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PERCEIVED RISK REMEDIES IN CROSS-BORDER E-COMMERCE – FROM THEORY TO PRACTICE VIA TRIANGULATION BETWEEN PLS-SEM & FSQCA

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Abstract

This study examines how seven dimensions of perceived risk interact to shape purchase intention in cross-border e-commerce (CBEC). Using survey data from 400 Hungarian CBEC users, the study applies a dual-method approach combining PLS-SEM and fuzzy-set qualitative comparative analysis (fsQCA). SEM results indicate that fraud risk and information risk exert significant negative net effects on purchase intention. However, fsQCA reveals multiple sufficient configurations, demonstrating that privacy risk and process & time loss risk become critical when combined with high fraud and information risk. The finding highlights that certain risk dimensions are configurationally important despite being statistically insignificant in linear models. By distinguishing between net and configurational effects, this study advances the multidimensional theory of perceived risk and provides actionable insights for SMEs prioritizing risk mitigation in cross-border markets.

Keywords: *Perceived risk, Cross-border e-commerce (CBEC), purchase intention, SEM, fsQCA*

JEL classification: *D71, D81, D91*

1. INTRODUCTION

Cross-border e-commerce (CBEC) refers to online transactions between buyers and sellers located in different countries, where goods are delivered through cross-border logistics services (Hsiao et al. 2017, p. 285). Despite its strong growth potential - projected to reach $7.9 trillion by 2030 - CBEC still accounts for less than 30% of global B2C e-commerce revenue (Statista 2023). Various barriers continue to constrain its development, including issues related to payment methods, currency exchange, customs procedures, shipping, and returns (Contentserv 2024). High cart abandonment rates, particularly on mobile devices (Statista 2023), further suggest that consumers perceive substantial uncertainty and risk in cross-border transactions. Consequently, perceived risk has become a critical construct for understanding consumer behavior in CBEC contexts.

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Extensive research has examined the relationship between perceived risk and purchase intention, generally confirming its negative impact (Sadiq et al. 2022; Zhou and Liu 2022). However, the literature reveals conceptual and methodological inconsistencies. First, perceived risk has been variously conceptualized as either a unidimensional or multidimensional construct (Ariffin et al. 2018; Chiu et al. 2014; Pappas 2016), with inconsistent categorization of its dimensions. Scholars differ in defining perceived risk, ranging from potential losses in online transactions (Ariffin et al. 2018) to concerns about product quality (Chidambaram et al. 2023) or reduced utility and convenience (Li and Huang 2009). Such inconsistencies have resulted in fragmented findings regarding which specific risk dimensions significantly influence purchase intention.

Second, structural equation modeling (SEM) dominates the field, often identifying only a subset of risk dimensions as significant predictors. For example, prior studies report that only some dimensions affect purchase intention, despite proposing multiple risk components (Hong and Cha 2013; Nguyen et al. 2021; Pentz et al. 2020). Strong correlations among risk dimensions further complicate clear structural modeling. This reliance on linear net-effects approaches may obscure the interactive and conditional nature of perceived risk in CBEC.

Recent calls suggest the need for alternative methodological approaches capable of capturing complex interdependencies among risk dimensions (Phamthi et al. 2024). While a few studies have applied fuzzy-set qualitative comparative analysis (fsQCA), most have examined perceived risk as a unidimensional construct (Abbasi et al. 2022; Alyahya et al. 2023; Gunawan and Huarng 2015), limiting the exploration of its multidimensional interplay. To address these gaps, this study investigates how seven dimensions of perceived risk jointly shape purchase intention in cross-border e-commerce (CBEC), namely fraud risk, financial risk, product risk, information risk, delivery risk, process & time loss risk, and privacy risk. Accordingly, the study is guided by the following research questions:

> RQ1: How do the seven dimensions of perceived risk interact to influence purchase intention in CBEC?
> RQ2: What configurations of perceived risk dimensions lead to high or low levels of purchase intention?

This study makes three key contributions. First, it advances the multidimensional conceptualization of perceived risk in CBEC by integrating perceived risk theory with complexity theory, thereby providing a more comprehensive explanation of consumer decision-making. Second, it adopts a dual-method approach combining PLS-SEM and fsQCA to distinguish between net effects and configurational effects of perceived risk dimensions. Third, by identifying necessary and sufficient combinations of risk conditions, the study offers actionable insights for SMEs seeking to prioritize risk mitigation strategies in cross-border markets.

2. Theoretical background

2.1. Multidimensional theory of perceived risk

Perceived risk refers to a consumer's subjective expectation of loss in a purchase decision (Bauer 2001). Due to uncertainty in outcomes, consumers anticipate potential negative consequences that influence their behavior. Early studies established that perceived risk is multidimensional rather than a single construct. Roselius (1971) identified key risk types - financial, physical, psychological, and time loss - while Jacoby and Kaplan (1972) further formalized five distinct dimensions, including financial, performance, physical, psychological, and social risks, forming the foundation of multidimensional risk theory.

Subsequent research has expanded these dimensions across contexts. For instance, privacy risk was introduced in e-services Featherman and Pavlou (2003), while later studies highlighted functionality, information misuse, and other digital risks (Glover and Benbasat 2010; Ariffin et al. 2018; Bashir et al. 2021). Table 1 summarizes key conceptualizations.

2.2. Perceived risk in Cross-border e-commerce

Cross-border e-commerce (CBEC) involves transactions between buyers and sellers in different countries, requiring international logistics and payment systems (Chen et al. 2023). Compared to domestic e-commerce, CBEC entails greater uncertainty due to geographic distance, cultural differences, regulatory diversity, and weaker institutional enforcement (Chen et al. 2023; Mou et al. 2020). These factors increase risks such as delivery delays, product damage, and difficulties in dispute resolution (Shao et al. 2021). Prior studies confirm that such uncertainties reduce trust and purchase intention (Sun and Li 2022).

Table 1. A summary of multiple perceived risk dimensions

Authors	No. of dimensions	
Roselius (1971)	4	financial risk, physical risk, psychological risk, and time loss
Jacoby and Kaplan (1972)	5	Financial risk, performance risk, physical risk, psychological risk, and social risk
Featherman and Pavlou (2003)	6	performance risk, financial risk, privacy risk, time risk, psychological risk, and social risk
Glover and Benbasat (2010)	3	risk of functionality inefficiency, risk of information misuse, and risk of failure to gain product benefit
Han and Kim (2017)	7	Social risk, financial risk, time risk, psychological risk, privacy risk, product risk, security risk
Ariffin et al. (2018)	6	Social risk, financial risk, time risk, psychological risk, product risk, security risk
Bashir et al. (2021)	11	high price risk, deception risk, transaction failure risk, dissimilar product risk, incapable service risk, illegitimate product risk, isolation risk, unease risk, displeasure risk, prior-purchase time delays risk, and post-purchase time delays risk

In this study, perceived risk is defined as consumers' subjective expectation of potential loss arising from cross-border transactional uncertainties. Drawing on prior research, this study adopts seven dimensions: fraud, financial, product, information, delivery, process & time loss, and privacy risk (Featherman and Pavlou 2003; Mou et al. 2020; Nguyen et al. 2021) (Table 2). These dimensions capture risks across pre-purchase, transaction, and post-purchase stages.

Although CBEC research identifies additional risks (e.g., customer duties or confiscation risk), these are conceptually embedded within the seven dimensions. For instance, tariff-related uncertainty reflects financial risk, while customs delays relate to delivery and process risks (Shao et al. 2021). Institutional enforcement issues are reflected in fraud risk (Mou et al. 2020), and information asymmetry is captured under information risk (Chen et al. 2023).

