

ORIGINAL SCIENTIFIC PAPER

Artificial Intelligence, Innovativeness, and Country-of-Origin Image as Drivers of High-Tech Product Choice: The Moderating Role of Product Customization

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ABSTRACT

The rapid development of high-technology markets has intensified the need for a deeper understanding of the factors influencing consumers' purchasing decisions regarding technologically advanced products. This study examines the effects of artificial intelligence, consumer innovativeness, and country-of-origin image on the choice of high-tech products, with a particular focus on computers and mobile phones. In addition, the study investigates the moderating role of product customization, conceptualized as consumers' perceived opportunities to adapt product features and functionalities to their individual preferences. The empirical research was conducted in the Republic of Serbia from January to April 2026 on a sample of 549 respondents, using a structured questionnaire administered through both online and in-person channels. Data were analyzed using covariance-based structural equation modeling (CB-SEM) in AMOS 24, with gender, age, and education included as demographic control variables. The results indicate that artificial intelligence, consumer innovativeness, and country-of-origin image are positively and statistically significantly associated with high-tech product choice, while these relationships remain significant after accounting for demographic controls. Product customization also exhibits a positive direct association with high-tech product choice and significantly strengthens the relationships between each of the three focal predictors and high-tech product choice. The study contributes to a better understanding of high-tech consumer behavior by jointly examining technological, individual, and country-related factors and by providing additional empirical evidence on the moderating role of perceived product customization. From a managerial standpoint, the findings suggest that firms operating in high-technology industries may benefit from combining favorable perceptions of AI-enabled functionality, innovation-oriented positioning, and country-of-origin image with opportunities for consumers to adapt product features and functionalities to their preferences.

Keywords: *artificial intelligence, consumer innovativeness, country-of-origin image, product customization, high-tech products, consumer behavior*

JEL Classification: A12, M20, M31

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INTRODUCTION

The accelerated development of high-technology markets has fundamentally transformed the way consumers evaluate, select, and adopt technologically advanced products (Gammoh et al., 2020). Rapid progress in artificial intelligence, increasing levels of consumer innovativeness, and the persistent relevance of country-of-origin perceptions have collectively reshaped competitive dynamics in industries characterized by high technological complexity (Curth et al., 2025; Seyed Esfahani & Reynolds, 2021; Zhang et al., 2026). In such an environment, understanding the interplay between technological capabilities, individual consumer characteristics, and symbolic product attributes has become increasingly important for both scholars and practitioners (Jiang et al., 2025).

Artificial intelligence represents a key technological driver in contemporary high-tech markets, influencing product functionality, user experience, and perceived value through intelligent features, automation, and adaptive systems (Malik et al., 2024). At the same time, Consumer Innovativeness reflects an individual-level predisposition toward technological novelty and adoption (Seyed Esfahani & Reynolds, 2021), while Country-of-Origin Image continues to serve as a cognitive and symbolic cue affecting quality perceptions, trust, and product evaluation (Fazli-Salehi et al., 2021).

Although these determinants have been examined individually in prior research (Papadopoulos et al., 2018; Seyed Esfahani & Reynolds, 2021; Sun et al., 2024), their combined relevance to consumer decision-making has received less attention. In particular, limited research has jointly examined technological, individual, and country-related determinants of consumer choice in high-tech product categories such as computers and mobile phones. Their simultaneous examination may therefore provide additional insight into how different sources of consumer evaluation operate within high-tech product choice.

Product customization provides an additional perspective on these relationships. Enabled by digital technologies and data-driven systems, customization can increase product relevance and value by aligning technological offerings with individual preferences (Li & Lev, 2025). In the present study, Product Customization does not refer exclusively to the physical configuration of computers or mobile phones prior to purchase but to consumers' perceived opportunities to adapt product features, functionalities, settings, and usage to their preferences. It is also distinguished from AI-enabled personalization: while the latter involves automated adaptation by intelligent systems, Product Customization emphasizes consumers' perceived opportunities to influence or adapt their technological experience. Previous research indicates that customization and personalization can enhance consumer evaluations by increasing the correspondence between product offerings and individual preferences (Marinković & Kalinić, 2017; Li et al., 2023; Zeng et al., 2022). However, its role as a mechanism conditioning the effects of other determinants remains comparatively underexplored (Hunt et al., 2013).

The study makes three main contributions. First, it provides an integrated empirical examination of technological, individual, and country-related determinants of High-Tech Product Choice. Second, it examines perceived Product Customization as a moderating mechanism rather than solely as a product attribute or direct source of consumer value. Third, by focusing on computers and mobile phones in Serbia, the study provides context-specific evidence on high-tech consumer behavior in Serbia as a developing-country market that has received comparatively limited attention in this research stream. From a practical perspective, the framework may help high-technology firms understand how favorable AI perceptions, innovation-oriented consumer characteristics, country-of-origin associations, and opportunities for product adaptation jointly contribute to consumer product evaluations and may inform differentiation and positioning strategies in technologically convergent markets.

LITERATURE REVIEW

Contemporary research in consumer behavior and technology management indicates that purchasing decisions related to high-tech products are shaped by a complex interplay of technological, individual, and contextual factors (Gammoh et al., 2020). Unlike traditional products, high-technology products require higher levels of cognitive involvement, greater tolerance for uncertainty, and a stronger willingness to adopt innovations (Bian & Lin, 2022). Consequently, integrative theoretical approaches have become increasingly relevant in explaining consumer behavior in high-tech market contexts.

The theoretical foundation of this study draws on several complementary frameworks. The Technology Acceptance Model (TAM) and its subsequent extensions, including the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasize the role of perceived usefulness and perceived ease of use in the adoption of new technologies (Davis, 1989; Venkatesh et al., 2003). In parallel, the Diffusion of Innovations Theory (Rogers, 2003) explains how individual differences in innovativeness influence consumers' propensity to adopt technological innovations (Seyed Esfahani & Reynolds, 2021). Furthermore, Signaling Theory (Spence, 1973) and the Heuristic-Systematic Model (Chaiken, 1980) explain the relevance of external cues, such as country-of-origin image, under conditions of product complexity and information asymmetry (Papadopoulos et al., 2018; Suter et al., 2021). In addition, consumer value perspectives (Zeithaml, 1988) and value co-creation (Vargo & Lusch, 2004) provide a theoretical basis for understanding Product Customization. Customization may increase product relevance and perceived value by aligning technological solutions with individual preferences (Mandolfo et al., 2020; Varriale et al., 2023). Consumers may also differ in the value they derive from customized products (Hunt et al., 2013), making customization an integrative mechanism linking technological capabilities with consumer heterogeneity (Li et al., 2019).

