendations, and also advances in computational technology as a whole, have made process features (information about search progress and response time) practically irrelevant to system performance.

2.1.1 RA Type

In order to implement its core function, identifying useful items for its users, an RA must predict that an item is worth recommending. When trying to accomplish this goal, it must be able to predict a utility function, or at least compare the utility of some items, and then decide what items to recommend, based on this comparison (Ricci, Rokach, Shapira, 2011). There are two underlying assumptions that drive this decision. One of them considers that users can be grouped according to their preferences and, consequently, similar users will have similar preferences. The other assumes that a user's previous preferences are the best predictors of her future behavior. The way an RA algorithm incorporates these assumptions is called filtering method. There are three main filtering methods being used to design recommendation agents: (i) collaborative filtering, (ii) content-based filtering and (iii) hybrid recommender systems.

The core of <u>Collaborative Recommendation Agents</u> is to find users with similar tastes to an active user. This will be achieved by considering the opinions and previously stated interests of other like-minded users (Kardan & Ebrahimi, 2013). The main goal of collaborative filtering is, therefore, to classify correctly groups of users and identify their common tastes (Schellens & Valcke, 2005; Liu, Mehandjiev, Xu, 2013). This can be achieved by establishing measures capable of detecting similarity among users, assuming that groups sharing common consumption patterns tend to search for the same kind of offers. Then it is possible to predict product preferences of a certain consumer if other similar consumers have already assessed the same target product.

The classification technique in collaborative filtering can be performed by comparing items, users or both. *Amazon*'s recommendation agent, for example, classifies by item, looking for products frequently bought together. That is, rather than matching the user to other similar customers, it matches each of the user's purchased and rated items to similar items, then combines those similar items into a recommendation list (Linden, Smith, York, 2003). This is why recommendations at Amazon's website are generally presented with the heading "Customers Who Bought This Item Also Bought..." The same reasoning is used by journalistic companies as *The Washington Post* and *Le Figaro* in order to suggest news to online readers. In those cases, once the user clicks at a link to read a given news report, she will be presented to related news read by previous users who have already visited that same link.

When using item-to-item logic, the system simply groups products/services commonly linked by the same stream of clickthroughs, but it does not analyze any information about whether the user liked the item or not. Other technique employed to generate recommendations using collaborative filtering is called user-to-user, and it is operationalized by recommending resources to users based on the ratings they have in common with other similar users (Picault *et al*., 2010). This tends to result in better accuracy and personalization, but requires a more proactive participation of the user. Comparing the current user's rating history with the history of every other user, the system finds user's potential peers - that is, other users who have rated the same items in a similar way the current user has rated (Salter & Antonopoulos, 2006). This logic is employed, for example, by Movielens Project, which aims to recommend films to users based on their ratings (https://movielens.org).

A third approach to collaborative filtering is called matrix factorization. In its basic form, matrix factorization characterizes both items and users by vectors of factors inferred from an item rating patterns. High correspondence between item and user factors leads to a recommendation (Koren, Bell, Volinsky, 2009). This is one of the most promising approaches, because it is able to analyze relationships between users and interdependencies among products to identify new user-item associations. As an example, Netflix uses this approach to recommend content to its consumers (Koren, Bell, Volinsky, 2009; Bennett; Lanning, 2007). The matrix factorization approach lends itself well to modeling temporal effects, since decomposing ratings into distinct terms allows the system to treat different temporal aspects separately, which can significantly improve accuracy (Koren, Bell, Volinsky, 2009).

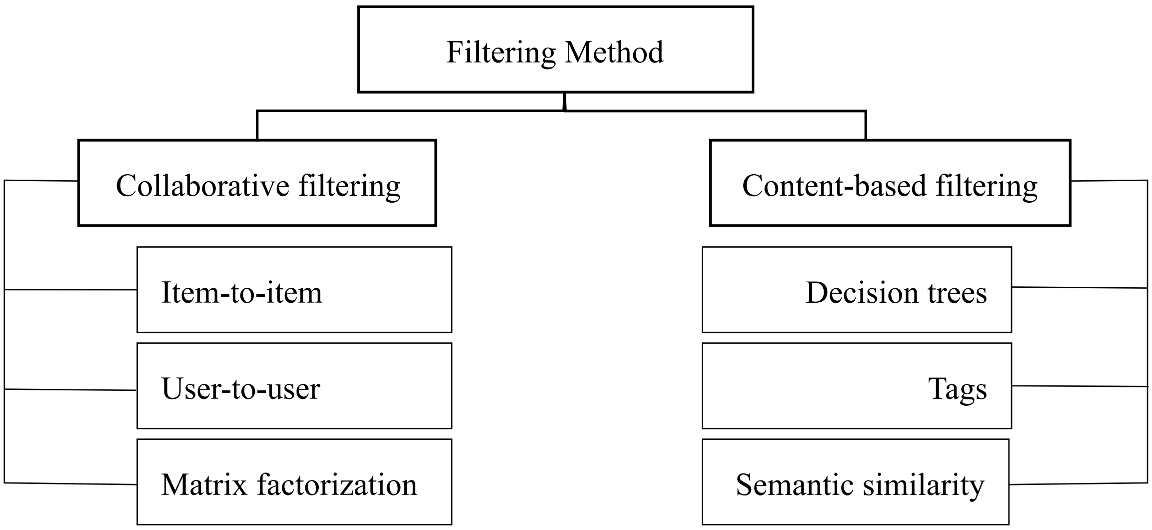
Content-based filtering, on the other hand, recommends products to target consumers based on their own profile, built from the analysis of previous behavior (Lin *et al*., 2010).The recommendation criterion in this system is based on similarity of content or preferences expressed in items, rather than the similarity between users (Kardan & Ebrahimi, 2013). That is, it is assumed that an active user will probably prefer an item similar to those in which she has shown previous interest (Kardan & Ebrahimi, 2013; Schimratzki *et al*., 2010; Shih *et al*., 2002). The recommendation process basically consists in matching up the attributes of the user profile against the attributes of a content object (Lops, De Gemmis, Semeraro, 2010). The result is a relevance judgment that represents the user's level of interest in that object.

One way to create a content-based recommendation system is to build sets of words, weighted according to their importance in the description of user interests, forming decision trees (Godoy, Schiaffino, Amandi, 2009). Decision trees are one of the most widely used techniques to produce discrete predictions about the interests of a user in a certain activity (Wang, Zhang, Vassileva, 2010). In this technique, users are recommended items similar to which they have already shown previous interest (Lemmens & Croux, 2006). An example is the study of Li *et al*. (2010) who developed a system of recommendations for consumption of media reports through a classification tree.

Other proposed recommendation systems are based on tags. These tags, or labels, are terms or words associated with groups of items that allow its classification and association with other similar items. Durao and Dolog (2012) present a recommendation agent, based on tags, that suggests web pages to users based on the similarity of their tags. Lee, Chung and McLeod (2011) propose a new technique for items recommendations within social networks that connect users and groups over time using clustering techniques of tags through topics.

The most prominent form of content-based filtering, however, is the semantic description of available resources and the personal preferences of users. This idea is linked to the emergence of the semantic web, whose purpose is to make sense of the content available on the Internet, creating the possibility that they are understood both by computers and by people. For this kind of recommendation, the system "understands" the meaning of the available user information and can establish deductions from previously prepared data (Schimratzki *et al*., 2010). Figure 1 presents a summary of the two mentioned approaches and the main classification techniques used by each one.

Figure 1 - Summary of main filtering methods



Source: The author

The collaborative and content-based techniques have several limitations and drawbacks. To overcome these limitations, hybrid recommender systems have been proposed. The hybrid systems combine the aforementioned techniques to enhance the advantages of both other methods (Kardan & Ebrahimi, 2013). Hybrid algorithms, therefore, draw ideas from these two different filtering paradigms in order to improve the results achieved when the selected paradigms are employed separately (Vozalis & Margaritis, 2003). In contexts where there is no prior information available about the users, the part of the system that performs content-based filtering can be set to generate initial estimates, while in situations where data about other users become accessible, the part of the system which performs collaborative filtering is enabled.

Most studies analyzing the performance of filtering methods so far have been concerned with measuring their accuracy and precision. Burke (2002) has found that hybrid recommender systems can offer more accurate predictions of users' preferences than the other types. Schafer *et al*. (2002) and Schafer *et al*. (2004) also found that hybrid recommender systems are seen as more useful than the others. It is important to note, however, that research comparing the effectiveness of different filtering methods has not yet been conclusive and the variables used to compare their performance do not measure directly consumer's responses to them (Salter & Antonopoulos, 2006). In fact, behavior related to recommendation agents is not dependent on the filtering method itself (consumers do not know them well), but is very much dependent on its effectiveness (Lin, Hsu, Li, 2014; Gorgoglione, Panniello, Tuzhilin, 2011).

It is also possible to classify recommendation agents by the way they deal with tradeoffs between attributes. This is related to the decision strategy to be adopted by the system. In the compensatory RA, all relevant attributes are evaluated and trade-offs are made in order to allow bad attributes of an alternative to be compensated by good attributes (Bader, 2013). Non-compensatory RAs only regard a fixed subset of attributes and do not allow trade-offs. These types of RA differ mainly in the amount of information processed. Tan, Teo and Benbasat (2010) found that an RA using both compensatory and non-compensatory strategies performs better than one using only one of these strategies when it comes to decision time and perceived system quality.

More recently, Punj and Moore (2007) have investigated if suggesting close items when no alternatives meet consumers' selection criteria completely could be effective. They differentiated knowledgeable RAs from smart RAs by their ability to deal with this problem during the matching process. Knowledgeable RAs can only recommend options that match exactly consumers' specified criteria, so when the matching process does not work well and no acceptable alternatives are found, the system usually asks the consumers to restate the selection criteria. Smart RAs do the same, but they also present the closest match found according to the criteria already specified by the consumer. That is, smart RAs can go one step further when pre-specified consumer preferences do not have an exact correspondent found in the system, and suggest the closest matches without asking for additional information from the user. Punj and Moore (2007) found that smart RAs can decrease consumer's decision effort leading to reduced perception of cognitive resources spent and more satisfaction, but does not necessarily help them to find products that better fit their needs. In contrast, a knowledgeable RA increases decision effort but does help consumers identify better fitting products.

Other feature being currently studied for RA type is context-awareness. Gorgoglione, Panniello and Tuzhilin (2011) found that a context-aware RA (that considers information such as consumer's mood and intent of purchase) performs better than content-based RA and random recommendations in terms of trust and other economics-based performance metrics. Ho, Bodoff and Tam (2011), in a similar manner, compare adaptive recommendation agents (that generates recommendations on the basis of consumers' answers to preference elicitation questions at the start of the shopping task and their current preferences as revealed in their browsing behavior) to static RAs (that generates recommendations solely on the basis of consumers' answers to preference elicitation questions). "The findings of a field experiment and a laboratory experiment showed that while the quality of recommendations (indicated by the level of match with consumers' preferences) improved when they were provided at a later stage of an online session, the likelihood that consumers would consider and accept a given recommendation diminished over the course of the session" (Xiao & Benbasat, 2014, p.411). Table 2 summarizes the main research findings comparing different types of RA.

Table 2 - Types of RAs: Main findings

Independent variable	**Levels of independent variable**	**Findings**
Algorithm	Content-based vs. Collaborative vs. Hybrid	Hybrid algorithms have better accuracy and precision for predicting recommendation than the other two methods.
Decision strategy	Compensatory vs. Non-compensatory vs. Hybrid	Decision-time and perceived system quality are optimized in RAs using both decision strategies.
Problem resolution capacity	Smart vs. Knowledgeable RAs	Smart RAs lead to less decision effort and more satisfaction, but achieve lower product fit.
Context-awareness	Adaptive vs. Static RAs	Adaptive RAs lead to better quality of recommendations, but diminish recommendation acceptance over the course of the section

Source: The author

2.1.2 Inputs to Recommendation Agents

Recommendation agents are concerned with obtaining relevant information to infer user preferences from previously collected data. In this sense, preferences can be elicited either by explicit or implicit methods (Xiao & Benbasat, 2007). Explicit preference elicitation methods ask users directly about product attributes that could define their choice. Implicit elicitation methods, on the other hand, use past behavior, profile and navigation data to infer user's characteristics and, from these, define recommendations that most likely match her preferences. Explicit elicitation methods require more effort from the user, but at the same time they tend to be seen as more reliable whereas implicit elicitation methods do not demand any additional effort from the user, yet they tend to prompt privacy issues (Yoo & Gretzel, 2011). Xiao and Benbasat (2007) believe that an implicit preference elicitation method can increase user's perceived ease of use and satisfaction with the recommendation agent, while explicit elicitation can be seen as more transparent and, consequently, lead to better decision quality.

The effort-accuracy paradox can be considered here to understand consumer's responses to recommendation agents as a function of preference elicitation methods. In this case, asking more questions demands a greater effort from the user, but it also enhances system's accuracy and user confidence. Lee and Benbasat (2011), for instance, believe many product purchase choices for which RAs are used require users to make trade-offs among conflicting product attributes and preference elicitation methods often compel users to make explicit trade-offs. They made comparisons between a preference elicitation method that made the trade-offs among product attributes explicit and other that hid such trade-offs. Their findings show that a higher trade-off difficulty perceived in explicit preference elicitation methods leads to lower perceived control and higher perceived effort (Lee & Benbasat, 2011).

Komiak and Benbasat (2006) used the amount of support provided by the RAs for the consumer purchase to distinguish other two types of RA: feature-based and needs-based. Feature-based RAs give recommendations based on the product features the consumers indicate to prioritize and help them to narrow down the available choices and recommended alternatives. Needs-based RAs, on the other hand, use personal information and product use information to generate the recommendations. Stolze and Nart (2004) also proposed a hybrid model which could allow consumers to specify both desired product features and product-related needs. Still, no empirical study available tested the differences in performance between these two types (Xiao & Benbasat, 2007, 2014).

Köhler, Breugelmans and Dellaert (2011) propose that the communication design can also play a determinant role in the preference elicitation process. In their definition, a concrete communication design asks consumers to reveal their preferences for observable attributes, whereas in an abstract communication design, they describe more high-level, physiological, and psychological needs. According to them, congruency between the timing of product consumption or recommendation presentation and RA communication design will increase the likelihood to accept the RA's recommendation, such that for products destined to immediate consumption concrete designs lead to higher likelihood of accepting the RA's recommendations. Conversely, for products whose consumption is distant, an abstract design leads to greater likelihood of accepting the RA's recommendations.

West *et al.* (1999) relate the preference elicitation methods to the amount of control users have over the interaction with the recommendation agent. According to Pereira (2000) users demonstrate more positive affective responses when they believe they have control of the system. Specifically, user interfaces which provide consumers control over the content, order, and duration of product-relevant information cause information to have higher value and to become increasingly usable over time (Pereira, 2000). Additionally, West *et al.* (1999) and McNee, Lam and Riedl (2003) also found that giving the users more control of the system increases their satisfaction and confidence with the recommendation agent. Komiak *et al.* (2005) and Wang (2005) studied the relation between control of the recommendation agent and trust and showed that control is one of the main drivers of trust. Complementarily, in Wang's study (2005) more restrictive RAs were considered as less trustworthy and useful by their users.

In addition to control, there are three structural characteristics of the preference elicitation process (namely relevance, transparency and effort), mentioned by Gretzel and Fesenmaier (2006), which can influence users' perceptions of the recommendation agent. They found that topic relevance, transparency in the elicitation process and the effort required positively influence users' perceptions of the value of the elicitation process (Gretzel; & Fesenmaier, 2006). In their findings there is evidence showing that the very act of asking questions communicates interest in the user's preferences causing the system to take a social role, wherein the more questions the system asks, the greater its potential to provide valuable feedback (Yoo & Gretzel, 2011). Dabholkar and Sheng (2012) also related the amount of information demanded during the elicitation phase to user perceptions. In their investigation, a larger amount of input generated higher perceived recommendation quality, satisfaction, trust, purchase intentions and reduced task effort. Table 3 presents a summary of the main findings regarding inputs to recommendation agents and their impact over user behavior.

Table 3 - Inputs to RAs: Main findings

Independent variable	Levels of independent variable	Findings
Preference elicitation method	Implicit vs. Explicit	Implicit methods reduce user effort and increase perceived ease of use. Explicit methods increase user effort but also lead to higher perceived transparency and better perceived decision quality
Communication design	Concrete vs. Abstract	Concrete designs perform better for products destined to immediate consumption and abstract designs are better suitable for products destined to consumption in the long-term
Amount of input	High vs. Low	Amount of user input is directly related to perceived recommendation quality, satisfaction, trust, purchase intentions and reduced task effort
User control	High vs. Low	Amount of user input is directly related to satisfaction and trust in the RA.

Source: The author

2.1.3 Outputs to Recommendation Agents

The output of a recommendation agent can be either a prediction or a recommendation (Vozalis & Margaritis, 2003). A prediction is usually expressed in the form of a numerical value, which represents the anticipated opinion of an active user for a certain item, within the same numerical scale as the input referring to the opinions already provided initially by the same user (Vozalis & Margaritis, 2003). This form of recommendation agent output is also known as individual scoring. A recommendation, on the other hand, is expressed as a list of items or a single item, which the active user is expected to like the most. The usual approach in that case requires this list to include only items that the active user has not already purchased, viewed or rated.

Traditionally, research on recommendation agents have considered two dimensions of the RA's output, namely the content and the presentation format (Yoo & Gretzel, 2011; Xiao & Benbasat, 2007). Investigations in Wang and Benbasat (2007), Xiao and Benbasat (2007), Sinha and Swearingen (2001) and Cosley *et al.* (2003) have argued that both content and format play a significant role on users' evaluations of recommendation agents, as it will be shown in the following subchapters.