2.3. Relationships between Perceived risk dimensions and Purchase intention in CBEC

Online purchase intention refers to the likelihood that a consumer will buy from an online merchant (Jadil et al. 2022). It is a key indicator of pre-purchase behavior, and higher perceived risk reduces this likelihood (Roselius 1971). Prior studies consistently show that perceived risks – such as financial, product, and psychological risks – negatively affect purchase intention (Pillai et al. 2022). In CBEC, risks including delivery, financial, and privacy concerns significantly reduce purchase and repurchase intentions, while weakening trust (Mou et al. 2020; Sun and Li 2022; Shao et al. 2021).

Fraud risk is particularly salient in CBEC due to high uncertainty and weak cross-border enforcement. It reflects concerns about opportunistic or deceptive seller behavior (Pavlou et al. 2007), which are intensified by information asymmetry and limited legal recourse (Nguyen et al. 2021; PhamThi 2022). These risks significantly reduce trust and transaction intention (Cui et al. 2020; Guo et al. 2018).

H1: Fraud risk negatively affects purchase intention in CBEC.

Financial and product risks are also critical. Financial risk involves potential monetary loss or additional costs such as tariffs and fees, while product risk refers to uncertainty about product quality or performance. Both significantly influence consumer trust and behavior (Yang et al. 2016; Mou et al. 2020).

H2: Financial risk negatively affects purchase intention in CBEC.

H3: Product risk negatively affects purchase intention in CBEC.

Information and delivery risks relate to information asymmetry and logistics uncertainty. Issues such as insufficient product information, delivery delays, or product damage discourage purchases (Nguyen et al. 2021; Alrawad et al. 2023; Ariffin et al. 2018)

H4: Information risk negatively affects purchase intention in CBEC.
H5: Delivery risk negatively affects purchase intention in CBEC.

Process & time loss risk reflects inconvenience and inefficiency during online purchasing (Pentz et al. 2020), while privacy risk concerns misuse of personal or financial data (Zhang et al. 2012; Alrawad et al. 2023). Both reduce purchase intention.

H6: Process & time loss risk negatively affects purchase intention in CBEC.
H7: Privacy risk negatively affects purchase intention in CBEC.

The SEM model is presented in Figure 1

Table 2. Operational definitions and instrumentations for constructs

Constructs	Operational Definition	Items	Instrumentation
Fraud Risk (FRA)	The perceived likelihood of transactional loss resulting from deceptive, opportunistic, or unreliable behavior by cross-border online vendors.	– Information about the product on this website may not true – It may be difficult to get support on this website when product fails – I may not find the place where to settle disputes on this website – This website may disappear after a short time – Sellers on this website may fail to keep the promise of post-services	5 items Naiyi (2004)
Financial Risk (FIN)	The likelihood of financial loss or paying supplementary fees while participating in CBEC	– Traditional stores may offer more discounts than this website – This website offers discount prices but the total cost may not lower. – Online payment on this website will charge extra fees – Delivering to the home will charge relatively higher fees	4 items Naiyi (2004)
Product Risk (PRO)	The prospective loss sustained when products fail to meet expectations in CBEC	– The quality of the product may not be accepted – The product performance may not be consistent with the expectation – The product may be false and the quality will be poor – It is difficult to return when the product is not satisfied	4 items Naiyi (2004)
Information Risk (INF)	The potential for asymmetric knowledge about sellers and items in CBEC	– The information about online suppliers on this website is not sufficient – The information about product to be purchased on this website is not sufficient	2 items Naiyi (2004)
Delivery Risk (DEL)	The likelihood of delayed product delivery or extended shipment duration in CBEC	– The delivered product may be lost – The product may be delivered a wrong place – The product may be damaged during the delivering	3 items Naiyi (2004)
Process & Time Loss Risk (PTL)	The potential for a consumer's complexity and aggravation to surpass the anticipated online purchasing experience in CBEC	– The process of purchasing on this website is complex and inconvenient – Accessing this website will take too much time – Information transformation is too slow during purchasing	3 items Naiyi (2004)
Privacy Risk (PRI)	The possible relinquishment of control over personal data when used without consent in CBEC	– My personal address, telephone number could be misused by others – My e-mail address could be misused by others – The account number of my credit or debit card could be misused by others	3 items Naiyi (2004)

Figure 1. SEM model

2.4. Applying Complexity theory (Set theory) to perceived risk in CBEC

Complexity theory explains consumer behavior as the result of interacting conditions rather than isolated effects (Woodside 2014). This perspective is well-suited to CBEC, where multiple perceived risks coexist and influence purchase decisions simultaneously. The theory is based on four principles: conjunctural causation, equifinality, causal asymmetry, and necessity/sufficiency. These suggest that outcomes arise from combinations of conditions, multiple pathways can lead to the same outcome, causal relationships are asymmetric, and some conditions may be necessary or sufficient only in combination (Ragin 2009; Woodside 2014).

In CBEC, consumers face multiple risks, including fraud, financial, product, information, delivery, process & time-loss, and privacy risks. Traditional linear methods such as SEM assume independent and symmetric effects of each risk on purchase intention (Chen et al. 2021; Yang et al. 2015). However, this additive approach may oversimplify decision-making, as risks often interact in nonlinear and asymmetric ways. For example, certain risks may only influence purchase intention when combined with others, with some acting as core conditions and others as peripheral (Fiss 2011).

Accordingly, purchase intention in CBEC is better understood as the outcome of configurations of perceived risks rather than isolated effects. This study therefore combines SEM and fsQCA. SEM identifies net effects of individual risks, while fsQCA captures configurational patterns and tests key principles of complexity theory, including equifinality and causal asymmetry (Ragin 2009; Woodside 2014). This combined approach provides a more comprehensive explanation of CBEC purchase intention.

2.5. Research Propositions

Complexity theory favors the use of “propositions” rather than “hypotheses,” reflecting the view that outcomes arise from nonlinear and interdependent relationships among multiple conditions (Chuah et al. 2021; Pappas 2016; Wang et al. 2023). A key principle is equifinality, which suggests that the same outcome can result from different combinations of causal conditions (Pappas 2016; Woodside 2014).

Prior research on perceived risk in e-commerce has largely relied on variance-based approaches, examining risks as independent or aggregate predictors of purchase intention (Featherman and Pavlou 2003; Nguyen et al. 2021). While studies confirm that lower perceived risk increases purchase intention (Gunawan and Huarng 2015; Alyahya et al. 2023), they often overlook how risk dimensions interact. Emerging research highlights the configurational role of perceived risk, showing that it interacts with other factors to shape consumer behavior (Badu-Baiden et al. 2025; Sun et al. 2021).

From a complexity perspective, CBEC purchase intention results from configurations of perceived risks, including fraud, financial, product, information, delivery, process & time-loss, and privacy risks. These risks interact through conjunctural causation, with some acting as core conditions and others as peripheral conditions (Ragin 2009; Fiss 2011). Moreover, consistent with causal asymmetry, configurations leading to high purchase intention differ from those leading to low purchase intention (Woodside 2014).

Accordingly, this study proposes:

P1: Different configurations of perceived risk dimensions negatively influence purchase intention in CBEC.

P2: Core risk dimensions drive purchase intention outcomes, while peripheral risks amplify these effects.

The fuzzy-set model is presented in Equation 1.

Equation 1: Fuzzy-set model

$$PI=\int(FRA, FIN, PRO, INF, DEL, PLT, PRI)$$

Where PI is Purchase intention, FRA is Fraud risk, FIN is Financial risk, PRO is Product risk, INF is Information risk, DEL is Delivery risk, PLT is Process & Time loss risk, and PRI is Privacy risk

3. Methodology

3.1. Research Context and Procedure

This study employs a cross-sectional quantitative online survey. Hungary was selected due to the relatively low adoption of cross-border e-commerce (CBEC), with only 37% of online shoppers engaging in CBEC (CMI 2023). This context provides valuable insights into barriers affecting purchase intention and may be applicable to other Central and Eastern European markets. To enhance realism, a simulated e-commerce website was used. Participants were asked to explore the site (see Appendix 1) before completing the survey, with all constructs measured self-reported items.

