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Assessing customers perception of online shopping risks: A structural equation modeling–based multigroup analysis

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ABSTRACT

Increasing evidence shows the role of perceived risk in customers' attitude and intention to use online shopping services. However, the literature shows disagreement regarding the types of risks that influence purchase intention. Therefore, this study aims to empirically identify the most relevant sources of risks and uncertainties associated with online shopping services and to investigate the influence of sociodemographic characteristics (e.g., gender, age, and online shopping experience) on the levels of perceived risk using data collected through a survey questionnaire. A total of 558 participants were selected across three countries (Jordan, Saudi Arabia, and Kuwait). The responses were evaluated using structural equation modeling and multigroup analysis. The analysis showed that of the tested types of risks and uncertainty, only three had a significant influence on customers' purchase decisions: financial risk, information risk, and privacy risk. Regarding the moderating role of sociodemographic variables, the analysis showed that previous experience has a significant moderating effect. At the same time, gender and age were found not to affect the relationship between perceived risks and customers' purchase intention. These findings may help online stores understand customers' concerns when considering online shopping. The limitations and theoretical and managerial implications of the present study are discussed.

1. Introduction

The rapid adoption of e-commerce applications in recent years has encouraged scholars in various fields of research—including information systems, consumer behavior, and decision making—to investigate customers' intentions and attitudes toward e-commerce applications, such as online shopping (Ariffin et al., 2018; Chang et al., 2016; Gurung and Raja, 2016; Hassan et al., 2006; Ray and Sahney, 2018), online banking (Alzaidi and Qamar, 2018; Khan et al., 2021), and Mobile commerce (Alsharif et al., 2022; Chawla and Joshi, 2019; Khanra et al., 2021; Park and Tussyadiah, 2017; Uhm et al., 2022; Wang et al., 2022). One common conclusion from the previous literature has indicated that perceived risk significantly influences customers' purchase decisions (Alsyouf et al., 2022; Glogoveţan et al., 2022; Li et al., 2020).

However, there is disagreement among researchers regarding the concept of perceived risk. Some researchers have defined perceived risk

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as a unidimensional concept that captures all sources of uncertainty associated with online shopping activities (Almaiah et al., 2022b; Bonnin, 2020; Liyanaarachchi, 2021; Nepomuceno et al., 2014; Thakur and Srivastava, 2015; Xie et al., 2020). However, others argue that the complexity of this concept requires considering perceived risk as a multidimensional concept. Therefore, researchers investigated the effect of perceived risk on customers' online purchase decisions by proposing and testing different forms of risks and uncertainties, such as uncertainties related to the product itself, including financial, physical, and functional (Almaiah et al., 2022a ; Amirtha et al., 2020); uncertainties related to the e-retailer, including after-sale, privacy, and information (Afshan et al., 2018; Amirtha et al., 2020; Osakwe et al., 2022; Song et al., 2022; Uhm et al., 2022); and uncertainty related to the technologies used in the procurement process, including psychological, social, time-loss, security, and delivery risk (Ariffin et al., 2018; Bashir et al., 2021; Chang, 2021; Marriott and Williams, 2018).

Therefore, the present study aimed to identify the most relevant source of risks and uncertainties related to online shopping services and to investigate the influence of sociodemographic characteristics on the levels of perceived risk using data collected from three countries. The following questions guided this study: What are the risks that affect online purchase decisions? Do sociodemographic characteristics (e.g., gender, age, and online shopping experience) moderate the relation between risks and online purchase decision?

This study makes several original contributions to the perceived risk literature. First, this study builds on previous literature by proposing, validating, and empirically testing a conceptual model of online perceived risk using data from three countries. Second, to the extent of our knowledge, this is one of the few studies in this line of research to use rigorous analysis techniques, such as multigroup analysis, standard method bias (CMB), and measurement invariance, across different groups of respondents to investigate the moderating effects of sociodemographic characteristics. Subsequently, this study represents a methodological foundation for future investigations. The rest of the paper proceeds as follows. In Section 2, the literature review and the theoretical foundations of the research topic are discussed. In Section 3, the development of the research model and hypotheses are presented. In Section 4, a detailed description of the research methodology and data collection procedures is provided. In Section 5, the data analysis and research results are discussed. Finally, in Section 6, the conclusion, implications, research limitations, and suggestions for future research are provided.

2. Literature review and hypothesis development

2.1. Perceived risk

Perceived risk is "the individual or group, judgment or valuation of the magnitude and likelihood of the possible 'bad' outcomes which may result from an action" (Gough, 1990, p. 16). Perceived risk was first introduced to consumer behavior by Raymond Bauer (1960, 1967). According to Bauer, purchase behavior involves uncertainty, influencing customers' buying decisions. This uncertainty mostly captures customers' feelings that the purchase decision's purpose may not be achieved and that the targeted products or services may not fulfill their intended purposes. Therefore, making a purchase decision requires customers to handle the level of uncertainty and the level of risk associated with the purchasing process by seeking information about the brand or product that can help inform their purchase decisions (Almaiah et al., 2022b; Bauer, 1967).

Nonetheless, Bauer's view of perceived risk is limited and focuses on the absence of information as the primary source of uncertainty that could influence the purchase decision. The concept was later refined and expanded to incorporate other possible sources of uncertainty. For instance, Cox and Rich (1964) reconceptualized perceived risk as a function that consists of four different components: all the financial and psychosocial consequences related to the purchase decision, the uncertainty related to the purchased products and services, the uncertainty related to the service provider and method of purchases, and all other forms of subjective uncertainty customers experience regarding their purchase decisions. Consequently, as Bauer suggested, seeking information is not adequate for forming purchase decisions; thus, customers need to use other means to reduce their current level of uncertainty. These means may include reducing the purchase decision's financial and psychosocial burden and increasing the level of certainty associated with the service provider and the purchase method (Stern et al., 1977).

Other researchers have examined perceived risk from a different perspective. For instance, in an attempt to measure perceived risk, Bettman (1973) decomposed the concept into inherent risk and handled risk. That study showed that inherent risk is a latent concept that captures all product class risks. Handled risk captures the effect of information associated with a product brand. Based on this conceptualization, if a customer has no information about the product brand and does not initiate a risk-reduction process, the two risks are the same, and the level of risk perceived by customers is expected to be high. However, suppose the customer has the appropriate information or previous experience with the brand. In that case, the level of handled risk is lower, and thus, the customer is more confident in their purchase decision, even if the inherent risk associated with the product class remains high (Ross, 1975).

2.2. Perceived risk dimensions and components

As previously stated, Cox and Rich's (1964) study was among the first to identify the sources of uncertainty in customer purchasing decisions. They proposed perceived risk as a function of uncertainty and consequences. Cox (1967) attempted to refine the concept by considering perceived risk as a multidimensional concept. Based on his proposition, perceived risks can be divided into two main categories: performance and psychosocial risks. The first category represents the uncertainty associated with the product itself and its expected performance. According to Cox (1967), performance risk may include several sources of uncertainty inherent to the purchase decision, such as financial, temporal, and effort. The second category captures all forms of psychological and social uncertainty associated with purchasing decisions (Cox, 1967; Cox and Rich, 1964). A broader view of performance risk was also proposed by Cunningham et al. (1967) when he decomposed the concept into four sources of risk—performance, financial, opportunity, and safety—while retaining psychosocial risks, as proposed by Cox and Rich (1964).

