Online Purchasing and its Determinants: An Experimental Approach

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ABSTRACT
With the rapid and worldwide emergence of electronic commerce in terms of both number of users and volume, the importance of an in-depth understanding of consumers' attitudes toward online purchasing has been increasing. There is a broad literature on this topic mainly based on Technology Acceptance Model (TAM) that is extended by including other factors such as trust and risk. This study brings a new angle to the existing literature by measuring risk factor in a laboratory experiment by employing an improved version of a widely used method in experimental economics. Risk preferences are measured for 64 university students who then answer a questionnaire about online purchasing. We propose a comprehensive model based on TAM and employ partial least squares approach to analyze the data. We find that experimentally elicited risk preference measure and variables of hedonic aspect of TAM have significant effects while trust, other risk measures and variables of utilitarian aspect of TAM have no significant effect on online shopping behavior. We finally discuss the implications and limitations of our study and provide some future study suggestions.

KEYWORDS: *experiment, online purchasing, questionnaire, risk preference elicitation, Technology Acceptance Model (TAM), trust.*

JEL CLASSIFICATION: *D12, D81, C91, C83, L81*

1. INTRODUCTION

Electronic commerce is defined as a range of online activities for products and services, both business-to-business and business-to-consumer, through the Internet (Rosen, 2002). Number of individuals using Internet and the volume of e-commerce has been rapidly growing all over the world. According to World Bank data, more than 50% of the world population and more than 90% of developed nations' population uses Internet and the global e-commerce sales are expected to be over $4.92 trillion by 2021. In addition, the share of retail e-commerce sales as a percent of total retail sales increased from 12.2% in 2018, to 14.1% in 2019 and is anticipated to become 16.1% in 2020. This figure may be expected to jump further with the effect of Covid-19 outbreak started at the beginning of 2020.
All these statistics clearly imply the crucial role of e-commerce in world trade. Since there are significant benefits of online trade for both sellers and buyers, it has been getting more prevalent and share of digital buyers has been rapidly increasing (it is expected that there will be over 2 billion online shoppers in 2020). However, in spite of the increase of the overall volume of e-commerce, there is still room for enhancing the total value created by online shopping. Apparently, this is a challenging and dynamic process that involves various factors. In order to better understand this process, we need to take a deeper look at consumers' attitudes toward online purchasing and its determinants.

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In this study, in order to understand consumers' online purchasing behavior and its determinants, we build up a framework based on Technology Acceptance Model (TAM, Davis, 1989) and added risk and trust constructs to this model that have been proven to play a significant role in this context. The novel aspect of our approach is to measure risk component in our model, along with other standard factors, via a laboratory experiment commonly used in experimental economics. Our framework is based on extended TAM that captures consumers' perception of both utilitarian and hedonic dimensions. In addition to including trust construct in our model, we also include three different risk measures. While risk perception and general risk-taking attitude are measured by questionnaires, risk preferences are elicited by using experimental methods.

Data regarding risky choices obtained by the laboratory experiment is first used to estimate risk preferences and then a partial least squares method is employed to test the hypotheses implied by our research model. We find that consumers' online purchasing behavior is well explained by TAM variables and risk preference estimates while trust construct and other risk measures do not have a significant effect. Specifically, while hedonic factors of TAM that capture enjoyment aspect of online purchasing have a positive effect on online shopping, as consumers get more risk averse, they use online platforms for shopping less. Our results imply that an experimentally elicited common risk measure strongly explains consumers' online shopping behavior along with the TAM variables.

The novelty of our paper is its new approach based on extensive TAM that measures risk factor by using a commonly used experimental risk elicitation method (multiple price list method). We improved this method by synthesizing it with another commonly used elicitation method (matching task procedure; Benhabib et al., 2010). To the best of our knowledge, a similar experimental method has never been used in this context. When this risk measure is incorporated, other risk measures become insignificant suggesting that this type of risk measurement captures risk component in online shopping behavior sufficiently well. Our analyses reveal that this measure turns out to be a significant and effective variable in explaining online shopping behavior in addition to other known factors. Our finding that almost half of the variance in subjects' usage of internet for shopping is explained by our extended TAM model implies that our model explains online consumers' behavior pretty well. It also suggests that our method can be considered as a better risk measure alternative that can be employed in studies trying to understand the determinants of online purchasing behavior.

Although our results have important methodological and practical implications, we need to be careful in interpreting and generalizing them. It is clear that our study has some limitations and further research is necessary for generalizability and robustness of our results. The most important limitations are the size of our data set and the sample selection. Using larger samples and different populations (not only university students) will surely improve our understanding of online purchasing behavior further. In spite of these limitations, we consider this study as a worthwhile first step in extending the existing literature exploring this promising topic.

The remainder of the paper is organized as follows. Section 2 presents the research model and hypotheses. Section 3 introduces the experimental design, describes the data and methodology in detail. Section 4 presents the analyses of data and results. Finally, section 5 concludes with a discussion of implications of our research findings, limitations and future research.

2. RESEARCH MODEL AND HYPOTHESES

In this section, we introduce our research model, define constructs of shopping behavior and present our hypotheses by summarizing the related literature.