3.2. Sample and Data collection

Respondents were Hungarian online shoppers with prior e-commerce experience, recruited through an online survey. Invitations were distributed randomly across multiple online channels in several waves to reduce selection bias. Screening questions ensured participants were adults (18+) with online shopping experience. Although participation was voluntary, the randomized distribution and eligibility criteria minimized bias, resulting in a quasi-random sampling approach commonly used in online consumer research.

The formula for calculating sample size is presented in Equation 2:

Equation 2. Sample size calculation

$$n = \frac{N * X}{X + N - 1}$$

Where:

$$X = (\frac{Za}{2^2} * P(1 - P))/MOE^2$$

n= Sample size,

P= Proportion of the sample

MOE= Margin of error, a 5% margin of error is usually selected

N= Population size

$Z\text{–}(a/2)$ = The critical value of the normal distribution at a $a/2$ (for a confidence interval level of 95%, a is 0.05 and the critical value is 1.96)

According to Etikan (2019), the sample size does not change much for a population larger than 20,000. Consequently, a minimum sample size of 385 was necessary for this study. The survey was pre-tested so that the questions might be refined. The primary data collection was conducted over a period of four months with 800 invitations. Responses were screened for completeness and attention checks, resulting in 400 valid cases (50% response rate).

3.3. Measurement and Data analysis

Measurement instruments are presented in Table 2. Perceived risk was measured using Naiyi's (2004) 23-item scale across seven dimensions, while purchase intention was measured using Zhang et al. (2012) with three items.

Data were analyzed using PLS-SEM due to its suitability for small samples and non-normal data. The dataset showed slight non-normality, with moderate negative skewness.

Additionally, fsQCA was employed to examine configurational relationships among variables (Fainshmidt et al. 2020). Following prior studies, Likert-scale data were calibrated into fuzzy sets using thresholds of 4 (full membership), 3 (crossover), and 2 (full non-membership) (Pappas and Woodside 2021). This approach ensures theoretically meaningful classification and avoids distortions from skewed data (Ordanini et al. 2014; Pappas et al. 2016).

Truth tables were constructed to identify configurations of seven conditions (2^7 = 128 combinations). A frequency threshold of 1 and a consistency threshold of 0.80 were applied to retain reliable configurations (Ragin 2009; Pappas and Woodside 2021). Additional validity checks included PRI and SYM consistency measures (Table 3). Finally, configurations were simplified using the Quine–McCluskey algorithm to derive solution paths.

Table 3. A sorted truth table in fsQCA

R	Conditions							No. of cases	Outcome	raw consist.	PRI consist.	SYM consist
	INF	FRA	DEL	FIN	PLT	PRO	PRI		PI			
1	0	1	1	1	0	1	1	2	0	0.991	0.988	0.988
2	1	1	1	0	1	1	1	1	0	0.988	0.982	0.982
3	1	1	1	1	0	1	1	6	0	0.987	0.980	0.980
4	0	1	1	0	0	1	1	1	0	0.984	0.978	0.978
5	1	1	0	1	1	1	1	2	0	0.984	0.983	0.988
6	0	1	1	1	1	1	1	2	0	0.971	0.951	0.951
7	1	1	1	1	1	1	1	215	0	0.969	0.955	0.977
8	0	1	0	0	0	0	0	1	0	0.967	0.949	0.949
9	0	1	1	0	1	0	1	2	0	0.951	0.902	0.902
10	1	0	0	0	0	0	1	1	0	0.950	0.935	0.935
11	0	1	0	0	0	0	1	1	0	0.939	0.874	0.874
12	0	0	0	0	0	0	0	39	1	0.938	0.921	0.945
13	0	1	1	0	0	0	1	1	0	0.930	0.862	0.862
14	0	1	1	0	1	0	0	1	0	0.926	0.843	0.843
15	0	1	0	1	1	0	1	2	0	0.924	0.880	0.880
16	0	1	0	0	1	0	1	2	0	0.924	0.883	0.883
17	1	1	1	0	1	0	1	2	0	0.909	0.835	0.851
18	1	1	0	1	1	0	1	6	0	0.905	0.818	0.818
19	0	1	1	1	1	0	0	1	0	0.900	0.819	0.819
20	0	1	0	1	1	1	0	1	0	0.883	0.800	0.803
21	0	0	1	0	0	0	0	4	1	0.872	0.768	0.768
22	1	0	0	0	0	0	0	1	1	0.872	0.739	0.739
23	0	0	0	0	1	0	0	1	1	0.854	0.656	0.656
24	1	1	1	1	1	0	1	6	0	0.844	0.617	0.617
25	0	0	0	1	0	0	0	2	1	0.831	0.652	0.652
26	0	1	1	0	1	1	1	4	0	0.825	0.592	0.592
27	1	1	1	1	1	1	0	1	0	0.813	0.517	0.517
28	1	0	0	0	1	0	0	1	1	0.800	0.483	0.483

Notes: Rows are labeled as follow: 1 – membership in the set, 0 – non-membership in the set 2^7

4. Results

4.1. The characteristics of the dataset

The demographic characteristics of the sample are presented in Table 4. The sample shows a balanced gender distribution (50% male, 50% female). Most respondents were relatively young, with 35% aged 18–25, 38.5% aged 26–35, and 26.5% aged above 36, reflecting the typical profile of active online shoppers in emerging CBEC markets. Employment status was evenly split between students (50%) and employed respondents (50%). Regarding monthly e-commerce spending, the majority of respondents (64.25%) reported spending less than USD 100 (approximately 35,000 Ft), while 19.75% spent between USD 100 and 500 and 16% spent more than USD 500. Although this amount represents a modest portion of the average disposable income of Hungarians, which is around $1500 per month (OECD 2024), this spending level aligns with typical consumer behavior (Statista 2021). Although the sample is skewed toward younger and lower-spending consumers, which may limit generalizability to older or more experienced segments, it provides a relevant representation of the emerging CBEC consumer base in Central and Eastern Europe.

Table 4. Demographic data

		Number	Percentage (%)
Sample size		400	100.00
Gender	Man	200	50.00
	Women	200	50.00
Age groups	18-25	140	35.00
	26-35	154	38.50
	Above 36	106	26.50
Employment status	Student	200	50.00
	Working	200	50.00
Monthly spending on e-commerce	Less than 100 USD	257	64.25
	100-500 USD	79	19.75
	Above 500 USD	64	16.00

Table 5. Measurement reliability

Indicator	Loadings	Dijkstra-Henseler's rho (ρA)	Jöreskog's rho (ρc)	Cronbach's alpha(α)	AVE	VIF
Fraud risk		0.892	0.890	0.889	0.618	
Fraudrisk1	0.816					2.478
Fraudrisk2	0.712					1.796
Fraudrisk3	0.827					2.355
Fraudrisk4	0.759					2.241
Fraudrisk5	0.810					2.237
Delivery risk		0.878	0.873	0.872	0.696	
Deliveryrisk1	0.889					2.264
Deliveryrisk2	0.752					2.174
Deliveryrisk3	0.856					2.753
Financial risk		0.867	0.866	0.865	0.617	
Financialrisk1	0.790					2.286
Financialrisk2	0.735					1.805
Financialrisk3	0.832					2.096
Financialrisk4	0.783					2.232
Process & time loss risk		0.845	0.842	0.840	0.640	
P&Trisk1	0.839					2.294
P&Trisk2	0.739					1.767
P&Trisk3	0.818					2.098
Product risk		0.866	0.864	0.863	0.614	
Productrisk1	0.766					2.102
Productrisk2	0.733					1.761
Productrisk3	0.827					2.401
Productrisk4	0.805					2.037
Privacy risk		0.844	0.837	0.835	0.633	
Privacyrisk1	0.878					2.086
Privacyrisk2	0.732					1.823
Privacyrisk3	0.768					1.973
Information risk		0.855	0.850	0.848	0.740	
Informationrisk1	0.907					2.181
Informationrisk2	0.812					2.181
Purchase intention		0.884	0.882	0.882	0.714	
PI1	0.870					2.532
PI2	0.868					2.528
PI3	0.795					2.340

4.2. Common Method Bias

Harman's single-factor test was conducted using exploratory factor analysis in SPSS to assess any common method bias. All elements from the study's constructs were included in an unrotated principal component analysis. The findings indicated many components with eigenvalues over 1, with the primary factor representing 47.24% of the total variance, falling short of the 50% benchmark (Podsakoff et al. 2003). Moreover, the VIF readings for all indices remain below 3. Consequently, common technique bias is not seen as a substantial concern in this study.

