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GENERATIONAL COHORT VARIATIONS IN E-COMMERCE BUYING INTENTIONS: A MULTI-GROUP STRUCTURAL INVARIANCE ANALYSIS (MICOM-MGA APPROACH)

Dr. Jigar Nagvadia[1], Dr. Virendra Chavda[2], Dr. Savita Nagar[3], Dr. Animesh Banker[4] and Mr. Rishu Singh[5]

[1]Assistant Professor, School of Management and Finance, Kaushalya, The Skill University, Ahmedabad, Gujarat- 382424, Email ID: jnagvadia@gmail.com
[2]Associate Professor, National Forensic Sciences University, Delhi- 110085
[3]Assistant Professor, Gandhinagar Institute of Commerce, Gandhinagar University, Gandhinagar, Gujarat- 382721
[4]Assistant Professor, Shanti Business School, Gujarat Technological University, Ahmedabad, Gujarat- 382424
[5]Research Scholar, National Forensic Sciences University, Gandhinagar- 382007

Corresponding Author: *Dr. Jigar Nagvadia; Email ID: jnagvadia@gmail.com*

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Abstract
Purpose: *The research investigates the structural factors behind the intentions of online purchasing in emerging digital retail economies by integrating technology acceptance model (TAM) principles with the consumer trust and risk-benefit economic framework. Moreover, it considers the variations brought by structural drivers among different generations, especially comparing those of the digital natives (Youth) to those of adapted generations (Mature).*
Methodology: *An active e-commerce user data collection was carried out through quantitative cross-sectional research using a stratified random sampling strategy based on probability proportionate. Structural characteristics, specific indirect mediation pathways, and multi-group path differences were assessed using Variance-Based Structural Equation Modelling (PLS-SEM). In seeking operational measurement invariance across demographic strata, the authors used a three-step sequence of the Measurement Invariance of Composites (MICOM) methodology followed by a non-parametric version of Partial Least Squares Multi-Group Analysis (PLS-MGA).*
Findings: *The obtained empirical data verify that the basic structural ways determined cognitive trust and utility are applicable universally throughout visitor path or consumer life cycle; platform quality (PQ→PT) and platform usefulness (PU→PT) remain true existential conditions for both groups ($p<0.05$). But at the same time, critical generational differences emerge in terms of behavioral execution: older people are more value-oriented regarding the perceived benefits to buying intention ($\beta=0.693$, p_"MGA" =0.090), whereas younger people do not rely on benefits but on continuous trust flow ($\beta=0.263$). Lastly, specific indirect path estimates indicate that perceived benefits are an efficient mediator of the relationship between usefulness of the platform and purchase execution for both groups.*
Originality/Value: *This study contributes to the field of e-commerce research by departing from broad classification in consumer models. Through innovative application of multi-group analysis (MGA) and validation techniques, this research proves that generational socialization influences the manner of consumer evaluation of value and trust in online transactions. Moreover, the outcome of the research offers online retailers data-based solutions for their strategies to adjust their websites for each target group of consumers.*
Keywords: *Electronic Commerce (E-Commerce); Technology Acceptance Model (TAM); Perceived Trust; Perceived Benefits; Multi-Group Analysis (PLS-MGA); Generational Cohort Theory*

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1. Introduction

The fast growth of electronic commerce (e-commerce) has transformed the global retail landscape, changing static market interactions into active, digitally driven interactions. In newly emerging digital economies, such changes bring along the presence of different Internet penetration levels and a much bigger variety of consumer categories. Traditionally homogeneous, early digital consumers could largely be described as people who have obtained certain education and have a certain level of purchasing ability. Modern retail ecosystems have experienced a structural democratization, resulting in a highly diversified online shopping environment with customers being very different in terms of demographic indicators of consumers (McCormick et al., 2014). Thus, constant reassessment of distinct generational cohorts' digital shopping behavior is required (Oblinger & Oblinger, 2005).

In order to comprehend how and why people behave and think in respect of e-commerce, we will rely on theoretical foundations. In e-commerce, consumers tend to make choices based on the usefulness of information, the effectiveness of the system, and the risks associated with transactions. This has been shown by a number of the existing behavioral models, such as the Technology Acceptance Model (TAM) and its successors, which regard such concepts as usefulness and system quality as the main determinants of acceptance (Iqbal et al., 2018; Kim et al., 2004). In virtual transactions, however, the simple infrastructure alone cannot explain consumer behavior. What is important is the fact that the consumer is separated from the seller in both time and space, which results in creating ambiguity for the consumer and risks of transaction (Kim et al., 2007, 2008). That is why researchers in e-commerce have been focusing on the significance of consumer trust in relation to decision-making (Kim et al., 2003, 2004). Trust is a significant psychological factor that input into decreased cognitive complexity, empowering individuals to deal with perceived risks and develop clear buying intentions (Kim et al., 2008). Such platforms should tap into their structural characteristics, including technical interface quality, self-service technology quality, and system usefulness, in order to foster trust intentionally and offer users of the platform tangible transaction benefits (Iqbal et al., 2018; Mohan et al., 2013). Even though the relationships between quality and usefulness and trust and between trust and benefits and intentions are well-known in consumer literature, they need to be verified for different generations. Generations are not just groups of people having the same age; these are people with marked macro-experiences, socio-economic changes, and time of technological socialization in their youth (Malmendier & Nagel, 2011; Mann, 2003). Such macro-experiences influence the basic vectors of trust, risk tolerance, and technology adoption behavior of a generation for the rest of their lives (Malmendier & Nagel, 2011).