Importantly, product customization in the present study is understood from the consumer perspective as the perceived opportunity to adapt product features, functionalities, settings, and usage to individual preferences, rather than exclusively as the physical configuration of a product before purchase. This conceptualization is particularly relevant to computers and mobile phones, which are commonly purchased as standardized products but provide consumers with various opportunities for subsequent adaptation and individualized use (Marinković & Kalinić, 2017; Li et al., 2023; Zeng et al., 2022). Accordingly, the construct captures respondents' perceptions of opportunities for adaptation and individualized use rather than objectively observed customization capabilities of particular devices. Product customization should therefore also be distinguished from AI-enabled personalization: the former emphasizes consumers' perceived opportunities to adapt the product to their preferences, whereas the latter refers primarily to automated adaptation generated by AI-based systems.

This distinction is theoretically important for the proposed moderating role of Product Customization. Rather than assuming that customization itself determines the evaluation of a high-tech product, the present framework proposes that perceived opportunities for adaptation may alter the strength with which other product- and consumer-related evaluations translate into High-Tech Product Choice. Prior research suggests that customization can condition consumer responses and that individual differences, including innovativeness, may influence how consumers evaluate and derive benefits from customized products (Hunt et al., 2013; Park & Yoo, 2018). Greater perceived customization may therefore increase the personal relevance of AI-related benefits, provide innovative consumers with greater scope for exploration and adaptation, and strengthen the correspondence between favorable country-of-origin perceptions and the consumer's individual product requirements. This reasoning provides the general theoretical basis for treating perceived Product Customization as a moderator rather than solely as an independent product-related evaluation. The specific mechanisms underlying these moderating relationships are developed further in the corresponding hypothesis sections.

Artificial Intelligence and High-Tech Product Choice

Artificial intelligence has emerged as a foundational technological force reshaping the design, functionality, and market positioning of high-tech products (Malik et al., 2024). In contemporary consumer electronics, particularly computers and mobile phones, artificial intelligence is embedded in a wide range of functionalities, including intelligent assistants, adaptive interfaces, predictive analytics, security systems, and personalized content recommendations (Arachchi & Samarasinghe, 2025). These AI-driven features can enhance product functionality and influence the nature of user-technology interaction (Dash & Mohanta, 2025). From a theoretical perspective, the Technology Acceptance Model (TAM) provides a useful framework for explaining how artificial intelligence may shape consumers' evaluations of high-tech products (Davis, 1989; Zhang et al., 2026). AI-enhanced functionalities may contribute to perceived usefulness through their potential to improve efficiency, convenience, and task performance, while adaptive and user-friendly interfaces may facilitate favorable perceptions of ease of use (Davis, 1989; Arachchi & Samarasinghe, 2025). As a result, favorable perceptions of AI-related attributes, particularly usefulness, ease of use, and perceived intelligence, may contribute to more positive consumer attitudes and purchase intentions (Arachchi & Samarasinghe, 2025).

Beyond functional considerations, artificial intelligence may also influence symbolic and perceptual dimensions of product evaluation. In high-tech markets characterized by rapid technological change and information asymmetry, consumers often face difficulties in accurately assessing product quality prior to purchase (Gammoh et al., 2020). In such contexts, favorable perceptions of AI integration may function as a cue of technological sophistication and innovation capability, potentially reducing uncertainty and strengthening confidence in technologically advanced products. Moreover, artificial intelligence can support adaptive functionalities that respond to user behavior, potentially contributing to a more individualized and evolving user experience (Malik et al., 2024). This capacity for adaptation may differentiate AI-enabled products from less technologically advanced alternatives and contribute to consumers' perceptions of their longer-term value. Consequently, consumers who perceive AI-related functionalities as useful, intelligent, and relevant may exhibit more favorable evaluations and stronger purchase intentions toward products associated with such technologies (Arachchi & Samarasinghe, 2025).

Accordingly, the present study does not assess the objective technological superiority or actual AI capabilities of specific products; rather, it examines consumers' perceptions of artificial intelligence as a product-related technological attribute and their association with reported High-Tech Product Choice.

H1: Artificial intelligence has a positive and statistically significant effect on high-tech product choice.

Consumer Innovativeness and High-Tech Product Choice

Consumer innovativeness represents a key individual-level determinant of technology adoption and reflects a person's tendency to seek novelty, experiment with new products, and accept technological change (Ekow Kelly, 2025). According to the Diffusion of Innovations Theory, individual differences in innovativeness are associated with consumers' propensity to adopt new products and technologies, with more innovative consumers generally exhibiting greater openness toward novel technological offerings (Seyed Esfahani & Reynolds, 2021). In the context of computers and mobile phones, consumer innovativeness may play an important role in shaping how individuals perceive and evaluate advanced technological features. High-tech products often involve sophisticated functionalities, frequent software updates, and continuous learning processes, which may be perceived as challenging by less innovative consumers (Bian & Lin, 2022; Chau et al., 2025). In contrast, highly innovative individuals may be more receptive to

technological complexity and novelty, contributing to more favorable evaluations of technologically advanced products (Singh et al., 2020).

Consumer innovativeness also influences information processing and learning behavior. Innovative consumers tend to demonstrate greater engagement with new technologies and may be more willing to search for product-related information, experiment with novel features, and develop the competencies required for their use (Seyed Esfahani & Reynolds, 2021). Such engagement may reduce uncertainty associated with technologically advanced products and strengthen consumers' confidence in evaluating and adopting them. Additionally, innovative consumers may be particularly receptive to novel technological attributes, including artificial intelligence-related features, which can contribute to favorable evaluations of high-tech products (Panjaitan et al., 2022). Empirical evidence provides support for a positive relationship between consumer innovativeness and consumers' intentions to adopt or select technologically advanced products (Gammoh et al., 2020; Seyed Esfahani & Reynolds, 2021; Singh et al., 2020).

H2: Consumer innovativeness has a positive and statistically significant effect on high-tech product choice.