4.3. Measurement assessment

The measurement model demonstrates satisfactory reliability and validity across all constructs (Table 5). Indicator loadings are generally above the recommended threshold of 0.70, indicating good indicator reliability. Internal consistency is supported, as Cronbach's alpha and composite reliability (Dijkstra–Henseler's rho_A and Jöreskog's rho_c) for all constructs exceed 0.80. Convergent validity is confirmed with all AVE values above 0.50, suggesting that the constructs explain a substantial portion of variance in their indicators. Additionally, VIF values are well below the critical threshold of 5, indicating no multicollinearity concerns.

The discriminant validity of the measurement model was assessed using both the Fornell–Larcker criterion and the HTMT ratio. As shown in Table 6, the square roots of AVE (diagonal values) for most constructs exceed their corresponding inter-construct correlations, indicating that each construct shares more variance with its own indicators than with other constructs. However, the Fornell–Larcker criterion is not fully satisfied for financial risk, product risk, and privacy risk, suggesting potential concerns regarding discriminant validity.

Table 6. Fornell - Larcker

Construct	Fraud risk	Delivery risk	Financial risk	Process &Time loss risk	Product risk	Privacy risk	Information risk	PI
Fraud risk	0.6177							
Delivery risk	0.5681	0.6962						
Financial risk	0.6823	0.5671	0.6172					
Process &Time loss risk	0.5981	0.3708	0.5013	0.6401				
Product risk	0.5596	0.553	0.6442	0.4085	0.6137			
Privacy risk	0.6641	0.4742	0.5926	0.576	0.5137	0.6325		
Information risk	0.4246	0.4104	0.6274	0.4141	0.5202	0.5111	0.7403	
PI	0.5865	0.4669	0.5679	0.4697	0.5148	0.5102	0.4849	0.7137
Squared correlations; AVE in the diagonal.								

Table 7. HTMT

Construct	Fraud risk	Delivery risk	Financial risk	Process &Time loss risk	Product risk	Privacy risk	Information risk	PI
Fraud risk								
Delivery risk	0.756							
Financial risk	0.828	0.752						
Process &Time loss risk	0.776	0.610	0.710					
Product risk	0.750	0.745	0.804	0.642				
Privacy risk	0.816	0.685	0.771	0.762	0.721			
Information risk	0.652	0.642	0.796	0.648	0.722	0.717		
PI	0.766	0.683	0.754	0.686	0.718	0.714	0.698	

Recent studies have highlighted that the Fornell–Larcker criterion may be insufficiently sensitive in detecting discriminant validity issues, particularly when indicator loadings are relatively homogeneous (Henseler et al. 2015; Voorhees et al. 2016). Therefore, discriminant validity was further assessed using the HTMT ratio, which is considered a more robust criterion. As reported in Table 7, all HTMT values fall below the conservative threshold of 0.85, supporting the adequacy of discriminant validity among the constructs.

Nevertheless, several constructs exhibit relatively high inter-construct correlations and HTMT values approaching the threshold, indicating that certain perceived risk dimensions are conceptually related and may partially overlap. This is not unexpected, as different types of perceived risk in CBEC often co-occur and jointly shape consumer evaluations. This observation further supports the integration of complexity theory and the use of a complementary configurational approach (fsQCA), which allows for the examination of how multiple interrelated risk conditions jointly influence purchase intention rather than assuming purely independent net effects.

4.4. Results from SEM

Table 8 presents the Goodness-of-Fit Indices of the SEM model. The SRMR is 0.0277 (<0.05) less than the threshold. The dULS and dG values are also below both the 95% and 99% confidence limits, which suggests a good fit overall.

Table 8. Goodness of fit

	Value	HI95	HI99
SRMR	0.0277	0.031	0.0344
dULS	0.2899	0.3638	0.4481
dG	0.2048	0.2074	0.2249

The results of the path modeling are presented in Figure 2. Accordingly, the explained variance of 67.6% (R^2=0.676) is relatively high, indicating that purchase intention is explained well by the seven dimensions of perceived risk.

The hypothesis testing results indicate that only fraud risk (H1) and information risk (H4) have a statistically significant negative effect on purchase intention (Table 9). Both paths show t-values close to or exceeding the 1.96 threshold, p-values below 0.05, and 95% confidence intervals that do not include zero, confirming their significance. Fraud risk exhibits the strongest effect ($\beta = -0.294$, $f^2 = 0.050$), while information risk shows a smaller but still meaningful effect ($\beta = -0.193$, $f^2 = 0.036$). The remaining risk dimensions (financial, product, delivery, P&T loss, and privacy risks) are not significant, as their confidence intervals include zero and their effect sizes are negligible. This pattern is not primarily due to multicollinearity, since VIF values are within acceptable limits. The results indicate that fraud risk and information risk emerge as the most salient and central predictors, whereas the remaining risk dimensions do not exert independent net effects.

Figure 2. Findings from PLS-SEM analysis

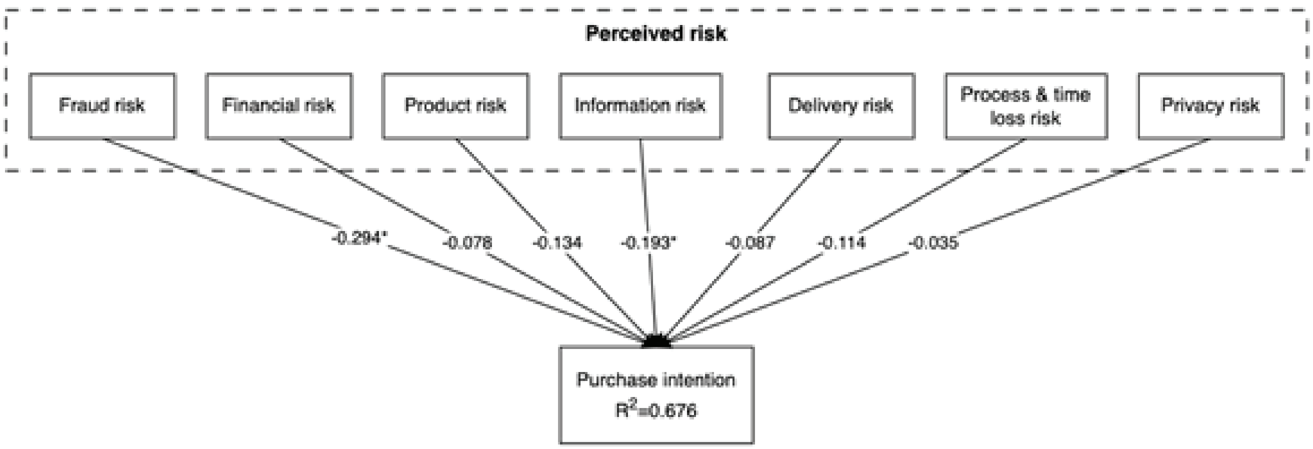

Table 9. Hypothesis testing - PLS-SEM results

Hypothesis	Original coefficient	t-value	p-value (2-sided)	F2	95% CI	Supported
H1: Fraud risk -> PI	-0.2935	-2.2368	0.0255	0.0501	[−0.5607, −0.0480]	Yes
H2: Financial risk -> PI	-0.078	-0.4829	0.6293	0.0034	[−0.4060, 0.2253]	No
H3: Product risk -> PI	-0.1337	-1.2441	0.2137	0.0159	[−0.3380, 0.0805]	No
H4: Information risk -> PI	-0.1928	-1.9652	0.0494	0.0361	[−0.4229, −0.0100]	Yes
H5: Delivery risk -> PI	-0.0867	-1.0884	0.2767	0.008	[−0.2443, 0.0802]	No
H6: Process &Time loss risk -> PI	-0.1141	-1.2971	0.1949	0.0137	[−0.2859, 0.0577]	No
H7: Privacy risk -> PI	-0.0351	-0.3208	0.7484	0.001	[−0.2252, 0.1988]	No

4.5. Results and analysis from fsQCA

Table 10 shows that no single risk condition reaches the conventional necessity threshold (consistency ≥ 0.90) for high/low purchase intention, indicating that high/low purchase intention cannot be explained by any single risk factor alone. This supports the configurational logic of fsQCA.