2.1.3.1 Outputs to Recommendation Agents - Content

Regarding output content, three aspects are cited by Xiao and Benbasat (2007) as especially relevant to users' evaluations of the Recommendation Agent: (i) the familiarity of the recommended option, (ii) the amount of information on recommended products, and (iii) the explanation on how the recommendation was generated.

Sinha and Swearingen (2001), studying the effects of familiar recommendations on user's trust in the Recommendation Agent, also found a direct relation between those variables, as well as Cooke *et al.* (2002) for whom unfamiliar recommendations were related to a decrease in user's evaluations of recommendation agents.

Other output aspect influencing user's perceptions of recommendation agents is the availability of product information (Yoo & Gretzel, 2012). According to Xiao and Benbasat (2007) presenting detailed information about the recommendations presented can signal to the users that the RAs care about them, act in their interests, and behave in an honest and unbiased fashion, thereby contributing to users' assessments of the RAs' benevolence and integrity. Sinha and Swearingen (2001) also explain that detailed information about products being recommended increases users' trust in the recommendation agent. Complementarily, Cooke *et al.* (2003) suggest that providing detailed information about the products being recommended increases the attractiveness of unfamiliar recommendations. At last, Xiao and Benbasat (2007) propose that detailed information can increase users' perceptions of RAs' usefulness and information quality by educating users about the products they search.

Despite the importance of familiarity and amount of information, the most studied aspect of output content is explanation. Explanations are generally used to clarify, justify or inform the user of the logic followed by the system to generate the recommendation. Thus, explanations can explicitly clarify the relations among user preferences and the presented recommendations. Once the consumer understands and appreciates the process through which recommendations were generated, her confidence, trust and recommendation acceptance, as long as her loyalty are increased (Tan, Tan, Teo, 2012; Tintarev & Masthoff, 2011). In this sense, Herlocker, Konstan and Riedl (2002) argue that it is possible to increase the user perceived transparency by exposing the underlying reasoning used by the system to generate the recommendations. Other studies also confirmed that explanations can enhance users' perceptions of RA transparency (Wang & Benbasat, 2009; Gregor & Benbasat, 1999; Sinha & Swearingen, 2001; Swearingen & Sinha, 2001).

Gregor and Benbasat (1999) use the content logic to classify four possible types of explanation facilities generally used by intelligent systems: (i) trace or line of reasoning, (ii) justification or support, (iii) strategic or control, and (iv) terminological. Explanation by trace provides an intuitive representation of the internal rule used by the recommendation agent (Gregor & Benbasat, 1999; Ye & Johnson, 1995; Tan, Tan, Teo, 2012). Justification, on the other hand, is an explicit description of the underlying rationale for the system's recommendations (Gregor & Benbasat, 1999; Ye & Johnson, 1995; Tan, Tan, Teo, 2012). Strategy defines the high level decision strategy used by the decision aid in formulating its recommendations (Gregor & Benbasat, 1999; Ye & Johnson, 1995; Tan, Tan, Teo, 2012). Terminological explanations are the "knowledge of the concepts and relationships of a domain that experts use to communicate with one another" (Swartout & Smoliar, 1987, p. 198).

Ye and Johnson (1995) and Tan, Tan and Teo (2012) proposed a classification considering only three categories (trace, justification and strategic). Tan, Tan and Teo (2012) found that a more elaborated explanation aid could heighten a consumer's decision confidence leading to a reduction in cognitive effort. In their work, explanation by trace is the most efficient to enhance confidence and, simultaneously, to reduce decision time, but it tends to lower the costumer evaluation of product quality. Strategic explanation, on the other extreme, is the most efficient in helping shoppers to find the best product alternative, but they tend to increase decision time and lower customer confidence.

For Wang (2005), it is also possible to classify different explanation techniques by the nature of explanation queries (e.g., what, why, how, when and where). He compares the <u>how</u> aspect with explanation by trace, because these kinds of explanations disclose the line of reasoning RAs use to generate recommendations. Wang (2005) also highlights <u>why</u> explanations, which provide justification for the recommendations presented after the consultation is complete. According to him "consumers' beliefs in the competence of recommendation agents can be increased by the use of <u>how</u> explanations, while their beliefs in the benevolence and integrity of the agents can be increased by the use of <u>why</u> explanations and <u>guidance</u>, respectively" (Wang, 2005, p. 129).

Other studies have not considered these classifications, but analyzed other aspects of explanation facilities. Pu and Chen (2007), for example, proposed using trade-off properties as a way of separating recommended products into categories, according to the attributes in which they show a superior performance. For Tintarev and Masthoff (2012) a recommendation agent could increase users' trust by allowing them to give feedback to the system when it is wrong, a characteristic they call scrutability. According to them, "explanations should be part of a cycle, where the user understands what is going on in the system and exerts control over the type of recommendations made, by correcting system assumptions where needed" (Tintarev & Masthoff, 2012, p. 485). Consequently, according to Tintarev and Masthoff (2007) explanations not only enrich the user experience, but also encourage users to interact with the system, fix wrong impressions and improve long-term accuracy. Table 4 presents a summary of the main findings regarding outputs to recommendation agents and their impact over user behavior.

Table 4 - Outputs to RAs (Content): Main findings

Independent variable	Level of independent variable	Findings
Output to recommendation - Content	Familiarity with product recommended	Familiarity is directly related to cognitive trust and user's evaluation of the RA
	Amount of information provided	Amount of information is directly related to trust in the RA and to the attractiveness of unfamiliar recommendations
	Explanation (Trace x Justification x Strategic)	More elaborate explanations increase decision confidence and reduce cognitive effort. Explanation by trace is considered to increase confidence in the system and to reduce decision time, but also lead to a reduction in the perceived product quality Strategic explanations lead to better product choice but demand higher decision time and generate lower confidence in the system

Source: The author

2.1.3.2 Outputs to Recommendation - Presentation Format

Tintarev and Masthoff (2012) identify five ways of presenting recommendations: (i) top item, (ii) top-n items, (iii) similar to top item(s), (iv) predicted rating for all items, and (v) structured overview. This classification is based on the structure of offering recommendations.

The top item format is, according to them, the simplest way of presenting a recommendation, which is showing to the user the top ranked item. In a similar manner, top-n items format presents a list of several items at once. The similar to top item(s) format is presented only when the user has already demonstrated a preference for one or more items; in this case the recommendation agent shows additional items to complement the previous recommendation. The predicted rating for all items format does not select any specific set of items to be presented, instead it shows all available items indicating the predicted rating of each one for the user. Finally in the structured overview format the recommendation agent can give a structure which displays trade-offs between items.

The main concern with this issue when designing the presentation format is the amount of options to be displayed to the user. According to Pu *et al.* (2012, p. 534), "showing one search result or recommending one item at a time allows for a simple display strategy which can be easily adapted to small display devices; however, it is likely to engage users in longer interaction sessions or only allow them to achieve relatively low decision accuracy". On the other hand, "displaying more products and ranking them in a natural order is likely to increase users' sense of control and confidence" (Pu *et al.*, 2011, p. 535) but it does not necessarily simplify the decision-making process. In their study, Goodman *et al.* (2012) found that too many recommendations could, in fact, increase user's effort, instead of reducing it. Xiao and Benbasat (2007) also argue that when too many recommendations are presented, consumers are led to compare a larger set of alternatives, what will increase their decision time and the size of the alternative sets.

Other concern emerges when recommending more than one item at a time: the ordering procedure. Regarding this matter, RAs can present sorted recommendation lists, in which the most promising options are at the beginning of the list, or provide them in a random order (Xiao & Benbasat, 2007; Diehl, Kornish, Lynch, 2003; Aksoy & Bloom, 2001). In all studies mentioned, sorted recommendation display methods demonstrated to overcome random display methods regarding size of the alternative sets (Dellaert & Häubl, 2005), decision quality (Diehl, Kornish, Lynch, 2003; Aksoy, Bloom, 2001) and price paid (Diehl, Kornish, Lynch, 2003). Additionally, Aksoy and Bloom (2006) also found that sorted recommendation display methods performed even better when there was similarity in the decision-making strategy as long as it was shown to the user.

There is still another issue related to the recommendation item that remains understudied and could be object of further investigation, the layout of product information and the navigational path to it (Xiao & Benbasat, 2007). There are no studies so far analyzing the effects of different layout types. Table 5 presents a summary of the main findings regarding outputs to recommendation agents and their impact over user behavior.

Table 5 - Outputs to RAs (Format): Main findings

Independent variable	**Level of independent variable**	**Findings**
Output to recommendation – recommendation format	Number of items recommended	Too many items demand higher user effort, higher decision time and increase the consideration set
	Ordering procedure (sorted vs. Random)	Sorted recommendation displays reduce the size of the consideration set and increase decision quality.

Source: The author

2.1.4 What to recommend

Other way to differentiate between RAs is to see if they are destined to recommend *what* to buy or *from whom* to buy. Guttman *et al*. (1998) define these two types of RA as product brokering and merchant brokering, respectively. The former is concerned with finding the best product to match, while the later is concerned with recommending the best store to buy from. We could not find any study so far comparing these two types of RA.

In addition to brokering, another issue that could determine consumer's responses to recommendations is the type of product being recommended. Traditional literature in online shopping tends to use a classification that differentiates between ‘‘search'' products and ‘‘experience'' products. Search products can be determined by inspection prior to purchase, while experience products are those for which full information cannot be acquired prior to purchase and use of the product, or for which information search is more costly and/or difficult than merely examining the product (Ochi *et al*., 2009; Huang, Lurie, Mitra, 2009). Huang, Lurie and Mitra (2009, p. 55) found that "consumers spend similar amounts of time online gathering information for both search and experience goods, but there are important differences in the browsing and purchase behavior of consumers for these two types of goods".

King and Balasubramanian (1994) found that consumers buying a search product are more likely to use own-based decision-making processes than consumers assessing an experience product, who rely more on other-based and hybrid decision-making processes than consumers assessing a search product. When it comes to online recommendations, research shows that recommendations for experience products tend to be significantly more influential than recommendations for search products (Senecal & Nantel, 2004; Moon *et al.,* 2008). Despite these results, several authors have suggested that because the Internet enables consumers to learn from the experiences of others and to gather product information that is often difficult to obtain in offline settings, it makes all attributes searchable and erases differences between search and experience goods (Peterson *et al.,* 1997; Klein, 1998; Lynch & Ariely 2000).

The design and implementation of recommendation agents by e-commerce stores is intended to generate some influence over consumer behavior. Considering the expected results can help the system designer to decide what are the best design choices to make regarding the factors discussed previously. Otherwise, it is also important to note that sometimes depending on the way a user perceives the recommendation agent, some unpredicted responses can arise. The two following subchapters are destined to discuss positive and negative responses to be expected from the use of recommendation agents.

2.2 Consumer responses to RA

In the face of the aforementioned definitions, it still remains unclear what is the main purpose of an online recommendation agent. Is it designed to remediate the lack of social interaction and the absence of personal sales consultation in online environments (i.e., Holzwarth, *et al.*, 2006)? Is it intended to help consumers to optimize their decision-making process by reducing decision effort and increasing decision accuracy (i.e., Bodapati, 2008; Wang & Benbasat, 2007; Zhang & Pu, 2006; Fitzsimons & Lehmann, 2004)? Or could it be just a new strategy companies use to persuade consumers and increase sales revenues?

Independently of the goal that motivated the inclusion of decision aids at a website, it seems reasonable to suggest that the ultimate measure of an RA effectiveness from a user's perspective is advice acceptance. Accepting a recommendation means that consumers analyzed the alternative proposed and considered it as the best option among all available. This will happen in the case that the recommendation presented is in accordance with the personal preferences of an individual (Komiak & Benbasat, 2006; Sinha & Swearingen, 2001) or if she believes the system is operating in her best interests (Wang & Benbasat, 2009; Chen & Pu, 2005; Häubl & Murray, 2003). Usually, online acceptance is a measure of accuracy and it can be calculated by different methods such as: (i) selection of nondominated alternatives, (ii) utility values, (iii) selection of target choice and (iv) selection of target choice among k-best items (Zhang & Pu, 2006).

Other important measure of RA effectiveness, when one assumes it is designed to help consumers to optimize decision-making process, is cognitive effort. Wang (2005) argues that there is an important role played by consumer's cognitive effort in their evaluations and acceptance of the recommendation agents. It is also argued that consumers tend to focus more in reducing effort than in increasing decision quality because feedback on effort expenditure can be accessed immediately while feedback on accuracy is subject to both delay and ambiguity (Wang, 2005; Todd & Benbasat, 1992). In line with that, thus, if two strategies will produce the same level of accuracy, the one which is expected to require less effort will be preferred (Todd & Benbasat, 1994).

Cognitive effort is frequently measured in two ways: (i) consideration set size and (ii) decision time (Wang, 2005). A consideration set is the amount of options a consumer considers seriously before decision-making (Häubl & Trifts, 2000). Consequently, too many options included in a consideration set will demand higher cognitive effort than smaller sets. Recommendation agents can actually decrease set size when consumers find them trustworthy (Häubl & Murray, 2003; Häubl & Trifts, 2000). Other measure for cognitive effort is decision time, which can be computed directly by measuring the time consumers spend in making a decision. Some authors have also argued for the use of indirect measures for cognitive effort, such as perceived cognitive effort (Kurzban *et al.*, 2013; Kleijnen *et al.*, 2007; Hu & Pu, 2006; Cooper-Martin, 1994). They argue user's perception of cognitive effort can be also determinant to intention and future behavior because it deals with the impressions primed in consumer's memory, especially because a consumer will rarely monitor the exact time spent to make a decision. There is also evidence in the literature supporting a link between subjective evaluations and adoption intention and adoption behavior (Gefen *et al.*, 2003; Venkatesh, 2000).

Intention to use has, therefore, been considered an important measure of RA effectiveness. Several studies have demonstrated that effort and quality are two important variables influencing users' choice behavior and their intentions to use decision aids (e.g., Payne, 1982; Todd & Benbasat, 1999). Dabhlokar and Bagozzi (2002) propose a model to measure intention to use an online system based on the reported probability of using it in the future. Wang and Benbasat (2005) also developed a similar scale adapted from Davis (1989) to be used specifically in decision aids.

Satisfaction is another important driver of future behavior and an important measure of an RA effectiveness. Research has considered three types of satisfaction as dependent measures resultant of RA use: satisfaction with the system (i.e. Knijnenburg & Willemsen, 2009; Zins & Bauernfeind, 2005), satisfaction with the search process (i.e. Punj & Moore, 2007) and satisfaction with the decision (i.e., Hostler *et al.*, 2005; Pedersen, 2000; Vijayasarathy & Jones, 2001).

According to Fitzsimons and Lehmann (2004), although much of the literature suggests that opinions and recommendations are desirable in decision-making, this only happens when the recommendation is consistent with individual choice preferences. Consequently, when recommendations contradict the consumer's initial impressions of choice options, there will be an increased level of difficulty in making the decision and, at the same time, an individual tendency to choose the alternative rejected by the recommender (Fitzsimons & Lehmann, 2004).

This kind of response can happen when the individual feels that, rather than a mechanism for facilitating decision-making, the recommendation agent is purposely limiting the consideration set, restricting her freedom of choice. According Fitzsimons and Lehmann (2004), based on the theory developed by Brehm in 1960, threats to freedom can motivate an individual to adopt behaviors that seek to regain the freedom once threatened or lost, even if these behaviors are not congruent with their immediate needs. The motivation for the recovery of this freedom is called psychological reactance.

Fitzsimons and Lehmann (2004) believe that reactant behavior can be stimulated when the recommendations are unwanted. They found that when the recommendation is contrary to personal choice preferences, some undesired patterns emerge. As decision-making difficulty increases, given the conflicting information, choice and confidence in the non-recommended alternative significantly increase, giving room for a reactant behavior.

Lee and Lee (2009) reached convergent conclusions conducting an experimental study at an e-commerce store. The empirical results of their work have shown that user expectations for personalized service induces the perception of usefulness, because choosing among too many alternatives may be a nuisance to the decision maker. Wang and Benbasat (2009) investigated the impact of perceived restrictiveness on user behavior and found that it significantly affects the perceived cognitive effort, advice quality and consumer's intentions to use online decision aids. They also found that decision strategy plays a significant role in perceived restrictiveness, in that "the additive–compensatory aid is perceived to be less restrictive, of higher quality, and less effortful than the elimination aid, whereas the hybrid aid is not perceived to be any different from the additive–compensatory aid" (Wang & Benbasat, 2009, p. 293). Table 6 presents the dependent measures exposed previously as both positive and negative responses to recommendations.

Table 6 - Measures used for analyzing responses to recommendations

Variable	**Proposed ways of measuring**
RA Acceptance	- Selection of nondominated alternatives - Utility values - Selection of target choice - Selection of target choice among k-best items
Cognitive effort	- Consideration set size - Decision time - Perceived cognitive effort
Intention	- Intention to use the system - Purchase intention
Satisfaction	- Satisfaction with the system - Satisfaction with search process - Satisfaction with decision
Reactance	- Intentional selection of a non recommended alternative - Perceived restriction of choice

Source: The author

2.2.1 Theoretical perspectives for understanding responses to recommendation agents

Xiao and Benbasat (2007) identify five theoretical perspectives regularly used by researchers in order to better comprehend the effects of recommendation agents on consumer behavior: (i) theories of human information processing; (ii) the theories of satisfaction; (iii) the theory of trust formation; (iv) the technology acceptance model; and (v) the theory of interpersonal similarity. The theories of human information processing have been mainly used in investigations studying RA-assisted consumer decision-making. The following three are used to study user's evaluations of RAs and their adoption intention. Finally, the theory of interpersonal similarity has been used by both streams of research.

Other theoretical perspective not mentioned by the referred authors is the theory of social response. It has been increasingly used by researchers investigating human-computer interactions, so it was also included in this brief theoretical review. The next sub-chapters will talk about them in more detail. Table 7 presents some assumptions derived form these six theoretical perspectives. They are all implicit in the research proposition presented in chapter 3, as they where used to infer the possible results of recommendations in consumer behavior for both studies.