Country-of-Origin Image and High-Tech Product Choice

Country-of-origin image remains an influential factor in consumer decision-making, even in markets characterized by technological sophistication and globalized production networks (Fazli-Salehi et al., 2021). Country-of-origin image reflects consumers' overall perceptions and associations related to a country's technological capabilities, innovation capacity, manufacturing standards, and reliability (Curth et al., 2025). These perceptions can serve as important extrinsic cues, particularly when consumers face difficulties in objectively evaluating complex products (Papadopoulos et al., 2018). From the perspective of Signaling Theory, country-of-origin image can function as a quality-related signal that helps consumers reduce uncertainty in purchase situations characterized by information asymmetry. Similarly, Heuristic Information Processing Theory suggests that consumers may rely on readily available external cues, such as country-of-origin associations, when comprehensive evaluation of complex product information is difficult. In high-tech markets, where certain aspects of product performance and durability may be difficult to assess prior to use, consumers may therefore rely on country-related associations and reputational cues when forming expectations about product quality and technological competence (Papadopoulos et al., 2018; Suter et al., 2021).

Although globalization and multinational production have blurred traditional country-of-origin boundaries, empirical research suggests that consumers continue to associate particular countries with technological leadership, innovation, and advanced engineering capabilities (Papadopoulos et al., 2018). Such associations may contribute to consumers' evaluations of product reliability, technological competence, and expected performance, which are particularly relevant in the evaluation of complex high-tech products such as computers and mobile phones (Curth et al., 2025). A favorable country-of-origin image may therefore enhance consumers' confidence in high-tech products and strengthen their willingness to select them (Fazli-Salehi et al., 2021; Papadopoulos et al., 2018). Furthermore, country-of-origin image may operate alongside technological and individual-level evaluations by shaping consumers' initial expectations regarding products associated with particular countries (Suter et al., 2021). When high-tech products are associated with countries perceived as technologically advanced, consumers may form more favorable expectations regarding their technological sophistication and ability to deliver the expected benefits (Papadopoulos et al., 2018; Suter et al., 2021).

H3: Country-of-origin image has a positive and statistically significant effect on high-tech product choice.

THE MODERATING ROLE OF PRODUCT CUSTOMIZATION

Product customization has become an important strategic tool in high-tech industries, enabling firms to differentiate their offerings and enhance consumer value by aligning product features with individual preferences (Kiangala & Wang, 2021). Advances in digital technologies and artificial intelligence have facilitated mass customization, allowing companies to deliver personalized solutions at scale without sacrificing efficiency (Mandolfo et al., 2020). From a theoretical standpoint, Value Co-Creation Theory emphasizes the active role of consumers in the value creation process. Customization enables consumers to participate in shaping product attributes, thereby increasing perceived control, relevance, and engagement (Gammoh et al., 2020; Li et al., 2019; Varriale et al., 2023). Prior research further indicates that customization can create additional consumer value by increasing the correspondence between product characteristics and heterogeneous individual preferences (Hunt et al., 2013; Marinković & Kalinić, 2017; Li et al., 2023; Xu et al., 2026; Zeng et al., 2022).

In the present study, Product Customization refers specifically to consumers' perceived opportunities to adapt the features, functionalities, settings, and usage of high-tech products to their individual preferences. It therefore does not imply that respondents physically configured computers or mobile phones prior to purchase. This distinction is particularly important because computers and mobile phones are frequently purchased as standardized products but subsequently allow different forms of adaptation and individualized use (Marinković & Kalinić, 2017; Li et al., 2023; Zeng et al., 2022). Furthermore, Product Customization is conceptually distinguished from AI-enabled personalization. Whereas customization emphasizes the consumer's perceived opportunity to adapt the product according to individual preferences, AI-enabled personalization primarily refers to automated adaptation generated by algorithms or AI-based systems.

As a moderating mechanism, perceived Product Customization may strengthen the relationship between favorable perceptions of Artificial Intelligence and High-Tech Product Choice by increasing the personal relevance of AI-related product attributes. Rather than assuming that consumers directly customize how an AI system operates, the proposed mechanism is that greater perceived opportunities for adapting product features and usage can make the benefits associated with AI more compatible with individual needs and preferences. Consequently, when perceived customization is higher, favorable evaluations of AI-related attributes may translate more strongly into High-Tech Product Choice (Arachchi & Samarasinghe, 2025; Li et al., 2023).

H4a: Product customization strengthens the positive effect of artificial intelligence on high-tech product choice.

Similarly, Product Customization may condition the relationship between Consumer Innovativeness and High-Tech Product Choice because innovative consumers are generally more receptive to opportunities for exploration, experimentation, and individualized interaction with technological products. Customizable products may provide these consumers with greater scope to adapt functionalities and usage patterns according to their preferences, thereby increasing the relevance of their innovative orientation for product choice. Prior research suggests that consumers differ in the benefits they derive from customization and that individual characteristics, including innovativeness, can shape responses to customized offerings (Hunt et al., 2013; Park & Yoo, 2018; Xu et al., 2026). Thus, the positive association between Consumer Innovativeness and High-Tech Product Choice is expected to become stronger as perceived Product Customization increases (Li et al., 2024).

H4b: Product customization enhances the positive relationship between consumer innovativeness and high-tech product choice.

In addition, Product Customization may condition the relationship between Country-of-Origin Image and High-Tech Product Choice. Country-of-origin image provides consumers with an

external cue regarding technological competence, quality, and reliability, whereas customization concerns the perceived fit of the product with individual preferences (Curth et al., 2025; Suter et al., 2021). When consumers simultaneously hold favorable perceptions of a product's country of origin and perceive greater opportunities to adapt the product to their own preferences, country-related evaluations may become more relevant to product choice because the product combines a favorable external quality cue with greater perceived personal fit. In this sense, customization does not alter the country-of-origin image itself; rather, it may strengthen the extent to which favorable country-related perceptions are associated with High-Tech Product Choice (Falheiro et al., 2022; Li & Lev, 2025).

H4c: Product customization amplifies the positive influence of country-of-origin image on high-tech product choice.

Figure 1 presents the conceptual research model, which integrates artificial intelligence, consumer innovativeness, and country-of-origin image as key determinants of high-tech product choice, while explicitly accounting for the moderating role of Product Customization.