There are different factors that affect consumers' online shopping behavior. In the literature, various determinants of online shopping are mentioned (Monsuwe et al. 2004; Chiu et al. 2009). Since Technology Acceptance Model (TAM; Davis, 1989) is one of the most commonly used frameworks that examines the users' willingness to use information technology and it is proven to be appropriate as a theoretical foundation for online shopping, we built up a comprehensive model based on TAM by adding some previously incorporated factors and a completely new variable to predict the consumers' online shopping behavior. TAM basically identifies two determinants of a person's attitude toward adopting a new technology, namely usefulness and ease of use. In addition to inclusion of these utilitarian aspects in the model, a hedonic aspect is later added to the model (Davis, 1992) that represents the embedded enjoyment in the action of online purchasing. Along with these core constructs, we also incorporated some other factors that have been shown to be important determinants of adopting a new technology (Monsuwe et al. 2004). Figure 1 shows our research model. Details about the core constructs of our model is explained in the following sections.

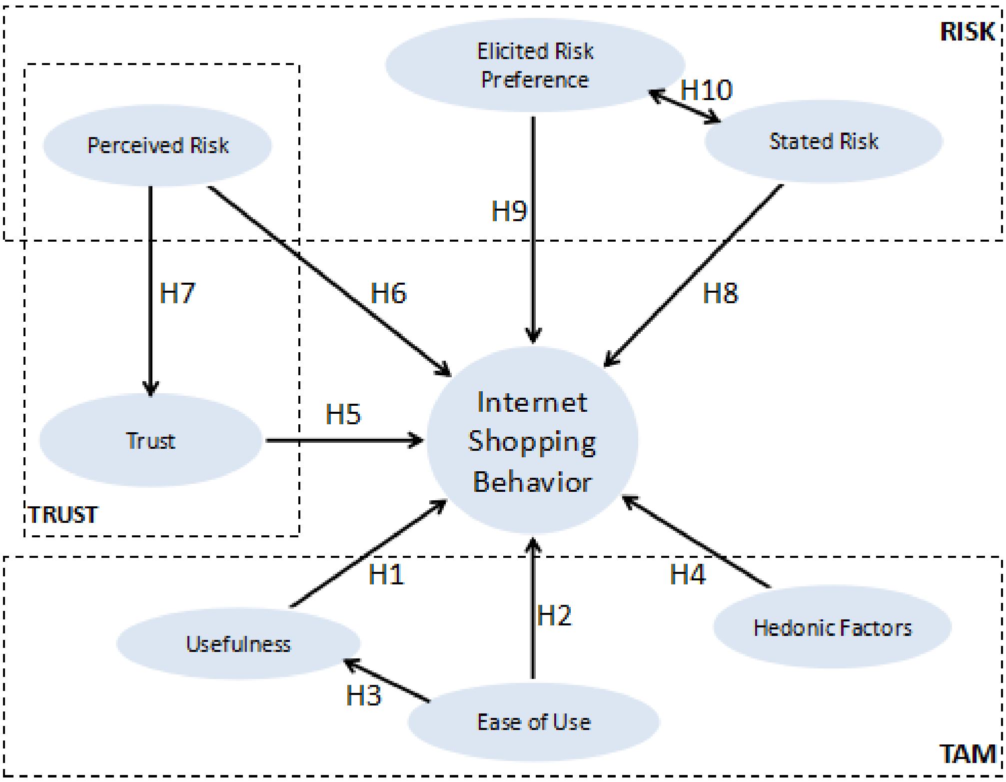

Figure 1. Research model

2.1 TAM

Technology Acceptance Model is a widely used model in the field of information systems. Although TAM originally was constructed to understand the IT based technologies in the workplace, it is then extended to the domain of electronic commerce and it was shown to be useful in understanding the dynamics of e-commerce adoption by consumers (Chen et al., 2002; Har and Eze, 2011; Hsu et al., 2016; Moon and Kim, 2001; Zhang and Prybutok, 2003). In the original construct, TAM proposes two main determinants of new technology usage of a person, namely *usefulness* and *ease of use*. Usefulness aspect is mainly related to the perception of the user about how the new technology enhance user's shopping experience and what kind of benefits and convenience it brings to the consumer. In our context, online shopping is perceived as useful because it does not necessitate car driving, leaving home, may bring better price and quality, provides home delivery and better selection etc.

Ease of use is the other core determinant in TAM. Consumers perceive online shopping as easy to use if they find easy to shop online, to find best price on the Internet etc. Hence, usefulness measures perception of experience but ease of use measures perception during the process leading to the final result. Moreover, there is also a link between usefulness and ease of use such that the former is affected by the latter because the easier a technology is to use, the more useful it would be (Davis, 1989).

The third construct of TAM that has been added later to the original model is the enjoyment factor that represents the hedonic aspect of the model. It directly links online shopping activity and how enjoyable the activity is (Davis et al., 1992).

Thus, we hypothesize that as usefulness, ease of use and enjoyment of online shopping are perceived to be higher, engagement in online shopping will be strengthened (Ashraf et al., 2014).

H1: Usefulness has a positive effect on consumers' online shopping behavior.

H2: Ease of use has a positive effect on consumers' online shopping behavior.

H3: Ease of use has a positive effect on usefulness.

H4: As enjoyment from online shopping increases, consumers will engage in it more intensively.