The notion of perceived risk as a multidimensional concept has gained significant attention in the consumer behavior literature. Thus, researchers explore and propose other sources of uncertainty that may have a significant influence on customer purchase decisions, including physical risk (Bhukya and Singh, 2015; Bruwer et al., 2013; Hong et al., 2020; Veloutsou and Bian, 2008), time risk (Cunningham et al., 1967;

Glogovețan et al., 2022; Hong et al., 2020; Martins et al., 2014; Park and Tussyadiah, 2017; Stone and Grønhaug, 1993; Veloutsou and Bian, 2008; Yang et al., 2015), overall risk (Featherman and Pavlou, 2003; Martins et al., 2014), functional risk (Yang et al., 2015), and service risk (Park and Tussyadiah, 2017). As a result, most of these uncertain sources have been investigated and are influential in forming customer purchasing decisions. For instance, Stone and Grønhaug (1993) demonstrated that around 88% of the variance in customers' perceived risk could be explained by six sources of uncertainty: financial risk, performance risk, time risk, physical risk, social risk, and psychological risk. Similar results were reported by Martins et al. (2014), who found that privacy, time, performance, and financial risks have a significant influence on customers' purchasing decisions. In the following section, the conceptual model and hypotheses are discussed.

2.3. Research model and hypothesis development

A review of the literature suggests that, by default, previous investigations of the role that perceived risk plays in forming customers' purchase decisions used shopping scenarios that involve buying generic food and grocery products (e.g., pasta, toothpaste, and drugs) using conventional shopping channels (e.g., brick-and-mortar stores). As a result, the most frequently cited forms of uncertainty in the literature are limited to the products and shopping channels used. However, with the development of e-commerce technologies and the appearance of digital products and services (e.g., MP3 files, computer software, and web hosting services), researchers have proposed new potential sources of uncertainty that may have evolved from the use of these technologies. The sources of uncertainty include privacy, delivery, and security (Almousa, 2014; Alsharif et al., 2021; Dai et al., 2014; Farzianpour, 2014; Lutfi, Ashraf, Watto, & Alrawad, 2022; Vinerean et al., 2022; Zheng et al., 2012). In the following subsections, the conceptual model is presented (Fig. 1) and the hypotheses are discussed.

2.3.1. Information risk

Information uncertainty is mainly associated with the information dissemination process. According to Soto-Acosta et al. (2014), customers are exposed to several information uncertainty sources during the dissemination process while using an online store, including a lack of information, information overload, and information disorganization. These conditions then add to the complexity of the information search process (Zha et al., 2013). Therefore, the complexity of this type of risk has increased the level of perceived risk associated with online shopping purchase decisions. Information risks have been found to have a significant direct effect (Al-Majali, 2020; Chen et al., 2009) and an indirect effect (Amirtha et al., 2020; Bashir et al., 2021; Song et al., 2022; Soto-Acosta et al., 2014; Uhm et al., 2022) on online shopping purchases. Thus, the following hypothesis is formulated:

H1. Information risk has a negative effect on customers' intention to use online shopping services.

2.3.2. Functional risk

Perceived functional risk is the probability that "the product does not perform up to expectations" (Mitchell V, 1992, p. 27). One of the main downsides of online shopping services is that customers have no means of physically viewing and testing a product before purchasing it (Nepomuceno et al., 2014). This situation increases uncertainty surrounding the product's quality and the possibility that it may not perform as expected (Almaiah et al., 2022c). This uncertainty could also capture the customer's concern that they may buy a counterfeit product (Al-Majali, 2020; Almousa, 2014; Amirtha et al., 2020; Zhang et al., 2012; Zheng et al., 2012). The level of uncertainty related to functional risk may vary based on the product category, brand, and purchasing method (Garbarino and Strahilevitz, 2004). For instance, Aldás-Manzano Joaquín et al. (2009) found that perceived functional risk is higher for products and services that allow for refunds or trial testing, such as financial services. Much of the previous research in this area has indicated that functional risk has significant effects on customer purchasing decisions (Bhukya and Singh, 2015; Bruwer et al., 2013; Dai et al., 2014;

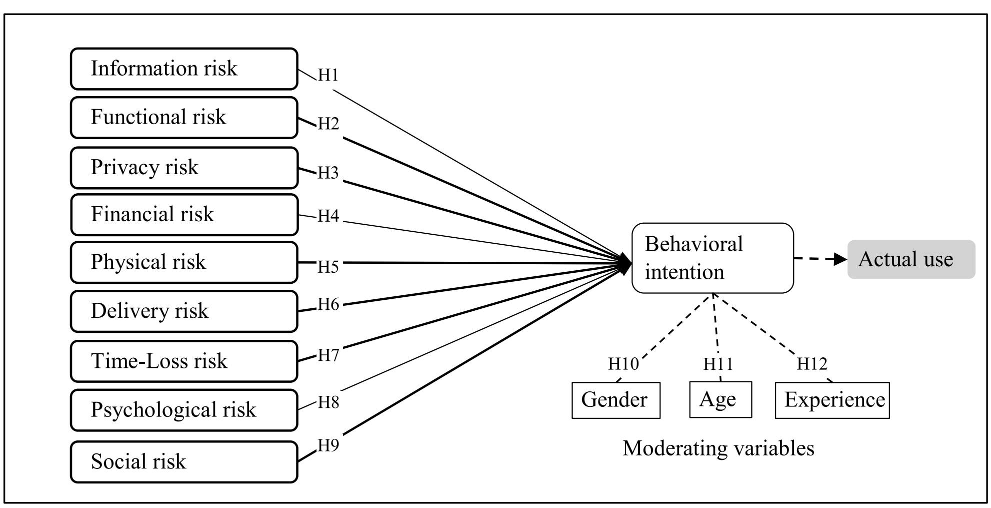

Fig. 1. The proposed research model and hypotheses.

Martins et al., 2014; Park and Tussyadiah, 2017; Ray and Sahney, 2018). Therefore, the following hypothesis is formulated:

H2. Functional risk has a negative effect on customers' intention to use online shopping services.

2.3.3. Privacy risk

Zhang et al. (2012, p. 3) conceptualize privacy risk as the "potential loss of control over personal information when the information is used without permission." This type of uncertainty signifies customers' concern that an online store may abuse their financial and personal information and disclose it to a third party or that the store may not have the capacity to safeguard their information from cybersecurity attacks (Almaiah et al., 2022b; Garbarino and Strahilevitz, 2004; Lutfi et al., 2022; Maignan and Lukas, 1997; Almaiah et al., 2022). Several studies have cited privacy concerns as a critical factor in the adoption and acceptance of e-commerce e-services (Gurung and Raja, 2016; Hong, 2015; Lutfi, 2022b; Xu et al., 2012). Conversely, several studies have reported no significant relation between privacy risk and individuals' intention to use online shopping services (Afshan et al., 2018; Bashir et al., 2021; Dai et al., 2014; Forsythe and Shi, 2003; Marriott and Williams, 2018; Song et al., 2022). For instance, Afshan et al. (2018) found that perceived privacy risk negatively influences users' intention to engage in online banking services. Therefore, the following hypothesis is formulated:

H3. Privacy risk has a negative effect on customers' intention to use online shopping services.