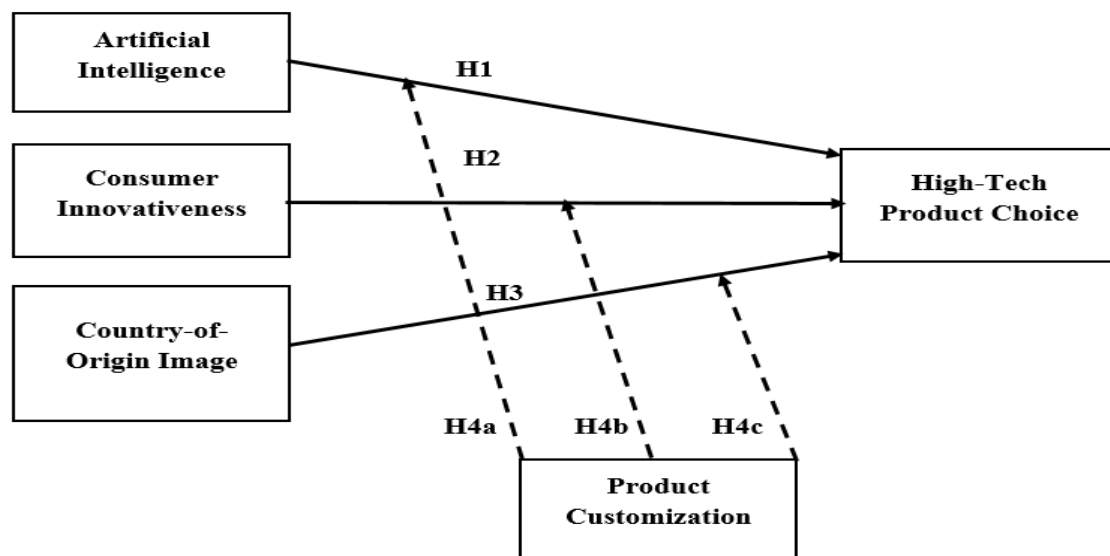


Figure 1: Conceptual model

Source: Authors

RESEARCH METHODOLOGY

This study employs a quantitative research design to examine the effects of AI, Consumer Innovativeness, and Country-of-Origin Image on High-Tech Product Choice, as well as the moderating role of Product Customization. The methodological procedure comprised three interrelated components: sample selection and data collection, measurement of the research constructs, and statistical analysis of the proposed measurement and structural models.

Sample and Data Collection

Empirical data were collected in the Republic of Serbia between January and April 2026 using a structured questionnaire administered through both online and in-person channels. For the online component, respondents were recruited through technology-related online forums and communities, social media platforms, and other digital networks frequented by consumers interested in computers, mobile phones, and related high-tech products. For the in-person

component, potential respondents were approached primarily at computer and mobile-device retail stores, as well as at university and other public locations where consumers from the targeted demographic groups could be reached. These complementary recruitment channels facilitated access to respondents with relevant purchasing experience while preserving the voluntary nature of participation. A non-probability purposive convenience sampling approach was employed. The purposive component was intended to ensure sufficient participation of consumers expected to have greater familiarity with contemporary high-tech products, whereas the convenience component reflected the accessibility and voluntary participation of eligible respondents. Accordingly, recruitment was oriented toward achieving greater representation of younger and more highly educated consumers, who were expected to have relatively greater exposure to computers, mobile phones, and contemporary technological functionalities. However, participation was not restricted to these demographic groups, and all consumers who satisfied the inclusion criterion were eligible to participate.

To qualify for the study, respondents were required to have independently purchased at least one product from the high-tech categories examined, specifically a computer or mobile phone. This inclusion criterion was applied to ensure that participants had relevant prior consumer experience and were able to meaningfully evaluate the constructs included in the questionnaire. A total of 588 questionnaires were collected. Following screening for completeness and compliance with the eligibility criterion, 39 questionnaires were excluded, resulting in a final sample of 549 valid responses and a usable response rate of 93.4%. Participation was voluntary, and respondents were informed that their responses would remain anonymous and be used exclusively for research purposes. Table 1 presents the demographic characteristics of the final sample.

Table 1. Demographic structure of respondents

		Number of respondents	% of respondents
Gender	Female	325	59.2%
	Male	224	40.8%
	Total	549	100%
Age	Up to 20 years	51	9.3%
	21-30 years	228	41.5%
	31-40 years	115	20.9%
	41-50 years	95	17.3%
	51-60 years	33	6.0%
	61 years and over	27	5.0%
	Total	549	100%
Education	Primary school	18	3.3%
	High school	211	38.4%
	Faculty	320	58.3%
	Total	549	100%

Source: Authors

The demographic profile indicates a comparatively high representation of younger and highly educated respondents, with individuals aged 21–40 accounting for more than 60% of the sample and respondents with higher education constituting the largest educational group. This composition is consistent with the purposive component of the sampling strategy, which sought sufficient participation of consumers expected to have greater familiarity with contemporary high-tech products. However, given the non-probability sampling procedure, the sample should not be regarded as nationally representative, and caution is required when generalizing the findings, particularly to older and less highly educated consumers. To partially account for demographic heterogeneity, gender, age, and education were included as control variables in the

structural model. Nevertheless, statistical control does not eliminate the limitations associated with the sampling procedure, which are explicitly acknowledged when interpreting the generalizability of the findings.

Measurement

All constructs were operationalized using multi-item Likert-type scales (1-7) adapted from established studies in the literature (Arachchi & Samarasinghe, 2025; Curth et al., 2025; Fazli-Salehi et al., 2021; Falheiro et al., 2022; Houshmandi et al., 2026; Keshavarz-Ghorbani et al., 2026; Li et al., 2019; Lin et al., 2024; Li & Lev, 2025; Panjaitan et al., 2022; Seyed Esfahani & Reynolds, 2021; Wei et al., 2026; Wu et al., 2026; Zdravković & Gašević, 2022; Zhang et al., 2026). The measurement instrument captured respondents' perceptions and attitudes rather than objectively observed technological functionalities or actual purchasing behavior. Accordingly, Artificial Intelligence, Product Customization, and High-Tech Product Choice were operationalized as perceptual constructs. Consistent with its conceptualization in the literature review, Product Customization specifically reflects respondents' perceived opportunities to adapt high-tech product functionalities and usage to their individual preferences. Table 2 presents the measurement items and the corresponding Cronbach's alpha and composite reliability coefficients.