2.2 Trust

In the context of online shopping, (lack of) trust is one of the most frequently cited factors that causes consumers not to engage in online shopping (Al-Agaga and Nor, 2013; Corbit et al., 2003; Gefen et al., 2003; Kim et al., 2008; Noor, 2013; Ong and Lin, 2015; Pavlou et al., 2007; Sam and Sharma, 2015). It has been shown that it positively affects consumers' attitude towards online shopping. Trust, in this context, is defined as the extent to which consumers expect that an e-retailer will meet their transaction expectations and will not engage in opportunistic behavior (Ashraf et al., 2014). Ha and Stoel (2009) found that perceived trust is a predictor of consumers' attitude toward online shopping. Given these findings, our hypothesis about the relationship between trust and online shopping behavior is as follows:

H5: Trust positively affects online shopping behavior.

2.3 Risk

Perceived risk that is closely related to trust in this context is another important factor affecting online shopping behavior (Bhatnagar et al., 2000; Heijen et al., 2003; Hsu and Chiu, 2004; SivaKumar and Gunasekaran, 2017). Shih (2004) indicated that the payment phase is one of the major concerns of consumers during online purchasing. Although consumers realize benefits of online buying, they may feel uncomfortable and concerned at the same time (Chen and Tan, 2004). Moreover, privacy concerns (Joines et al., 2003) and risk of Internet-fraud have a detrimental effect on online shopping by undermining consumer trust (Ha and Coghill, 2008). Along with the security and privacy concerns, there are also functionality and psychological risks in online shopping relative to traditional shopping since quality inspection and testability of products are limited (see Featherman and Pavlou, 2003 and Biucky et al., 2017, for a comprehensive description and definition of all perceived risk types). In addition to the mentioned direct negative effect of risk on online shopping behavior, it has an indirect effect through trust. Corbitt et al. (2003) showed that perceived risk has a negative effect on trust. Thus, we propose the following hypotheses regarding the effect of this context specific risk perception on online shopping behavior:

H6: Perceived risk has a negative effect on online shopping behavior.

H7: As perceived risk gets higher, trust in online shopping weakens.

Since risk is a multidimensional concept, it is hard to develop a single hypothetical measure that effectively captures risk preference (Hudson et al., 2005). In this context, impact of perceived risk on users' buying behavior has been examined by using various aspects of risk. For these risk constructs, various survey items are generated that were used in numerous studies. In this study, in addition to the standard survey risk items, we use two different measures of risk. First, we added a question to our questionnaire that is used as a measure of how individuals perceive themselves in terms of risk-taking in general. Second, we elicited risk preferences of the participants by using experimental methods.

For the first one, we asked whether they agree on the following statement "I am a risk-taker in general", by using a seven-level Likerd scale (7 being "completely agree" and 1 being "completely disagree"). One's self-perception about risk taking may potentially affect this person's attitude towards online shopping. We hypothesize that this self-perception of risk has a negative effect on online shopping and propose the following hypotheses:

H8: Stated risk-taking attitude in general has a negative effect on online shopping behavior.

The most significant contribution of our paper is to incorporate experimentally elicited risk preferences into the existing models in the literature. Risk preference elicitation method we employed -details will be explained in the next section- is the multiple price list/MPL method (Holt and Laury, 2002) and it is commonly used especially by economists to elicit risk and time preferences. By presenting different choices of lotteries to the subjects, their attitude towards how much they are willing to take risk regarding financial gain and losses can be measured by this method. This is an incentive compatible method in the sense that choices of participants are implemented and they get payments accordingly. We actually synthesized MPL method with another commonly used method called matching task procedure (Benhabib et al., 2010) to elicit risk and time preferences. This hybrid methodology allows us to make point predictions for risk preferences.

Since online shopping involves similar tradeoffs and somewhat risky transactions, we argue that elicited risk preferences has the potential to explain consumers' attitudes in this context. Namely, a more risk averse consumer is expected to engage in online transactions less. This leads to the following hypothesis:

H9: As one gets more risk averse which is measured by experimental methods, she/he will be less willing to engage in online shopping.

Finally, we touch on the relationship between stated general risk-taking attitude and the elicited risk preference. Using survey questions to estimate general risk attitude, as in most of the studies reviewed above, has both advantages and disadvantages. Surveys can be conducted with low cost and effort and sample size can be increased relatively easily. Moreover, surveys offer the possibility to measure individual attitudes directly. However, it is uncertain whether these survey answers overlap with the actual preferences since there is no explicit incentive that makes participants to reveal their true preferences or beliefs.

Regarding the risk measures obtained by experimental and survey methods, there are studies that support both consistency and inconsistency between results of these methods. On the one hand, Dohmen et al. (2011) verified the behavioral validity of the survey method in eliciting individuals' risk perceptions with an incentive-compatible field experiment. They used a survey and a complementary experiment to examine risk attitudes and found that the question about risk-taking in general is the best predictor of risk behavior across different contexts. Moreover, Cummings et al. (2009) reported the consistency of the observations elicited from the field experiments (related with tax compliance behavior) with the survey data regarding the perception of risk. On the other hand, Anderson and Mellor (2009) found that for most of the subject, preferences are not stable across risk elicitation methods, and subjects exhibit instability in their risk preference estimates across different contexts. Besides, Kruse and Thompson (2003) used a survey question and an experiment to check whether there is a difference between the subjects' perceptions and actual behavior and observed inconsistencies across the two procedures. In addition, Lönnqvist et al. (2015) run a laboratory experiment that compares two empirical measures of individual risk attitudes: MPL method and questionnaires. Their results suggested that there is no correlation between risk preferences elicited by using different methods.