Table 7 - Assumptions derived from each theoretical perspective

Theoretical perspective	**Derived assumption**	**Related variables**
Human information processing	Consumers will appreciate decision aids trying to reduce cognitive effort spent to make a decision.	- Decision time - Perceived cognitive effort
Theories of satisfaction	User satisfaction is an important measure of future intention to use the system.	- Satisfaction with the system - Satisfaction with search process - Satisfaction with decision
Theories of trust formation	Consumers will only accept recommendations from sources they trust.	- Recommendation acceptance - Trust in RA (transparency, competence and confidence) - Reactance
The technology acceptance model	Intention to adopt a new technology is determined by the perceived usefulness of using the technology and the perceived ease of use of the technology.	- Recommendation acceptance - Adoption intention
Theory of interpersonal similarity	Consumers will be more prone to accept recommendations when they perceive similarities between them and the RA.	- Recommendation acceptance - Perceived product fit
Theory of social response	RAs will be more persuasive when they leverage social aspects from their users.	- Recommendation acceptance - Social presence

Source: The author

2.2.2 Brief assessment of existent research on responses to recommendations

The first article in the field of recommendation agents using a behavioral approach is dated from1998, only four years after Resnick *et al.* (1994) published the first research paper on collaborative filtering, which inaugurated this whole stream of academic research. It is important to note that the boundaries of this subject are still unclear because it deals with interdisciplinary and relatively new phenomena (Kim & Chen, 2015). In order to give a clear delimitation for the purposes of this dissertation thesis, Verruck and Nique (2017) propose a classification of these studies in two different categories, one destined to solve computational problems and the other addressing behavioral and managerial problems related to the use of recommendations. They performed a bibliometric study on the articles classified in the second category. Results quantifying academic production in the field are shown in Table 8.

Table 8 - Classification of articles in behavioral studies

Type	Classification	Number of articles		Number of citations	
		Total	%	Total	%
Empirical	Experimental	81	47.93	8027	39.11
Theoretical	Structured Literature Review	38	22.48	9722	47.37
Empirical	Econometric	11	6.51	849	4.14
Theoretical	Working paper	16	9.47	684	3.33
Empirical	Survey	14	8.28	555	2.70
Empirical	Qualitative	6	3.55	390	1.90
Theoretical	Editorial	3	1.77	298	1.45

Source: Verruck & Nique (2017)

Verruck and Nique (2017) also analyzed quantitative studies to identify the variables they used and how such variables were linked to the effects of recommendations. Based on these results, they classified the identified variables into five categories: (i) direct behavior: variables that measured certain acts of the user not based on self reports; (ii) perception: measures of the impressions reported from subjects after interactions with RA's; (iii) evaluation: measures assessing the degree to which consumers reported to have been impacted by the use of recommendations; (iv) intention: planned behavior caused by the use of recommendations; and (v) attitude. The most used variables in the studies were intention to use a RA (19 studies), trust (12 studies), user satisfaction (9 studies), purchase intention (9 studies) and time to make a decision (6 studies). A summary of the data found is presented in Table 9.

Table 9 - Dependent variables used in Behavioral RA research

Classification	**Dependent Variable**	**Number of studies**
Direct Behavior	Time to make a decision (decision effort)	6
	Recommendation Acceptance	2
	Reactance	1
	Consideration set size	2
	Behavior Complexity	1
	Amount of information search	3
	Impulsive purchase	1
Perception	Perceived cognitive effort	2
	Trust	12
	Social presence	2
	Perceived enjoyment	5
	Perceived ease of use	6
	Perceived Usefulness	8
	Perceived product fit	3
	Perceived transparency	2
	Perceived accuracy	4
	Perceived control	5
	Perceived benefits	1
Evaluation	User satisfaction	9
	Choice liking	3
	User rating	1
	Consideration set quality	1
	Choice quality	5
	Decision confidence	5
	Cognitive load	2
	Product diagnosticity	1
Intention	Intention to use RA	19
	Purchase intention	9
Attitude	Attitude towards product	4

Source: The author

As independent variables, empirical studies generally considered factors related to RA characteristics, user characteristics and vendors characteristics. Table 10 outlines the main variables used in the identified studies.

Table 10 - Dependent variables used in Behavioral RA research

Classification	**Independent Variable**
RA Characteristics	Type or design of RA
	Explanation
	RA Source
	Anthropomorphic characteristics
	Recommendation Signage
	Type of scale used for rating
	Argument form
	Attractiveness of recommended option
User Characteristics	Initial trust
	Attitude towards e-vendors
	Attitude towards the recommended product
	Domain Knowledge
	User motivations
	User familiarity with the product
	Shopping experience
	Age
	Gender
Vendors Characteristics	Assortment size
	Product type

Source: The author

It is interesting to note that some variables were used both as dependent and independent variables in some studies. It happened more specifically with variables related to trust and attitudes. Although it seems paradoxical at a first glance, this could indicate that such variables may be operating as mediators or moderators of the recommendation effects over consumer behavior. Those relations have actually been hypothesized by Xiao and Benbasat (2007, 2014), but most of them have not been thoroughly tested empirically yet.

2.2.3 Hypotheses development

Most of the choices people make when purchasing a given product are the result of weighing their own opinions with advice from other sources (Gino & Moore, 2006). Previous research has suggested that consumers have a preference to look for relatively little pre-purchase information (Beatty & Smith, 1987). Thus, it would be logical to expect that many consumers will probably simply consider the options presented by a decision aid before proceeding to a final product choice. Ironically, when consumers turn to an information source to assist in decision making, they are faced with the added responsibility of having to make a decision about the information source itself (Gershoff *et al.*, 2001). The contradiction in this case is that consumers will look for advice in order to reduce decision effort but, in fact, will be adding a new item to their decision, which is whether to believe or not in the recommendation that is being given. At the same time, consumers will only consider recommendations from sources they trust (Nass & Moon, 2000; Fogg, 2002; Bart *et al.*, 2005). In particular, online trust is considered to be a two stage process in which initial trust depends on the cues received from the first interaction with the site (Wang *et al.*, 2004) and develops with repeated visits and purchases (Urban *et al.*, 2009). That is, individuals develop trust over time as they accumulate knowledge through their experiences with another party (Bart *et al.,* 2005; Büttner & Göritz; 2008).

Following the same line of reasoning, Komiak and Benbasat (2006) believe that familiarity is an important driver of trust. They argue that "familiarity with an RA is acquired through one's prior and direct experiential exchanges with the recommendation agent" (Komiak & Benbasat, 2006, p. 946). They found significant relation between user's familiarity with how an RA makes recommendations and cognitive trust in RA competence and integrity, which in turn, are significantly related to emotional trust. In face of the aforementioned, it is plausible to suppose that whenever a new recommendation agent comes to play, its influence on decision effort will not be immediately noticeable. Instead, it will probably take some time before it is possible to observe a significant influence of recommendations over consumer's decision effort, as measured by time to make a decision. Therefore, in purchases characterized by the presence of some kind of advice mechanism:

Hypothesis 1: The effects of recommendations generated by implicit elicitation methods on time to make a decision will be moderated by the number of previous purchases.

In a real purchase situation, decision effort will probably suffer the influence of the consumption problem that generated the necessity of purchasing. Studies conducted either in traditional or online shopping environments have documented that task complexity, specially in cases where subjects were confronted with too many choices, increases the probability of responses such as deferring the decision to buy, making suboptimal decisions, or feeling unhappy with the choice (Häubl & Trifts, 2000; Iyengar & Lepper, 2000; Schwartz, *et al.*, 2002).

The strategy people use to weigh advice, consequently varies with task difficulty (Gino & Moore, 2007; Gershoff *et al.*, 2001). Lynch *et al.* (1982) have already proppposed that task difficulty is one of the main influencers of consumers' processing time. In the same way, Bonato *et al.* (2013) also found that task difficulty is the major determinant of performance in a situation involving decision making. Investigating the influence of other people's advice on decision processes, Gino and Moore (2007) found that task difficulty influenced the acceptance of the advice of others in such a way that people tend to overweight advice on difficult tasks and underweight advice on easy tasks.

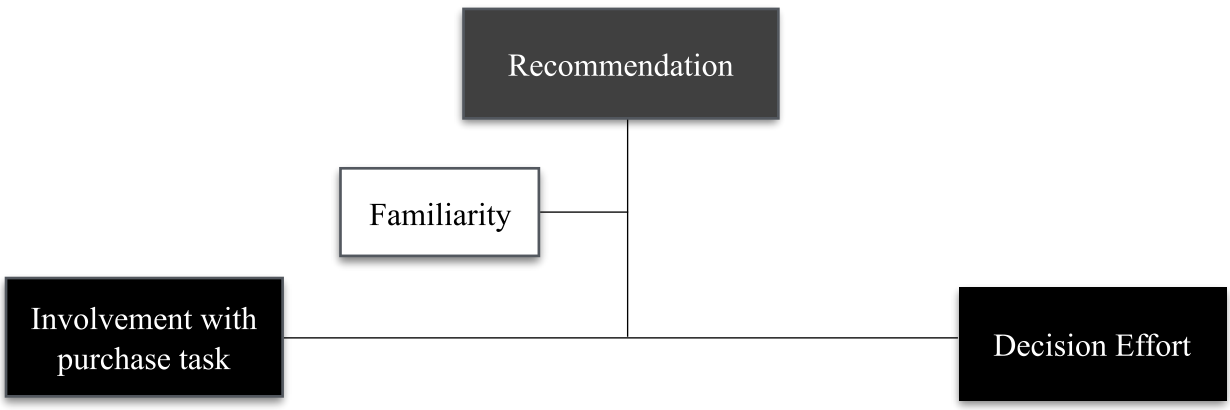
Doner and Scholz (2013), for example, found evidences to support the idea that task difficulty is determinant to the size of the consideration set. So far, research has treated the presence of recommendations at a website as the main independent variable, whereas task difficulty is the moderator. The relation, however, appears to be quite the opposite. It seems more likely to assume that the main driver of decision effort will not be the presence/absence of recommendations, but the level of involvement a consumer demonstrates to a given purchase task. In this case, recommendations would be playing the role of moderators, and not the other way around. If that is true, the following hypothesis will be confirmed:

Hypothesis 2: The presence/absence of recommendations at a website will moderate the effects of involvement with the task on time to make a decision.

In their literature review on advice taking, Bonaccio and Dalal (2006) have alleged for the possibility of a three-way interaction between task difficulty, presence of advice and familiarity with the website determining some aspects of consumer choice. Their focus, however, was on decision accuracy and not on decision effort. Additionally, their proposition has not been tested so far. Bang and Wojdynski (2016) have also found that the level of cognitive demand exerts a moderating role in consumers' attention on personalized advertising. Xiao and Benbasat (2007, 2014) had already proposed this moderating influence of product complexity and product type on decision processes and decision outcomes in purchases assisted by recommendations.

It is possible, however, that the moderating function, in this case, is being performed by the recommendation agent itself, whereas the level of involvement with the purchase task is, in fact, the main variable influencing decision effort. Considering the aforementioned, when it comes to the variable time to make a decision, it is reasonable to suppose that its main driver will not be the presence or absence of recommendations but the level of importance attributed to the product that is being purchased, as well as the purchase task itself. Since the effects of recommendations on decision effort is already hypothesized to be moderated by familiarity with the website, a moderated moderation model (as in Hayes, 2013) seems to be plausible. Furthermore, if Hypotheses 1 and 2 are to be true, than the model presented in Figure 2 will be confirmed.

Figure 2 - Proposed research model



Source: the author

In order to test the whole model presented in Figure 2, the hypothesis to be analyzed is as follows:

Hypothesis 3: Recommendations will moderate the effects of the level of involvement with the purchase task on time to make a decision only in situations where consumers have already developed familiarity with the website.

Considering the aforementioned, one might be tempted to argue that the reduction in time to make a decision is a consequence of a consumer accepting the recommended option and, consequently, purchasing the suggested product. Nevertheless, that may not be quite accurate, especially if recommendations are considered to function as decision aids and not as persuasion agents themselves. Although some authors have proposed possible influences of recommendation agent as persuasion tools (Komiak & Benbasat, 2004b; Fogg, 2005; Gretzel & Fesenmaier, 2007), the prevailing assumption in recommendation agents research is that they function as decision aids offering shortcuts to complex decision processes (Ricci *et al.*, 2015). Considering that to be true, then even in cases where the recommended option is not the final purchase choice, recommendations will cause a significant reduction in time to make a decision (Bonaccio & Dalal, 2006; Adomavicius *et al.*, 2011; Adomavicius *et al.*, 2013).

Instead of looking at the recommended option as the ultimate answer to their decision problems, consumers will rely on recommendations to make a final decision. In such case, recommendations would be causing some sort of anchoring effect. Adomavicius *et al.* (2013) have alleged that recommendations may be provoking anchoring effects that drive consumers to consider biased decision options. That might be true if one considers the system that generated the recommendations as biased or flawed. In other situations, if the system is capable of inferring correctly consumers' preferences, it may be actually helping consumers to ease their decision processes by creating frames of reference, specially when the consumer does not have previous knowledge about the product. If that is to be true, the following hypothesis can be derived:

Hypothesis 4: Consumers will use recommendations as frames of reference and will prefer to buy products that have similar characteristics with the recommended option.

Following the previous reasoning, if it is true that consumers use recommendations as references for their purchase choices, then time to make a decision will be reduced when a recommendation is presented, even if the recommended option in not the purchased product. In these cases, recommendations will not act as means of persuasion, yet they will play the expected role of a decision aid.

The same way, purchasing a recommended option does not mean that the consumer has bought the product because s/he was influenced by the system. In those kinds of situation, it can happen that the recommended product is, in fact, the best option for the consumer, and the system ways being accurate when presenting it. Although it seems counterintuitive at a first glance, it is probably the case that if recommendations do not actually provide assurance for the decision maker, than people purchasing in websites with recommendations will pass through the same internal processes of cognitive dissonance as any other consumer.

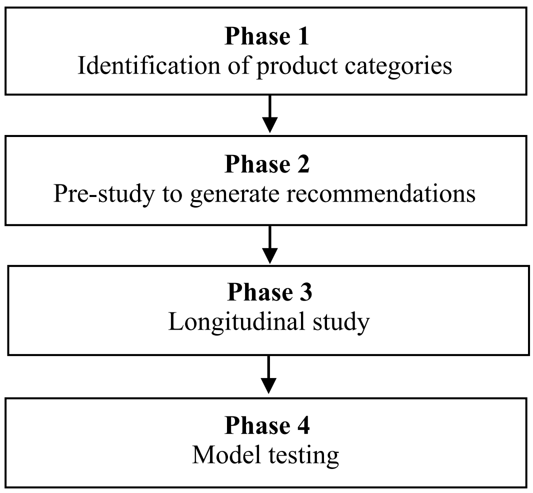
Hypothesis 5: Recommendation acceptance will not be determinant for decision effort and confidence in the decision.

3 METHOD

The main issues related to the method developed for this research will be presented in this chapter. It is important to note that it consists of four complementary phases. In phase 1, product categories for which consumers are more susceptible to recommendations when purchasing online were identified based on a thorough bibliographic research. After defining the best category, five products were chosen to be used in the experimental sets.

In the second phase, a pre-study was conducted with a group of subjects selected to perform the purchase tasks reported in Appendix 1. During this step, the purchase choices made by the respondents were analyzed and used to create product recommendations for the experimental phase. In phase 3, a longitudinal experiment was conducted with a test and a control group, to analyze changes in decision process along the execution of the tasks. The final phase consisted on modeling consumers' responses to recommendations based on empirical data. Figure 3 depicts the whole research framework.

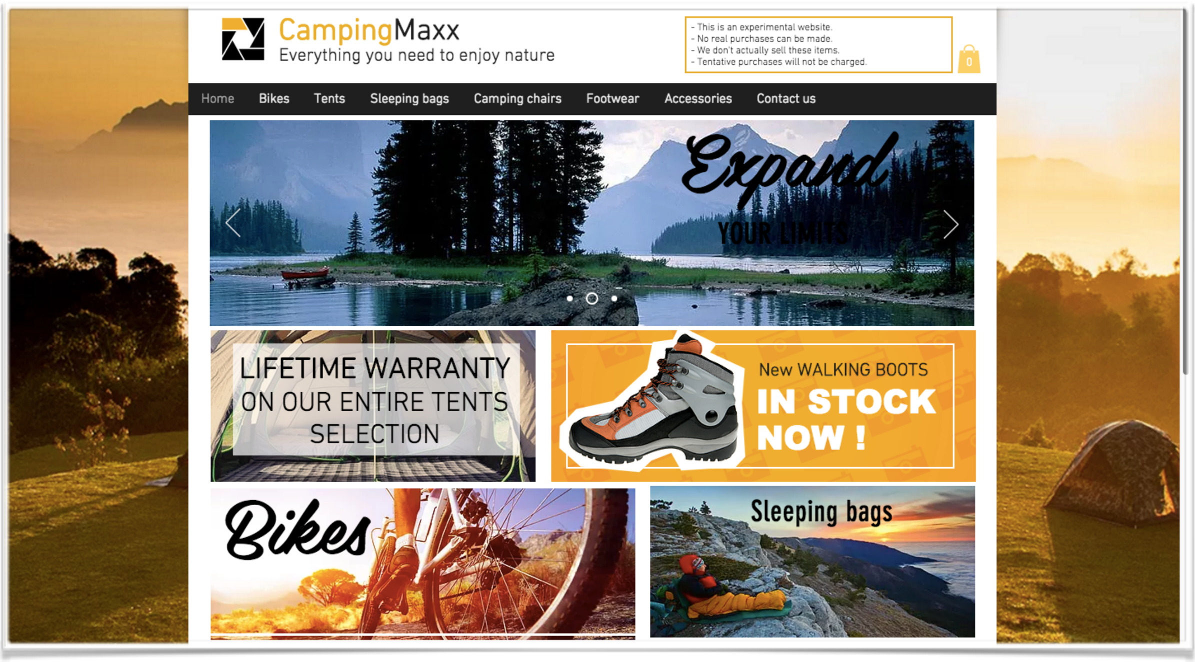
Figure 3 - Framework of research process



Source: The author

An experimental website store was created to be used in phases 2 and 3 and was made available at the following address: www.campingmaxx.online. The website is no longer on air due to maintenance costs, but some screenshots will be shown in the following sections. Website's name and design were created mimicking a real ecommerce store selling the same items. All the products and prices were copied from that website with the aim of making the simulated purchase tasks as close to a real purchase as possible. Figure 4 shows a screenshot of the website's first page. A more detailed sample of the website's design can be found in Appendix 3.