The core condition analysis shows clear asymmetry between high and low purchase intention (Table 11). High purchase intention is explained by a single configuration—the absence of fraud and privacy risks (~FRA * ~PRI)—with strong coverage (0.657) and consistency (0.833), indicating these are key prerequisites for purchasing.

In contrast, low purchase intention is driven by multiple configurations. Privacy risk alone (PRI) has the highest coverage (0.904), while combinations such as fraud risk with process & time loss risk (FRA * PLT) and process & time loss risk with information risk (PLT * INF) also contribute, all showing high consistency (0.919–0.962).

Overall, high solution coverage (0.948) and consistency (0.912) confirm robust results. These findings highlight that low purchase intention arises from multiple risk combinations, whereas high purchase intention depends on the absence of key risks, supporting fsQCA asymmetry.

Table 12 presents the intermediate fsQCA solutions explaining high and low purchase intention. For high purchase intention (Solutions 1a–1c), all configurations are characterized by the absence (low level) of fraud risk and privacy risk as core conditions. This

Table 10. Results of necessary conditions analysis

	High Purchase intention		Low Purchase intention	
	Consistency	Coverage	Consistency	Coverage
Fraud risk	0.405	0.113	0.859	0.929
~Fraud risk	0.746	0.718	0.123	0.427
Delivery risk	0.406	0.121	0.856	0.924
~Delivery risk	0.746	0.589	0.186	0.530
Financial risk	0.353	0.105	0.871	0.938
~Financial risk	0.793	0.631	0.169	0.485
Process & time loss risk	0.415	0.122	0.870	0.925
~Process & time loss risk	0.744	0.614	0.174	0.517
Product risk	0.337	0.104	0.845	0.939
~Product risk	0.801	0.589	0.193	0.512
Privacy risk	0.433	0.122	0.804	0.919
~Privacy risk	0.714	0.674	0.136	0.465
Information risk	0.355	0.110	0.835	0.936
~Information risk	0.795	0.572	0.206	0.536
~ denotes the absence (low level) of a condition				

Table 11. Core condition analysis

High Purchase intention				Low Purchase intention			
Conditions	Raw coverage	Unique coverage	Consistency	Conditions	Raw coverage	Unique coverage	Consistency
~FRA*~PRI	0.657	0.657	0.833	PRI	0.904	0.094	0.919
				FRA*PLT	0.831	0.017	0.943
				PLT*INF	0.769	0.005	0.962
Solution coverage	0.657			Solution coverage	0.948		
Solution Consistency	0.833			Solution consistency	0.912		
Frequency cutoff	1			Frequency cutoff	1		
Consistency Cutoff	0.8			Consistency cutoff	0.8		
~ denotes the absence (low level) of a condition							

Table 12. Sufficient analysis

Conditions	High Purchase intention			Low Purchase intention			
	S1a	S1b	S1c	S2a	S2b	S2c	S2d
Fraud risk	⨂	⨂	⨂	⬤	⬤	⬤	●
Delivery risk	⊗		⊗	●	●		●
Financial risk	⊗	⊗		●		●	●
Process & time loss risk		⊗	⊗	⬤	⬤	⬤	
Product risk	⊗	⊗	⊗	●			●
Privacy risk	⨂	⨂	⨂		⬤	⬤	⬤
Information risk		⊗	⊗	⬤	⬤	⬤	
Raw coverage	0.541	0.513	0.5	0.658	0.687	0.704	0.709
Unique coverage	0.06	0.032	0.019	0.014	0.003	0.022	0.056
Consistency	0.914	0.926	0.926	0.983	0.98	0.975	0.971
Solution coverage	0.593			0.833			
Solution consistency	0.896			0.937			
Frequency Cutoff	1						
Consistency Cutoff	0.8						

●: *the high-level conditions,*
⊗: *the low-level conditions,*
core conditions are denoted by the larger circles,
peripheral conditions (i.e., supporting factors) are denoted by smaller circles.

Table 13. Summary of Robust Configurational Findings Across Model Specifications

Condition	High Purchase Intention (PI)	Low Purchase Intention (~PI)	Baseline (2–3–4)	Stricter Threshold (Freq=4; Cons=0.9)	Alternative Calibration (20–50–80)
Fraud risk (FRA)	Absent (~FRA)	Present (FRA)	x	x	x
Financial risk (FIN)	Mixed	Present (FIN)	x	x	x
Privacy risk (PRI)	Absent (~PRI)	Present (PRI)	x	x	x
Delivery risk (DEL)	Peripheral	Peripheral	x	x	x
Product risk (PRO)	Peripheral	Peripheral	x	x	x
Process & time loss risk (PLT)	Peripheral	Peripheral	x	x	x
Information risk (INF)	Peripheral	Peripheral	x	x	x

Table 14. Model-level comparison

Model Specification	High PI Coverage	High PI Consistency	Low PI Coverage	Low PI Consistency
Baseline (2–3–4)	0.593	0.896	0.833	0.937
Stricter Threshold	0.481	0.938	0.712	0.967
Alternative Calibration	0.714	0.727	0.559	0.884

indicates that minimizing these two risks is a central prerequisite for achieving high purchase intention in CBEC. Other perceived risk dimensions - delivery risk, financial risk, product risk, process & time loss risk, and information risk - appear only in some solutions as peripheral conditions, suggesting that they support high purchase intention by further reducing uncertainty but are not independently sufficient. The presence of multiple solutions with high consistency (0.914–0.926) and moderate solution coverage (0.593) demonstrates that high purchase intention can be achieved through different combinations of peripheral risk reductions, provided that fraud and privacy risks remain low. In contrast, low purchase intention (Solutions 2a–2d) is explained by several configurations dominated by the presence (high level) of fraud risk, privacy risk, process & time loss risk, and information risk, which frequently function as core conditions. These core risks are accompanied by delivery, financial, and product risks as peripheral conditions, which intensify the negative effect of the core risks when present. The low purchase intention solutions exhibit very high consistency (0.971–0.983) and strong solution coverage (0.833), indicating that unfavorable purchase outcomes arise through multiple, well-defined combinations of elevated perceived risks. The results, therefore, supported P1 and P2.

To assess the robustness of the findings, we estimated the fsQCA models in two methods: (1) by adjusting frequency and consistency cutoffs for both high and low purchase intention (frequency = 4; consistency = 0.90) and (2) by an alternative calibration based on the 20th, 50th, and 80th percentiles, suggested by Cangialosi (2023); Pappas (2017) when data are asymmetrical or do not conform to normality assumptions.

Table 13 and 14 summarize the key configurational findings across the baseline model and alternative specifications. The results clearly show that core conditions - particularly fraud risk, financial risk, and privacy risk - remain stable across all analyses. Specifically, high purchase intention is consistently associated with the absence of fraud and privacy risks, whereas low purchase intention is driven by the presence of fraud, financial, and privacy risks. While variations in coverage and the number of configurations is observed under stricter thresholds and alternative calibration, the overall configurational logic and core causal conditions remain unchanged. This provides strong evidence for the robustness of the findings.