Since mentioned studies use different methods and designs in different contexts that makes benchmarking particularly problematic, it is difficult to come up with a clear hypothesis about this relationship. Data regarding risk preferences we obtained from the survey and from the experiment we conducted allows us to explore this relationship. In spite of this ambiguity, we hypothesize that they are expected to be compatible with each other:

H10: Stated risk-taking attitude is negatively correlated with the experimentally elicited risk preference.

The negative relationship comes from the fact that for the elicited risk preferences, as risk parameter (r) goes up, one gets more risk averse while for the survey question, as the stated score increases, one gets more risk loving.

3. METHODOLOGY AND DESIGN

We used a laboratory experiment to collect the necessary data. We recruited a total of 64 undergraduate students. There were two sessions in the experiment. The first session involved the explanation of the experiment's structure and a set of questions that were designed to elicit risk preferences of the subjects by using a hybrid multiple price list (MPL) method. Employing this hybrid methodology allows us not only to identify the relationship between different risk measures and online purchasing behavior but also to test the consistency within mentioned different risk measures. In the second session, participants filled out surveys including questions about online purchasing behavior, risk perception in general and some demographics. Details about the demographic information is in the appendix. The payment range was 40 TL − 100 TL (one dollar was approximately 2 TL at the time of the experiment) and in addition, show-up fee was 5 TL.

The first session was conducted through a new hybrid method of MPL and matching task procedure. Everything was computer based in this part. Subjects were presented tables including the lotteries and a range of certain amounts. There were totally 16 questions. First 15 questions were for MPL part and question 16 was for matching task procedure. The MPL part involved 15 different questions (See Table 1). There were 24 different MPL tables on which subjects make decisions. Probabilities and highest amounts were changed at each table. At each table, subjects saw 15 questions that include three options. One of the options was a lottery that was the same for a given table. The other option was a certain amount that reflects, if chosen, the preference of the agent for this certain amount over the lottery. This option starts from a low amount (lower than the expected value of the lottery) and increases up to the higher amount in the lottery (e.g., 300 TL in Table 1).

In the MPL elicitation method, subjects are expected to switch from one option to the other option depending on their risk appetite. In Table 1, for example, subjects are expected to start choosing option B (if they are not extremely risk averse) and then switch to option A at some point because in the last question, rationally, option A has to be chosen. (Subjects can choose the equal sign between the options to reveal that they are indifferent between that certain amount and the lottery). Moreover, consistency requires at most one switching. The last question in the table that appears after all 15 questions were answered asks for an exact indifference point based on the answers given in the previous 15 questions such that the entered amount should be between the certain amounts at which switching occurred (e.g., in Table 1, if one chooses option A in alternative 4 but B in alternative 5, the answer to the last question should be between 190 and 200 TL). Actually, adding this last question makes our approach a hybrid one, that combines MPL method and the matching task procedure. Namely, the former method, since interval responses are obtained from switching points, only allows for estimating intervals for risk parameters, not exact values. The latter method that directly asks for the certainty amount for a given lottery is cognitively costly and vulnerable to usage of some undesirable rules of thumb that may bias the results although it gives exact indifference points. This hybrid method handles these two problems by allowing subjects to think step by step.

The last question was in the following form:

'What amount of money, x Turkish Lira (TL), if paid to you for sure would make you indifferent to the above lottery?' ____TL

The amounts in the lotteries were determined dynamically based on the subjects' answers. As shown in Table 1, a typical lottery is as follows:

'0 TL with probability 0.1; 300 TL with probability 0.9'

Table 1. An example MPL table

Alternatives	**Option A (Certain payment in TL)**		**Option B (Lottery)**
1	160	≡	0 TL with prob. 0.1; 300 TL with
2	170	≡	0 TL with prob. 0.1; 300 TL with
3	180	≡	0 TL with prob. 0.1; 300 TL with
4	190	≡	0 TL with prob. 0.1; 300 TL with
5	200	≡	0 TL with prob. 0.1; 300 TL with
6	210	≡	0 TL with prob. 0.1; 300 TL with
7	220	≡	0 TL with prob. 0.1; 300 TL with
8	230	≡	0 TL with prob. 0.1; 300 TL with
9	240	≡	0 TL with prob. 0.1; 300 TL with
10	250	≡	0 TL with prob. 0.1; 300 TL with
11	260	≡	0 TL with prob. 0.1; 300 TL with
12	270	≡	0 TL with prob. 0.1; 300 TL with
13	280	≡	0 TL with prob. 0.1; 300 TL with
14	290	≡	0 TL with prob. 0.1; 300 TL with
15	300	≡	0 TL with prob. 0.1; 300 TL with

Becker-DeGroot-Marschak (BDM) incentive mechanism (Becker et al., 1964) was employed to determine how and what amount the subjects would be paid. A computerized random number generator randomly selects a number between 1 and 16. If one of the first 15 questions is drawn, then the agent gets the certain amount if option A or indifference is chosen. If the lottery is chosen, it is implemented by the randomization device. If the last question is drawn from the chosen table, since the subject reports the indifference amount, the lottery or the reported indifference amount is randomly chosen and implemented. At the end of the experiment, eight participants were randomly chosen and paid as described above (others earn only the show up fee in this part). The purpose of this random draw was to make subjects reveal truthfully by attaching monetary incentives to their answers in order to prevent random responses from the subjects. It is a weakly dominant strategy to report the true indifference value in the BDM mechanism (Noussair et al., 2004).