Figure 4 - CampingMaxx's homepage



Source: The author

In order to avoid misunderstandings, the header of every website page had a warning telling about its experimental intents. Additionally, the website could only be accessed by typing its URL in the browser's address bar and could not be reached by search engines. This was to assure that only invited subjects would be able to browse it. The following subsections will detail the methodology used in each one of the four phases of this research.

3.1 Phase 1 - Identification of product categories

This phase consisted of analyzing all published papers using a behavioral approach to recommendations, in order to identify how they dealt with empirical investigations in their experimental designs. Detailed information about this study can be found in Verruck and

Nique (2017). After a complete scan and tabulation of all published papers, studies about recommendations were split into two different categories: one destined to solve computational problems and the other addressing behavioral and managerial problems related to the use of recommendation agents. It is again necessary to reinforce the focus of the mentioned study solely on the later.

Since the classification in the proposed categories was arbitrary and was not previously defined in other publications, the first step of the mentioned bibliometric study was to find all published papers with either one of the mentioned approaches. The data collection was made in two different sources: Google Scholar and Web of Science Database. For that, four key words were used, and their variations: (i) recommendation agents; (ii) recommendation systems; (iii) recommender agents; and (iv) personalization agents in both databases. These two datasets of bibliographic records were retrieved using a topic search and a citation expansion.

After filtering the results, 979 articles that where considered as directly related to the field of recommendation agents research. These articles where, then, classified in one of two groups, according to the research questions they addressed. Research questions related to modeling and algorithmic approaches where classified in one group and the remaining where classified in the second group. At the final filtering, a total of 175 articles using behavioral approach remained, from which 76 used an experimental methodology.

The experimental studies were analyzed to understand the type of products they used in their designs. The products were related to a wide range of consumption experiences going from tangible products to highly intangible services. A great deal of them, however, focused on tangible products. Table 11 presents the findings.

Table 11 - Type of products used in the experimental studies

Product	**Nr.**	**Product**	**Nr.**	**Product**	**Nr.**
Digital cameras	17	Mouse	2	Multimedia speaker	1
Movies	8	Calculator	2	Wireless printer	1
Laptop	7	Red wine	2	Shoulder massager bag	1
Music	5	Washing Machines	1	Tv show	1
Books	4	Thumbdrive	1	Jokes	1
Cell phone	3	Spring Break destinations	1	Rug	1
Backpacking tent	3	Car	1	Fragrance	1
Mp3 Player	2	Greetings card	1	Tooth brush	1
Energy bar	2	GPS	1	Behavior adoption	1
Apartment	2	Compact stereo system	1	News	1

Source: Research data

It is possible to note that most of the studies (75%) focused on physical products and, from these, a great amount (61.4%) used electronic devices for the purchase simulations in the experimental sets. As one of the intentions of present research was to be as close to a real purchase as possible, it was considered that electronics could not be the best option, since they are too sensitive to brand evaluations and omitting this information would make the experimental set lose an important part of external validity. Some other products as books, music and films were also not considered a good option because they are too sensitive to personal taste, so it would make it harder to manipulate the recommendations.

It was opted, then, to simulate purchase tasks with camping equipment, because these products are not commonly known by the general public, what would allow to isolate variables such as brand awareness and internet purchase experience more easily (Senecal & Nantel, 2004; Senecal *et al.*, 2005). A series of five purchase tasks was created for the next phases. As previously mentioned, the tasks can be found in Appendix 1. A list of the products is shown at Table 12.

Table 12 - Products used in the experimental tasks

Product	Goal price	Number of options available at the goal price	Price range		Total number of options available at the website
			Price of the cheapest option	Price of the most expensive option	
Camping chair	-	-	6.00	130.00	95
Tent	125.00	15	15.00	899.99	95
Sleeping bag	50.00	15	8.00	240.00	95
Walking boots	190.00	15	30.00	470.00	95
Mountain bike	550.00	15	34.97	1399.99	95

Source: The author

The order of the experiments was as applied as exposed in Table 12. Task number one functioned as a calibration phase, so both groups executed the purchase task without recommendations. The order was arbitrarily chosen as a way to establish some kind of plot to all the tasks. There was also an intention to keep the most expensive products in the final rounds, so it would be possible to accompany the influence of recommendations as the level of monetary involvement rises. With the intention to isolate other variables that could be interfering with task complexity, the total number of alternatives available for each product was set fixed in 95 and in 15 for the number of options available at the goal price, condition based on guidelines provided in previous research (Häubl & Trifts, 2000; Widing & Talarzyk, 1993). The high number of alternatives was intentionally chosen based on Punj and Moore (2007), who found that as the number of alternatives increase, consumers tend to focus more on effort reduction than accuracy.

3.2 Phase 2 - Pre-study to determine product recommendations

Since the main objective of present research was not to test system accuracy, but to understand how consumers respond to recommendations along time, purchase tasks were manipulated in such a way that the best product options would be clearly predefined. There were, then, three options for each set of products that, once thoroughly considered, would be clearly the best alternatives for the purchasing test. Before executing the longitudinal experiment, a pre-study was performed as a way to confirm if the recommendations would match consumers' preferences. Participated of this phase a group of 32 subjects that performed tasks 2 to 5 shown in Appendix 1, with no recommendations presented. Participants' responses were analyzed and the results are depicted in Table 13.

Table 13 - Analysis of recommended products used in the experimental tasks

Product	Option 1	Option 2	Option 3	Other options	Concentration
Tent	29.57%	16.38%	9.32%	44.73%	55.27%
Sleeping bag	18.66%	17.18%	18.96%	45.20%	54.80%
Walking boots	9.09%	9.09%	9.09%	72.73%	27.27%
Mountain bike	12.20%	8.50%	6.10%	73.20%	26.80%

Source: The author

Considering the two initial tasks, it is possible to note that consumers' choices are concentrated around the three options manipulated to be the best alternatives to choose in each task. For the two final tasks, it was possible to note that consumers' choices were more dispersed, what suggested that there were factors influencing decision processes other than the conditions established in the task assignments. After a deeper analysis, it was possible to observe that these factors were, in fact, related to the subject's gender. Since the two mentioned products are more sensitive to design issues, it was possible to note that men and women considerably differed in the products they chose. After separating these groups from the analysis, data showed the same levels of concentration as in the other products. Table 14 shows the results.

Table 14 - Altered products used in the experimental tasks

Product	Option 1	Option 2	Option 3	Other options	Concentration
Walking boots - men	28.36%	24.44%	13.32%	33.88%	66.12%
Walking boots - women	17.78%	15.18%	12.36%	54.68%	45.32%
Mountain bike - men	19.12%	23.19%	14.15%	43.54%	56.46%
Mountain bike - women	14.26%	18.65%	21.10%	45.99%	54.01%

Source: The author

It is possible to note that, after the reported adjustments, the predictive power of the task over consumer's choice settled at around 0.5. One could argue that this number is low, given the fact that the best purchase options were actually manipulated to fit three specific products, but it is common that in experimental sets where many alternatives are presented participants' choices will be dispersed around several alternatives, even if there is a specific set of products that better fit some predefined preferences (Punj & Moore, 2007, Häubl & Trifts, 2000; Widing & Talarzyk).

3.3 Phase 3 - Longitudinal study executed in a simulated ecommerce store

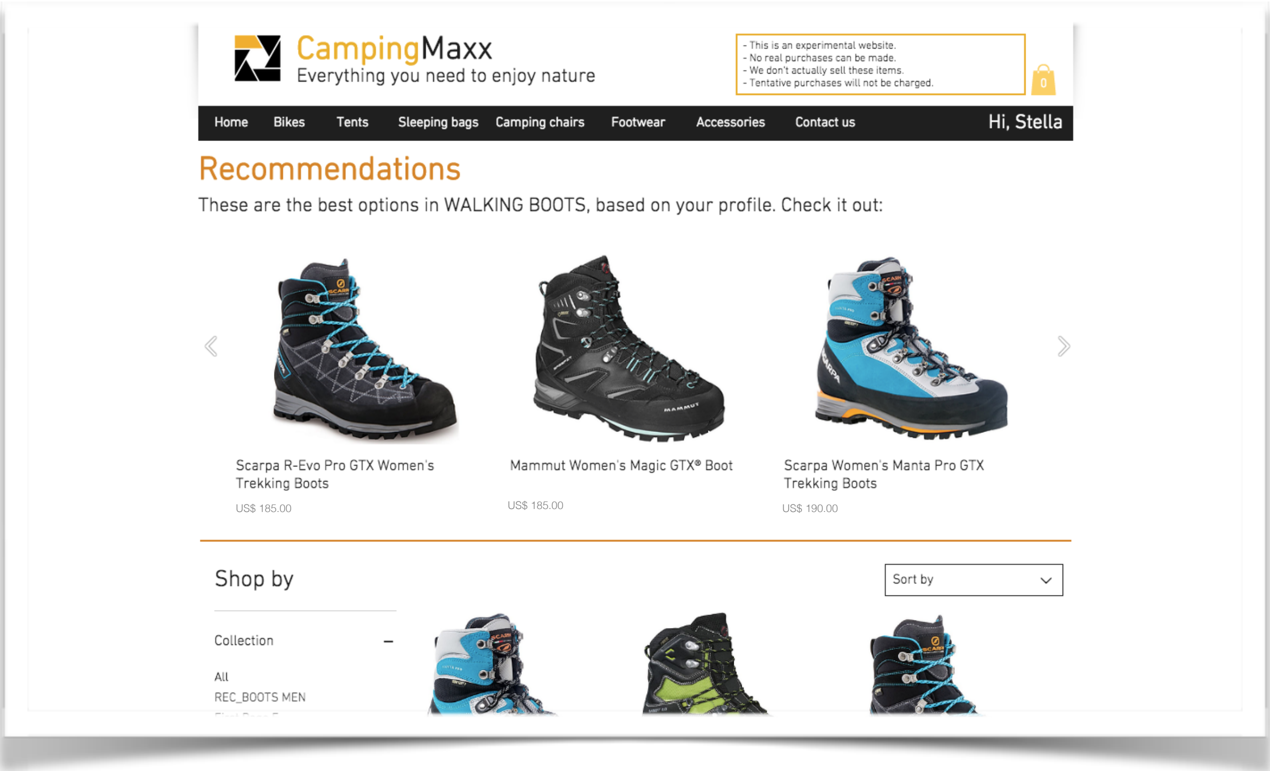
A controlled experiment was conducted to test the effects of number of interactions with the same recommendation agent on decision effort and some possible moderating effects when considered, in a model, with involvement level and the following profile variables: (i) gender, (ii) age, (iii) frequence of online purchasing, and (iv) shopping skills. The whole longitudinal phase consisted of five purchase tasks to be executed with a one-week interval between each other. The one-week interval was stablished considering previous concerns already resported in literature (i.e. Charness *et al.*, 2012, Kaplan *et al.*, 2017) based on the assumption that this lag would provide enough time to minimize the impact of practice and retest effects (Thorndick, 1922, Benedict & Zgaljardic, 1998, Jones, 2015).

Task number one functioned as a calibration phase, so both groups executed the purchase task without recommendations. The order was also arbitrarily chosen as a way to establish some kind of plot to all the tasks. There was an intentional purpose to keep the most expensive products in the final rounds, so it would be possible to accompany the influence of recommendations as the level of involvement rises. With the intention to isolate other variables that could be interfering with task complexity, the number of options available and the number of alternatives at the goal price were set fixed.

Since the main objective of present research was not to test system accuracy, but to understand the way consumers responses to recommendations changed along time, purchase tasks were manipulated in such a way that the best product options would be clearly predefined. For each product category, ten nondominated alternatives were made available. That is, 10 out of 95 products in each category were mutually nondominated and would fulfill each task requirements. The choice to have ten best alternatives for each purchase problem, instead of only three (as in the number of recommendations to be presented), was to allow a greater possibility of choices and not to force people to choose the product being recommended.

The simulated purchase tasks where distributed to a test and a control group to be executed within the period of two months. The only manipulated variable between both groups was the presence/absence of recommendations at the website. The recommendations were presented as a Top n list of 3 items, based on the results reported in Tables 13 and 14, as depicted in Figure 5.

Figure 5 - Screenshot of product page with recommendations



Source: the researcher.

3.3.1 Sample and incentive

An initial sample of 945 people participated in the calibration phase. However, after five weeks the drop-out rate was of 75.8%, remaining only 229 subjects at the final wave.

Although the drop-out rate is above the reported average of 47% (Jadidi *et al.*, 2017; Brüdel & Trappman, 2017), it can be attributed to distance between researcher and subjects during the application of the experiments and also to the time constraints imposed for the participation in each wave (subjects were only allowed to participate within four hours after the release of the task).

All participants were randomly assigned to either the test or control group after the first task and continued in the same group for the following waves. In addition to a pre-specified payment for each task accomplished, subjects were offered an extra payment in the case they were able to complete the five tasks in compliance with all predefined conditions. This was intended to increase the validity of the findings by making the shopping task more consequential. At the end, all respondents who could accomplish the requirements were, in fact, awarded the promised bonus. Data were collected through Qualtrics and Amazon Mechanical Turk with participants from the United States.

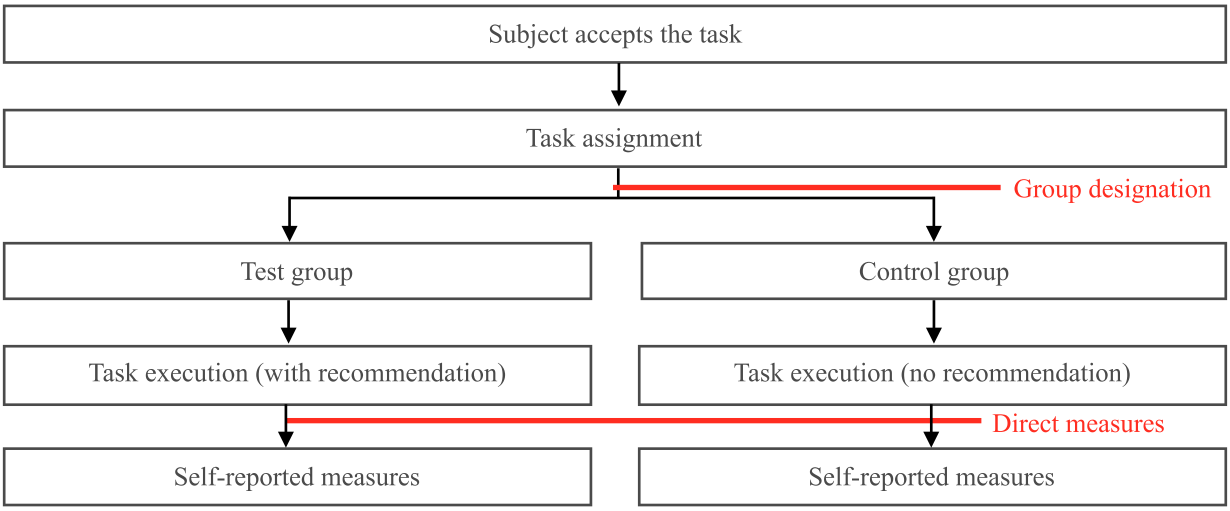
3.3.2 Procedures

After accepting the task, participants were directly presented to a purchase problem they should solve by accessing CampingMaxx website using a link available in the task form. The link would randomly direct each participant to a test or a control website, whose only difference was in the presence or absence of recommendations at the product's page, respectively. The website design and the home page were the same in both groups. The task should be performed, as in any real purchase, until an order number was provided. All measures related to website browsing were registered using Google Analytics. Data collected through this tool were (i) time to make a decision, (ii) purchased product, and (iii) number of alternatives in the consideration set.

After executing the task assignment, participants were asked to fill a self-reported questionnaire indicating the following variables: (i) perceived decision effort, (ii) involvement with the task, (iii) confidence in the decision. A manipulation check was also performed in order to assure that subjects in the test group had seen and considered the recommendations presented. Subjects who alleged not have seen the recommendations were excluded from the final sample.

Other measures collected in alternated waves (see Table 15) were (i) perceived recommendation quality, (ii) trust in RA and (iii) reactance to recommendations. Profile and control data, similarly, were collected in alternated waves, as a way to balance the amount of information subjects needed to provide each week. All the proposed tasks should be executed at the same time and day of the week, in order to reduce the occurrence of possible contextual factors influencing decision processes. Figure 6 presents the flowchart of the procedures adopted in the experiment.

Figure 6 - Flowchart of the experiment execution design



Source: The author.

3.3.3 Measures

During the purchasing process, the following dependent measures were collected: (i) time spent to make a decision and (ii) recommendation acceptance. Time to make a decision was computed directly, starting when the results page was first shown and finishing when the purchase was completed. In order to facilitate statistical calculations, time was computed in seconds.