In the digital market, this phenomenon appears as a distinct segmentation in ages among consumers, often referred to as the "Youth" and "Mature" groups. The youth group comprises the consumers who are digital natives, and have grown up engulfed in technology, making them young individuals who are very adaptable, though they express differences in their expectations from the interactivity provided by the platforms used (Oblinger & Oblinger, 2005). On the other hand, mature consumers tend to experience technological risks and the processes arising from using platforms in a different way, needing to establish some level of experience and trustworthiness regarding technological platforms prior to making a purchase (Malmendier & Nagel, 2011; Mann, 2003). This difference between generations presents many questions toward e-commerce strategies. One path configuration that serves to convert impulse members of a specific generation into buying behavior may work very differently with the same generation represented by a different group. For instance, the emphasis on trust level versus benefits within transactions may vary between the transactions of digital natives and older consumers.

This research fills in those gaps by investigating an all-encompassing consumer decision-making model that indicates Perceived Quality and Perceived Usefulness as the key precursors affecting Perceived Trust and Perceived Benefits and thus determining Buying Intention, adding a comprehensive cross-validation to the process by employing Partial Least Squares Structural Equation Modeling (PLS-SEM) with a complementary MultiGroup Analysis (MGA) to establish the differences in the behavioral patterns of structural paths among Youth and Mature customer segments. By verifying the equivalence of measurements across the units using the modern MICOM regime, the paper has made a purport to study the dynamics of generational processes from a methodological standpoint.

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Literature Review and Hypothesis Development:

2.1. Theoretical Framework Overviews:

2.1.1. Technology Acceptance & Quality Infrastructures (TAM/UTAUT):

Consumer behavior theories concerning the digital context are primarily based on the Technology Acceptance model and its more developed forms like the TAM3 or the UTAUT. Initially used for workplace technology adoption, these models mainly deal with the notion of Perceived Usefulness (how effective the implementation of technology is in performing tasks) and Perceived Quality (quality of system and interface). In fact, in the modern online retail, interactive fashion spaces, or auto service process, technology quality and utility serve as the first points for customers' evaluation (Iqbal et al., 2018; McCormick et al., 2014). High system quality and definite self-service advantages are believed to reduce cognitive pressure and make complex operations what works for consumers (Iqbal et al., 2018).

2.1.2. Cognitive Trust and Risk-Benefit Economics in E-Commerce:

While utilitarian models seem promising in recording functional adoption indicators, they tend to neglect the problems brought by psychological uncertainty of non-physical transactions. In contrast to traditional physical retail, e-commerce transactions are subject to a different space-time continuum that necessitates the exchange of financial and personal data before the consumer can receive the goods (Kim et al., 2007, 2008). This gap creates a constant state of transactional risk and cognitive susceptibility (Kim et al., 2008). Consumer trust is an important psychological tool used to fill this gap, as it reduces perceived risk (Kim et al., 2003, 2008). Consumers are always calculating their risks when making digital transactions (Kim et al., 2007, 2008). Hence, platforms should focus on their structural components and use them to increase consumer trust effectively, as the trust is the way of decreasing perceived risk (Iqbal et al., 2018; Mohan et al., 2013).

2.1.3. Generational Cohort Theory & Consumer Risk Socialization:

The Generational Cohort Theory states that those who undergo the same macro-environment and economic disruptions form similar values and habits during their formative stage (Malmendier & Nagel, 2011; Mann, 2003). According to this idea, shared macro-experiences form core financial risk profile (Malmendier & Nagel, 2011). In the digital consumer environment, this is reflected in the fact that there are differences in behavior between the technology-savvy "younger generation" and the adapted "older generation" (Oblinger & Oblinger, 2005). The younger generation grew up in a saturated digital environment with social media actively promoting different brands, which makes them flexible but unpredictable (Arango-Botero et al., 2020; Oblinger & Oblinger, 2005). Meanwhile, older generational cohort approaches online spaces with experience obtained before the digital era and tries to develop trust while experiencing online purchasing (Malmendier & Nagel, 2011; Mann, 2003).

2.2. Structural Antecedents of Perceived Trust and Perceived Benefits:

2.2.1. Perceived Usefulness → Perceived Benefits (H_1):

Perceived usefulness acts as an essential cognitive influence on a consumer's estimate of total transaction value. The positive impact of optimized search effectiveness and efficient checkout processes by an e-commerce site makes consumers acknowledge the benefits of these attributes. This way, the functional aspect of online shopping helps improve perceived usefulness as compared to conventional shopping methods. Thus.

H_1: Perceived Usefulness has a significant positive effect on Perceived Benefits.

2.2.2. Perceived Usefulness → Perceived Trust (H_2):

A platform's perceived usefulness not only provides short-term economic benefits, but it also offers structural assurance that helps the consumer to build trust towards the merchant. If the digital retailers' systems can deliver reliable performance and fulfill their promises, consumers view this reliability as proof of the merchants' competence, integrity, and goodwill (Kim et al., 2004, 2008). If a certain platform has demonstrated high levels of usefulness, consumers feel assured that the digital vendor is able to carry out secure transactions, reducing psychological barriers, and enhancing cognitive trust. Thus:

H_2: Perceived Usefulness has a significant positive effect on Perceived Trust.