Table 2. Measurement items, Cronbach's alpha, and Composite reliability

Variables	Statements	CA	CR
Artificial Intelligence	AI1: High-tech products that incorporate artificial intelligence provide superior functionality compared to conventional technological products. AI2: The presence of artificial intelligence enhances the overall usefulness and efficiency of high-tech products. AI3: Artificial intelligence features positively influence my perception of the technological advancement of high-tech products.	0.875	0.891
Consumer Innovativeness	CI1: I am usually among the first to try new high-tech products when they become available on the market. CI2: I enjoy experimenting with innovative technologies, even if they require time and effort to learn. CI3: Compared to other consumers, I am more willing to adopt technologically advanced products.	0.884	0.902
Country-of-Origin Image	COO1: The country in which a high-tech product is developed or manufactured strongly influences my perception of its quality. COO2: High-tech products originating from technologically advanced countries are more reliable than those from less developed countries. COO3: A favorable country-of-origin image increases my confidence in the performance of high-tech products.	0.907	0.918
Product Customization	PC1: The possibility to customize high-tech product features according to my personal preferences increases their value for me. PC2: I prefer high-tech products that allow a high level of personalization in their functionality and usage. PC3: Product customization enhances my satisfaction with high-tech products.	0.923	0.931

Variables	Statements	CA	CR
High-Tech Product Choice	HTPC1: I prefer purchasing high-tech products that offer advanced technological features. HTPC2: When choosing computers or mobile phones, I tend to select technologically sophisticated products. HTPC3: Technological advancement is a key factor influencing my choice of high-tech products (computers and mobile phones).	0.944	0.948

Source: Authors

The results indicate a high level of internal consistency and reliability across all research variables. Cronbach's alpha values range from 0.875 to 0.944, exceeding the commonly recommended threshold of 0.70, while composite reliability values range from 0.891 to 0.948, further confirming the robustness of the measurement model (Hair et al., 2019; Nunnally, 1978). These findings demonstrate that all constructs are measured reliably and that the selected items consistently capture the underlying latent variables. Consequently, the reliability results provide an appropriate basis for further assessment of the measurement model and subsequent structural model estimation within the CB-SEM framework.

Data Analysis

Data analysis was conducted using covariance-based structural equation modeling (CB-SEM) implemented in AMOS 24. Given the confirmatory nature of the research, the theoretically specified relationships among the latent constructs, and the objective of evaluating both the measurement and structural models, CB-SEM was considered appropriate for the present study. Recent methodological literature has emphasized the importance of aligning the selection of a structural equation modeling approach with the objectives of the research, theoretical specification of the model, and underlying measurement assumptions (Cadogan & Lee, 2023; Rönkkö et al., 2023; Henseler et al., 2024).

The empirical analysis followed a two-step procedure. First, confirmatory factor analysis (CFA) was conducted to evaluate the adequacy of the measurement model. Construct reliability was assessed using Cronbach's alpha and composite reliability; convergent validity was examined using Average Variance Extracted (AVE), and discriminant validity was evaluated using the Fornell-Larcker criterion. Overall model adequacy was additionally assessed using established CB-SEM goodness-of-fit indices, including χ^2/df , GFI, CFI, TLI, IFI, and RMSEA. The standardized CFA factor loadings for all measurement items and the measurement-model fit statistics are reported in Appendix A. Second, following satisfactory assessment of the measurement model, the structural model was estimated to examine the hypothesized direct and moderating relationships.

Gender, age, and education were additionally incorporated into the structural model as demographic control variables. Their inclusion was intended to account for potential demographic differences in High-Tech Product Choice and to assess whether the hypothesized relationships remained statistically significant after controlling for these characteristics. This procedure was considered particularly relevant given the demographic composition of the sample and the possibility that age and education may be associated with consumers' familiarity with and responses to technologically advanced products.

In testing the moderating role of Product Customization, its direct effect on High-Tech Product Choice was included in the structural model together with the corresponding interaction effects. Prior to testing the moderating relationships, the interaction terms were constructed using the residual-centering (orthogonalization) approach described by Little et al. (2006). This procedure separates the interaction terms from their corresponding lower-order components, thereby

reducing non-essential multicollinearity and facilitating the estimation and interpretation of interaction effects.

The resulting interaction terms were incorporated into the structural model to examine whether Product Customization moderates the relationships between Artificial Intelligence, Consumer Innovativeness, Country-of-Origin Image, and High-Tech Product Choice. The statistical significance and direction of the estimated structural relationships were evaluated using unstandardized coefficients (B), standardized coefficients (β), standard errors (S.E.), critical ratios (C.R.), and corresponding p-values.

RESEARCH RESULTS

Table 3 reports the Average Variance Extracted (AVE) values for the research variables included in the measurement model.

Table 3. Average variance extracted (AVE) for research variables

Research variables	Average Variance Extracted (AVE)
Artificial Intelligence	0.731
Consumer Innovativeness	0.754
Country-of-Origin Image	0.726
Product Customization	0.769
High-Tech Product Choice	0.801

Source: Authors

The results indicate that all AVE values exceed the recommended threshold of 0.50, ranging from 0.726 to 0.801, which confirms adequate convergent validity for all constructs (Fornell & Larcker, 1981). These findings suggest that each latent variable explains a substantial proportion of the variance in its corresponding indicators, indicating that the measurement items are strongly associated with their underlying constructs. Consequently, the results provide further evidence of the validity of the measurement model and support its suitability for subsequent structural model analysis within the CB-SEM framework.

Table 4 presents the results of the discriminant validity assessment using the Fornell–Larcker criterion, which compares the square root of the Average Variance Extracted (AVE) for each construct with its correlations with the other constructs included in the measurement model.

Table 4. Discriminant validity based on the Fornell–Larcker criterion

Constructs	Artificial Intelligence	Consumer Innovativeness	Country-of-Origin Image	Product Customization	High-Tech Product Choice
Artificial Intelligence	0.855				
Consumer Innovativeness	0.472	0.868			
Country-of-Origin Image	0.438	0.491	0.852		
Product Customization	0.516	0.547	0.503	0.877	
High-Tech Product Choice	0.558	0.593	0.571	0.624	0.895

Note: Diagonal values (in bold) represent the square root of AVE; off-diagonal values represent inter-construct correlations.

Source: Authors' calculations

The results presented in Table 4 confirm adequate discriminant validity. For each construct, the square root of AVE (0.852–0.895) exceeds its correlations with all other constructs (0.438–0.624), indicating that each construct shares more variance with its own indicators than with other latent constructs. Thus, the Fornell–Larcker criterion is satisfied (Fornell & Larcker, 1981), providing further support for the adequacy of the measurement model and subsequent structural model estimation.

Following the satisfactory assessment of the CFA measurement model reported in Appendix A, Table 5 presents the goodness-of-fit statistics for the structural model.