2.3.4. Financial risk

In online shopping, financial risk is defined as an individual's "concern over any financial loss that might be incurred because of online shopping" (Hassan et al., 2006, p. 41). This risk captures the uncertainty that customers may suffer from financial loss due to online shopping services. The risk evolves from the likelihood that customers may find a similar or identical product cheaper in a different place (Dai et al., 2014) or find that they paid a higher price for the same product and services (Dai et al., 2014; Forsythe and Shi, 2003; Mitchell V, 1992) or have been overcharged by the online store and had to pay extra in terms of handling fees, tax, and delivery costs (Chang and Tseng, 2013; Dai et al., 2014; Forsythe and Shi, 2003). The literature has established the role that financial risk plays in affecting customers' intention to use online shopping (Afshan et al., 2018; Al-Majali, 2020; Amirtha et al., 2020; Chang, 2021; Hong, 2015; Lutfi, 2022a; Lopes et al., 2020; Marriott and Williams, 2018; Mortimer et al., 2020). Therefore, the following hypothesis is formulated:

H4. Financial risk has a negative effect on customers' intention to use online shopping services.

2.3.5. Physical risk

According to Mitchell (1992, p. 26), "physical risk captures individuals' concerns that the online purchased item or services may cause a mental and physical threat to their health and wellbeing." Several attempts have been made to test the effect of physical risk on customers' purchase decisions (Amirtha et al., 2020; Arslan et al., 2013; Bashir et al., 2021; Bhukya and Singh, 2015; Bruwer et al., 2013; Chang, 2021; Lopes et al., 2020; Mortimer et al., 2020; Ray and Sahney, 2018). Many of these studies support the influence of physical risk on customer buying behavior. Therefore, the following hypothesis is posited:

H5. Physical risk has a negative effect on customers' intention to use online shopping services.

2.3.6. Delivery risk

Delivery risk captures the uncertainty arising from the process of delivering purchased items. This type of risk captures several potential issues related to the product delivery process. These issues may include delays in product delivery due to logistics or the warehouse management system, product damage occurring during delivery, and non-receipt of the product (Almaiah et al., 2022e; Ariffin et al., 2018; Zheng et al., 2012). Previous researchers have confirmed the influence of perceived delivery risk on customers' intention to use online shopping (Amirtha et al., 2020; Ariffin et al., 2018; Bashir et al., 2021; Bonnin, 2020; Masoud, 2013; Osakwe et al., 2022; Zheng et al., 2012). Therefore, the following hypothesis is suggested:

H6. Delivery risk has a negative effect on customers' intention to use online shopping services.

2.3.7. Time-loss risk

Time-loss risk is defined as "the risk that the consumer will waste time, lose convenience or waste effort in getting a service redone" (Mitchell V, 1992, p. 27). According to Hassan et al. (2006), customers may experience time loss while shopping in an online store. The reasons for this time loss can be grouped into three categories. First, issues related to the use of the store website, including webpage technical aspects, website search facility, complexity, and accessibility, arise. Second, according to Forsythe et al. (2006), creating an account on the store website and the authentication process of this account require users to spend extra time and effort to finalize the process. Third, the delivery process can take several days or even weeks, especially if the store is located outside the country (Afshan et al., 2018; Almaiah et al., 2022a, 2022c; Forsythe and Shi, 2003; Hong et al., 2020; Thakur and Srivastava, 2015). Thus, the following hypothesis is proposed:

H7. There is a negative relationship between time risk and customers' online purchase intention.

2.3.8. Psychological and social risks

According to Jacob and Leon B (1972), psychological and social risks (or psychosocial risk) are linked risks that capture customers' perceptions of self-image from different perspectives. On the one hand, psychological risk captures customers' feelings of frustration or disappointment when they receive different purchased items or services (Mitchell V, 1992). On the other hand, social risk is associated with customers' feelings of embarrassment in front of others (e.g., colleagues, friends, and family members) if they decide to purchase products or services from an online store. Social risk is more relevant to customers' purchase decisions and their effects on customers' status within society or a social group (Featherman and Pavlou, 2003). Psychosocial risk (individually or collective) is a significant influencer of customers' purchasing decisions in several studies (Almaiah et al., 2022b; Alrawad et al., 2022; Bashir et al., 2021; Bhukya and Singh, 2015; Chang, 2021; Farzianpour, 2014; Hong et al., 2020; Lopes et al., 2020; Lutfi et al., 2020; Marriott and Williams, 2018; Mortimer et al., 2020; Zhang et al., 2012). Therefore, the following hypotheses are posited:

H8. Psychological risk has a negative effect on customers' intention to use online shopping services.

H9. Social risk has a negative effect on customers' intention to use online shopping services.

2.3.9. The moderating effect of sociodemographic variables (age, gender, experience)

In general, the literature regarding the use of sociodemographic variables (e.g., age, gender, income, level of education, culture, and experience) in risk perception studies is scarce, and the reported findings are inconsistent (Siegrist and Árvai, 2020). However, the literature indicates some significant differences in the level of perceived risk between gender, age, and experience groups (Li et al., 2020a). For instance, in a meta-analysis, Li et al. (2020a) reported several studies that investigated the influence of sociodemographic variables, including age, gender, income, family status, level of education, and the relationship between perceived risk and customer purchase behavior.

Table 1
Sociodemographic profile of the sample.

Profile	Category	Country			
		Jordan	KSA	Kuwait	%
Gender	Male	102 (47.4%)	84 (39.8%)	25 (18.9%)	38
	Female	113 (52.6%)	127 (60.2%)	107 (81.1%)	62
Age groups	≤ Twenties	179 (83.3%)	188 (89.1%)	120 (90.9%)	87
	≥ Thirties	36 (83.3%)	23 (10.9%)	12(9.1%)	13
Previous experience in online shopping	Yes	81 (37.7%)	113 (53.6%)	119 (90.2%)	56
	No	134 (37.7%)	98 (46.4%)	13(9.8%)	44
Frequency of online shopping	<5 times	128 (59.5%)	103 (48.8%)	29(22%)	47
	>5 times	87 (40.5%)	108 (51.2%)	103 (78%)	53
Length of Internet Experience	<5 years	128 (59.5%)	103 (48.8%)	29(22%)	47
	>5 years	87 (40.5%)	108 (51.2%)	103 (78%)	53

However, many of these studies did not report correlation coefficients. Other studies have also reported previous research on the role of sociodemographic variables in purchasing decisions (Alsyouf et al., 2021; Hong, 2015; Jain and Kulhar, 2019; Li et al., 2020a; Lopes et al., 2020; Lutfi et al., 2022a,b,c,d,e; Song et al., 2021; Uhm et al., 2022).

Previous literature has demonstrated that women perceive the risks associated with online shopping to be higher compared to men (Almaiah et al., 2022a; Alreck and Settle, 2002; Amirtha et al., 2020; Garbarino and Strahilevitz, 2004; Rodgers and Harris, 2003; Zhou et al., 2007). Studies have also found a significant relationship between perceived risk and online shopping. For instance, Lopez-Nicolas and Molina-Castillo (2008) found that the Internet experience is a critical factor in reducing the perceived risks associated with online shopping. Therefore, the following hypotheses are posited:

H10. The relationship between perceived risk and customers' intention to use online shopping services is moderated by gender.