In the second part, subjects were asked to 'fill out surveys'. In these surveys, there were questions about the subjects' Internet usage, online shopping behavior, risk perception, demographics, etc. In addition to what they earned from the first session, subjects who fully filled out the surveys were also paid a fixed amount (40 TL). Survey questions included items both with binary questions and Likert-type scale most of which are adapted from the previous research. Each item was measured on a five or seven point Likert-type scale. To be able to get a measure of how individuals perceive themselves in terms of risk-taking in general, an additional question was asked that is used as a proxy for the subjects' own risk perceptions and this is compared with the risk parameters obtained in the experimental part. The respondents answered all questions on a five-point scale except this general risk-taking item which was measured on a seven point scale (either *completely disagree* being 1 and completely agree being 7 or *just like me* being 1 and *not at all like me* being 5). All the items and their descriptive statistics can be seen in the Appendix at the end.

4. ANALYSES AND RESULTS

In this part, we first focus on the estimation of risk preference parameters obtained from the first part of the experiment and present the details of the estimated parameters. We then give the details of the structural model we employed by using SmartPLS 3.0 software and present the results.

4.1 Risk Parameter Estimation

We obtained data to estimate risk preferences from the first part of the experiment in which subjects made choices in the MPL tables including risky lotteries. By using this data, the following von Neumann-Morgenstern utility function with constant coefficient of relative risk aversion (CRRA) was estimated. The estimation is standard and based on the presented lotteries and certainty equivalents that the subjects report for each lottery. If the agent's certainty equivalent value is smaller than the expected value of the lottery, then the agent is called as risk-averse and vice versa. The following CRRA utility function is used in the estimations:

$$u(x) = \frac{x^{1-r}}{1-r}$$

$$u(ce) = pu(reward1) + (1-p)u(reward2)$$

$$\frac{(ce)^{1-r}}{1-r} = p\frac{(reward1)^{1-r}}{1-r} + (1-p)\frac{(reward2)^{1-r}}{1-r}$$

where *"r"* is the coefficient of relative risk aversion we would like to estimate. Subject is risk averse, risk neutral and risk lover if $1 >= r > 0$, $r = 0$ and $r < 0$, respectively. By using the data, risk parameter '*r*' values are estimated where *ce* is the certainty equivalent that the subject reports for a given lottery.

Since each subject filled out 24 tables, there were 24 distinct data points for each subject. The collected data from 64 subjects was fitted to the mentioned utility function to find each of the subjects' risk parameter (individual *r* values). The analyses were performed in EViews by using least squares method. One of the disadvantages of the MPL method is the subjects' possible misunderstandings of the tables. Due to unusual switching patterns and other inconsistencies, we excluded 5 of the subjects and included remaining 59 subjects' data in our analysis.

The r values are as expected. As can be seen from Figure 2, since the mean value is between zero and one, most subjects exhibit risk aversion. Only twelve of the subjects can be characterized as risk-loving and the rest is risk-averse. Seven of the subjects can be categorized as risk-neutral since their risk preference parameters are not significantly different from zero. The mean value (standard deviation) of CRRA coefficients is 0.165 (0.249). Minimum and maximum values are -0.502 and 0.685, respectively.

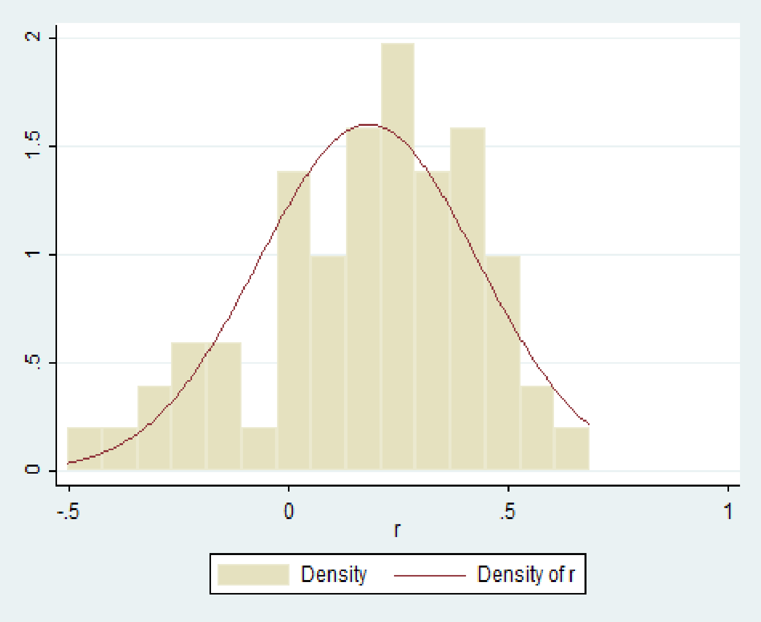

Figure 2. Histogram of CRRA coefficients

4.2 Structural model

In order to analyze our proposed research model, we used SmartPLS 3.0 software's PLS (Partial Least Squares) algorithm and bootstrapping (Garson, 2016). We first checked the construct reliability and validity of the model and examined the average variance extracted (AVE), and composite reliability (CR). Based on the results, we dropped the items with factor loadings less than 0.55 (Gefen et al., 2000). We then rerun the model. All composite reliability values are between 0.82 and 0.89 which is considered good for convergent validity. Cronbach's Alpha values are also greater than 0.70 (except for perceived risk construct whose value is 0.6). All values of AVE are greater than 0.6. Together all these indicators confirmed the validity of the model.