Table 5. Structural model fit assessment

Model fit indicators	Estimated values	Benchmark criteria
χ^2/df	1.842	< 3.00
GFI	0.936	> 0.90
CFI	0.958	> 0.90
TLI	0.949	> 0.90
IFI	0.957	> 0.90
RMSEA	0.039	< 0.08

Source: Authors' calculations

The results indicate that the structural model demonstrates a satisfactory overall fit to the empirical data. The χ^2/df value of 1.842 is below the recommended threshold of 3.00, while GFI (0.936), CFI (0.958), TLI (0.949), and IFI (0.957) exceed the commonly accepted benchmark of 0.90. In addition, the RMSEA value of 0.039 is well below the recommended threshold of 0.08 (Hair et al., 2019). Taken together, these indices support the adequacy of the structural model for examining the hypothesized relationships within the CB-SEM framework.

Table 6 presents the CB-SEM results examining the direct effects of the main predictors on High-Tech Product Choice, together with the direct effect of Product Customization and the effects of the demographic control variables.

Table 6. CB-SEM results – Direct effects on High-Tech Product Choice

Predictor	Unstandardized B	Standardized β	S.E.	C.R.	p-value	Decision
Artificial Intelligence	0.411	0.421	0.061	6.738	<0.001	H1 supported
Consumer Innovativeness	0.343	0.356	0.058	5.914	<0.001	H2 supported
Country-of-Origin Image	0.253	0.274	0.052	4.865	<0.001	H3 supported
Product Customization	0.216	0.231	0.049	4.408	<0.001	—
Gender (control)	0.041	0.041	0.037	1.108	0.268	—
Age (control)	−0.084	−0.096	0.032	−2.625	0.009	—
Education (control)	0.071	0.073	0.034	2.088	0.037	—

Notes: B = unstandardized path coefficient; β = standardized path coefficient; S.E. = standard error; C.R. = critical ratio. Gender, age, and education were included as demographic control variables. The direct effect of Product Customization was estimated as part of the specification of the moderation model.

Source: Authors' calculations

The CB-SEM results provide empirical support for the proposed hypotheses concerning the direct effects of the three main predictors on High-Tech Product Choice. The analysis **supports H1**, demonstrating that artificial intelligence has a positive and statistically significant association with High-Tech Product Choice ($\beta = 0.421$, C.R. = 6.738, $p < 0.001$). Among the three hypothesized predictors, artificial intelligence exhibits the strongest standardized effect. H2 is also supported, as consumer innovativeness has a positive and statistically significant effect on High-Tech Product Choice ($\beta = 0.356$, C.R. = 5.914, $p < 0.001$). Furthermore, the results support H3, showing that country-of-origin image is positively associated with High-Tech Product Choice ($\beta = 0.274$, C.R. = 4.865, $p < 0.001$). These findings provide additional empirical evidence that technological perceptions, individual innovativeness, and country-related perceptions are associated with consumers' preferences for high-tech products.

In addition to the hypothesized relationships, the direct effect of Product Customization on High-Tech Product Choice was estimated as part of the moderation model. The results indicate a positive and statistically significant effect ($\beta = 0.231$, C.R. = 4.408, $p < 0.001$), suggesting that stronger perceptions of Product Customization are associated with greater preference for technologically advanced products. This direct effect was included to account for the main effect of the moderator when evaluating the subsequent interactions. Gender, age, and education were also included as demographic control variables. Gender has no statistically significant effect ($\beta = 0.041$, C.R. = 1.108, $p = 0.268$), whereas age has a small negative effect ($\beta = -0.096$, C.R. = -2.625, $p = 0.009$) and education a small positive effect ($\beta = 0.073$, C.R. = 2.088, $p = 0.037$). Importantly, all three hypothesized relationships remain statistically significant after controlling for these demographic characteristics, supporting the robustness of the main structural relationships.

Table 7 presents the results of the CB-SEM moderation analysis examining the moderating role of Product Customization in the relationships between Artificial Intelligence, Consumer Innovativeness, Country-of-Origin Image, and High-Tech Product Choice. The interaction terms were constructed using the residual-centering (orthogonalization) approach described by Little et al. (2006), as specified in the methodology section.

Table 7. CB-SEM results – Moderating effects of Product Customization on High-Tech Product Choice

Interaction effect	Unstandardized B	Standardized β	S.E.	C.R.	P-value	Decision
Artificial Intelligence x Product Customization	0.248	0.276	0.052	4.769	<0.001	H4a supported
Consumer Innovativeness x Product Customization	0.207	0.229	0.050	4.140	<0.001	H4b supported
Country-of-Origin Image x Product Customization	0.164	0.181	0.047	3.489	<0.001	H4c supported

Notes: B = unstandardized interaction coefficient; β = standardized interaction coefficient; S.E. = standard error; C.R. = critical ratio. Product Customization was specified as the moderator of the relationships between the three focal predictors and High-Tech Product Choice.

Source: Authors' calculations

The results indicate that Product Customization plays a significant moderating role in all examined relationships. The interaction effect between Artificial Intelligence and Product Customization is positive and statistically significant ($\beta = 0.276$, C.R. = 4.769, $p < 0.001$), **supporting H4a**, and indicating that higher perceived levels of Product Customization strengthen the positive relationship between Artificial Intelligence and High-Tech Product Choice. More

specifically, the positive interaction suggests that respondents who perceive greater possibilities for adapting high-tech product features to their individual preferences exhibit a stronger association between favorable perceptions of artificial intelligence and High-Tech Product Choice.

Similarly, the interaction between Consumer Innovativeness and Product Customization is positive and statistically significant ($\beta = 0.229$, C.R. = 3.489, $p < 0.001$), **supporting H4b**. This finding indicates that the positive relationship between Consumer Innovativeness and High-Tech Product Choice becomes stronger at higher perceived levels of Product Customization. Thus, consumers characterized by greater innovativeness appear to respond more positively to high-tech products when they perceive greater opportunities to adapt product functionalities and usage to their individual preferences.

Furthermore, the interaction between Country-of-Origin Image and Product Customization is positive and statistically significant ($\beta = 0.181$, C.R. = 3.489, $p < 0.001$), **supporting H4c**. The positive interaction indicates that the association between a favorable Country-of-Origin Image and High-Tech Product Choice is stronger when respondents perceive greater possibilities for Product Customization. Accordingly, customization may reinforce the relevance of favorable country-related perceptions by increasing the perceived fit between technologically advanced products and individual consumer preferences.

Overall, these results provide empirical evidence that perceived Product Customization conditions the relationships between the three focal predictors and High-Tech Product Choice. Rather than implying that actual customization capabilities or purchasing behavior were directly observed, the findings indicate that respondents' perceptions of customization opportunities strengthen the associations of Artificial Intelligence, Consumer Innovativeness, and Country-of-Origin Image with their reported High-Tech Product Choice.