H11. The relationship between perceived risk and customers' intention to use online shopping services is moderated by age group.

H12. The relationship between perceived risk and customers' intention to use online shopping services is moderated by experience.

3. Research methods

The present study aimed to identify the most relevant source of risks and uncertainties related to online shopping services and to investigate the influence of sociodemographic characteristics. Accordingly, a research model was constructed based on the literature and tested using data from a survey questionnaire adopted from previous studies. The data were then validated and analyzed in line with the research objectives using several statistical techniques, including CMB, measurement invariance, and structural equation modeling (SEM). The following is a detailed description of the research methods.

Table 2
Mann-Whitney test for non-response bias.

Country	Item	Manna-Whitney U	Wilcoxon W	Z	Asymp. Sig. (Two-tailed)
Jourdan	Int1	1104.500	1965.500	0.492	0.623
	Fina1	817.500	1678.500	−1.854	0.064
	Priv1	1104.500	1965.500	0.492	0.623
Kuwait	Int1	1.221.500	2652.500	−0.903	0.367
	Fina1	1.338.000	2769.000	−0.091	0.927
	Priv1	1329.500	2760.500	−0.148	0.882
Saudi Arabia	Int1	1439.500	2714.500	1.150	0.250
	Fina1	1471.000	2746.000	1.376	0.169
	Priv1	1440.000	2715.000	1.157	0.247

3.1. Survey development

The questionnaire, comprised of 44 questions and statements, emerged from the literature review and aimed to measure the variables in this study (Al-Rawad et al., 2015; Bashir et al., 2021; Hassan et al., 2006). All questions and statements used in this study were translated from English to Arabic through a back-translation translation procedure, as Brislin (1973) recommended. The questionnaire was divided into three parts. Part 1 contained questions to gather demographic information, including age, gender, education level, Internet experience, daily Internet usage, previous online shopping experience, and online shopping frequency. Part 2 contained statements measuring the respondents' intention to use online shopping technology. Finally, Part 3 contained statements to measure the respondents' perceptions of various online risks and uncertainties. All items in parts 2 and 3 were measured using a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

3.2. Sample and data collection

The participants were recruited from three countries—Jordan, Kuwait, and Saudi Arabia—using a simple random sampling method. Specifically, 300 questionnaires were distributed with the help of three research assistants in each country. Before the data collection process began, the research assistants were briefed by the researchers in each country about the study's objectives and selection criteria. The research assistants were also informed about the necessity of not collecting respondents from one location, gender, or age group to maintain a representative sample that met the research objectives. The average time to fill out the questionnaire was around 5–10 min. Therefore, the research assistants were asked to hand out the questionnaire to prospective respondents after receiving their verbal consent and to collect the questionnaire after 10 min.

A total of 623 (69.2%) questionnaires were completed and collected in all countries. Sixty-five were omitted from the analysis because more than 20% of the items had not been answered. Thus, 558 valid responses were used in the analysis. The sample distribution based on country, gender, age group, previous online shopping experience, and online shopping frequency is shown in Table 1. According to the participants' country profiles, 38.5% ($n = 215$) were from Jordan, of whom 52.6% ($n = 113$) were women; 23.7% ($n = 132$) were from Kuwait, of whom 81.1% ($n = 107$) were women; and 37.8% (n = 211) were from Saudi Arabia, of whom 60.2% ($n = 127$) were women. The age group profile showed that 87.2% ($n = 487$) of the respondents were in their 20s or younger, and 12.6% ($n = 71$) were 30 years old or older. The profile also showed that 56.1% ($n = 313$) of the respondents had previously used online shopping tools regarding their online shopping experience. Of the 313 respondents who had used online shopping tools, 62.9% ($n = 197$) had done so fewer than five times, and only 37.1% ($n = 116$) had used online shopping tools more frequently (more than five times).

The collected data were then analyzed for early and late respondents' bias. Respondents' bias implies that potential respondents who declined or were less ready to return the questionnaire might have had characteristics that could influence the external validity of the research and bias its results (Armstrong and Overton, 1977; Lutfi, 2021). Accordingly, we tested the data for non-response error to support the sample representativeness using the Mann-Whitney U test. To carry out the test, the first 100 responses from each country were selected and divided into two groups. The first group of responses, numbered 1 to 50, was treated as early responses, and the second group of responses, from 51 to 100, was treated as late responses. These groups were then compared for each

Table 3
Results of principal component and confirmatory factor analysis of the nine perceived risk.

Latent construct	Measured variable	Rotated factor loading (PCA)	Standardized factor loading (CFA)	AVE	MSV	CR. (t-value)	Alpha	Composite reliability
Delivery	Deliv4	0.883	0.980			–		
	Deliv3	0.805	0.786	0.708	0.275	26.87	0.897	0.906
	Deliv2	0.793	0.823			29.72		
	Deliv1	0.767	0.759			24.96		
Intention	Int1	0.878	0.841			–		
	Int2	0.861	0.822			22.01		
	Int4	0.856	0.815	0.660	0.017	21.78	0.884	0.886
	Int3	0.839	0.771			20.27		
Functional	Fun3	0.813	0.880			–		
	Fun4	0.810	0.866			25.61		
	Fun5	0.781	0.729	0.632	0.278	19.93	0.867	0.872
	Fun2	0.693	0.688			18.33		
Privacy	Priv3	0.910	0.982			–		
	Priv2	0.867	0.902	0.849	0.243	40.94	0.900	0.944
	Priv1	0.856	0.876			37.08		
Financial	Fina2	0.768	0.737			–		
	Fina3	0.767	0.730			15.49		
	Fina4	0.708	0.687	0.506	0.351	14.66	0.802	0.804
	Fina1	0.595	0.689			14.70		
Information	Info3	0.780	0.785			–		
	Info2	0.723	0.701	0.512	0.351	15.84	0.802	0.807
	Info4	0.679	0.722			16.31		
	Info5	0.667	0.647			14.57		
Physical	Phy4	0.879	0.985			–		
	Phy1	0.841	0.813	0.770	0.278	27.65	0.900	0.909
	Phy2	0.840	0.823			28.36		
Social	Soc4	0.926	0.984			–		
	Soc1	0.873	0.792	0.728	0.062	23.39	0.878	0.888
	Soc3	0.864	0.769			22.38		
Psychological	Psyh4	0.842	0.974			–		
	Psyh2	0.778	0.760	0.687	0.315	21.88	0.840	0.866
	Psyh1	0.748	0.733			20.76		

Table 4
Goodness of fit statistics for the measurement of CFA and structural model SEM.

Classification	Fit index	CFA model	SEM model	Acceptable values
Chi-square	χ^2	595.9	738.41	–
Degrees of freedom (*df*)	df	396	424	–
Absolute fit indices	χ^2/df	1.505	1.742	<5.00
	GFI	0.940	0.922	>0.90
	AGFI	0.919	0.902	>0.90
	RMSEA	0.030	0.036	<0.08
Incremental fit measurements	CFI	0.982	0.972	>0.90
	TLI	0.978	0.967	>0.90
	NFI	0.950	0.937	>0.90

country based on three independent variables (Intention, financial risks, and privacy risk). The test results indicated that the differences between the groups were not significant.