2.2.3. Perceived Quality → Perceived Trust (H_3):

The nature of the technical and visual structure of a digital platform is the main indicator of a store's reliability in the online market. Having high perceived quality, represented by the stable structure of the system, the secure self-service concept, the ease of navigation, and the visual appeal, suggests that the online store is reputable and reliable (Iqbal et al., 2018; Mohan et al., 2013). On the contrary, unintegrated user interfaces, slow loading time, and ineffective security system only increase consumers' tension and create barriers for conducting Internet purchases (Kim et al., 2008; Iqbal et al., 2018). Thus:

H_3: Perceived Quality has a significant positive effect on Perceived Trust.

2.3. Direct Determinants of Online Buying Intentions:

2.3.1. Perceived Benefits → Buying Intention (H_4):

Rational choice theory posits that a consumer's intention to purchase is determined by constant calculation of the rewards of a transaction in relation to the costs. The perceived benefits cover a wide variety of benefits, such as competitive pricing, time-saving features, large assortment of products, and multichannel flexibility. When the benefits overweigh the costs of purchasing online, they become a strong stimulus for the intention to buy immediately. Thus:

H_4: Perceived Benefits have a significant positive effect on Buying Intention.

2.3.2. Perceived Trust → Buying Intention (H_5):

As digital transactions occur outside of physical products and face-to-face interaction, consumers are always confronted with structural vulnerabilities and risks (Kim et al., 2007, 2008). In this respect, the construct of perceived trust functions as a vital psychological link. It makes consumers feel that digital merchants will safeguard sensitive financial data, protect their privacy and make the promised deliveries without any kind of unjust exploitation (Kim et al., 2004, 2008). By reducing perceived risks, trust creates a solid psychological base, which enables consumers to proceed from consideration to purchase intention. Thus:

H_5: Perceived Trust has a significant positive effect on Buying Intention.

2.4. Structural Mediation Architecture:

2.4.1. The Mediating Role of Perceived Benefits (H_6):

The connection between the basic platform function (Perceived Usefulness) and the final purchase action (Buying Intention) is not always very direct due to the role of mediating cognitive evaluations. Although it is through systemic usefulness that we are able to confirm mechanical effectiveness of the platform, this operational usefulness has to acquire presence of the customer value in order to prompt the customer to take action. The perceived value is acting as such key mediating factor. The functional benefits of an extremely useful platform are perceived and interpreted as personal benefits influencing consumer's motivation. Thus:

H_6: Perceived Benefits significantly mediate the relationship between Perceived Usefulness and Buying Intention.

2.5. Moderating Dynamics of Generational Cohorts (Multi-Group Hypotheses):

The direct effects related to this structural model should mostly be positive in general, but the comparative strength and significance of the said path coefficients will vary according to the profiles of consumers. The younger generation was born into the world of instant internet and technology, meaning that these digital consumers view interaction with the system as expected behavior rather than as an added value (Oblinger & Oblinger, 2005). Being technology natives, younger customers care more about aspects like the presence of trust ideas and high level of interactivity at the moment of buying online.

On the other hand, older buyers often see online channels through an experience-based lens defined by the typical retail criteria. Therefore, they place a lot of emphasis on tangible utilitarian results and practical rewards like savings and established conveniences before making a purchase online. These different historical circumstances and technology-related socialization patterns imply that the structural factors affecting purchasing intentions will work at varying levels of strength in the case of younger and older groups. Hence, we formulate our last hypotheses.

H_{7a}: The positive effect of Perceived Usefulness on Perceived Benefits significantly differs between Youth and Mature consumer cohorts.

H_{7b}: The positive effect of Perceived Usefulness on Perceived Trust significantly differs between Youth and Mature consumer cohorts.

H_{7c}: The positive effect of Perceived Quality on Perceived Trust significantly differs between Youth and Mature consumer cohorts.

H_{7d}: The positive effect of Perceived Benefits on Buying Intention significantly differs between Youth and Mature consumer cohorts.

H_{7e}: The positive effect of Perceived Trust on Buying Intention significantly differs between Youth and Mature consumer cohorts.

2.6. Conceptual Framework:

This study employed the theoretical integration of technological acceptance infrastructures, risk-benefit economics, and generational cohort theory to create a robust structural framework. This structural framework highlights two key independent technical concepts, which are Perceived Quality and Perceived Usefulness as

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core precursors of online purchase intent. In turn, these elements affect the secondary cognitive level of the consumer's mindset in the form of Perceived Trust and Perceived Benefits variables. These aforementioned constructs culminate in the final outcome variable, Buying Intention. Besides, the theory clarifies the procedure of indirect impact by the use of technology (Perceived Usefulness) on the outcome (Perceived Benefits). Additionally, the study aims to investigate the generational variance throughout the whole e-commerce process by including the Youth and Mature generations represented as multi-group moderators, facilitating the moderated impact of the different generations through every direct structural pathway of e-commerce modeling. The full depiction of the conceptual framework and proposed paths is given in Figure 1 below.