Discussion of Research Results

The findings of this study provide empirical support for the proposed conceptual model and offer additional insights into the determinants of High-Tech Product Choice. By simultaneously examining Artificial Intelligence, Consumer Innovativeness, and Country-of-Origin Image, and incorporating perceived Product Customization as a moderating mechanism, the study provides a more integrated empirical perspective on consumer decision-making in high-technology markets, complementing previous research that has primarily examined particular technological, individual, or product-related determinants (Bian & Lin, 2022; Chau et al., 2025; Curth et al., 2025; Fazli-Salehi et al., 2021; Li & Lev, 2025; Mandolfo et al., 2020; Panjaitan et al., 2022; Zhang et al., 2026). Importantly, all three hypothesized direct relationships remain statistically significant after controlling for gender, age, and education.

The results support H1 and indicate that Artificial Intelligence has the strongest standardized association with High-Tech Product Choice ($\beta = 0.421$, $p < 0.001$). This finding is consistent with the general reasoning of the Technology Acceptance Model and related technology-adoption perspectives, which emphasize the relevance of consumers' evaluations of technological attributes in technology acceptance. Rather than providing additional validation of these established theoretical perspectives or demonstrating the objective superiority of particular AI functionalities, the present result offers context-specific empirical evidence that favorable perceptions of AI are associated with stronger preferences for technologically advanced products. Importantly, the finding concerns consumers' perceptions of AI as a product-related technological attribute and should not be interpreted as evidence of the objective performance or superiority of specific AI capabilities (Arachchi & Samarasinghe, 2025).

Consumer Innovativeness is also positively associated with High-Tech Product Choice ($\beta = 0.356$, $p < 0.001$), supporting H2. This relationship is consistent with the general reasoning of the Diffusion of Innovations Theory, according to which individual differences in innovativeness are relevant to consumers' receptiveness to technological novelty. In the present context, consumers

with a stronger tendency to experiment with and adopt new technologies report greater preferences for technologically advanced products (Seyed Esfahani & Reynolds, 2021). However, given the cross-sectional and self-reported nature of the data, this finding should be interpreted as context-specific evidence of an association rather than as confirmation of the established theoretical framework or evidence of actual adoption behavior.

The study also supports H3, demonstrating a positive relationship between Country-of-Origin Image and High-Tech Product Choice ($\beta = 0.274$, $p < 0.001$). This finding can be interpreted in light of Signaling Theory and Heuristic Information Processing Theory. In technologically complex product categories, where consumers may face difficulties in evaluating all relevant product attributes, country-of-origin information may serve as an external or heuristic cue that simplifies product evaluation and reduces perceived uncertainty. The present findings suggest that such country-related perceptions remain relevant even in increasingly globalized high-tech markets. However, they should not be interpreted as evidence that products from particular countries are objectively technologically superior; rather, they indicate that favorable Country-of-Origin Image is associated with stronger reported preferences for high-tech products in the examined Serbian context (Papadopoulos et al., 2018; Suter et al., 2021).

Perceived Product Customization also has a positive direct association with High-Tech Product Choice ($\beta = 0.231$, $p < 0.001$). Although no separate hypothesis was formulated for this relationship, respondents who perceive greater opportunities to adapt high-tech products to their preferences tend to report stronger preferences for technologically advanced products (Hunt et al., 2013; Marinković & Kalinić, 2017). More importantly for the proposed framework, the interaction analyses support H4a, H4b, and H4c, indicating that perceived Product Customization significantly conditions all three focal relationships.

The interaction between Artificial Intelligence and Product Customization is positive and statistically significant ($\beta = 0.276$, $p < 0.001$), supporting H4a. The positive association between AI perceptions and High-Tech Product Choice becomes stronger when respondents perceive greater opportunities to adapt product features, functionalities, settings, and usage to their preferences. Rather than implying that consumers directly customize AI functionalities, this finding suggests that perceived opportunities for product adaptation may increase the personal relevance of favorable AI-related evaluations (Li et al., 2023). This result should therefore be viewed as evidence of a conditional association within the examined context rather than as evidence that customization objectively enhances AI capabilities.

Similarly, the positive interaction between Consumer Innovativeness and Product Customization ($\beta = 0.229$, $p < 0.001$) supports H4b. Consumers characterized by greater innovativeness may derive greater value from opportunities to explore, adapt, and individualize technologically advanced products. This interpretation is consistent with previous research showing that consumers differ in the benefits derived from customization and that individual characteristics may shape responses to customized offerings (Hunt et al., 2013; Park & Yoo, 2018). Perceived customization may therefore represent a context in which innovative tendencies are more strongly associated with reported product preferences, without implying a causal effect on actual purchasing behavior.

Finally, the positive interaction between Country-of-Origin Image and Product Customization ($\beta = 0.181$, $p < 0.001$) supports H4c, although its magnitude is weaker than the other two moderating effects. Country-of-Origin Image may provide an external cue regarding technological competence and quality, while perceived customization may increase the perceived fit between the product and individual preferences. Their combination may therefore be associated with more favorable product evaluations by linking a positive external cue with greater perceived personal fit. Importantly, customization does not alter Country-of-Origin Image itself but conditions the strength of its association with High-Tech Product Choice.

The demographic controls provide additional context for these relationships. Gender is not significantly associated with High-Tech Product Choice ($\beta = 0.041$, $p = 0.268$), whereas age has a

small negative association ($\beta = -0.096$, $p = 0.009$) and education a small positive association ($\beta = 0.073$, $p = 0.037$). Thus, younger and more highly educated respondents report somewhat stronger preferences for technologically advanced products. Given their comparatively high representation in the sample, this finding reinforces the need for caution when generalizing the results to the overall Serbian consumer population. Nevertheless, Artificial Intelligence, Consumer Innovativeness, and Country-of-Origin Image remain statistically significant after controlling for these demographic characteristics.

CONCLUSION

This study provides empirical evidence that Artificial Intelligence, Consumer Innovativeness, and Country-of-Origin Image are positively associated with High-Tech Product Choice, while perceived Product Customization strengthens each of these relationships. By examining these relationships jointly in the context of computers and mobile phones in Serbia, the study provides context-specific evidence on the conditional role of perceived customization in high-tech product evaluation.