The data set was assessed for non-response error to support the sample representativeness using the Wilcoxon-Mann-Whitney test. The test results shown in Table 2 indicate no significant differences between the early and late response groups, with Asymptotic Significance (two-tailed) ($p > 0.05$) for all groups. That is, non-response error was not an issue in the data set.

4. Results

The data analysis was divided into two main phases. In the first phase, the measurement model was built and validated using several statistical techniques, including exploratory factor analysis (EFA), to identify the model dimensions and the pattern matrix for the collected data. Confirmatory factor analysis (CFA) was used to test convergent and discriminant validity, CMB, and composite reliability. Finally, a series of multigroup CFAs was used to assess measurement invariance. In the second phase, the research model was evaluated, and the proposed hypotheses were tested using path analysis, multigroup SEM, and chi-square difference tests. In the following section, a detailed description of the study analysis procedures is presented.

Table 5
Correlation matrix of principle constructs.

	Mean	SD	Correlation matrix								
			1	2	3	4	5	6	7	8	9
Delivery	3.34	1.12	**0.841**								
Intention	3.49	1.12	0.130	**0.813**							
Functional	3.65	1.23	0.444	0.128	**0.795**						
Privacy	3.42	1.19	0.389	−0.085	0.378	**0.921**					
Financial	3.23	1.17	0.481	0.003	0.519	0.485	**0.711**				
Information	3.19	1.19	0.525	0.006	0.496	0.492	0.592	**0.715**			
Physical	3.49	1.24	0.481	0.046	0.527	0.340	0.435	0.371	**0.878**		
Social	2.42	1.15	0.145	0.012	0.076	0.126	0.220	0.249	−0.013	**0.854**	
Psychological	3.32	1.17	0.381	0.083	0.384	0.328	0.557	0.562	0.286	0.243	**0.829**

The bold diagonal values are the Average Variance Extracted (AVE) square root.

Table 6
Common method bias test.

Test	Model	χ^2	df	Δ χ^2	Δ df	P-value
	Unconstrained	595.906	396	–	–	–
Variance presents	Zero constrained	769.433	428	32	173.527	0.000
Equal variance	Equal constrained	808.971	428	32	213.065	0.000

4.1. Measurement model

4.1.1. Measurement validity and reliability

To test the study model and determine the underlying dimensions of online perceived risk, as recommended by Netemeyer et al. (2003), EFA was performed using SPSS 23.0. The software was set to extract factors with eigenvalues greater than one using principal component analysis with varimax rotation, as recommended by Hair et al. (2010) and Malhotra (2010). Based on these settings, EFA was performed for four rotations. During these attempts, five items were deleted from the analysis. Four were deleted for having more than one significant load (cross-loading of 0.4 with more than one factor), while one item was deleted for loading poorly onto the respective factor (lower than 0.3).

The final EFA rotation was performed using the remaining 32 items. This rotation revealed a pattern matrix with only nine factor solutions, which explained 75.63% of the data's total variance. The EFA results are displayed in Table 3. The test of sampling adequacy, the Kaiser-Meyer-Olkin score, was found to be acceptable (0.879), and Bartlett's test of sphericity was significant ($p < 0.0001$). The extracted factors were labeled following the proposed model: "Delivery risk," "Intention," "Functional risk," "Information risk," "Privacy risk," "Financial risk," "Physical risk," "Social risk," and "Psychological risk." However, items related to time-loss risk did not load onto the prospective factor and thus were excluded based on validity and reliability issues. The internal consistency of the model measurement was then established using Cronbach's alpha. The results suggest that the coefficients of all items were higher than the cut-off value recommended by social science researchers to indicate a study instrument's high reliability: 0.70.

The next step was to assess the scale development and construct validity for the study model using CFA, as recommended by MacCallum and Austin (2000) and Brown (2006). Thus, CFA was performed using Amos 23 software based on the maximum likelihood (ML) technique. The model fit indices of the measurement model are summarized in Table 4; the structural model had a good overall fit, and all the indices exceeded the recommended thresholds: chi-square ($\chi^2 = 595.9$), degrees of freedom (df = 396), χ^2/df = 1.505, p = 0.000, goodness-of-fit index (GIF = 0.940), adjusted goodness-of-fit index (AGFI = 0.919), comparative fit index (CFI = 0.982), normed fit index (NFI = 0.95), and root mean square error of approximation (RMSEA = 0.03).

4.1.2. Measurement of psychometric properties

The psychometric properties of the measurement model were also tested using CFA. Three types of validity—convergent, discriminant, and nomological—were considered in this test. Convergent and discriminant validity were assessed using several measures, including average variance extracted (AVE), maximum shared variance (MSV), composite reliability (CR), and critical ratio (CR). Accordingly, convergent validity is assumed if three requirements are met: First, the standardized factor loading for each tested item should exceed 0.7; second, the AVE should be higher than 0.5; and third, the CR values should be 0.7 or higher. Discriminant validity was achieved in this study if the calculated MSV was lower than the AVE, and the CR value exceeded 1.96. As shown in Table 3, all items in the measurement model met the recommended criteria and showed sufficient convergent and discriminant validity (Hair et al., 2010). Finally, nomological validity is assumed if the correlation between the measured constructs proposed by the research model is significant. As shown in the correlation matrix in Table 5, several correlations existed between the dependent variables (functional risk, privacy risk, information risk, and physical risk) and an independent variable (intention to purchase online).

4.1.3. Common method bias

According to Podsakoff et al. (2003), CMB indicates that the observed variance between the model constructs could be due to the method used in collecting data, and not because of a correlation between constructs. The authors also suggested several methods for testing CMB, including the Harman single-factor test, the partial correlation procedure, the directly measured latent method, and the unmeasured latent method. In this study, CMB was tested using two common approaches: the Harman single-factor test and the unmeasured latent method. The Harman method uses EFA and constrains all items from loading onto one factor without rotation. CMB is assumed if the variance explained by this factor exceeds 50% (Harman, 1976). The Harman CMB test results revealed that only one factor could explain only 27.21% of the variance. Thus, CMB was not problematic in this study.

The unmeasured latent method, regarded as more rigorous than the Harman method, is performed by modifying the measurement model to include an extra latent factor to account for the variance shared by all measured variables (usually named the common latent factor, CLF). In this method, the extra factor is connected to all observed items. Subsequently, three models are tested using chi-square difference tests ($\Delta\chi^2$). The first model represents the nonexistence of measurement bias. This is completed by fixing the factor coefficient between the CLF and setting the model items to zero. The second model represents the assumption of existing bias, and no constraints are imposed on this model. The third model tests whether the CMB is evenly distributed among all measured items; thus, all factor regression weights are fixed to be equal. Next, the chi-square and degrees of freedom are calculated for all models (constrained, unconstrained, and equally constrained). If the result of the chi-square difference test between the unconstrained and zero constrained is significant ($p < 0.05$), then the two models are different, and CMB is assumed (Schwarz et al., 2017).