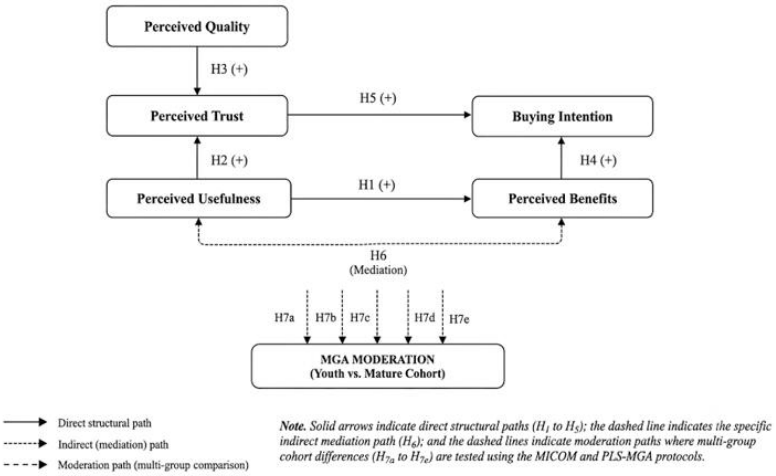

Figure 1: Proposed Conceptual and Hypothesized Framework

3. Research Methodology:

3.1. Research Design and Data Collection:

This research utilizes a cross-sectional quantitative research approach to validate the structural model and analyze generational differences in the online shopping ecosystem. The sample population is made up of active audiences of digital consumers within the urban e-commerce location. The probability proportionate stratified random sampling technique was adopted to enhance external validity and minimize the selection bias. The sample frame was developed using verified consumer directories across popular digital business districts in the city.

In order to perform a proper multi-group analysis, the whole study population was divided into two generational groups in line with age-related criteria.

Youth Cohort: Digital consumers aged up to 30, who are highly communicated within the system of modern communication.

Mature Cohort: The mature group, which includes consumers aged over 30 whose formative communication has taken place in a different environment.

The youth group corresponds to the parameters of digitally-savvy generations Y/Millennials (aged up to 30), while the mature group incorporates the consumer characteristics of the older generation – Gen X (aged over 30).

Random sampling was conducted independently within each group, ensuring all consumers had equal, non-zero chances of being chosen from the defined group. Data collection was carried out via an electronic questionnaire directly sent to the randomly chosen respondents through verified channels for consumers.

3.2. Operationalization of Constructs:

The scales for measuring were adapted from existing psychometric scales that are valid in literature of e-commerce to ensure high content validity. The questionnaire utilized is made up of five main latent reflective constructs:

Buying Intention (BI): Defined through 9 items describing the possibility and willingness of a consumer to conduct an online buying.

Perceived Benefits (PB): Measured using 9 items related to the transactional value, price advantages,

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convenience, and product assortment.

Perceived Trust (PT): Evaluated using 7 items depicting a consumer's beliefs about the integrity of the company and its platform and the trustworthiness of this vendor.

Perceived Usefulness (PU): Measured using 9 items examining the performance of the platform in terms of facilitating the transaction process.

Perceived Quality (PQ): Evaluated using 9 items focusing on the stability of the interface and system setup and design.

All items are assessed using a uniform 5-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.3. Statistical Estimation Technique:

This study uses Variance-Based Structural Equation Modeling to assess the measurement characteristics and structural relations such as Partial Least Squares Structural Equation Modeling (PLS-SEM). The use of PLS-SEM is effective since this analysis technique makes it possible to successfully work with complicated, layered predictive paths without adhering to strict requirements for multivariate distribution of data (Hair et al, 2019, 2022). The most important is the possibility to apply advanced non-parametric Multi-Group Analysis (MGA) necessary for verifying differences between various demographic groups. All the statistical calculations have been made using SmartPLS software.

3.4. Measurement Invariance Protocol (MICOM):

The utilization of structural path coefficients to make comparisons between different generational cohorts requires establishing the stability of the model measurement across generations. Differences in the representation and perception of constructs by younger generations versus older generations can result in any differences in path coefficients being a matter of measurement mistake, rather than a matter of behavioral difference. That is the reason why the three-stage Measurement Invariance of Composites (MICOM) protocol was applied in accordance with the perspective of this study before going for a multi-group analysis (Hair et al., 2018; Matthews, 2017).

Step 1: Configural Invariance:

Configural invariance establishes that the structure of measurement is the same for both older and younger generations. This step established that the older and younger subsamples use the same assignments of indicators to latent variables, the same rules for data processing, and the same algorithms for processing data in the PLS environment. Completion of this step further guarantees the same basic model across the two generations.

Step 2: Compositional Invariance:

The concept of compositional invariance verifies whether the composite score is generated in the same manner within each group. In simple terms, this is evaluated through the correlation normalized for the composite scores derived from the Youth subsample (using appropriate weights) and the Mature subsample using appropriate weights. In mathematical terms, compositional invariance is satisfied if the correlation coefficient equals to $c=1$ as established through a non-parametric permutation test with 5000 iterations. This satisfies the requirement of establishing that the particular weights assigned to the indicator blocks do not modify any meaning in the latent variables of both groups.

Step 3: Equality of Composite Means and Variances:

The last stage assesses the mean scores and variances for the composite variables across both sub-samples. In the case where the means and variances are statistically identical, all data can, therefore, be pooled into a consolidated model. However, even if steps 1 and 2 are accepted, one would establish the model's classification as possessive of partial measurement invariance when step 3 suggests considerable disparities between means and variances. This partial measurement invariance permits one to go ahead and carry out multi-group comparison of the path coefficients, as this confirms that the variations in paths are genuine structural dimensions representing diverse generations.