Recommendation acceptance was computed as a binary variable coded as 1 if the subject bought one of the recommended items and 0 otherwise. After finishing the purchase, subjects were finally asked to answer a self-reported questionnaire indicating their perceived cognitive effort and their confidence in the decision. Both indicators measured based on Cooper-Martin (1994). Trust in the recommendation agent was measured based on Cramer *et* *al*. (2008). These were all used as possible covariates to be tested during statistical procedures.

To determine participants' level of involvement or engagement with the task, we inquired, in accordance with Karmarkar and Tormala (2010), two questions adapted from past research (e.g., Petty & Cacioppo 1979): "How involved did you feel with the task?" and "How interested were you in the task?" Responses were provided on scales ranging from 1 (not involved at all, not interested at all) to 9 (very involved, very interested). (Karmarkar & Tormala, 2010).

The manipulation check was made by asking participants to indicate if they visualized the recommendation and if they considered the recommendation when making the decision. It was also asked about participant's previous experience with the purchased product. Subjects who did not visualize the recommendation or show previous knowledge of the product were eliminated from the sample. As an additional measure, information to identify possible reactant behavior was collected, based on Hong and Faedda (2006).

Some control measures were also necessary, in order to test possible effects of covariables interfering with the results. The control variables measured were subject's expertise with online shopping (Novak & Hoffman, 2000) and with the product (Teichmann, 2011). Demographic data were also collected, so possible interference of profile variables could be tested during statistical analysis. Due to the explicit characteristics of some of these measures, they were only assessed in specific rounds. Table 15 shows the schedule for each round and their correspondence to the questions in the self reported in Appendix 2 .

Table 15 - Measures collected in each wave

	Round 1	**Round 2**	**Round 3**	**Round 4**	**Round 5**
Time to make a decision*	x	x	x	x	x
Recommendation acceptance*	x	x	x	x	x
Perceived effort	x	x	x	x	x
Involvement level	x	x	x	x	x
Confidence in the decision	x	x	x	x	x
Manipulation check		x	x	x	x
Recommendation assessment		x			x
Reactance		x			x
Trust in RA		x			x
Profile information				x	
Shopping experience			x		

* Direct Measure (data collected directly from the website via Google Analytics)
Source: the researcher

3.4 Phase 4 - Modeling recommendation effects on decision making effort

The underlying assumption in which this thesis is constructed states that the benefits of using recommendation agents are not immediate, yet they evolve across time the same way human relationships do. A great amount of research in the field thus far analyzes consumer responses to unknown electronic agents. This is relevant, considering the large number of websites and electronic agents currently available, what takes consumers to interact with unknown agents frequently. However, as the use of specific online retail stores for regular shopping tends to become a habit, consumers will likely visit the same agent multiple times and begin to form stable evaluations of the agent's performance (Cooke *et al.*, 2002).

This means that during the initial purchases, even if the system were capable of inferring correctly user preferences by implicit elicitation methods, this probably will not generate a reduction in decision-making time, because consumers will tend to evaluate not only the options available but also the recommendations presented (and the recommendation agent itself). During these initial steps, then, consumers will more likely prefer accuracy to effort-saving, that is, they will prefer spending more time to carefully consider the options and recommendations presented than to reduce the effort necessary to make a decision.

Additionally, in repeated purchases, it is plausible to assume that consumers will have different levels of involvement with the purchase task. These different levels of involvement may vary due to some characteristics of the product (such as price or importance attributed to it), consumer expertise and level of formulation of the decision problem. Therefore, it seems that consumers purchasing in any condition (with or without recommendations) will have their decision effort mainly defined by the level of involvement with the task.

If the previous assertions are to be significant, then it is possible to hypothesize an interaction effect between the mentioned variables will occur. This interaction effect will, in fact, account for the moderating role of involvement with purchase task in amplifying (or, in this case, reducing) the effect of the manipulated variable. That being true, a predictive model for measuring average time to make a decision will be defined by the following equation:

$$Y = \alpha + \beta_1 r + \beta_2 v + \beta_3 t + \beta_4 vt + \beta_5 rt + \beta_6 rv + \beta_7 rtv + \varepsilon \qquad (1)$$

Where the notation used is stated as follows:

Y	time spent to make a decision (measured in seconds)
r	dummy variable measuring the treatment condition (presence of recommendation)
v	level of involvement
t	number of waves (measured as an integer starting from zero)

The main effects will be given by the levels of β_1, β_2 and β_3, while the moderating effects will be represented by the interaction between variables, with the levels for β_4, β_5, β_6 and β_7.

Another important issue to consider is that most probably recommendation acceptance will not be directly related to decision effort. It means that the mechanism that provokes effort reduction in purchases with the presence of implicit recommendations will not actually be leading consumers to buy the recommended options. This may happen because recommendations are supposed to act as decision aids and not as means of persuasion. Considering that, recommendations will be used as parameters to confirm or refuse certain purchase options but not as direct shortcuts for consumers' choices. A possible evidence of that would be a significant difference in the variances in the number of products chosen and also in the average price for both groups. Accordingly, the inequalities accounting for these evidences would be:

$$\sigma_c^2 > \sigma_t^2 \qquad (2)$$

In this formula the symbol $\boldsymbol{\sigma}_c^2$ represents the price variance for purchase options in control group and $\boldsymbol{\sigma}_t^2$ represents the same measure in the test group.

4 RESULTS AND DATA ANALYSIS

This study counted with 229 subjects participating in the experimental study until the final round, other 32 had to be eliminated from the sample for containing missing values or not having responded adequately to the manipulation. Before data analysis, following Hair et al.'s (2005) suggestion, some preliminary verifications were conducted as a way to identify outliers, normality and homoscedasticity of the data.

By calculating Mahalanobis distance, it was possible to identify the existence of outliers. In the present research, a total of 8 cases had to removed from the dataset according to this criteria. At the end, a total of 189 valid responses were considered, being 95 in the test group and 94 in the control group. In the sample, 61.5% was composed by male participants and 84.9% had college degree or higher. The age average was of 25.3 years.

Complementarily, the normality of the distribution was initially verified by analyzing the values of skewness and kurtosis. In the analysis, values of skewness and kurtosis were, respectively, 1.477 and 3.295. Besides these measures, the Kolmogorov-Smirnov (K-S) test was also applied, from which the value of 0.122 with a significance level of $p=0.000$, confirmed the normality distribution of the dependent variable time to make a decision.

The performed tests confirmed the necessary assumptions for the adequacy of the statistical techniques adopted in the following analyses. The test for the main effects followed a case-by-case approach, according to Bollen and Curran (2006) propositions. The follow-up analyses considered the existence of possible covariates influencing the variance of the dependent variable across time. Based on the obtained results, a model considering a three-way interaction (in which the number of interactions was treated as a continuous variable) was tested, using the analytical procedures proposed by Hayes (2013).

4.1 Testing for simple effects

In order to test if there was a significant difference between groups purchasing with the assistance of recommendations when compared to a control group, statistical tests focused on the latent curve model, using a case-by-case approach. This approach posits the existence of continuous underlying or latent trajectories. The pattern of change in the repeated measures provides information on the trajectories. Latent means a process that is not observed directly. The trajectory process is observed only indirectly using the repeated measures. Importantly, this trajectory can differ by individual case. The statistics for purchasing time are shown in Table 16.

Table 16 - Descriptive data: time to make a decision

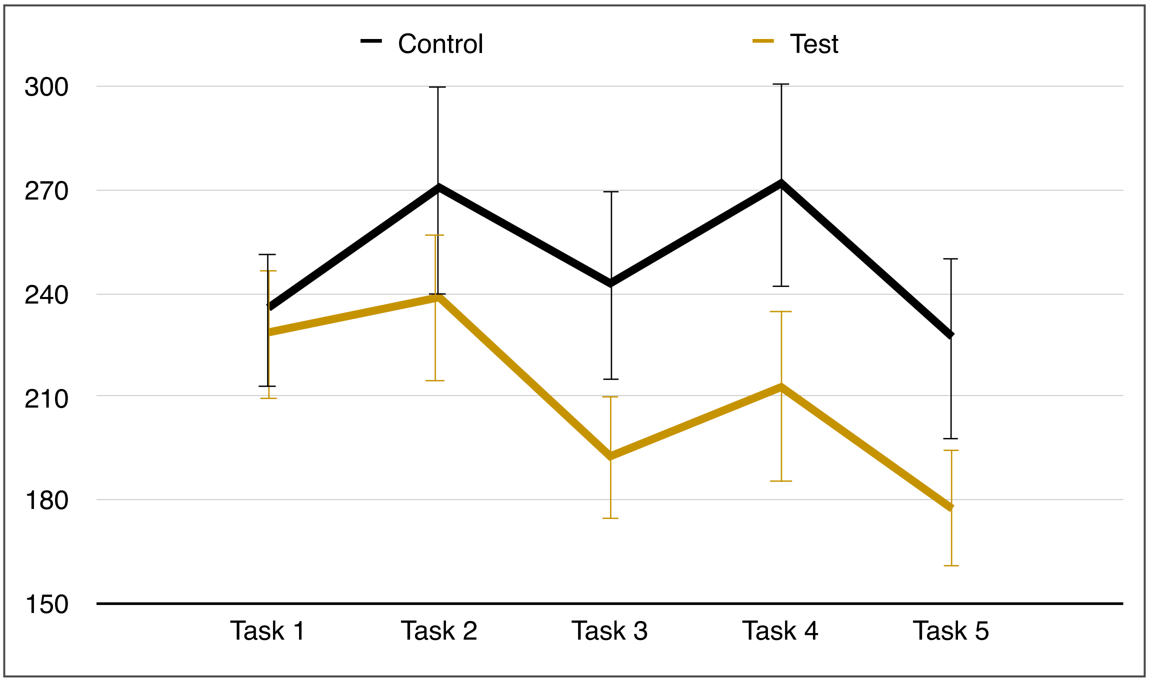
Round	Group	N	Time Average	Standard deviation	Confidence interval		t	Sig.
					Maximum	Minimum		
Round 1	Test	95	228.688	107.549	250.31	207.06	-0.437	0.662
	Control	94	235.813	93.427	254.70	216.93		
Round 2	Test	95	238.858	107.558	260.49	217.23	-1.514	0.132
	Control	94	270.702	149.555	300.94	240.47		
Round 3	Test	95	192.761	89.550	210.77	174.75	-2.664	0.008
	Control	94	242.912	138.464	270.90	214.92		
Round 4	Test	95	212.833	112.038	235.36	190.30	-2.824	0.005
	Control	94	271.930	144.919	301.23	242.63		
Round 5	Test	95	177.548	81.947	194.03	161.07	-2.491	0.014
	Control	94	227.427	155.122	258.79	196.07		

Source: research data

At baseline, the test and control groups have very similar mean scores, the same happened in the second round. Using a t test for independent samples, it was possible to find significant differences for means in purchases number 3 ($t = -2.664$, $df = 187$, $p < 0.05$), number 4 ($t = -2.824$, $df = 187$, $p < 0.05$) and number 5 ($t = -2.491$, $df = 187$, $p < 0.05$). As for purchases number 1 ($t = -0.437$, $df = 187$ $p > 0.05$) and number 2 ($t = -1.514$, $df = 187$, $p > 0.05$), no significant differences could be found. No mean differences were indeed expected for task number 1, since it was only a calibration phase, and participants were not subjected to any kind of treatment in neither of the groups. Data from this phase show that individuals in both groups initially demonstrated to have similar kinds of purchase behavior when executing the same purchase task without recommendations.

As for task number 2, although there is a numerical difference between the two groups, it was not statistically significant. This indicates that only after the first interaction with recommendations, subjects were actually influenced by them. In tasks 3, 4 and 5, reduction in time to make a decision was of 20.6%, 21.7% and 21.9%, respectively. These summaries suggest that the manipulation had a significant effect on time to make a decision, whereas a relatively small improvement is seen over time in the control group. This implies that recommendation effects may be stable over time, although a few previous interactions may be needed before that happens. Figure 7 shows the respective mean values and confidence intervals.

Figure 7 - Averages on time to make a decision for test and control group



Source: Research data

Following Bollen and Curran (2006) and Maxwell et al. (2008), results analysis also considered a case-by-case approach to compare the trajectory equation and equations for the mean intercept and mean slope using a regression analysis for each individual observation in both groups. According to Bollen and Curran (2006) conceptualizing stability and change in terms of individual trajectories enables the articulation and assessment of a large array of research questions that might not be easily accommodated with other techniques. Then, each case can have a separate trajectory, and a mean group trajectory and variability around the mean are available. This way, there is a possibility to incorporate predictor variables and model individual differences in trajectories across cases. Table 17 shows point estimates from OLS Regressions for Case-by-Case Approach for Test and Control Group.

Table 17 - Point Estimates from OLS Regressions for Case-by-Case Approach for Test and Control Group

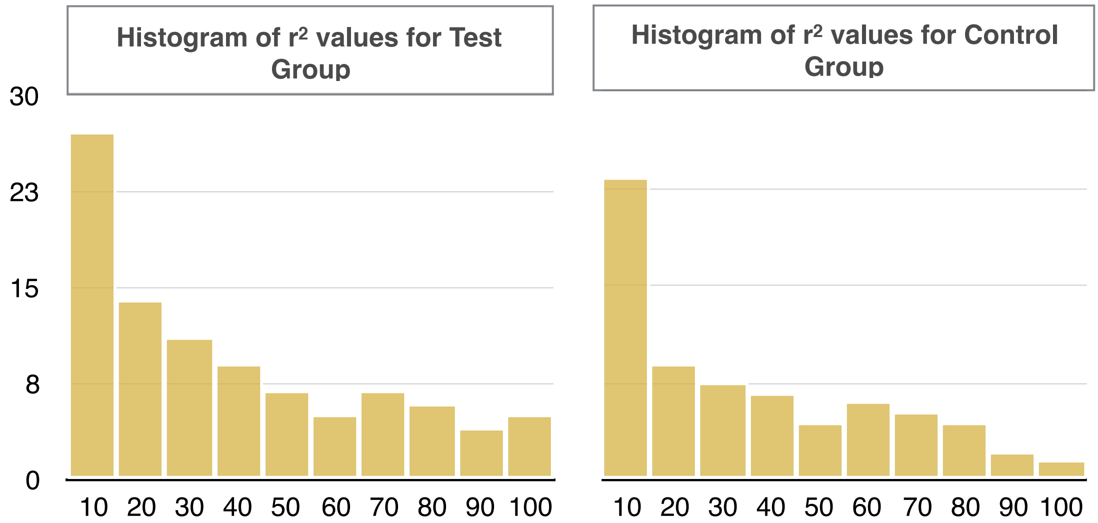
Parameter	Estimator	
	Test Group	**Control Group**
n	95	94
r^2 (mean)	0.34	0.31
var (ϵ)	66.412	148.369
$\mu\alpha$	235.80	252.87
$\mu\beta$	-12.83	-1.55
$\psi_{\alpha\alpha}$	85.248	204.61
$\psi_{\beta\beta}$	5.799	29.38

Source: Research data

Here the mean r^2 value for all 95 regressions in test group is 0.34 whereas in control group the variance explained was of 0.31. This indicates that the estimation of an underlying linear trend of the number of interactions with the system on average accounts for a slightly fair amount of the observed variance in time to make a decision, in both groups. However, this distribution has considerable spread where many subgroup regression lines have r^2 values of 0.5 or more, reflecting strong linear trends. Others are more moderate. Still others are quite low (< 0.1), indicating that in some subgroups the linear trend is weak.

Additional analysis is needed to better understand why the trajectory model is not a good fit for these individual cases. For Bollen and Curran (2006), the r^2 values for each regression provide information on the closeness of the linear trajectory to the data points observed. A distribution of r^2's clustered at high values indicates that the variance in the points observed is well described by the linear trajectory. Histograms of r^2 values for OLS regressions of number of interactions on time for both groups are depicted in Figure 8.

Figure 8 - Histogram of r^2 values for OLS regressions of number of interactions on time to make a decision

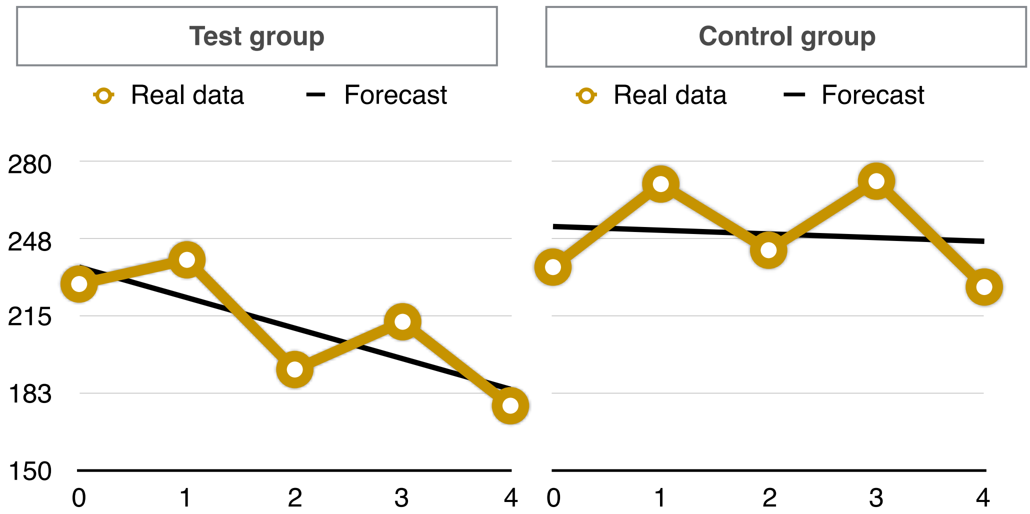


Source: Research data

A closer examination of the plots of those cases with small r^2 values reveals that there may be other variables influencing decision effort together with the presence/absence of recommendations. This calls for other analyses that can account for analyzing interactions with other treatments as well as the occurrence of mediating and moderating variables. Bollen and Curran (2006) also suggest to plot the trajectory line traced by the mean of the intercepts and the mean of the slopes against the mean value of the y values for each point in time. This reveals whether the mean trajectory line does an adequate job of tracing the means of the observed variables. If it does not, they defend that the researcher should consider alternative nonlinear forms for the trajectory. Figure 9 superimposes the mean trajectory line on the mean values of each wave of data for both groups.