Similarly, if the chi-square difference between the unconstrained and equally constrained models is significant, then the two models are

Table 7
Hypotheses testing results.

Hypotheses	Path	Path coefficient	SE.	C.R. (t-value)	P-value	Remarks
H1	Intention < – Information	−0.252	0.114	−2.771	0.006*	Supported
H2	Intention < – Functional	−0.051	0.076	−0.722	0.470	Rejected
H3	Intention < – Privacy	−0.252	0.053	−4.204	***	Supported
H4	Intention < – Financial	−0.295	0.124	−3.282	0.001*	Supported
H5	Intention < – Physical	−0.107	0.049	−1.879	0.060	Rejected
H6	Intention < – Delivery	−0.010	0.064	−0.165	0.869	Rejected
H7	Intention < – Time-Loss risk	***Not Tested***	–	–	–	–
H8	Intention < – Psychological	−0.089	0.049	−1.754	0.079	Rejected
H9	Intention < – Social	−0.036	0.041	−0.759	0.448	Rejected

Note: *p < 0.050, **p < 0.010, ***p < 0.001.

Table 8
CFA goodness-of-fit statistics for all groups.

Group			χ^2/df	CFI	SRMR	RMSEA	PClose
Threshold	**Model**	**χ^2 (df)**	**1–5**	**> 0.95**	**< 0.080**	**< 0.06**	**> 0.05**
Country	Combined	1415.459(1188)	1.191	0.980	0.0551	0.019	1.000
	Kuwait	1708.914(1188)	1.438	0.979	0.0551	0.019	1.000
	KSA	1681.426(1188)	1.415	0.982	0.0422	0.018	1.000
	Jordan	1603.043(1188)	1.349	0.985	0.0387	0.016	1.000
Gender	Combined	975.695(792)	1.232	0.984	0.0390	0.020	1.000
	Male	1027.201(792)	1.296	0.985	0.0390	0.020	1.000
	Female	1140.749(792)	1.440	0.981	0.0380	0.022	1.000
Age	Combined	1059.869(792)	1.338	0.977	0.0370	0.025	1.000
	The twenties	1184.287(792)	1.495	0.982	0.0370	0.022	1.000
	The Thirties	1067.670(792)	1.348	0.978	0.0650	0.024	1.000
Experience	Combined	950.783(792)	1.200	0.986	0.0410	0.019	1.000
	With experience	1070.530(792)	1.352	0.984	0.0410	0.020	1.000
	Have no experience	1082.243(792)	1.366	0.983	0.0359	0.021	1.000

different, and the CMB is not evenly distributed between measurement items. The results for both tests are summarized in Table 6. As indicated in the table, measurement bias was detected and found to be unevenly distributed. Therefore, CMB was considered when the research hypotheses were tested.

4.2. Structural model and hypothesis testing

The research hypotheses were tested and validated with SEM using Amos 23 software. SEM was performed using ML estimation. The variance caused by CMB was considered in the structured model. As presented in Table 4, the fit statistics supported the tested model (χ^2 = 738.412, df = 424, p = 0.000), and all the model fit indices exceeded the commonly accepted values. The tested model results, including the standardized regression weights, significance level, and variance explained by the independent variables (R^2), are displayed in Table 7.

All of the modeled main hypotheses were tested simultaneously. The results indicated that three (H1, H3, and H4) of the nine hypotheses were supported. Thus, the three perceived risk components significantly influenced customers' intention to purchase online. In total, 24% of the variance in the respondents' intention to purchase online can be explained by perceived risk. Nonetheless, five hypotheses—related to the effect of functional risk (H2), physical risk (H5), delivery risk (H6), psychological risk (H8), and social risk (H9) on customers' intention to purchase online—were not supported.

4.3. Measurement invariance

Measurement invariance was performed using multiple-sample CFA to assess whether the study constructs had the same meaning across all groups of respondents based on age, gender, country, and online shopping experience (Byrne, 2016). Three levels of invariance were tested: configural, metric, and scalar. Configural or equal form invariance evaluates whether the same pattern of factors and factor indicators emerges from a different group of respondents (Vandenberg and Lance, 2000). Configural invariance was assessed using model fit indices (Kline, 2011). As shown in Table 8, all models for each group (combined and subgroup) surpassed the model fit indices' thresholds (CFI >0.95, SRMR <0.08, RMSEA <0.06, and PClose >0.5). This indicates that the measurement model passed the configural invariance for all tested groups.

After configural invariance is achieved, the next step is to establish metric and scalar invariance. Metric invariance assumes equal factor loading across groups (Byrne, 2016; Kline, 2011), whereas scalar invariance assumes that measurement intercepts and structural covariance are equal across groups. Metric invariance requires testing the measurement model while imposing constraints on the factor coefficients for both subgroups. Subsequently, the differences in the chi-square ($\Delta\chi^2$), degrees of freedom (Δdf), and ΔCFI between the constrained and unconstrained models are calculated and assessed if the chi-square and degrees of freedom results are significant ($p < 0.05$), and if ΔCFI is less than or equal to 0.01 (Steenkamp and Baumgartner, 1998; Vandenberg and Lance, 2000), then the two models are different, and metric invariance cannot be assumed.

Scalar invariance can be determined by imposing constraints on the items' intercepts to be equal across the tested groups. Similar to metric invariance, to assume scalar invariance, the chi-square differences test and the ΔCFI criteria must be met. However, configural and metric invariance should be fulfilled before inspecting scalar invariance.

The test results presented in Table 9 and Table 10 show that metric and scalar invariance are assumed between respondents from different groups (different ages, genders, experiences, and countries) based on a chi-square test for gender, age, and country and the ΔCFI criteria for experience (ΔCFI <0.01).).

4.4. Multigroup analysis

A multigroup analysis using SEM was performed to assess the moderating effects of age, gender, and experience. Following the procedures suggested by Gaskin (2016) and Lutfi et al. (2020, 2023), two nested models were built for each group. One model was built with constraints imposed to be equal on the regression weights, and the other model was built without any constraints. Constraints were added to all regression weights simultaneously to test for interaction effects for the entire model, and then $\Delta\chi^2$ was calculated. Furthermore, all the model paths (intention ← information, intention ← privacy, and intention ← financial) were tested separately to investigate whether the interaction effect partially existed. Therefore, paths were assessed by adding constraints only on the target path and then calculating the chi-square differences. The results for calculating the chi-square differences for the entire model and the individual paths indicated as shown in Table 11 below that the constrained and unconstrained models were similar in subgroup age ($\Delta\chi^2 = 2.78$, df = 3, p = 0.425), subgroup gender ($\Delta\chi^2$ = 0.984, df = 3, p = 0.805), and subgroup country ($\Delta\chi^2 = 8.141$, df = 8, p = 0.42). However, for the experience group, the test indicated significant differences between the models ($\Delta\chi^2 = 9.3$, df = 3, $p < 0.05$).

These results suggest that the magnitude of the relationship between perceived risks and customers' intention to use online shopping services differs based on their previous experience. The path coefficients for all perceived risks (information, privacy, and financial risk) also indicate that perceived risk is higher for customers with no previous experience.