Table 2 presents the number of items of the variables, their mean values, standard deviations and reliability measures of these variables: the Cronbach's Alpha (α), CR and AVE values. Based on the means of the questionnaire answers we can say the followings about the variables. Participants on average find easy to shop online (1.7/5; 1 means 'just like me', 5 means 'not at all like me'). They find online shopping useful (2.67/5). Enjoyment factor and trust on average can be considered as neutral since the average score is very close to the mid value 3 (3.03/5 and 2.88/5, respectively). Online purchasing is somewhat seen as a risky activity (2.36/5). Average value of the elicited risk parameter is between zero and one (0.165) implying that on average participants are risk averse. Likerd score for general risk-taking is higher than the average score 4 which implies that people report themselves as risk seekers/lovers (4.98/7; remember that 1 means completely disagree and 7 means completely agree with the statement "I am a risk taker in general.").

Table 2. Descriptive Statistics and Reliability of the Variables

	Items	Mean	S.D.	Loadings	Cronbach's α	CR	AVE
Ease of use	3	1.700	1.287	0.842	0.772	0.869	0.689
				0.885			
				0.758			
Usefulness	5	2.671	1.042	0.849	0.851	0.893	0.627
				0.863			
				0.724			
				0.784			
				0.726			
Hedonic factors	2	3.033	1.320	0.845	0.700	0.866	0.764
				0.903			
Perceived Risk	2	2.364	1.099	0.739	0.600	0.823	0.701
				0.925			
Elicited Risk	1	0.165	0.249	1.000	1.000	1.000	1.000
General risk-taking	1	4.983	1.359	1.000	1.000	1.000	1.000
Trust	3	2.887	1.287	0.764	0.741	0.850	0.654
				0.802			
				0.857			

Figure 3 summarizes the results of the structural model. According to the model assessment, hypothesis 3, 4, 7 and 9 are supported while the others are not. All the path coefficients have their expected signs except stated risk (Most signs are negative due to the structure of the questionnaire. For example, a higher score of trust means less trust implying that as trust gets stronger, usage rates increase as expected. In other words, negative sign of a coefficient should be interpreted as a positive relationship between the variables and vice versa.). Regarding TAM variables, using internet for shopping is significantly and positively affected only by hedonic/enjoyment factors (H4). Although the effect of other variables (usefulness and ease of use) on usage is positive, coefficients are small especially for ease of use and insignificant (H1 and H2). Hypothesis 3 which emphasizes the effect of ease of use on usefulness finds support in our data. As participants find internet shopping easier to use, they find it more useful (Adj. $R^2 = 0.3$).