5. Discussion and implications

This study examines the relationship between seven perceived risk dimensions and purchase intention in CBEC using PLS-SEM and fsQCA. The results show both convergence and complementarity, offering a deeper understanding of consumer behavior .

Convergence is found for fraud risk and

information risk, which significantly reduce purchase intention in SEM and appear as core conditions in fsQCA configurations. This confirms their role as key deterrents, consistent with prior research (Alrawad et al. 2023; Nguyen et al. 2021; Shao et al. 2021).

Complementarity emerges for other risks (delivery, financial, product, privacy, and process & time loss). While insignificant in SEM, fsQCA shows they influence purchase intention within specific configurations, supporting the idea that risks interact rather than act independently (Pappas 2016; Pillai et al. 2022). High correlations among risk dimensions further suggest that consumers perceive risks simultaneously, which may obscure individual effects in SEM (Koufteros et al. 2009; Hong and Cha 2013; Pentz et al. 2020).

For example, privacy risk is insignificant in SEM but becomes important in fsQCA when combined with other risks, illustrating conjunctural causation. Similarly, other risks act as peripheral or amplifying conditions. These findings align with prior studies emphasizing the multidimensional nature of perceived risk (Ariffin et al. 2018; Shao et al. 2021).

Overall, SEM identifies average net effects, while fsQCA reveals configurations and interactions, highlighting that fraud and information risk are universally important, whereas other risks exert conditional influence. This supports the need for a configurational approach to capture the complexity of perceived risk in CBEC.

5.1. Theoretical implications

This study strengthens the theoretical understanding of perceived risk and behavioral intention by integrating complexity theory with the multidimensional risk framework. Unlike prior research that examines risks independently or as aggregate constructs, the findings show that consumers evaluate multiple risks simultaneously and interactively, challenging traditional linear assumptions (Bauer 2001; Dowling and Staelin 1994).

PLS-SEM identifies significant effects of perceived risk dimensions, while fsQCA reveals that low fraud and privacy risks, combined with other low-risk conditions, encourage purchase intention. Conversely, high levels of fraud, privacy, process & time loss, and information risks discourage purchasing. These effects are configurational rather than linear, with multiple pathways leading to similar outcomes.

The study identifies 17 configurational pathways, supporting equifinality and explaining why some risks appear insignificant in linear models but are influential in combinations. It also highlights heterogeneity in risk perception, suggesting consumers can be segmented based on risk configurations rather than only demographics or preferences.

Finally, by combining PLS-SEM and fsQCA, the study demonstrates the value of mixed-method approaches in capturing complex consumer behavior, addressing limitations of variance-based models (Koufteros et al. 2009).

5.2. Practical implications

This study offers practical implications for enhancing purchase intention in CBEC across Hungary and global markets. First, reducing key risk dimensions - particularly privacy, fraud, process & time loss, and information risk - is essential. Firms should prioritize improving data security (e.g., encryption, authentication), strengthening seller credibility (e.g., verified badges, reviews), and reducing information asymmetry through clear product details and return policies.

Second, firms do not need to address all risk dimensions simultaneously. The identification of multiple configurations (17 solutions) enables companies, especially resource-constrained SMEs, to adopt targeted risk management strategies by focusing on specific risk combinations.

Third, as risk perception varies across consumers, businesses should adopt a segmented approach, tailoring strategies to different risk sensitivities. For example, risk-averse consumers require strong trust and security signals, while others may prioritize convenience, pricing, or product quality.

Overall, a focused and configurational approach to risk management and marketing can more effectively enhance purchase intention.

5.3. Limitations and Future research

The research acknowledges some limitations. For instance, the results are not universally applicable as the sample was collected in Hungary, a nation with a low proportion of borderless eCommerce (around 37%). Therefore, developing comparative analysis across nations may be promising. The study only investigates the effect of perceived risk dimensions (i.e., the aspect of consumer's cognition) while other aspects, such as consumer's emotions and cultural values, are overlooked. It would be meaningful to analyze more conditions to provide a comprehensive assessment of consumer behavior.