5. Discussion

This study aimed to assess the effects of perceived risks and uncertainty on customers' intention to purchase online products and services. Accordingly, a conceptual model was developed based on the previous literature and validated using data from three countries: Jordan, Kuwait, and Saudi Arabia. Furthermore, the study also aimed to investigate the

Table 9
Measurement invariance test for all groups (different constrained models).

Model	Model	χ^2 (df)	χ^2/df	CFI	TLI	RMESA
Country	Configural	1924.795 (1384)	1.391	0.953	0.949	0.027
	Metric	1961.315 (1416)	1.385	0.952	0.950	0.026
	Scalar	1996.325 (1452)	1.391	0.952	0.951	0.027
Gender	Configural	1233.388 (856)	1.441	0.967	0.962	0.028
	Metric	1271.619 (888)	1.432	0.966	0.962	0.028
	Scalar	1315.958 (924)	1.424	0.966	0.963	0.028
Age	Configural	1282.522 (856)	1.498	0.963	0.957	0.030
	Metric	1318.999 (888)	1.484	0.962	0.958	0.030
	Scalar	1369.805 (924)	1.483	0.961	0.958	0.029
Experience	Configural	1185.238 (856)	1.385	0.971	0.966	0.026
	Metric	1237.310 (888)	1.393	0.969	0.965	0.027
	Scalar	1299.979 (924)	1.385	0.967	0.964	0.027

Table 10
Delta Chi-square significance test.

Model	Model	Δ df	Δ χ^2	P- value	Δ CFI
Country	Δ (Configural and Metric)	32	36.520	0.267	0.001
	Δ (Metric and Scalar)	36	35.010	0.516	0.000
Gender	Δ (Configural and Metric)	32	38.231	0.207	0.001
	Δ (Metric and Scalar)	36	44.339	0.160	0.000
Age	Δ (Configural and Metric)	32	35.377	0.312	0.000
	Δ (Metric and Scalar)	36	50.806	0.051	0.001
Experience	Δ (Configural and Metric)	32	52.073	0.014	0.002
	Δ (Metric and Scalar)	36	62.668	0.004	0.002

effect of sociodemographic characteristics, such as gender, age, and previous online shopping experience, on the relationship between perceived risk and customer purchase intention to buy products and services from online shopping stores. Accordingly, a conceptual model consisting of information risk, functional risk, privacy risk, financial risk, physical risk, delivery risk, time-loss risk, psychological risk, social risk, and three moderating variables (gender, age, and experience) was proposed. Hypotheses concerning the relationships among these constructs were developed and tested. The overall results indicated that 24% of the variance in online purchase intention could be explained by perceived risk. Moreover, only three of the nine proposed forms of risk and uncertainties were relevant to online purchase intention: financial risk, information risk, and privacy risk. Conversely, functional, physical, delivery, psychological, and social risks were found to have no significant effect on online purchase intention.

One of the essential findings of this study is that perceived financial risk emerged as the most influential form of risk regarding customers' online purchase intention. This risk is associated with financial loss if a customer uses online shopping services. Three primary sources of uncertainty were used to measure financial risk: the possibility that the product is cheaper elsewhere, the possibility that the product is overpriced, and the possibility that the website may overcharge the customer by including extra shipping and handling charges. These results are similar to those found by previous researchers (Bhukya and Singh, 2015; Hong et al., 2020; Lutfi et al., 2022; Yang et al., 2015). For example, Bhukya and Singh (2015) found that perceived financial risk has direct negative effects on consumers' intention to purchase retailers' private labels. Similarly, Hong et al. (2020) showed that perceived financial loss significantly influences online purchasing behavior. Accordingly, if customers perceive that an online store has any form of financial loss (e.g., product overpriced or overcharged), they will be reluctant to shop online at that store.

The findings also indicate that information and privacy risks negatively influence customers' intention to use online shopping services. On the one hand, privacy risk captures individuals' feelings that online marketers may abuse their information and share it with third parties. Privacy risk also refers to customers' perception that the service provider may not protect their information from cyberattacks. The present study's findings are somewhat consistent with those of previous studies. For instance, Hong et al. (2020) found no support for the influence of privacy on purchase decisions. Some researchers have found mixed results regarding the influence of privacy risk (Almaiah et al., 2022b; Park et al., 2004). In a cross-cultural study, Park et al. (2004) found that privacy risk appeared to be a significant barrier to e-commerce adoption by customers in the United States, while it had a non-significant influence on Korean respondents. This has led researchers to suggest that culture significantly affects individual perceived privacy (Afshan et al., 2018; Bashir et al., 2021; Lutfi et al., 2022; Liyanaarachchi, 2021; Marriott and Williams, 2018; Mombeuil and Uhde, 2021; Park and Tussyadiah, 2017; Song et al., 2022; Xie et al., 2020). Therefore, the inconsistent findings regarding the influence of privacy risk found in the literature could be propelled by cultural differences (Rivers et al., 2010). Information risk, on the other hand, captures the uncertainty associated with the information dissemination process (Lutfi, 2020). Several types of uncertainty were used to measure customer perception of information risk, including lack or shortage of information, information overload, and information disorganization. The present study's findings are

Table 11
Results of Chi-square difference test for multi-group analysis.

Hypotheses	Relation	β (p-value)	β (p-value)	β (p-value)	$\Delta\chi^2$	Δ *df*	P- value
	Paths for Country	**Jordan**	**KSA**	**Kuwait**	**8.141**	**8**	**0.420**
	Intention < – Information	−0.031(0.733)	−0.325(0.014)	−0.031(0.733)	3.215	7	0.200
	Intention < – Privacy	−0.147(0.037)	−0.226(0.011)	−0.147(0.037)	0.545	7	0.762
	Intention < – Financial	−0.111(0.227)	−0.269(0.057)	−0.111(0.227)	0.383	7	0.826
	Paths for Gender	**Male**	**Female**		**0.984**	**3**	**0.805**
H10.1	Intention < – Information	−0.039(0.724)	0.079(0.396)	–	0.807	2	0.668
H10.3	Intention < – Privacy	−0.143(0.049)	−0.092(0.221)	–	0.980	2	0.613
H10.4	Intention < – Financial	−0.088(0.457)	0.048(0.570)	–	0.578	2	0.749
	Paths for Age	**The twenties**	**The Thirties**	**–**	**2.789**	**3**	**0.425**
H11.1	Intention < – Information	0.267(0.021)	−0.008(0.945)	–	2.034	2	0.362
H11.3	Intention < – Privacy	0.025(0.758)	−0.052(0.668)	–	2.618	2	0.270
H11.4	Intention < – Financial	0.221(0.041)	−0.074(0.591)	–	1.651	2	0.438
	Paths for Experience	**Exp**	**No exp**		**9.301**	**3**	**0.026**
H12.1	Intention < – Information	0.110(0.236)	−0.368(0.197)	–	9.467	2	0.009
H12.3	Intention < – Privacy	0.013(0.863)	−0.402(0.007)	–	6.829	2	0.033
H12.4	Intention < – Financial	0.068(0.459)	−0.527(0.091)	–	7.670	2	0.022

consistent with those of previous studies (Almaiah et al., 2022d; Chen et al., 2009; Marriott and Williams, 2018; Sicilia and Ruiz, 2010; Song et al., 2022; Soto-Acosta et al., 2014).