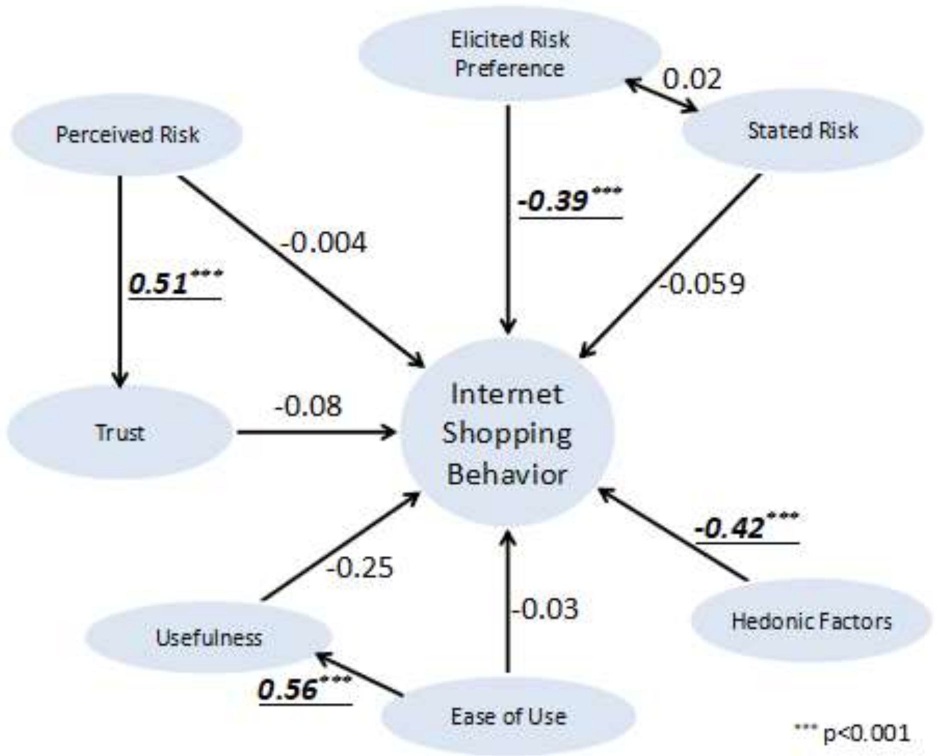

Figure 3. Results of the structural model

One of the important factors found in the literature that positively affects usage of internet for shopping is trust. In our data, this hypothesis does not find any support. Although its coefficient's sign is as expected, it is small and statistically insignificant (H5). Perceived risk is another important factor in the literature but this does not find any support in our data either. Our construct for perceived risk positively affects usage but the coefficient is very small and statistically insignificant (H6). Hypothesis 7 asserts that perceived risk has a negative effect on trust and our data supports this hypothesis. The coefficient is high and statistically significant (Adj. $R^2 = 0.25$). We hypothesized that stated risk has a negative effect on the internet shopping usage but this is not supported in the data, even its sign is negative although it is expected to be positive.

The most important point that separates our paper from the previous literature is the inclusion of experimentally elicited risk parameters into our analysis. We estimated risk parameters of the subjects participated in a laboratory experiment and claimed that the elicited risk measure will have a negative effect on the internet shopping behavior. In other words, as people gets more risk averse, they tend to use internet less for shopping purposes (H9). We find that the coefficient is negative and highly significant which supports our hypothesis.

When we look at the overall results, 44.4% of the variance in subjects' usage of internet for shopping is explained by the variables we included in the analysis (Adj. $R^2 = 0.444$). We look at the standardized root mean square residual (SRMR) value as a goodness of fit measure reported by SmartPLS. A value less than 0.10 is considered a good fit (Hu and Bentler, 1999; Henseler et al. 2014). Our model has a value of 0.097 which implies good fit of our model. Analysis also reveal that all heterotrait correlation values (HTMT) are less than 0.9 (Henseler, Ringle, & Sarstedt, 2015) which implies that discriminant validity has been established between all the pairs of reflective constructs.

Finally, hypothesis 10 says that general risk-taking attitude obtained by the survey question is supposed to be positively correlated with the experimentally elicited risk parameters (this again implies that the correlation coefficient should be negative due to the wording in the survey question). As we noted, the average risk parameter value, *r*, is positive (0.165) referring to risk aversion on average, while average risk perception (4.97/7.0) is higher than 4 referring to risk-loving. This implies that they are not compatible with each other (See Corbitt et al., 2003 for a study in line with the finding here). To further examine this relationship, we checked Spearman's rank correlation coefficients between these two variables and found that correlation coefficient is very small and insignificant ($p = 0.66$). This result also shows that self-reported risk-taking behavior in general is not correlated with the risk parameters elicited through incentivized lottery choices. Thus, hypothesis 10 did not find any support in our data.

Moreover, we get an interesting result when we segregate the participants' experimental data as risk-averse and risk-loving and analyze their corresponding stated risk-taking scores. The average of the stated risk-taking score of the ones who are risk-loving based on the lottery choices is 4.83, which is higher than the mid score 4 (t-test, $p = 0.012$). This means that the ones who show risk-loving behavior in experimental data consistently see themselves as risk-loving as one can expect. However, the average of the risk score of the ones who are risk-averse is 5, which is higher than the mid score 4 (t-test, $p = 0.001$). This score is even higher than that of risk lovers (but this difference is not statistically significant, t-test, $p = 0.711$). This implies that the ones who are risk-averse based on the lottery choices tend to see/report themselves as similarly risk-loving as the ones who exhibit risk-loving behavior in the experiment. This result can be potentially explained by subjects' overconfidence in this context since risk-taking may possibly be perceived as a desirable characteristic by the subjects. As observed in the literature, the majority of the subjects in the sample is risk-averse (approximately 80%) which implies that when data is segregated, it is divided asymmetrically. Moreover, since the sample size is relatively small in our study, further in-depth research with larger data sets is necessary for more reliable results. Nonetheless, our study stands as an important first step in exploring this promising topic.

5. DISCUSSION AND CONCLUSION

The purpose of this paper is to take a deeper look at consumers' online purchasing behavior. We extended the technology acceptance model (TAM) by introducing different risk variables along with trust and enjoyment factors. We estimated risk preferences via experimental methods and used this data to analyze the extended TAM model. Participants were university students and answered standard survey questions mostly related to online purchasing and questions including lottery choices. We employed partial least squares approach to analyze our model.

Our results imply that elicited risk preference is a good predictor of online purchasing behavior together with the enjoyment factor of TAM while trust, other risk constructs and other components of TAM turn out to be insignificant. Thus, we can argue that estimating the risk variable by experimental methods which is one of the most important determinants of online purchasing can be considered as a viable and reliable alternative in this literature although it necessitates further research and confirmation. We will now discuss the implications and limitations of our study and suggest some extensions.

5.1 Implications

Since understanding consumers' motivations for online shopping is critical for e-tailors in order to increase both base and volume of online sales, our research is relevant and has practical implications. We extend technology acceptance model by adding hedonic aspect and risk and trust constructs. We find that the core constructs of TAM, except enjoyment factor, namely usefulness and ease of use, turn out to be insignificant in our analysis. We think that this may be specific to the participants of our study who are university students. Since almost all members of this group are digital natives, it can be expected that they find using internet for purchasing easy to use and useful. This can also be seen from their questionnaire answers especially for ease of use. For this group, ease of use and usefulness to some extent appear to be uncritical for determining online purchasing. We think that for older group of customers, the weights and significance of these core constructs may be different. Therefore, in addition to determining target customer groups appropriately, it is also crucial for e-marketers to emphasize the enjoyable aspects of online shopping provided that the utilitarian aspects meet some minimum level.