4. Empirical Results and Analysis:

4.1. Evaluation of the Reflective Measurement Model:

4.1.1. Indicator Reliability and Cross-Loadings:

The outer measurement model underwent analysis so as to confirm that all the variables correctly measured their respective latent variables. The indicator reliability was computed by checking that all the individual outer factor loadings were exceeding the normally accepted academic standard of 0.70. The Table 1 below shows that the outer loadings of all variables demonstrates a situation where the outer factor loadings have values ranging from a minimum of 0.829 and a maximum of 0.994 which indicates high individual indicator

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reliability. The outer factor loading found for PT2 variable was recorded at 1.067. It should be noted that while all the standardized parameters in classical confirmatory model should be 1, the unstandardized composite weights optimization may lead to the loading estimation beyond 1 as a result of certain collinearity effects in particular. Since all other factors were fine, this indicator was kept in the model to sustain the fact that the data from this variable is considerably important (Lohmöller, 1989).

Table 1: Factor loadings

Construct	Indicator	Outer Loading
Buying Intention	BI1	0.841
	BI2	0.895
	BI3	0.955
	BI4	0.988
	BI5	0.994
	BI6	0.926
	BI7	0.901
	BI8	0.916
	BI9	0.857
Perceived Benefits	PB1	0.833
	PB2	0.896
	PB3	0.943
	PB4	0.942
	PB5	0.932
	PB6	0.929
	PB7	0.907
	PB8	0.938
	PB9	0.916
Perceived Trust	PT1	0.895
	PT2	1.067
	PT5	0.908
	PT6	0.905
	PT7	0.886
	PT8	0.903
	PT9	0.919
Perceived Usefulness	PU1	0.829
	PU2	0.841
	PU3	0.948
	PU4	0.948
	PU5	0.937
	PU6	0.933
	PU7	0.913
	PU8	0.93
	PU9	0.915
Perceived Quality	PQ1	0.864
	PQ2	0.877
	PQ3	0.939
	PQ4	0.956
	PQ5	0.906
	PQ6	0.925
	PQ7	0.892
	PQ8	0.891

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4.1.2. Construct Reliability and Validity

Different metrics were deployed to determine internal consistency and reliability for all reflective latent variables, namely: Cronbach's alpha (α), Dijkstra-Henseler's rho (ρ_A), and Composite Reliability (CR) (see Table 2). These metrics demonstrate that all latent variables' reliability metrics are very good, since: Cronbach's α values from 0.948 to 0.979, ρ_A values between 0.974 and 0.980, and CR values exceeding the necessary threshold of 0.70 in the range of 0.943 to 0.979. The Average Variance Extracted (AVE) metrics were calculated for all constructs to assess convergent validity. All AVE values exceed the already established threshold of 0.50, the lowest value being 0.605 for Perceived Trust and the highest value being 0.838 for Perceived Benefits (Fornell & Larcker, 1981).

Table 2: Reliability and Convergent Validity of Constructs

Online shopping dimensions	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Buying intention	0.963	0.979	0.964	0.722
Perceived Benefits	0.979	0.980	0.979	0.838
Perceived Trust	0.948	0.971	0.943	0.605
Perceived usefulness	0.978	0.979	0.978	0.831
Perceived Quality	0.974	0.974	0.974	0.822

4.1.3. Discriminant Validity Validation

The discriminant validity confirms that every latent construct is statistically different from all other variables in the structural network. This concept was validated using two different approaches; the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations. According to the Fornell-Larcker criterion, a construct can only be said to be valid in terms of discriminant validity only if the square root of its AVE (shown on the diagonal) is more than the construct's correlations with the other constructs (the off-diagonal values). The results in the Table 4 confirm that this condition is met for the pairs of all the variables.

Table 3: Fornell-Larcker Criterion

	Buying Intention	Perceived Benefits	Perceived Trust	Perceived Usefulness	Perceived Quality
Buying Intention	0.850				
Perceived Benefits	0.666	0.916			
Perceived Trust	0.375	0.245	0.778		
Perceived Usefulness	0.378	0.589	0.689	0.911	
Perceived Quality	0.300	0.278	0.618	0.697	0.907

To demonstrate a more updated and thorough test of discriminant validity, the HTMT ratio was assessed. In order to demonstrate distinct conceptual delineations, all HTMT ratios must not go beyond the strict value of 0.85 (Henseler et al., 2015). As stated in Table 4, the greatest ratio observed was 0.697 (between Perceived Quality and Perceived Usefulness), meaning all variables can comfortably pass the bar and show strong discriminant validity.

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Table 4: Heterotrait-Monotrait Ratio (HTMT)

	Buying Intention	Perceived Benefits	Perceived Trust	Perceived Usefulness	Perceived Quality
Buying Intention					
Perceived Benefits	0.653				
Perceived Trust	0.359	0.219			
Perceived Usefulness	0.364	0.590	0.652		
Perceived Quality	0.294	0.278	0.598	0.697	

4.2. Evaluation of the Structural Model (Baseline Global Fit):

4.2.1. Explanatory Power (R^2) and Predictive Relevance (f^2):

To assess the explanatory power of the structural model, the coefficients of determination of the endogenous constructs were calculated. The model accounts for 49.1% of the variance in Buying Intention (R2=0.491), 34.7% of the variance in Perceived Benefits (R2=0.347), and 51.2% of the variance in Perceived Trust (R2=0.512). In consumer behavioral modeling, these results indicate significant explanatory power (Shmueli et al., 2019).