From a theoretical perspective, the findings are broadly consistent with the established theoretical perspectives employed in the study and should be viewed as complementary empirical evidence rather than as an extension or validation of these theories. The positive association between Artificial Intelligence and High-Tech Product Choice is consistent with the general reasoning of the Technology Acceptance Model regarding the relevance of favorable technological evaluations. Similarly, the relationship between Consumer Innovativeness and High-Tech Product Choice corresponds with the Diffusion of Innovations perspective, while the association between Country-of-Origin Image and product choice is consistent with Signaling Theory and Heuristic Information Processing Theory, according to which external cues may facilitate consumer evaluations under conditions of product complexity and information asymmetry. These findings are specific to the examined Serbian high-tech product context and concern consumers' perceptions and reported preferences rather than objective technological performance or actual adoption behavior.

The moderating role of perceived Product Customization provides additional context-specific insight into these relationships. The findings suggest that perceived opportunities to adapt product features, functionalities, settings, and usage may strengthen the associations of Artificial Intelligence, Consumer Innovativeness, and Country-of-Origin Image with High-Tech Product Choice. This result is compatible with value co-creation perspectives emphasizing the relevance of consumer participation and perceived personal fit, but it does not imply an extension of these established theoretical frameworks. Rather, perceived Product Customization can be interpreted as a conditional factor that may influence how strongly established technological, individual, and country-related evaluations are associated with reported product preferences. The demographic controls further indicate that these relationships remain significant after accounting for gender, age, and education, although the observed effects of age and education suggest that demographic heterogeneity remains relevant.

From a practical perspective, the findings provide several implications for firms operating in high-technology markets. First, given the comparatively strong association between favorable AI perceptions and High-Tech Product Choice, firms should communicate the consumer-relevant value of AI-related attributes rather than presenting AI merely as a technological label. Marketing communication should emphasize how AI-related functionalities can contribute to usefulness, convenience, efficiency, and the overall user experience, while avoiding unsupported claims regarding technological superiority.

Second, the significant role of Consumer Innovativeness suggests that firms may benefit from differentiating their communication across consumer segments. Innovation-oriented consumers may be approached through messages emphasizing technological novelty, experimentation,

advanced functionality, and opportunities to explore new product capabilities. In contrast, communication directed toward less innovation-oriented consumers may place greater emphasis on accessibility, comprehensibility, ease of use, and the practical benefits of technological features.

Third, the positive association between Country-of-Origin Image and High-Tech Product Choice indicates that favorable country-related associations can remain relevant even in globally integrated high-tech markets. Firms may therefore incorporate credible associations with technological expertise, innovation capability, manufacturing quality, and reliability into their positioning strategies. Such communication should, however, be based on credible product information rather than generalized claims about the superiority of products originating from particular countries.

Finally, the moderating effects of Product Customization suggest that firms should consider customization not merely as an additional product feature but as a means of increasing the personal relevance of other favorable product evaluations. Providing accessible opportunities to adapt functionalities, interfaces, settings, applications, and patterns of use may strengthen the extent to which favorable AI perceptions, consumer innovativeness, and country-of-origin associations are reflected in product preferences. Firms should therefore make customization opportunities visible, understandable, and easy to use rather than assuming that consumers will recognize their value automatically. These implications nevertheless derive from reported consumer perceptions and preferences and should not be interpreted as evidence that particular AI or customization functionalities directly cause actual purchasing behavior.

Despite these contributions, the study is subject to **several limitations** that should be considered when interpreting the findings. First, the use of a non-probability purposive convenience sampling procedure limits the representativeness of the sample. Younger and more highly educated respondents are comparatively strongly represented, reflecting the purposive effort to include consumers with greater familiarity with contemporary high-tech products. Consequently, the findings should not be generalized to the overall Serbian consumer population without caution, particularly to older and less highly educated consumer groups. Although gender, age, and education were incorporated as control variables and the principal structural relationships remained statistically significant, statistical control cannot eliminate potential selection bias arising from the sampling procedure. Future studies should therefore employ probability-based sampling or more demographically balanced samples and examine whether the identified relationships remain stable across different consumer segments.

Second, the empirical analysis was conducted exclusively in Serbia, which limits the generalizability of the findings across different cultural, economic, and technological environments. Consumer perceptions of AI, technological innovativeness, country-of-origin cues, and customization opportunities may vary considerably across markets. Cross-national and cross-cultural studies could therefore replicate the proposed model and examine whether the direct and moderating relationships differ across developed, emerging, and other market contexts.

Third, the study relies on cross-sectional and self-reported measures of consumer perceptions and preferences. Accordingly, the estimated relationships should be interpreted as statistical associations rather than evidence of causal effects or actual purchasing behavior. The study does not objectively assess the technological capabilities of specific AI systems, the actual customization functionalities of particular computers or mobile phones, or consumers' observed purchase decisions. Longitudinal, experimental, and behavioral research designs could provide stronger evidence regarding temporal and causal relationships and determine whether the identified perceptual associations translate into actual product choice.

Fourth, Product Customization was conceptualized as consumers' perceived opportunities to adapt product features, functionalities, settings, and usage rather than as objectively observed customization capabilities. Although this conceptualization corresponds to the examined product context, the boundaries between customization, AI-enabled personalization, and individualized

product use warrant further investigation. Future research could examine these concepts separately and compare their effects across high-tech products with different levels of configurability.

Finally, the proposed model focuses on a specific set of technological, individual, and country-related determinants. **Future research** could incorporate additional mechanisms, such as perceived technological risk, trust in AI, digital literacy, and environmental concerns, as potential predictors, moderators, or mediators of High-Tech Product Choice. Further studies could also examine demographic characteristics and technological experience as sources of consumer heterogeneity rather than solely as statistical controls.

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APPENDIX A. CONFIRMATORY FACTOR ANALYSIS RESULTS

Panel A. Standardized CFA factor loadings

Construct	Item	Standardized loading
Artificial Intelligence	AI1	0.842
	AI2	0.861
	AI3	0.862
Consumer Innovativeness	CI1	0.854
	CI2	0.872
	CI3	0.879
Country-of-Origin Image	COO1	0.839
	COO2	0.851
	COO3	0.866
Product Customization	PC1	0.861
	PC2	0.879
	PC3	0.891
High-Tech Product Choice	HTPC1	0.881
	HTPC2	0.897
	HTPC3	0.907

Source: Authors

PANEL B. CFA MEASUREMENT MODEL FIT

Fit index	CFA measurement model	Recommended threshold
χ^2/df	1.790	< 3.00
GFI	0.941	> 0.90
CFI	0.963	> 0.90
TLI	0.954	> 0.90
IFI	0.962	> 0.90
RMSEA	0.037	< 0.08

Source: Authors