Furthermore, since experimentally elicited risk preference is a specific consumer characteristic and it is a crucial factor that negatively affects online shopping behavior, e-tailors should not treat all consumers alike. In order to provide a safe and reliable customer experience and mitigate risk perception, risk reducing strategies has to be pursued such as offering guarantees and services providing secure online payment systems and emphasizing sensitivity about privacy issues.

5.2 Limitations and future research

Our results have important implications mentioned above for both practitioners and e-tailors. However, for generalizability and robustness of the results, further research is necessary. As mentioned above, the fact that the participants of our study are university students presumably drives some of our results. This might have potentially led to insignificance of some variables that are found to be consistently significant in the previous studies possibly due to not enough variation in the data. Thus, it is necessary to replicate the study with different samples, for example, having different age groups and user experience.

Another limitation is the relatively small sample size we had that is partially due to constraints imposed by the used experimental method. Replication with a larger sample that has a more balanced ratio of male and female subjects, would be helpful to test the findings' generalizability and robustness.

Although we have a comprehensive framework to understand the determinants of online shopping, there are always other factors influencing consumers’ behavior such as situational factors and strategic design of websites etc. Thus, it would be good to enlarge the research base by developing more extensive and wide-ranging survey questionnaires that include not only more careful examination of existing constructs but also different constructs. Another possible extension is to measure online shopping behavior in a more detailed manner. We directly asked a very general question that necessitates a binary answer on whether participants made any online purchase in the last year. Specific product types (e.g., high vs. low touch products or complex vs. standard products) or different product characteristics (e.g., whether they require personal interactions, pre-trial or privacy/anonymity) might be playing a critical role on the decision of traditional vs. online shopping. In our study, we abstracted from these considerations to simplify the model. However, these may be important factors and our new approach to measuring risk may give different results depending on these details.

Last but not least, there are studies examining cross cultural differences in this context (Ganguly et al., 2010). Although we do not think that our results would change substantially in different cultures, this has to be tested by conducting cross cultural studies.

To sum up, results of our study should be interpreted by keeping in mind the mentioned limitations. Our new approach presents a novel methodological extension of existing literature and has a high explanation power. Although it has some limitations, we consider this study as a promising endeavor in exploring the consumers’ online shopping behavior.

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APPENDIX

Demographics

Variable	Classification	N	%
Gender	Male	49	77
	Female	15	23
Age	<20	7	11
	20<…<22	51	80
	22<	6	9
Income (TL)	<500	21	33
	500<…<1000	36	57
	1000<	6	10

Questionnaire Items, Constructs and Descriptive Statistics	
Variable	**Mean (Std. Dev.)**
Binary (1 if yes, 0 if no)	
Did you personally make any purchases on the Internet in the last year?	0,508 (0,504)
Likerd-Scale	
"How well do the following statements describe you?"	
1. Usefulness (1 just like me, 5 not at all like me)	
1.1 I think Internet shopping offers better selection than local stores.	2,763 (1,150)
1.2 I like having products delivered to me at home.	2,407 (1,233)
1.3 I like it that no car is necessary when shopping on the Internet.	2,712 (1,190)
1.4 I would like not having to leave home when shopping.	3,407 (1,191)
1.5 I think the Internet offers lower prices than local stores.	2,356 (1,079)
1.6 I think Internet shopping offers better quality than local stores.	3,119 (1,035)
2. Ease of Use (1 just like me, 5 not at all like me)	
2.1 I don't know much about using the Internet.	4,441 (0,856)
2.2 Finding the best price on the Internet is easy for me.	1,814 (1,058)
2.3 Using an Internet shopping boot is easy.	1,949 (1,195)
2.4 Making a purchase on the Internet is easy for me.	1,339 (0,757)
2.5 I'd have a hard time searching the Internet to find what I need.	3,729 (1,127)
3. Enjoyment (1 just like me, 5 not at all like me)	
3.1 I enjoy buying things on the Internet.	3,051 (1,252)
3.2 I think online buying is (or would be) a novel, fun way to shop.	3,017 (1,396)
4. Trust (1 just like me, 5 not at all like me)	
4.1 I just don't trust Internet retailers.	2,746 (1,092)
4.2 I don't want to give out my credit card number to a computer.	2,695 (1,453)
4.3 Buying things on the Internet scares me.	3,220 (1,247)

5. Risk *Stated Risk*	
5.1 "I am a risk taker in general." (1: completely disagree, 7: completely agree)	4.983 (1,371)
5.2 Risk preference parameter elicited by using experimental methods	0,165 (0,251) r (Continuous variable) ≤1
5.3 Risk Perception (1 just like me, 5 not at all like me)	
5.3.1 I worry about my credit card number being stolen	2,610 (1,083)
5.3.2 It is hard to judge the quality of merchandise on the Internet.	2,169 (1,003)
5.3.3 I want to see things in person before I buy.	2,119 (1,068)