Table 5: R Square

	R Square	R Square Adjusted	Explanatory Tier
BUYING-INTENTION	0.491	0.490	Substantive/Moderate – to - High
PERCEIVED-BENIFITS	0.347	0.346	Moderate
PERCEIVED-TRUST	0.512	0.511	Substantive/High

To determine the predictive power and contribution of each of the independent exogenous constructs on the dependent variables, Cohen's effect sizes (f2) were computed. In accordance with the established thresholds, f2≥0.02 reflects the small effect, f2≥0.15 stands for medium effect, and f2≥0.35 is indicative of the large effect. In Table 6, it is indicated that the Perceived Benefits has the large positive direct effect on the Buying Intention (f2=0.689), and the Perceived Usefulness has a quite strong influence on the Perceived Benefits (f2=0.532).

Table 6: F Square

	Buying Intention	Perceived Benefits	Perceived Trust	Perceived Usefulness	Perceived Quality
Buying Intention					
Perceived Benefits	0.689				
Perceived Trust	0.093				
Perceived Usefulness		0.532	0.266		
Perceived Quality			0.076		

4.2.2. Model Fit Assessment

The fit of the global model was assessed by the means of the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). The Saturated Model SRMR was recorded at 0.063, which is well within the conservative cut-off value of 0.080 required for the satisfaction of an acceptable baseline structural fit. The overall Estimated Model NFI was found to be equal to 0.888. Although the value of 0.90 is commonly considered acceptable, the obtained value of 0.888 was sufficiently close to represent an acceptable result considering the complexity of the behavioral model applied, which deals with the multi-group character of the structural model.

Table 7: Model Fit summary

	Saturated Model	Estimated Model
SRMR	0.063	0.088
NFI	n/a	0.888

4.3. Evaluation of Intra-Group Structural Path Significance:

In order to assess the structural changes among various generations in a systematic form, the conduct of empirical research was carried out at three successive stages. At the first stage, the estimation of the basic path coefficient was completed separately for each generation by means of a non-parametric method of bootstrapping with 5,000 replications. The resulting t-values and p-values are presented in Table 8 for each generation. After identifying substantial baseline indicators, PLS-MGA analysis was performed to study structural transformations. Finally, the analysis was completed by conducting the estimation of the specific indirect effect.

According to this empirical methodology, the validating of model parameters should be conducted separately for each cohort group prior to comparing them structurally. Such workaround assures all original paths are statistically valid for both subsection of sample. As stated in Table 8 of the work, path coefficients are considerably significant ($p<0.05$) in case of both generations. This full initial validation of parameters completes the first stage of the analytical methodology by backing the structural model to work properly with both cohorts to provide grounds for Multi-Group Analysis.

Table 8: Path Coefficients and Bootstrapping Output

Structural Direct Path Configuration	**Cohort Group**	**Path Coeff. Original (β)**	**Path Coeff. Mean (M)**	**STDEV**	**t-Value**	**p-Value**
Perceived Benefits → Buying Intention	Youth	0.49	0.493	0.065	7.524	0
	Mature	0.693	0.695	0.062	11.127	0
Perceived Trust → Buying Intention	Youth	0.263	0.264	0.069	3.797	0
	Mature	0.16	0.158	0.068	2.36	0.019
Perceived Usefulness → Perceived Benefits	Youth	0.634	0.632	0.07	9.062	0
	Mature	0.576	0.573	0.063	9.195	0
Perceived Usefulness → Perceived Trust	Youth	0.329	0.331	0.109	3.008	0.003
	Mature	0.452	0.459	0.136	3.317	0.001
Perceived Quality → Perceived Trust	Youth	0.291	0.293	0.108	2.688	0.007
	Mature	0.397	0.393	0.133	2.979	0.003

4.4. Multi-Group Analysis and Structural Path Comparisons:

With intra-group network baselines duly established, we performed non-parametric PLS-MGA, which reveals the pathways through which different generations operate. We applied the Welch parametric formulation for variance adjustment among subsamples since it allows us to calculate the path coefficients

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differences ($\beta_{\text{Youth}} - \beta_{\text{Mature}}$) with their respective multi-group p-values (Sarstedt et al., 2011).

Table 9: Multigroup Analysis (MGA Comparison)

Structural Direct Path Comparison	Path Coeff. Diff (Youth - Mature)	p-Value New (Youth vs Mature)	Result
Perceived Benefits → Buying Intention	-0.146	0.09	Marginally Significant (10%)
Perceived Trust → Buying Intention	0.055	0.532	Not Statistically Significant
Perceived Usefulness → Perceived Benefits	0.061	0.498	Not Statistically Significant
Perceived Usefulness → Perceived Trust	-0.295	0.485	Not Statistically Significant
Perceived Quality → Perceived Trust	0.104	0.452	Not Statistically Significant

The multi-group analysis offers notable behavioral findings in relation to the model. The structural relationships related to the internal trust formation process (perceived usefulness and perceived quality) display structural constancy and lack of statistically significant difference across groups ($p>0.05$). Thus, high quality of a platform and its systematic usefulness are seen as prerequisites for creating trust and benefits for consumers in general.

Nonetheless, a notable difference between the generations is noticed in the Perceived Benefits → Buying Intention link. Specifically, the path coefficient is much higher for Mature consumers ($\beta=0.693$) than for Youth consumers ($\beta=0.490$). The p-value for the Mann-Whitney test is 0.090, meaning that the observed difference is statistically significant at the 10% level. This suggests that young consumers have a more diversified approach toward purchasing items, while older people focus much more on the value they can get from purchases and generally prefer very well-defined and tangible benefits before making an actual purchase online.