Furthermore, contrary to previous research, the results of the present study show no significant support for the influence of functional risk, physical risk, delivery risk, psychological risk, and online purchasing decision (Akturan and Tezcan, 2012; Ariffin et al., 2018; Hong et al., 2020; Martins et al., 2014; Park and Tussyadiah, 2017; Ray and Sahney, 2018; Yang et al., 2015). In this regard, one potential explanation for the unexpected relationship could be related to the significant correlation found between financial risk and the other forms of risk: physical risk (r = 0.435, $p < 0.001$), delivery risk (r = 0.81, $p < 0.001$), and functional risk (r = 527, $p < 0.001$). Therefore, these uncertainties may indirectly affect a customer's shopping intention via financial risk. However, there are other possible explanations related to cultural influences on perceived risks (Ahmad et al., 2018; Rivers et al., 2010). For instance, Keysar et al. (2012) found that using a foreign language influences decision-making processes regarding risk and uncertainty by reducing the biases surrounding the intended decision. As many online stores provide their content in English, and the respondents in the present study were recruited from non-English-speaking countries, their intention to use online shopping services could be subject to foreign-language effects. Thus, the respondents may have strong intentions to use these services, regardless of the level of uncertainty associated with online shopping.

Regarding the sociodemographic moderating effect, the present findings support the moderating effect of previous experience on the relationship between all types of risk (financial, information, and privacy) and customers' intention to use online shopping services. Accordingly, customers with previous online shopping experience tend to be less concerned about all forms of risk and uncertainty associated with online shopping channels. This finding is consistent with those of previous studies. For instance, Lopez-Nicolas and Molina-Castillo (2008) and Dai et al.'s (2014) findings demonstrated that respondents with previous experience perceived online shopping as safe. Contrary to expectations, the present study's findings indicated no significant support for the moderating effects of age and gender. These findings are inconsistent with much of the previous literature on online shopping risks (Al-Majali, 2020; Chang, 2021; Garbarino and Strahilevitz, 2004; Lopes et al., 2020; Rodgers and Harris, 2003). However, a narrative review of risk perception research suggested that previous research on the relation between risk perception and sociodemographic variables (including age, gender, level of education, and income) has produced inconsistent results, ranging from these variables having a small to non-significant influence on individual risk perception (Siegrist and Árvai, 2020).

5.1. Managerial and academic implications

This study has several practical and academic implications. First, e-commerce providers are interested in understanding and influencing customers' online purchasing behaviors. Therefore, identifying the most relevant risks and uncertainties affecting online purchase intention may improve customers' experiences and minimize their worries about online shopping services (Almaiah et al., 2022). Accordingly, based on this study's findings, online stores can take several steps to reduce customers' perceived online risks. For example, to reduce financial uncertainty, online stores could provide their customers with online price comparison services, guarantee the lowest price, offer product guarantees and extended warranties, and adopt flexible return policies with no extra delivery costs. Stores can also reduce the uncertainty associated with information by paying extra attention to their websites' content and design. Similarly, online stores can address customer privacy concerns by implementing and updating their security systems.

Second, this study has theoretical implications for the relevant literature because a conceptual model of online perceived risk was developed and validated using data from three countries. Furthermore, this is one of the few studies in this line of research to use analysis techniques such as multigroup analysis, CMB, and three levels of measurement invariance across different groups of respondents (age, gender, experience, and county) to achieve cross-country validation and to investigate the moderating effects of sociodemographic variables. Subsequently, this study could represent a methodological foundation for future investigations in this stream of research. Furthermore, the current study makes several important theoretical contributions to the literature on online purchase decision and online perceived risk. It contributes to the e-commerce literature in relationship to online purchase adoption as well as its perceived risk in developing country such as Saudi Arabia, Jordan, and Kuwait. To the best of the researchers' knowledge, this study is the first to specify either theoretically or empirically test the most relevant sources of risks and uncertainties associated with online shopping services and to investigate the influence of sociodemographic characteristics (e.g., gender, age, and online shopping experience) on the levels of perceived risk. As stated earlier, the literature review shows disagreement regarding the types of risks that influence purchase intention and revealed that, despite a great deal of attentions being concentrated on the behavioural intention and actual use of online purchase services, a very little has been related specifically to online perceived risk context. Subsequently, this research enhances the knowledge by providing a comprehensive model that can be applied to explain and describe how several types of risk influence customer's decisions and intention to use online purchase. The conceptual model involves a number of factors related to risk. As such, the model offers a structured lens through which to explore how these types of risks affect online purchase use.

Additionally, this research was designed to fill the gaps in perceived risk literature by testing the most relevant source of risks and uncertainties related to online shopping services, and testing the influence of sociodemographic characteristics on the levels of perceived risk using data collected from three countries. By doing so, the aim was to differentiate and deepen the understanding of the risks and uncertainties related to online purchase. Meanwhile, testing the behavioural intention to use online purchase under the context sociodemographic characteristics (e.g., gender, age, and online shopping experience) was designed to capture the constraints and opportunities that may influence the occurrence and meaning of online shopping. Therefore, including sociodemographic characteristics as moderators further enhances the understanding of the association between risks and online purchase decisions, and makes our understanding more sensitive to the context of such association.

Although the moderating effects of functional (H2), physical (H5), delivery (H6), psychological (H8), and social risk (H9) on the intention to buy online were not supported in this study, the moderating effects of information (H1), privacy (H3) and financial (H4) risks were supported. This has an insightful theoretical implications. Despite the mention of financial, information and privacy risks in the literature as significant drivers of online purchase decision, a paucity of empirical research exists that has specifically investigated the moderating impact of such factors among e-commerce research. This research provides empirical evidences on the moderating effects of financial, information and privacy risks. This implies that the risks from financial, information and privacy sources are an important variables that interacts with online purchase behavioural intention.

5.2. Recommendations and limitations

Finally, although the present study adds to the existing body of knowledge, several significant limitations must be acknowledged and considered in future research. First, the study's sample was selected from three countries in the Arab region. These countries share cultural aspects that may affect purchase decisions, including language. Thus, attempts to generalize the study results to other contexts or cultures should be carried out with caution. Future research could also involve a cross-cultural comparison to better understand cultural influences on perceived risk. Similarly, the respondents were not distributed based on the selected sociodemographic variables. Therefore, a cross-country comparison among the three countries was not possible. Third, this study was based on a hypothetical online purchasing decision. Furthermore, the collected sample was not appropriate for conducting sound country comparisons using SEM multigroup analysis (Kuwait = 132, Jordan = 215, and Saudi Arabia = 211). Therefore, we used a complete sample to test the research hypotheses. This aimed at strengthening the generalizability of the findings and maintaining appropriate statistical power, as recommended by slu.

The focus was on the effect of risk uncertainties on customer intention rather than on the actual use of technology. Future studies, therefore, could extend the scope to involve actual purchasing decisions to test whether the same forms of uncertainty emerge. Furthermore, future research could expand on the present research findings and evaluate them across countries or cultures using a larger sample size. Future studies may also expand this study and consider the effect of trust and risks of customer purchase decisions and test whether sociodemographic characteristics influence purchase decisions with the existence of trust in the model.

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Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jretconser.2022.103188.

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