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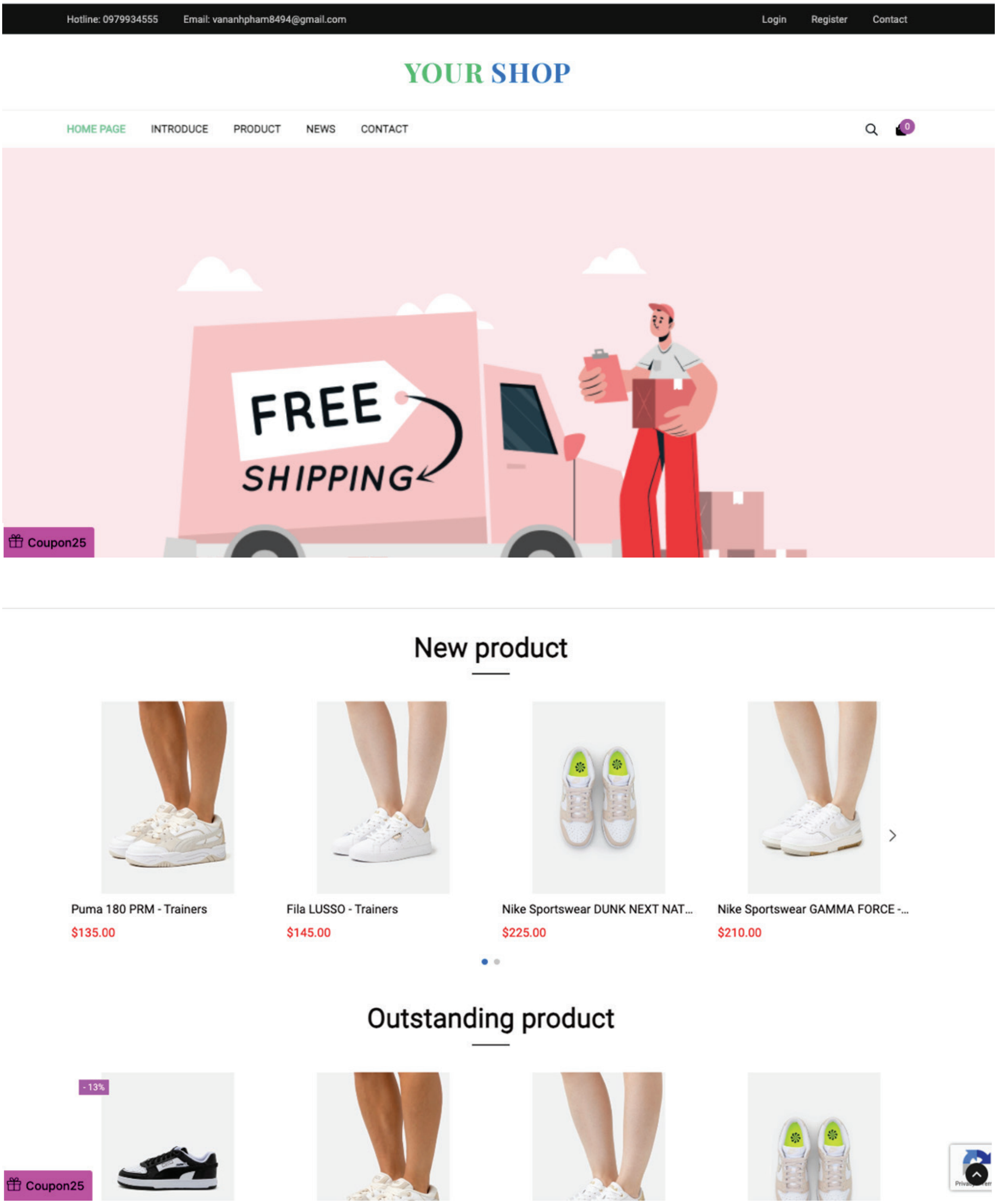
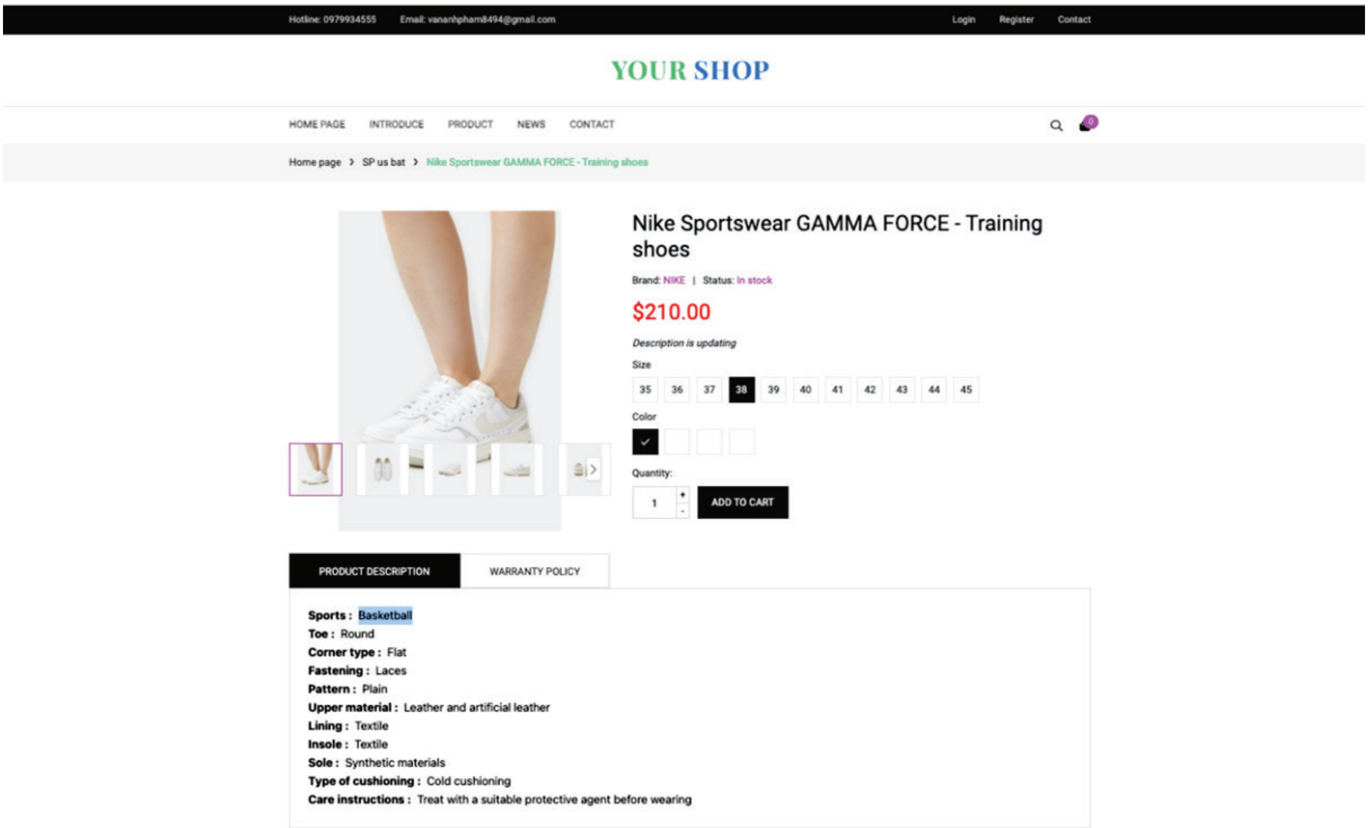
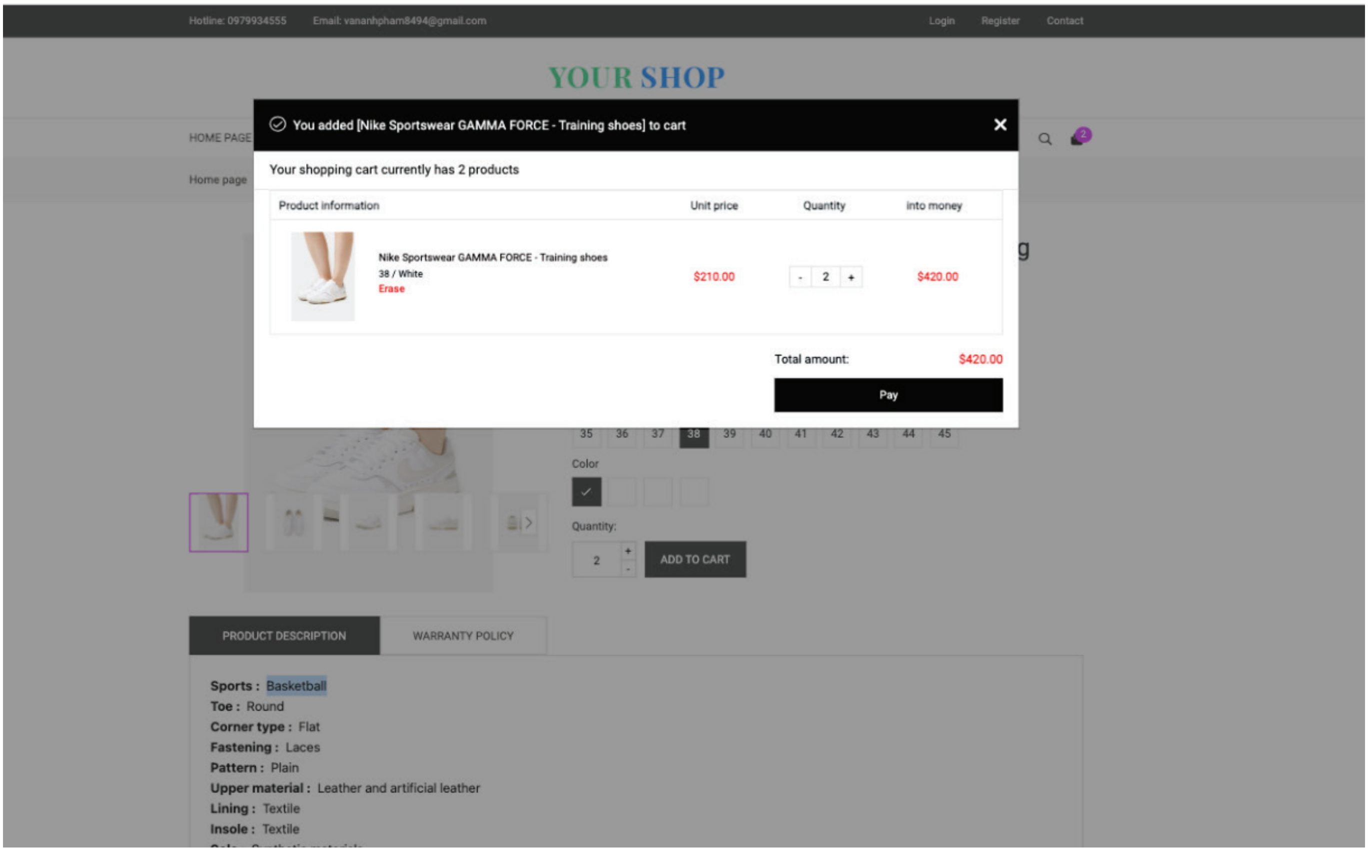
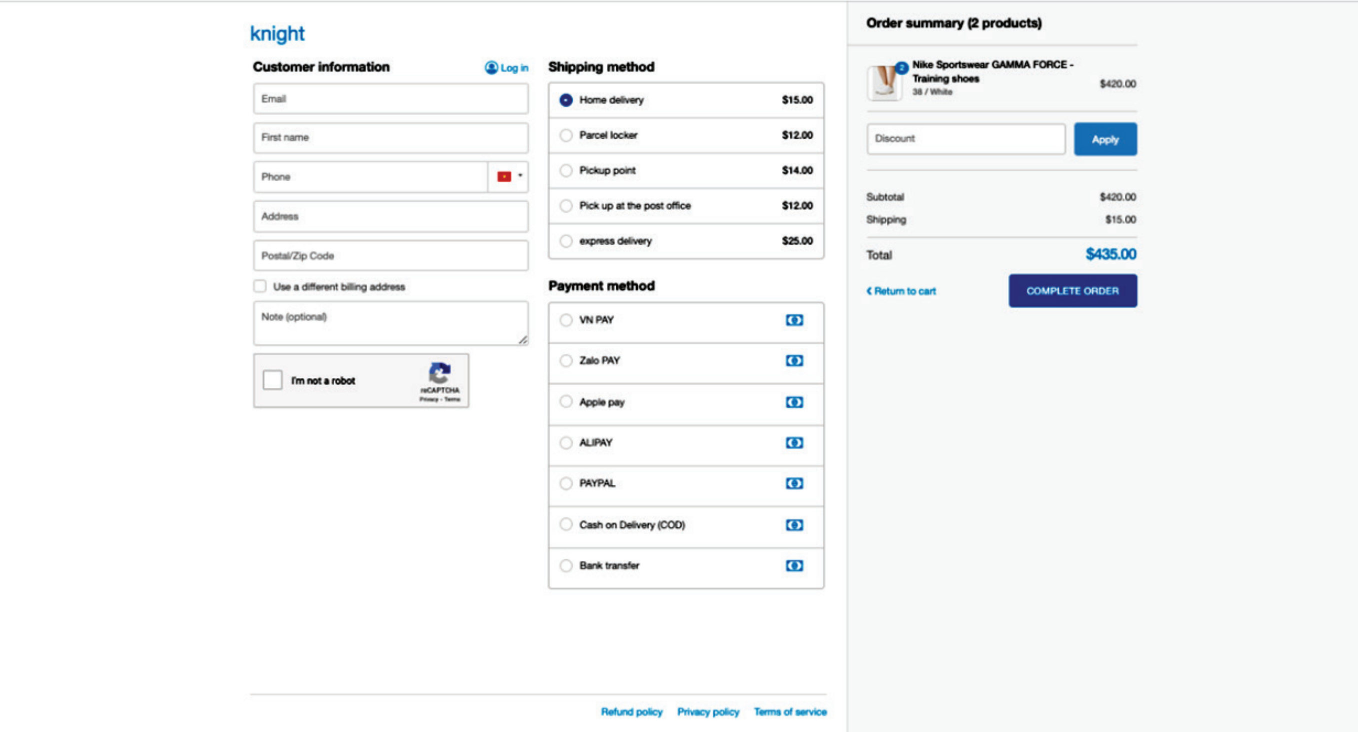
Appendix 1:

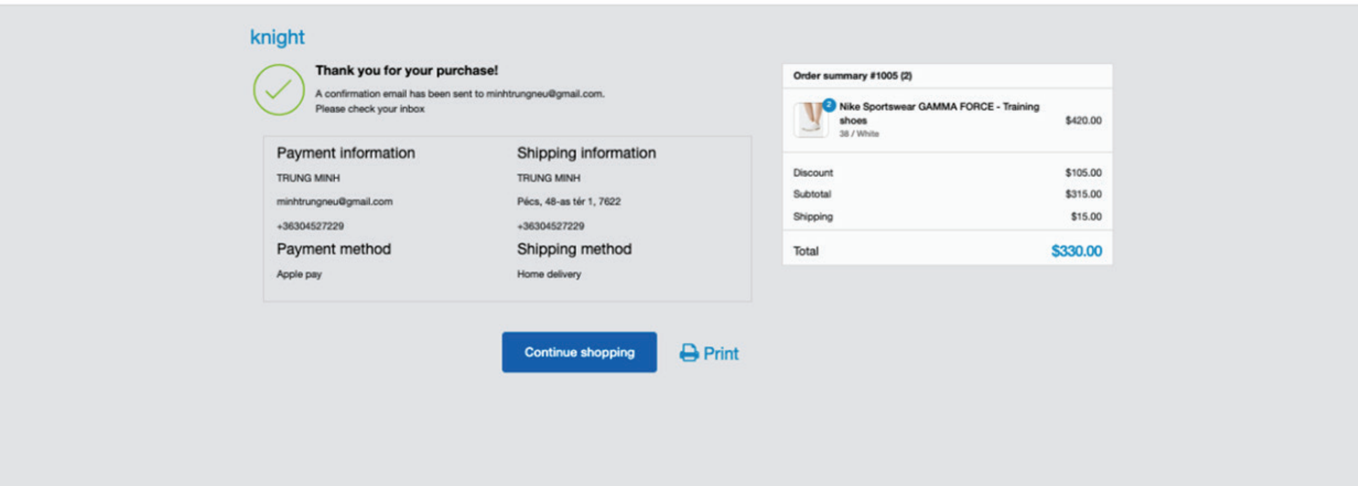
The simulating website designed for this study




Hotline: 0979934555
Email: vananhpham8494@gmail.com
Login
Register
Contact
YOUR SHOP
HOME PAGE
INTRODUCE
PRODUCT
NEWS
CONTACT
Home page > SP us bat > Nike Sportswear GAMMA FORCE - Training shoes
Nike Sportswear GAMMA FORCE - Training shoes
Brand: NIKE | Status: In stock
$210.00
Description is updating
Size
35 36 37 38 39 40 41 42 43 44 45
Color
Quantity:
1
ADD TO CART
PRODUCT DESCRIPTION
WARRANTY POLICY
Sports : Basketball
Toe : Round
Corner type : Flat
Fastening : Laces
Pattern : Plain
Upper material : Leather and artificial leather
Lining : Textile
Insole : Textile
Sole : Synthetic materials
Type of cushioning : Cold cushioning
Care instructions : Treat with a suitable protective agent before wearing


Hotline: 0979934555
Email: vananhpham8494@gmail.com
Login
Register
Contact
YOUR SHOP
You added [Nike Sportswear GAMMA FORCE - Training shoes] to cart
Your shopping cart currently has 2 products
Product information
Unit price
Quantity
into money
Nike Sportswear GAMMA FORCE - Training shoes
38 / White
Erase
$210.00
2
$420.00
Total amount:
$420.00
Pay
35 36 37 38 39 40 41 42 43 44 45
Color
Quantity:
2
ADD TO CART
PRODUCT DESCRIPTION
WARRANTY POLICY
Sports : Basketball
Toe : Round
Corner type : Flat
Fastening : Laces
Pattern : Plain
Upper material : Leather and artificial leather
Lining : Textile
Insole : Textile


knight
Customer information
Log in
Email
First name
Phone
Address
Postal/Zip Code
Use a different billing address
Note (optional)
I'm not a robot
reCAPTCHA
Privacy - Terms
Shipping method
Home delivery $15.00
Parcel locker $12.00
Pickup point $14.00
Pick up at the post office $12.00
express delivery $25.00
Payment method
VN PAY
Zalo PAY
Apple pay
ALIPAY
PAYPAL
Cash on Delivery (COD)
Bank transfer
Refund policy
Privacy policy
Terms of service
Order summary (2 products)
Nike Sportswear GAMMA FORCE - Training shoes
38 / White
$420.00
Discount
Apply
Subtotal $420.00
Shipping $15.00
Total $435.00
Return to cart
COMPLETE ORDER


knight
Thank you for your purchase!
A confirmation email has been sent to minhtrungneu@gmail.com.
Please check your inbox
Payment information
TRUNG MINH
minhtrungneu@gmail.com
+36304527229
Payment method
Apple pay
Shipping information
TRUNG MINH
Pécs, 48-as tér 1, 7622
+36304527229
Shipping method
Home delivery
Order summary #1005 (2)
Nike Sportswear GAMMA FORCE - Training shoes
38 / White
$420.00
Discount $105.00
Subtotal $315.00
Shipping $15.00
Total $330.00
Continue shopping
Print