Regardless, when it comes to analyzing the Perceived Trust → Buying Intention process, it appears that younger customers rely significantly more on direct trust relationships ($\beta=0.263$) than older ones ($\beta=0.160$). Despite the fact that the difference in the paths does not fulfill the requirement of the structural difference ($p=0.532$), the difference in the internal path coefficients indicates the high level of sensitivity of younger clients to trust mechanisms when making purchases online.

4.5. Mediation and Specific Indirect Effects Analysis:

In the final analysis, an indirect mediation analysis was done to find how system design affects buying intentions. The analysis showed that the Perceived Benefits measure carries out the role of a mediator between the Perceived Usefulness and Buying Intentions measures. Through the analysis of the Youth sample data, we found that the specific indirect effect of the Perceived Usefulness measure working through the Perceived Benefits measure leads to an increase in Buying Intentions measure is significant ($\beta_{\text{indirect}} = 0.311,\ t = 5.792,\ p = 0.000$). In the case of the Mature sample, the specific indirect effect is greater ($\beta_{\text{indirect}} = 0.399,\ t = 7.114,\ p = 0.000$). Such results suggest that platforms cannot really optimize purchasing conversions effectively by just allowing being useful. The functions of the platform must be transformed into benefits.

5. Discussion and Implications

5.1. Theoretical Synthesis of Generational Divergences

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The empirical findings provide substantial structural backing to the integrated e-commerce model of behavior, as there are some minor differences by generation. One key finding of the study is an unexpected uniformity of core channels of trust and utility generation. Non-significant results on multi-group comparisons for the paths H_{7a}, H_{7b}, and H_{7c} suggest that the main psychological mechanisms contributing to the perception of platform credibility are the same for both digital natives and structured adaptives. Good quality of system infrastructure (PQ→PT) and powerful functional value (PU→PT) are believed to be the requirements applicable to all consumers.

At this point, however, the decisive difference occurs in the process of translating the cognitive state into practical behavioral action (H7d). The journey from Perceived Benefits to Buying Intention is much stronger for the Mature group (β=0.693) than for the Youth one (β=0.490). The reason for this statistical difference lies, in particular, in the Generational Cohort Theory and macro-socialization approach (Malmendier & Nagel, 2011; Mann, 2003). Mature customers view digital transactions from a pragmatic and risk-sensitive perspective formed by previous retail experience beyond the Internet. In this case, going from the idea of trust to the act of buying requires careful calculation of concrete benefits, namely cost savings, time efficiency, and safe transactions.

On the other hand, the youth group shows a more decentralized model of decision-making. The younger customers have been exposed to technology for all their lives, which makes them view online shopping systems as a normal part of life rather than something new. As a result, although utilitarian factors play a role in the decisions of the group, the youth still put much emphasis on the concept of trust (β=0.263) when making their purchases. They are very responsive to interactive features, and social proof and show interest in the data security measures that take place when they check out, requiring constant reassurance.

5.2. Managerial and Strategic Insights for E-Commerce Platforms

Digital merchants and creators of platforms can find straightforward data-based recommendations that will help target their marketing and customize their interfaces.

Valued Campaigns for Older Consumers: As elderly consumers exist under the strong influence of direct benefits, marketing campaigns directed at this particular segment should focus on straightforward communication of perceived benefits. Therefore, it is convenient to highlight all kinds of clear savings, loyalty rewards, simplified returns and functional benefits. Reducing the number of steps needed to complete the transaction and making special emphasis on time-saving tools can appeal to older consumers as consumers motivated by utility.

Trust-Centered Interfaces for Young Customers: When working with young audiences, online platforms should place a high value on providing permanent trust assurance to their clients. Technologies used in the process should include real-time reviews related to peer's experience, clear data privacy policies, visible third-party badges, and technologically advanced payment instruments.

Common Priority of Quality and Usefulness: As platform quality and usefulness serve as the basis for building consumer trust and value, structural optimization cannot be ignored.

5.3. Limitations and Future Research Directions

Despite the valuable information provided by this study, there are some limitations that must be acknowledged. First of all, cross-sectional data gathering is able to measure consumers' attitudes at a certain moment only. Due to the fact that consumer behavior is developing rapidly, future research can benefit from using longitudinal study designs that will allow observing changes in generations over time. Secondly, this study identifies generations with the help of a simple binary division (Young vs. Adult). Future empirical research may improve upon this by distinguishing among different generations, like Gen Z, Millennials, Gen X, since it will allow identifying more specific behavioral variations. Last but not least, there is a need to include actual transaction information to improve the predictive accuracy of the behavioral model.

6. Conclusion

Research provides a plausible method for analyzing the structure of changes in purchasing intentions in different generations in the context of the digital market. Utilizing TAM and structural components of trust and risk-benefit economics, the article shows how the characteristics of selected platforms are changed into the actual choices of consumers. In terms of methods, the research explored the issue of structural validity through the implementation of probable sampling and determined multi-group variances using PLS-MGA and MICOM techniques.

The empirical results produce two important results for contemporary theories and strategies in e-commerce:

Universal Foundational Paths: In the first place, the sequential configurations that provide basis consumer

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confidence are universal stable. The requirement for a high-quality operation of a system interface and high-importance system usefulness both serve as the prerequisite that is common for the digital-native (Youth) and the structurally adapted (Mature) customer segments.