It can be seen that the OLS trajectory fitted to the means of time to make a decision over all cases appears to reflect a good fit to the data means observed in test group. As for the control group, average time to make a decision appears to be less affected by the number of interactions, although it seems to have followed the same patterns as in test group.

Figure 9 - OLS-fitted trajectory line superimposed on means of time to make a decision



Source: Research data

It is possible to note that the mean slope in the test group is significantly steeper than in control group, indicating a significant effect of the treatment on the dependent measure as already shown in Table 17 and Figure 7. It is possible, now, to test for the magnitude of the effects of recommendations in decision effort. A regression analysis was, then, performed on the collected data, using presence/absence of recommendations (*r*) as a dummy variable and round number (**λ**) as an ordering variable, representing time passage, in number of weeks. In this case, λ_t is a constant where a common coding convention is to have $\lambda_1 = 0$, $\lambda_2 = 1$. In the case of a linear trajectory model, $\lambda_t = t - 1$, for all t. This procedure makes $\boldsymbol{\alpha}_{10}$ values equal to the initial total average in the whole sample for both groups, avoiding possible biasing, since group assignment was posterior to the first task execution. Results are shown in Table 18.

Table 18 - Regression analysis for time to make a decision comparing experimental groups

	Beta	Standard model	t	Sig.
(Constant)	271.423	11.182	24.273	0.000
r	-39.619	8.765	-4.502	0.020
λ	-7.222	3.099	-2.331	0.000

Source: research data

Since r_i is a binary response variable, it is possible to interpret the coefficient of beta in Table 18, as differences in means comparing $r_i = 1$ to $r_i = 0$. It is possible to note the highly significant effects of both time passage and recommendations on time to make a decision. Nevertheless, consumers' decision processes are complex and subjected to several contextual variables and some other constraints that are sometimes hard to predict, making additional analyses necessary.

Any model trying to understand consumer behavior will only access reality in a partial manner. So far, it was possible to identify longitudinal differences in response time for consumers in purchases assisted by recommendations as opposed to unassisted purchases, however, experience with recommendations may not be the only driver of this longitudinal changes. In the present research, they actually account individually for only 2.7% of the total variance in decision time.

That leads, then, to the supposition that maybe some other variables are operating in conjunction with recommendations and the passage of time, to increase or decrease response time. Looking at the variations for both groups along the five tasks, and realizing that they follow similar patterns, it is possible to infer that some characteristics of the task could also be influencing time spent to make a decision. The level of involvement with the task, which is a consequence of the importance attributed to the product and to the purchase task itself, could be one of these. Additionally, since the passage of time itself also causes latent variations, it is possible to derive an interaction effect, in such a way that it would be interfering with the whole model. The next subchapter will account for these analyses, but first it looks interesting to see the relation of time to make a decision with perceived decision effort.

Before that, following the suggestion of other authors (e.g. Kurzban *et al.*, 2013; Kleijnen, De Ruyterr, Wetzels, 2007), perceived cognitive effort was measured for each task and, although the results for these repeated measures seemed to have followed the same patterns as in time to make a decision, using a t test for independent samples, it was not possible to find significant differences for means between test and control group in waves number 1, 2 and 4, as shown in Table 19.

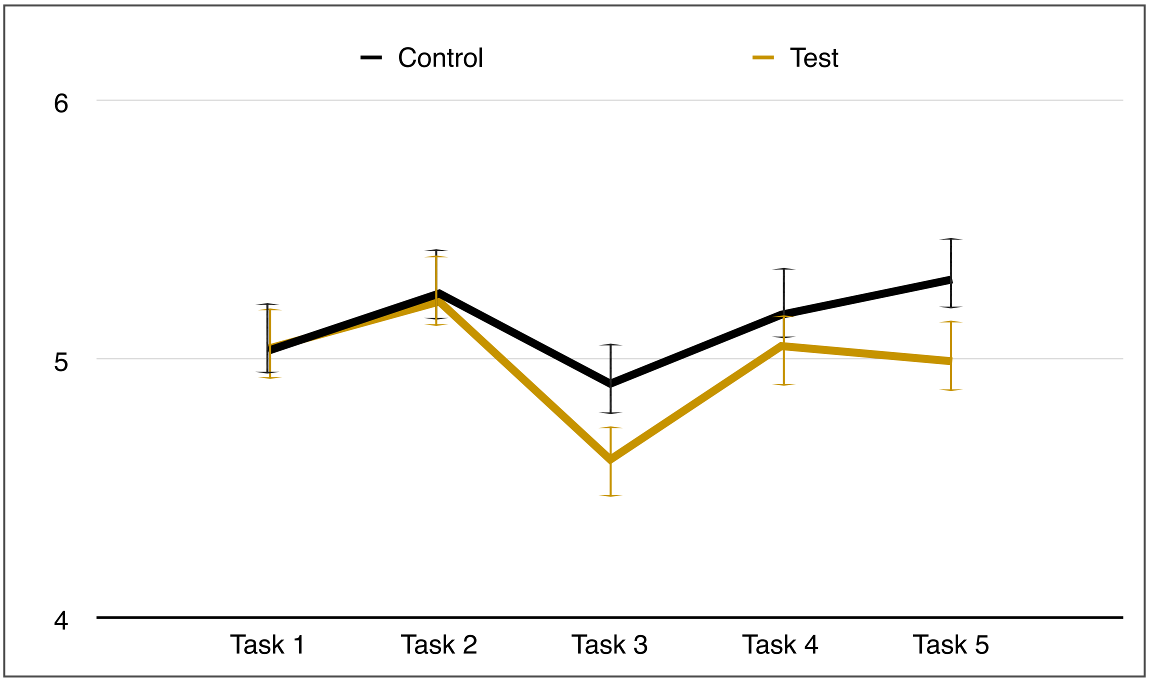
Table 19 - Descriptive data: perceived decision effort

Round	Group	N	Mean	Standard deviation	Confidence interval		t	Sig.
					Maximum	Minimum		
Round 1	Test	95	5.139	1.043	5.349	4.929	0.049	0.961
	Control	94	5.132	0.909	5.316	4.948		
Round 2	Test	95	5.303	0.901	5.484	5.122	-0.214	0.830
	Control	94	5.331	0.873	5.507	5.154		
Round 3	Test	95	4.753	0.756	4.905	4.601	-2.337	0.021
	Control	94	5.017	0.799	5.178	4.856		
Round 4	Test	95	5.148	0.655	5.279	5.016	-0.959	0.339
	Control	94	5.257	0.903	5.440	5.075		
Round 5	Test	95	5.095	0.752	5.246	4.944	-2.631	0.009
	Control	94	5.380	0.737	5.529	5.231		

Source: research data

At baseline, the test and control groups have very similar mean scores, the same happened in the second wave. Using a t test for independent samples, it was possible to find significant differences for means only in purchases number 3 ($t = -2.337$, $df = 187$, $p < 0.05$), and number 5 ($t = -2.631$, $df = 187$, $p < 0.05$). As for purchases number 1 ($t = 0.049$, $df = 187$, $p = 0.961$), number 2 ($t = -0.214$, $df = 187$, $p = 0.830$) and number 4 ($t = -0.959$, $df = 187$, $p = 0.339$) no significant differences could be found. It is interesting to note that for purchase number 4, although perceived effort was smaller in number for the test group, it was not significant at $p < 0.05$. This is probably related to the fact that the purchased product in this task was a product with high involvement, for which people generally appreciate to purchase, leading them to enjoy the purchase process and not noticing decision effort the same way as in the other tasks. Figure 10 shows the respective mean values and confidence intervals.

Figure 10 - Averages on time to make a decision for test and control group



Source: Research data

It was possible to observe a small but significant correlation between these two variables (ρ = 0.160 , p<0.01). This may be related to the fact that people do not have a precise account of the time they take to make a decision, but may also be indicating that other variables are influencing perception. It is important to note, however, that after task number 2, there is a tendency for reducing perceived effort in the same way that for time to make a decision.

4.2 Moderating variables

As already mentioned, some variables were controlled with the intent to evaluate their impact in the found results. Therefore, the control variables were included in the analysis (treated as covariates in the analysis of covariance), and their effects on the dependent variables were identified, as it is about to be shown.

For identifying covariates, first an ANCOVA test was performed on the collected data. This statistical technique evaluates whether population means of a dependent variable are equal across levels of an independent variable, while statistically controlling for the effects of other continuous variables that are not of primary interest, known as covariates. Therefore, ANCOVA is a process through which the effects of one or more strange variables are removed from independent variable before observing the differences among means of two or more populations. This way it is possible to minimize the influence of external variables over the expected effect. The occurrence of covariates among the control variables measured during the experiments was analyzed. Results are depicted in Table 20.

Table 20 - ANCOVA for the dependent variable time to make a decision

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Eta**
Corrected model	6752229.900[a]	4	1688057.475	146.733	0.000	0.384
Intercept	533247.016	1	533247.016	46.352	0.000	0.047
Involvement (*v*)	5741836.859	1	5741836.859	499.106	0.000	0.347
Shopping skill (*s*)	229475.380	1	229475.380	19.947	0.000	0.021
Recommendation (*r*)	305435.303	1	305435.303	26.550	0.000	0.027
Wave (t)	61738.264	1	61738.264	5.367	0.021	0.006
Error	10813999.380	940	11504.255			
Total	67488208.176	945				
Corrected total	17566229.280	944				

a. R squared = .384 (Adjusted R squared = .382)
Source: research data

As it can be seen in Table 20, the treatment (presence or absence of recommendations) caused a significant effect in the amount of time spent to make a decision (F = 30. 67, p = 0.000). Size effect, verified through eta partial squared, represented a total of 2.7% of global variations of the dependent measure. The other mentioned variables also demonstrated to have a significant influence over the dependent variable, what lead to a proposition about some possible moderating effects of these variables, to be explored further in this subchapter.

As for demographic patterns, one-way ANOVA was used for testing differences between all variables related to demographic characteristics (gender, age, education level and frequency of internet usage). At the significance level of 0.05, there are no significant differences for each demographic characteristics. As shown in the table 21, none of demographic characteristics and online shopping patterns are factors influencing time to make a decision, recommendation acceptance or shopping skills.

Table 21 - One-way ANOVA Analysis of the influence of general demographic characteristics*

Source	Time to make a decision	Recommendation acceptance	Shopping skills
Gender	0.315	0.489	0.300
Age	0.958	0.697	0.697
Education	0.904	0.549	0.331
Frequency of purchase	0.868	0.963	0.876

* Table shows levels of significance for the ANOVA test
Source: research data

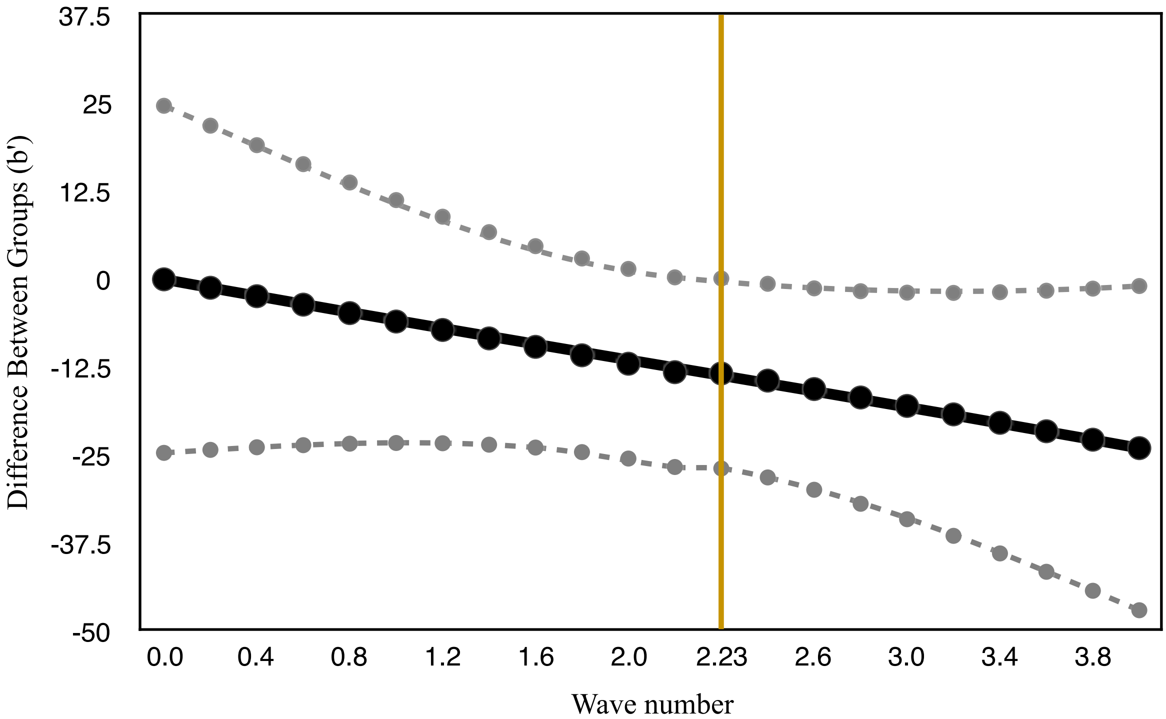
Based on the previous analyses, it was opted for performing an analysis of threeway interaction considering the significant relations of the variables (i) time, (ii) involvement with the task, and (iii) presence/absence of recommendations on decision effort. The analysis followed the procedures described by Hayes (2013). The moderation analysis was ran by Model 3 from PROCESS macro for SPSS by Hayes (2013), which considers the impact of an independent variable X on a dependent variable Y and a moderation of an M variable. The bootstrap sample size was 5000 as recommended by Hayes (2013). The method for confidence interval generation via bootstrapping was the bias corrected, and the Johnson-Neyman test was performed to identify in what point of the moderator variable the independent variable impacts on the outcomes.

The analysis was held considering time as independent factor, time to make a decision as dependent factor and involvement and presence/absence of recommendation as covariates. Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality, linearity, homogeneity of variances, homogeneity of regressions slopes, and reliable measurement of the covariates for the three variables. The proposed model demonstrated to be significant and with a good potential for predicting decision effort ($F(7,397) = 99.9938$, $p<.0001$, $r^2 = .4025$).

As already demonstrated, time directly influences time spent to make a decision (b = -5.3102, se = 2.3158, t = -2.2931, p =.0221, LLCI: -9.8549, ULCI= -.4650). Involvement also influences directly on time spent to make a visit (b = 75.4254, se = 3.4330, t = 21.9706, p < .0001, LLCI = 68.681, ULCI= 82.1627), as well as presence/absence of recommendations (b = -38.9033, se = 6.9884, t = -5.5669, p < .0001, LLCI: -52.6179, ULCI= -25.1887).

Complementarily, the interaction between familiarity and involvement has a statistically significant impact on time to make a decision (b = 14.2026, se = 2.5079, t = -5.6631, p < .0001, LLCI: -19.1243, ULCI= -9.2808), the same way as recommendation and time (b = -14.1623, se = 4.6370, t = -3.0542, p = .0023, LLCI: -19.1243, ULCI= -9.2808). The interaction between recommendations and involvement demonstrated to be slightly significant (b = -12.1072, se = 6.8612, t = -1.7646, p = .0780, LLCI: -19.1243, ULCI= -9.2808) while the interaction between the three could not be accepted (b = -5.9929, se = 5.0146, t = -1.1951, p = .2324, LLCI: -15.8340, ULCI= 3.8483). Figure 11 explicits how the moderators influence these relations.

Figure 11 - Conditional effect of the interaction between involvement and presence of recommendations at different values of number of interactions



Source: research analysis

Regressing presence of recommendations on the manipulation (no recommendation = 0, recommendation = 1), number of interactions with the recommendation agent and their interaction revealed a significant interaction (t = -14.1623, p = 0.0023). To decompose this interaction, the Johnson-Neyman technique was used to identify the range of interactions for which the simple effect of the manipulation was significant. This analysis revealed that there was a significant positive effect of recommendation presentation on time to make a decision for any interaction higher than three (time starts to count on zero). In fact, the number of interactions start to exert a marginally significant effect at interaction number 3 ($t = -1.7646$, $p = 0.078$).

4.3 Relationship between recommendation acceptance and decision effort

A follow-up analysis considered if time to make a decision was somehow related to recommendation acceptance. This may be theoretically consistent if one considers that the mechanism causing effort reduction operates through recommendation acceptance. A descriptive analysis of recommendation acceptance, coded as a dummy variable for all the simulated purchases, showed that 42.6% of participants in test group actually bought the recommended option, although 70.2% of them reported to have actually considered the recommended option before making their choice.

The number of 42.6% of recommendation acceptance is very close to the concentration in product choices obtained in the pre-study, as Tables 13 and 14 previously showed. This suggests that recommendation acceptance is not, in fact, linked to effort reduction. In order to verify that, a *t* test on the subsample was performed comparing, in the test group, the means on time to make a decision between consumers who had bought the recommended option and consumers who have bought different products. Table 22 shows the results of this test.

Table 22 - T test for differences in means for recommendation acceptance

Round	Group*	N	Mean	Standard deviation	Standard mean error	Sig.
Round 2	Yes	41	232.4524	133.755	14.76555	0.651
	No	54	243.7210	108.504	20.88908	
Round 3	Yes	41	183.4356	111.375	17.39383	0.443
	No	54	199.8409	89.882	12.23141	
Round 4	Yes	35	199.5357	132.045	17.04693	0.146
	No	60	212.2565	113.831	17.55071	
Round 5	Yes	44	184.44323	84.314	12.71087	0.497
	No	51	171.6088	96.926	13.57233	

* Did the subject purchase the recommended option?
Source: research data

Results show that there are no significant differences in both groups, attesting that recommendation acceptance may not be an important driver of effort reduction. However, the percentage of consumers in test group who have actually considered the presented option in their consideration sets also indicates that there may be some other heuristics being triggered by recommendation visualization, which is actually the cause of the reduction in time to make a decision.