Generational Behavioral Splits: In the second place, there are clear generational differences in the final stages of the behavioral process. Especially mature customers have a high value-orientation in their purchases, requiring a much greater obvious achieved benefits (β=0.693) for making an online purchase compared to younger people. On the contrary, youngsters will have a more balanced and trust-oriented approach to the e-commerce market.

In the end, these conclusions reveal that success in e-commerce in mature digital economies will rely on the ability of a business to combine universal service quality indicators with targeted design solutions that are aimed at a specific group of customers.

References:

1. Arango-Botero, D., Valencia-Arias, A., Herrera-Restrepo, O., & Cruz, J. E. (2020). Factors shaping youth consumer behavior in digital environments. International Journal of Interdisciplinary Studies, 12(2), 85-102.
2. Choudhury, K. (2014). Service quality and customers' behavioral intentions: A study of the Indian banking sector. International Journal of Bank Marketing, 32(1), 10–27. https://doi.org/10.1108/ijbm-02-2013-0009
3. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
4. Flavián, C., Guinalíu, M., & Gurrea, R. (2006). The role played by perceived usability, reputation and familiarity on website trust, and a website's loyalty. Information & Management, 43(1), 1–14. https://doi.org/10.1016/j.im.2005.01.002
5. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50. https://doi.org/10.1177/002224378101800104
6. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519
7. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24. https://doi.org/10.1108/ebr-11-2018-0203
8. Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). Advanced issues in partial least squares structural equation modeling (PLS-SEM). SAGE Publications.
9. Hair, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2022). Partial least squares structural equation modeling (PLS-SEM) in business research. Journal of Business Research, 148, 370-380. https://doi.org/10.1016/j.jbusres.2022.04.054
10. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
11. Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405–431. https://doi.org/10.1108/imr-09-2014-0304
12. Iqbal, M. S., Deari, M. I. A., & Jamil, S. A. (2018). Impact of self-service technology (SST) service quality on customer loyalty and behavioral intention in e-banking. International Journal of Electronic Business, 14(2), 128–149. https://doi.org/10.1504/ijeb.2018.093952
13. Kim, C., Galliers, R. D., Shin, N., Ryoo, J. H., & Kim, J. (2007). Factors influencing Internet shopping value and trust: A multi-group analysis. Information & Management, 44(8), 691-702. https://doi.org/10.1016/j.im.2007.07.001
14. Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544–564. https://doi.org/10.1016/j.dss.2007.07.001
15. Kim, H. W., Xu, Y., & Koh, J. (2003). A comparison of online trust-building mechanisms. Journal of Organizational Computing and Electronic Commerce, 13(3), 163-180. https://doi.org/10.1207/S15327744JOCE1303_1

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ISSN: 2208-2190 Pages- 27-40
DOI: https://doi.org/10.69980/mth8gh23

16. Kim, J., & Park, J. (2004). An empirical validation of a consumer acceptance model for electronic commerce. Journal of Electronic Commerce Research, 5(1), 32-44.
17. Lohmöller, J. B. (1989). Latent variable path modeling with partial least squares. Physica-Verlag. https://doi.org/10.1007/978-3-642-52465-3
18. Malmendier, U., & Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? The Quarterly Journal of Economics, 126(1), 373–416. https://doi.org/10.1093/qje/qjq004
19. Mani, Z., & Chouk, I. (2017). Drivers of consumers' resistance to smart products. Journal of Marketing Management, 33(1-2), 76–97. https://doi.org/10.1080/0267257x.2016.1245212
20. Mann, S. L. (2003). Generational cohort theory and consumer risk socialization: Analyzing long-term technological transformations in retail markets. Journal of Consumer Behaviour, 3(2), 170–188. https://doi.org/10.1002/cb.132
21. Matthews, L. M. (2017). Applying the MICOM procedure in PLS-SEM multi-group analysis. Journal of Applied Structural Equation Modeling, 1(1), 1-15. https://doi.org/10.47263/jasem.1(1)02
22. McCormick, H., Cartwright, J., Perry, P., & Duan, L. (2014). Fashion retailing — Past, present and future. Textile Progress, 46(3), 227–301. https://doi.org/10.1080/00405167.2014.973216
23. Mohan, G., Sivakumaran, B., & Sharma, P. (2013). Impact of store environment on impulse buying behavior. European Journal of Marketing, 47(10), 1711–1732. https://doi.org/10.1108/ejm-03-2011-0110
24. Oblinger, D., & Oblinger, J. (2005). Is it age or IT: First steps toward understanding the net generation. Educating the Net Generation, 2(1), 2-15.
25. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275
26. Ringle, C. M., Sarstedt, M., Sinkovics, N., & Sinkovics, R. R. (2023). A perspective on using partial least squares structural equation modelling in data articles. Data in Brief, 48, Article 109074. https://doi.org/10.1016/j.dib.2023.109074
27. Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares structural equation modeling. In Measurement and Research Methods in International Marketing (pp. 195-219). Emerald Group Publishing. https://doi.org/10.1108/s1474-7979(2011)0000022012
28. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM. Journal of Business Research, 105, 321-329. https://doi.org/10.1016/j.jbusres.2019.08.016
29. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540
30. Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412
31. Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. Journal of Marketing, 52(3), 2–22. https://doi.org/10.1177/002224398805200302