This can be happening because recommendations are supposed to act as decision aids and not as means of persuasion. Considering that, recommendations are probably being used as parameters to confirm or refuse certain purchase options, but not as direct shortcuts for consumers' choices. A possible evidence of that is the significant difference in the variances in the number of products chosen and also in the price paid for participants in both groups. In order to test that hypothesis, outcomes of the treatment group were compared with the control group using the Wilcoxon–Mann–Whitney two-sample rank-sum test. It is possible to observe that the distributions in both groups differed significantly (Mann–Whitney $U = 77842.500$, $n1 = n2 = 836$, $p < 0.05$ two-tailed).

4.4 Other impacted variables

Finally, scales used to measure recommendation quality, reactance and trust were used to compare participant's evaluations and responses to recommendations at the second and fifth rounds. Results show there was an improvement in all variables between the initial task with recommendations and the final task. Mean differences showed to be significant for either recommendation quality ($M_2 = 4.25$, $M_5 = 5.15$, $t = -4.274$, $p < 0.005$), trust in RA ($M_2 = 5.45$, $M_5 = 5.82$, $t = 2.850$, $p < 0.005$) and reactance ($M_2 = 3.80$, $M_5 = 3.34$, $t = -2.465$, $p < 0.05$).

These variables were not measured in all five rounds in order to avoid possible effects from demand artifacts. It is already well documented that when participating in experiments, specially for behavioral studies, subjects look for clues that help them to discover the real research intention (Orne, 1962) and, based on their inferences, they attribute themselves certain roles either trying to help the researcher to find the expected results or the opposite (Sawyer, 1975). It was considered that asking the same questions about recommendations too many times would call attention for this particular issue, possibly provoking demand artifacts.

One of the consequences of that decision was that, since the variables were not measured in all five waves, due to the high probability of response bias, the relation between them with the model proposed in Figure 13 can only be hypothesized, but not confirmed. Figure 12 shows the evolution of these variables in both rounds.

Figure 12 - Variations in perceived recommendation quality, trust and recommendation along time

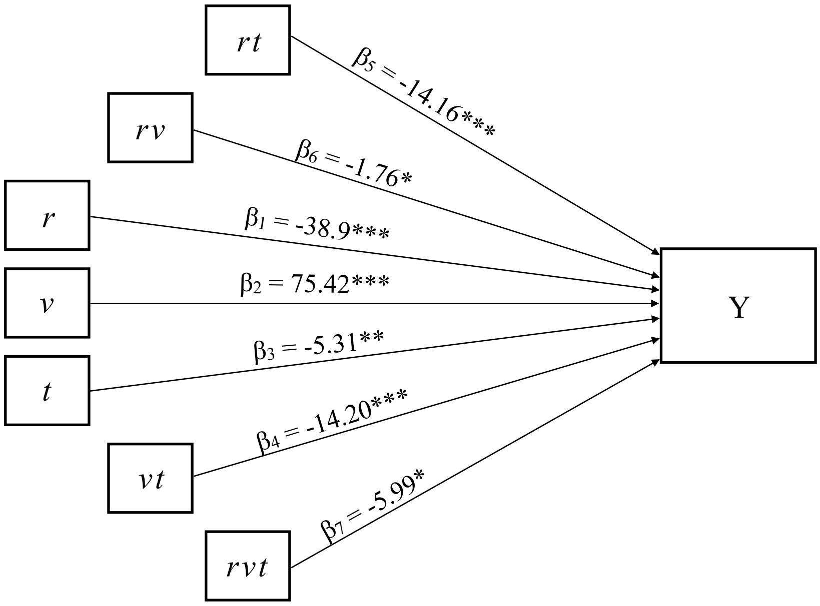
Source: Research data

It is possible to observe an increase in perceived recommendation quality and trust in recommendation, while there was a decrease in reactance levels, although the last was already originally low. The tendency to improve evaluations of the recommendation agent after a few interactions is an important observation, although further tests need be performed to identify possible interactions with decision effort.

4.5 General discussion

Following the tradition in business research, it is important to elaborate visual representations of consumer phenomena as a way to simplify the understanding of the complex realities that one is trying to unveil. Based on the previous analyses, it was possible to confirm the model proposed in Figure 2, which was capable of accounting for 40.25% of total variance observed in time to make a decision. In this model, recommendations play a moderating role in the relation between involvement with the task and decision effort. This effect is only activated, however, once the user has developed previous familiarity with the recommendation agent, what suggests the existence of a conditional interaction, as already shown. Figure 13, depicts a framework model accounting for this interaction.

Figure 13 - Statistical diagram of three-way interaction between recommendation, familiarity and involvement with the purchase task



* Beta values are significant at $p<0.10$
** Beta values are significant at $p<0.05$
*** Beta values are significant at $p<0.01$
Source: research data

A complete description of the outputs obtained from statistical analysis can be found in Appendix 4. For a mathematical representation of the relations according to the results found in the experimental phase, the final equation including the beta values for each one of the variables proposed in 3.4 could be represented by the following:

$$Y = 229.37 - 38.90r + 75.42v - 5.31t - 14.20vt - 14.16rt - 1.76rv - 5.99rtv \qquad (3)$$

The significant values of $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_3$ and $\boldsymbol{\beta}_5$ found in equation 3 account for the moderated effect of the presence of recommendations on time to make a decision. This moderation in the equation is confirmed by the significant value of $\boldsymbol{\beta}_5$, which attests that the treatment effect varies as a function of the value of the moderator (see Baron & Kenny, 1986; Muller et al., 2005). Considering that familiarity is a consequence of repeated purchases at the same website (Komiak & Benbasat, 2006), it is possible to find evidence to support Hypothesis 1. It means that the effects of recommendations are dependent on the level of familiarity with the website and, more than that, decision effort in initial purchases will not be affected by recommendations that use implicit elicitation methods.

It is important to reinforce that these results bring evidence to confirm that, unlike frequently hypothesized, the effects of being exposed to recommendations on decision effort may not be immediate in cases where consumers had not acquired familiarity with the website. Decision effort will reduce along time, as familiarity with the website (and its recommendations) grows.

The majority of studies so far have favored a different point-of-view (Alba et al., 1997; Bechwati & Xia, 2003; Bodapati, 2008; Xiao & Benbast, 2014), what opens space for discussion. Perhaps this is happening because, in general, studies tend to prefer a transversal approach, analyzing the effects of recommendations that use explicit elicitation methods (Verruck & Nique, 2017). On the other hand, it is in line with studies made in related fields of research, specially studies investigating personalization on the web, for which consumers will show resistance to personalized messages when they do not understand the real motives behind this personalization (Lambrecht & Tucker, 2003; Bang & Wojdynski, 2016; Kang *et al.*, 2016).

Following the same reasoning exposed above, by looking at the significant values of $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$ and $\boldsymbol{\beta}_6$, it is possible to note the moderating effect that the presence of recommendations exerts over the direct influence of the level of involvement on time to make a decision, what gives support to confirm Hypothesis 2. In line with Lynch *et al.* (1982), Gino and Moore (2007) and Done and Scholz (2013), it is possible to observe the direct influence of involvement level on decision effort. It was also identified the moderating influence of recommendations in reducing decision effort, as the negative values of $\boldsymbol{\beta}_6$ show.

In order to test the three-way interaction hypothesized in Hypothesis 3, the analytical procedures suggested by Hayes (2013) were followed, as previously reported. The significant values of β_7 show evidences to support the moderated moderation model and, consequently, the whole research model proposed in Figure 2. It is possible to note that the level of involvement with the task has a reduction effect on time to make a decision, while the remaining variables, and their interaction, cause a reduction in the levels of the dependent variable. The conditional effect of involvement on time to make a decision is given by:

$$Y = 75.42v - 14.20vt - 1.76r - 5.99rtv \quad (4)$$

It is interesting to note, however, that it was not possible to relate the confirmed interactions to recommendation acceptance, neither theoretically nor empirically. No significant differences in time to make a decision could be found between subjects that purchased the recommended product in comparison with subjects that chose another alternative, in the test group. These evidences are in line with theoretical assumptions that consider recommendations as decision aids, but not as persuasive agents (Bonaccio & Dalal, 2006; Adomavicius et al., 2011; Adomavicius *et al.*, 2013). Nevertheless recommendations proved to be providing important parameters for decision making (as defended by Adomavicius *et al.*, 2013), helping consumers to reduce decision effort even in cases where they do not choose the recommended product.

Hypothesis 4 was confirmed by analyzing the significant difference between variances for the prices of purchased products. It was verified that in the control group, the variance in prices for purchase products were more dispersed, whereas variance in prices of purchased products for test group were more concentrated around the goal price.

The lack of difference in decision effort and confidence in the decision between subjects that bought the recommended option and subjects that bought another product also helps to provide evidence for Hypothesis 5.

5 CONCLUSIONS

Personalization emerged as a powerful tool for facilitating consumer's decision making process and also to increase website performance (Kang *et al.*, 2016; Bang & Wojdynski, 2016). It also has demonstrated to be an important and useful instrument for helping users to deal with information overload (Aljukhadar *et al.*, 2012). In e-commerce stores, efforts to achieve higher levels of personalization have converted into product recommendations for consumers. These recommendations are generally generated using an approach that considers (i) similarities among users classified into the same group, (ii) purchase patterns showed by the same user along time or even (iii) purchase choices made by the majority of consumers of the same products.

Apart from the underlying assumptions used to generate recommendations, consumers do not really understand (or care for) these technical procedures. What consumers can actually assess is only how useful the recommendations were and how much effort they could save (McNee *et al.*, 2006; Lin *et al.*, 2014). In the case of recommendations generated by implicit methods, this assessment is made harder because there is no explicit elicitation procedure before recommendations are shown. As during initial interactions with the same website consumers are still forming and confirming perceptions, the effects of personalized recommendations on decision effort cannot be noticed and they may be even inexistent.

The present thesis is the first attempt of a series of studies directed at understanding longitudinal effects of the familiarity with website recommendations on decision effort. In order to do that, an experimental study was elaborated that could account for analyzing such effects. The methodology for achieving these goals was executed in four successive and complementary phases.

In the experimental phase of the methodology proposed in the present study, five different purchase tasks were executed in a period of five weeks with a one-week interval between each other. During this period, the execution of the purchase tasks was monitored and registered using Google Analytics services. Based on these data and on a self reported questionnaire applied at the end of each task, result analysis considered the main effects using the latent curve model approach and the influence of possible covariates with ANCOVA techniques.

Results demonstrated that recommendations have the potential to reduce decision effort only after a few interactions take place. More precisely, it was noted that from the third to the fifth interaction, the amount of time spent to make a decision was steadily reduced, on average, by 21.4% in the test group, when compared to a control group. This suggests that although implicit recommendations may take sometime to produce noticeable effects on decision effort, after some point consumers start to rely on recommendations to ease decision making processes.

Additionally, using ANCOVA analysis, it was possible to notice the interference of two important covariates: (i) level of involvement with the purchase task and (ii) purchase skills. Both variables, when isolated from each other together with presence/absence of recommendations proved to account for nearly 48,6% of all the variance in the dependent measure.

All these results may seem trivial, and even obvious if one looks at it from a logical perspective. However some counter-intuitive discoveries seem to arise from the experimental results. First, it is important to reinforce that, unlike frequently hypothesized, the effects of being exposed to recommendations on decision effort are not immediate. They come with time, as familiarity with the website (and its recommendations) grows. The majority of studies so far have favored a different point-of-view, what opens space for discussion. Perhaps this is happening because, in general, studies tend to prefer a transversal approach and, as a consequence, to analyze the effects of recommendations that use explicit elicitation methods.

Another important issue arising from the results analysis is the nonsignificant correlation between recommendation acceptance and decision effort. That is, even for subjects who did not choose the recommended option in the treatment group, mean differences were significantly different from the control group, but not different from people who actually accepted the recommendation. In order to complement this observation, it is possible to note that the level of recommendation acceptance does not significantly change as the number of interactions grows.

These results suggest that maybe the mechanism through which recommendations operate is not, in fact, related to presenting an ultimate choice option that consumers will certainly buy, but to establishing some referential parameters on which consumers will rely when choosing a purchase option. The low levels of reactance found in the self reported questionnaires also help to confirm this possibility.

If the previous assertion is to be true, then it is also the case that recommendations may not be performing the persuasive role some authors defend they have. This suggests that recommendations will be used as decision aids that make some stages of the decision process faster, but not as shortcuts capable of effectively altering previous established decision heuristics.

Finally, variances in the price ranges of products chosen by subjects in treatment and control groups showed to be significantly different, and smaller for subjects in the treatment group. This indicates that the drivers of choice for consumers in purchases without recommendations followed more disperse and nonlinear patterns.

5.1 Implications for practice

From a managerial perspective, the results found in this dissertation thesis may have interesting applications. Firstly, they can help to solve an important dilemma for programmers, specially those using content-based filtering approaches. They also provide some insights to managers of ecommerce websites on how to set goals and performance indicators when applying recommendations in their websites. Finally, they call for the necessity of considering previous experiences from the same costumer when generating recommendations.

A major problem faced by recommender systems in the first interaction with a given user is the lack of previous information from which to derive recommendations. Knowing that users do not actually base their decisions on these recommendations at first, the cold start problem becomes a minor thing in the elaboration of mathematical rules to generate recommendations. Before presenting personalized recommendations, initially, it could be the case that recommendations should be presented in a more general manner, such as “most purchased items in this category”, or “top-ranked items” in the case of recommendations using a rating system in their algorithms. Further, the presentation format of recommendations could be adapted to a specific user’s reality as more interactions take place.

Complementarily, knowing that recommendations are actually used as parameters of reference for purchase decisions and not as persuasive automatized sellers, performance of recommendation agents should not be based on recommendation acceptance or click-through rates. Rather, indicators used to manage the performance of recommendations at a website might consider a reduction in time to make a decision and the distance between the chosen option and the recommended ones in relation to one or more product attributes, such as price, quality, or any other quantifiable measure that could be considered as important to a given class of products.

5.2 Limitations and suggestions for future studies

As in any academic study, it is important to stress research limitations and the way they could be impacting the results found. The major problems with the reported study arise from the option to use an experimental methodology. It is already well documented that some implicit characteristics of experiments may lead to the lost of external validity (due to the necessity of manipulating scenarios that sometimes become unrealistic) and exacerbating the effects of some variables (as a consequence of isolating their interactions from other also important ones). These problems actually do not diminish the importance of experimental results, but they make a call to consider such results with some restrictions.

In the present research, one of the main aspects to point out relates to the way purchasing tasks were manipulated. It is possible to argue that such a sequence of purchase problems may not exist in the real world, especially with such a specific level of problem formulation. That is, in fact, true. People frequently start the search for a product, once the purchase problem is recognized, with much less information and without any previously specified preferences, as opposite to the purchase tasks reported in this study. So, it is possible, and plausible, that the level of formulation of the purchase problem in a real situation, would also be performing an important role in decision effort. Even more, it is very likely that it will be interacting with other variables to influence decision effort. If that is true, however, it is reasonable to suppose that recommendations could also play a role in decision effort, by the very same mechanisms already reported in the results analysis.

Other related question is that recommendations in this study were manipulated in such a way to be always accurate. This means that the sequence of tasks executed in the experimental sets did not consider possible, and probable, situations of recommendation failure, that is, cases in which the system was not capable of accurately predict users' preferences. This, actually, remains as an interesting follow up of the present study, in order to account for relevant undesired situations in recommendation agents' performance and their consequences for consumers decision effort.

Additionally, as in any field experiment, the problem with other contextual variables is also worth emphasizing. Since consumers were not purchasing in a strictly controlled environment (although efforts to restrict possible interfering situations were made), it is possible that context was interfering with consumers' decision process. That, actually, may be the main reason why variance explained by recommendations and by the moderation model was not very high. This is not to say that the obtained results are invalid, on the contrary, it means that even considering all complex relations impacting consumers' choices, the presence of recommendations at a website continue to exert a noticeable influence.

Finally, once subjects were dealing with simulated purchases, the feedback on the website performance was inexistent. So participants did not have an adequate assessment on attributes related to satisfaction, that could be interfering with their behavior in the next purchases. One can assume that since consumers are revisiting the website for a posterior purchase, it is probably the case that the website succeeded in delivering the chosen product, so this question would be solved. Such inference could only be proven, however, in an experiment capable of accounting for the whole purchase process.

From the reported results, it is suggested that further studies should address the underlying psychological mechanisms that are intermediating these effects. It is possible, for example, that the effects of the number of interactions on decision effort are being actually influenced by a growth in the level of trust in the website and in the recommendation system. Such studies could also consider moderating effects of some other variables such as shopping expertise and product involvement on the amount of time spent to make a decision. Using a more managerial approach, researchers could also try to establish connections between recommendations and time to make a decision with consumer loyalty and satisfaction and, consequently, with companies' long-term revenues. It is also expected that the results of this research may help marketing managers to develop processes and strategic alternatives to adapt and increase the effectiveness of recommendations in websites considering users' familiarity and level of involvement.

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APPENDIX 1

Purchase tasks

Task 1:

GOAL - Buy a camping chair at the CampingMaxx website.

CONDITIONS - when buying the camping chair, please have in mind the following:

- Consider your own preferences and your personal budget to choose the item you want.
- If you can't see yourself buying this product, please imagine buying it as a present for a close friend or a relative who would like it.
- You need to go through the whole purchasing process until the system generates an order number.
- For the shipping information, you can just type in anything, since this information will not actually be used.
- A committee will evaluate the product you choose to see if you made a good decision. If so, you will be awarded an extra for your participation.e.

Task 2:

GOAL - Consider the following hypothetical situation: A very close friend of yours is having his birthday next week. You know he loves camping and he is looking for a new tent for his outdoor activities. You and four other friends decided to get togheter to buy him the present he wants. Your task is to go to the CampingMaxx website and buy a TENT.

CONDITIONS - when buying the tent, please have the following in mind:

- You have $ 125.00 available.
- Your friend always invites one other person to go camping with him, so a 2-person tent would be the best option.
- You need to go through the whole purchasing process until the system generates an order number.
- For the shipping information, you can just type in anything, since it will not actually be used.
- Your choice will be examined by a committee that will evaluate if you found the best option for this task. In such case you will be awarded a bonus for you work.

Task 3:

GOAL - Consider the following hypothetical situation: Your friend from the last task was thrilled with your present. He was so excited with the tent you bought him that he already scheduled a camping activity with you by the beginning of the Spring. You now need to buy a sleeping bag to go with him. Your task is to go to the CampingMaxx website and buy a SLEEPING BAG.

CONDITIONS - when buying the sleeping bag, please have the following in mind:

- You plan to spend around $ 50.00 in this product.
- If you can't see yourself buying this product, please imagine buying it for someone you know who could be in a similar situation.
- You need to go through the whole purchasing process until the system generates an order number.
- For the shipping information, you can just type in anything, since this information will not actually be used.

Task 4:

GOAL - Consider the following hypothetical situation: You are preparing for your camping activity with your friend at the beginnig of the Springtime and now you realized that this may end up more expensive than you first expected. Anyway, you really need new walking boots to be comfortable there. Your task is to go to the CampingMaxx website and buy a WALKING BOOT.

CONDITIONS - when buying the boots, please have the following in mind:

- You plan to spend around $ 190.00 in this product.
- If you can't see yourself buying this product, please imagine buying it for someone you know who could be in a similar situation.
- You need to go through the whole purchasing process until the system generates an order number.
- For the shipping information, you can just type in anything, since it will not actually be used.

Task 5:

GOAL - This time we are going directly to your task: You are planning to buy a new bike for yourself, since lately you decided to spend more time outdoors enjoying nature. Your task is to go to the CampingMaxx Website and buy the bike that you think would better suit your prefferences.

CONDITIONS - when buying the bike, please have the following in mind:

- You have recently been drawn in a raffle and CampingMaxx webstore awarded you $ 550.00 to spend on the website, so that is the maximum amount you would be willing to pay for the bike.
- If you can't see yourself buying this product, please imagine buying it as a present for a close friend or a relative who would like it.
- You need to go through the whole purchasing process until the system generates an order number.
- For the shipping information, you can just type in anything, since it will not actually be used.

APPENDIX 2
Measurement scales

Obs.: All self reported variables were were collected after the execution of the task.

A Profile information	
Gender: ☐ Male ☐ Female	Age:
Educational level: ☐ College education or higher ☐ Less than college education	
How frequently do you perform on line transactions? ☐ At least once per week ☐ At least once each one month ☐ At least once each three months ☐ At least once each six months ☐ At least once per year ☐ Less than once per year	

B Shopping skill	
I am extremely skilled at using the Web.	1 2 3 4 5 6 7
I consider myself knowledgeable about good search techniques on the Web.	1 2 3 4 5 6 7
I know somewhat less than most users about using the Web.	1 2 3 4 5 6 7
I know how to find what I am looking for on the Web.	1 2 3 4 5 6 7
When I use the Web, I tend to lose track of time.	1 2 3 4 5 6 7
I enjoy visiting unfamiliar websites just for the sake of variety.	1 2 3 4 5 6 7
Even though there are thousands of different kinds of websites, I tend to visit the same types of websites.	1 2 3 4 5 6 7
When I hear about a new website, I'm eager to check it out.	1 2 3 4 5 6 7
Surfing the Web to see what's new is a waste of time. (R)	1 2 3 4 5 6 7
I like to browse the Web and find out about the latest sites.	1 2 3 4 5 6 7
I like to browse shopping sites even if I don't plan to buy anything.	1 2 3 4 5 6 7
I often click on a link just out of curiosity.	1 2 3 4 5 6 7

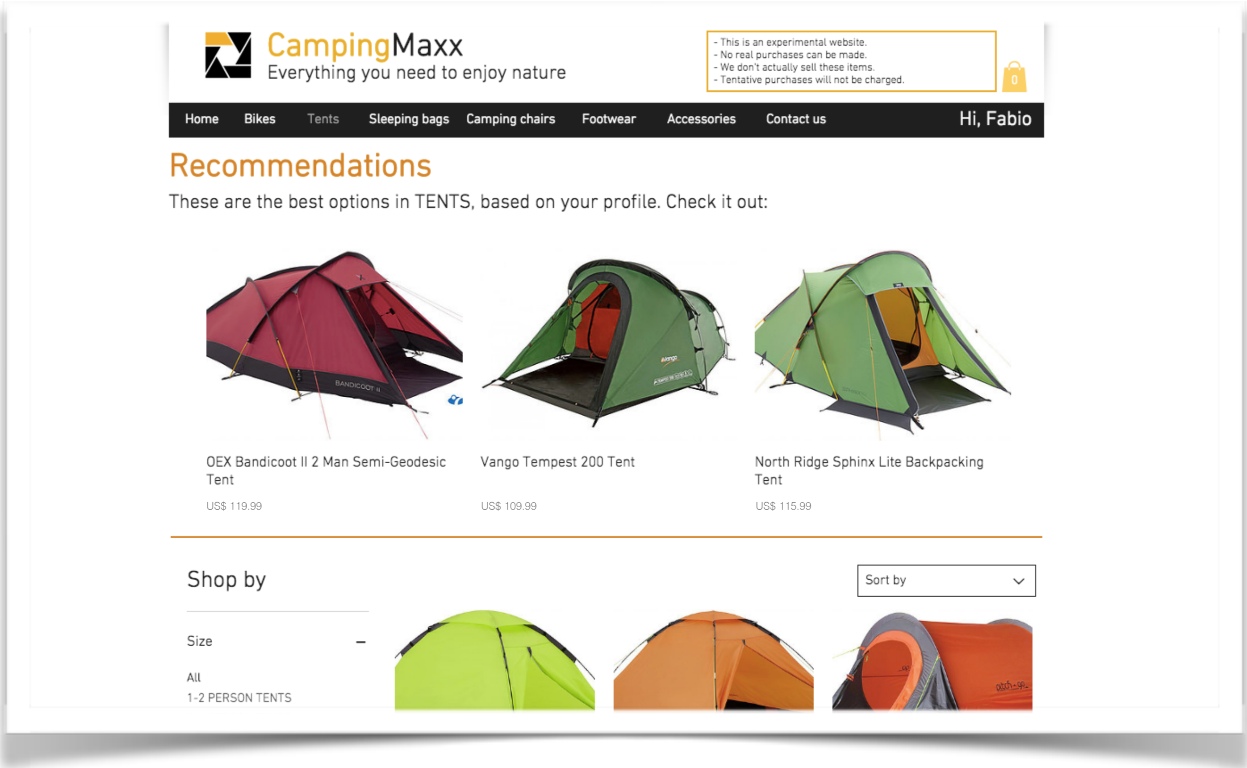
C Involvement with the task	
How involved did you feel with the task?	1 2 3 4 5 6 7 8 9
How interested were you in the task?	1 2 3 4 5 6 7 8 9
D Confidence in the decision	
I believe that I have found the best product option for this purchase task	1 2 3 4 5 6 7
E Perceived effort	
It was difficult for me to make this choice.	1 2 3 4 5 6 7
I didn't take a lot of time to choose a <product>.	1 2 3 4 5 6 7
I concentrated a lot while making this choice.	1 2 3 4 5 6 7
I have put a lot of effort in this decision.	1 2 3 4 5 6 7
I thought very hard about which <product> to pick.	1 2 3 4 5 6 7
I didn't pay much attention while making this choice. (R)	1 2 3 4 5 6 7

F Website trust	
The website is trustworthy.	1 2 3 4 5 6 7
I have the feeling that the website would keep its promises and commitments.	1 2 3 4 5 6 7
I believe this website offers products that are in accordance with my own interests.	1 2 3 4 5 6 7
G Manipulation check and control variables	
While evaluating the available options, were you offered any recommendation (only for people in the test group)? ☐ Yes ☐ No ☐ Not sure	
Have you ever bought a <this product> before?	☐ Yes ☐ No
How much do you think you knew about this product before executing this task?	Nothing 0 1 2 3 4 5 6 7 8 9 10 A lot
H Perceived recommendation quality	
I understand why the website recommended the tents it did.	1 2 3 4 5 6 7
I understand what the website bases its recommendations on.	1 2 3 4 5 6 7
I think that the website's criteria in choosing recommendations for me are similar to my own criteria.	1 2 3 4 5 6 7
I like the <products> the website recommended to me.	1 2 3 4 5 6 7
I think the website should use other criteria for recommending <products> to me than it uses now. (R)	1 2 3 4 5 6 7
The <products> that the website recommended really interest me.	1 2 3 4 5 6 7
I think that the <products> that the website recommends correspond to my own interests.	1 2 3 4 5 6 7
I Trust in RA	
The website provides unbiased product recommendations.	1 2 3 4 5 6 7
This website has the ability to understand my needs and preferences about <products>.	1 2 3 4 5 6 7
When offering me products, this website puts my interest first.	1 2 3 4 5 6 7
The recommendations provided are honest.	1 2 3 4 5 6 7
J Reactance to recommendations	
The recommendation given by the website is a restriction on my freedom of choice.	1 2 3 4 5 6 7
The recommendation given by the website made me analyze more carefully the other options available.	1 2 3 4 5 6 7
I would rather choose another tent not to select the recommended <products>.	1 2 3 4 5 6 7
K Debriefing	
What do you think this whole research was really about? (only for task number 5)	

APPENDIX 3

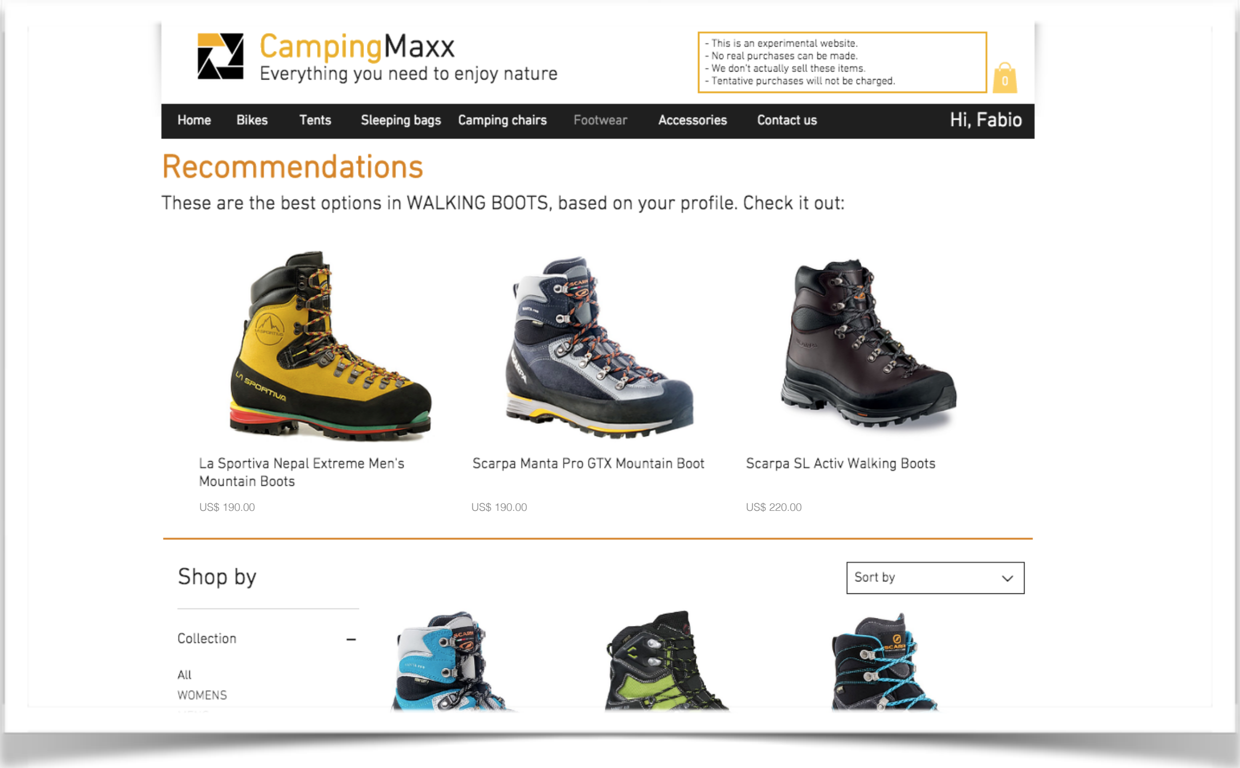
Sreen shots of the experimental website

Tents Page

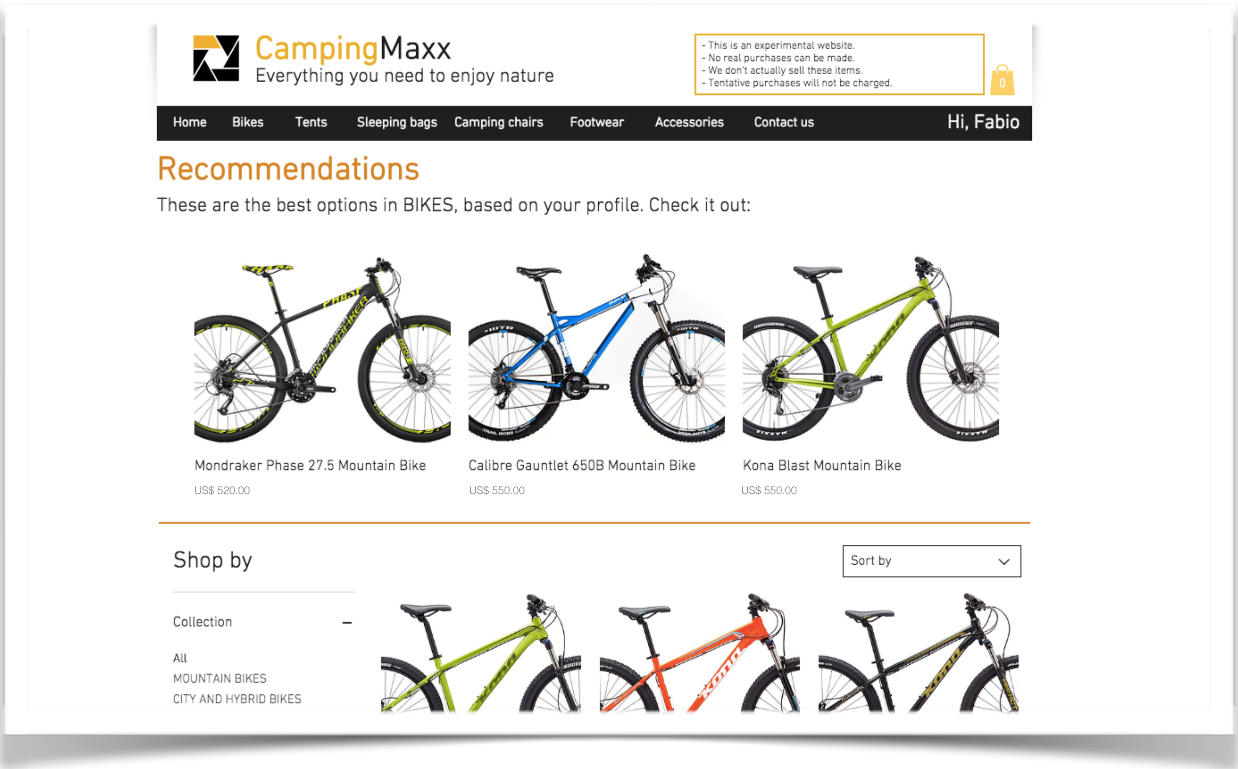


Sleeping Bags Page

Walking Boots Page



Bikes Page



APPENDIX 4

Outputs of the three-way interaction analysis

Run MATRIX procedure:

************* PROCESS Procedure for SPSS Release 2.16.3 ******************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com

Documentation available in Hayes (2013). www.guilford.com/p/hayes3

****

Model = 3

Y = TIME (time to make a decision)

X = INVOL (v)

M = GROUP (r)

W = WAVE (t)

Sample size   945

****

Outcome: TIME

Model Summary

R	R-sq	MSE	F	df1	df2	p
,6344	,4025	11201,0357	99,9938	7,0000	937,0000	,0000

	Model					
	coeff	**se**	**t**	**p**	**LLCI**	**ULCI**
constant	229,3754	3,4909	65,7064	,0000	222,5244	236,2263
GROUP	-38,9033	6,9884	-5,5669	,0000	-52,6179	-25,1887
INVOL	75,4254	3,4330	21,9706	,0000	68,6881	82,1627
WAVE	-5,3102	2,3158	-2,2931	,0221	-9,8549	-,7655
int_1	-12,1072	6,8612	-1,7646	,0780	-25,5722	1,3579
int_2	-14,2026	2,5079	-5,6632	,0000	-19,1243	-9,2808
int_3	-14,1623	4,6370	-3,0542	,0023	-23,2624	-5,0622
int_4	-5,9929	5,0146	-1,6951	,0824	-15,8340	3,8483

Product terms key:

int_1   INVOL   X   GROUP

int_2   INVOL   X   WAVE

int_3   GROUP   X   WAVE

int_4   INVOL   X   GROUP   X   WAVE