IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN:2278-487X, p-ISSN: 2319-7668. Volume 27, Issue 6. Ser. 17 (June 2025), PP: 52-59
www.iosrjournals.org

"Antecedents of Gen Z Customer Purchase Decision in E-Commerce Platforms: An In-depth Investigation of the Process"

[1]Dhruthi B, [2]Prof. Mithun DJ
[1](2nd Year MBA, RV Institute of Management, Bangalore, Karnataka, India)
[2](Coordinator BAP, RV Institute of Management, Bangalore, Karnataka, India)

Abstract: *In a world where Gen Z is setting the tone for digital behavior, understanding what drives their online purchase decisions isn't just interesting—it's necessary. This study explores the core factors that influence how Gen Z consumers interact with e-commerce platforms, with a focus on social media influence, perceived security, and purchase intent. Using data from 302 respondents, I found that while social media and security do matter, it's purchase intent that acts as the real game-changer. Once Gen Z decides they want something, they usually go for it—fast. Interestingly, social media doesn't directly trigger purchases; instead, it subtly builds trust and emotional connection, which then strengthens intent. The data also shows that trust and authenticity aren't just buzzwords for this generation—they're deal-makers. For brands and platforms, this means focusing less on pushing products and more on creating a transparent, secure, and genuinely engaging user experience. This research helps fill a gap in how we understand digital-native consumers in a developing economy, offering insights that are both practical and future-focused. It's not just about what Gen Z buys—it's about why and how they decide to click "buy now."*

Key Word*: Social Media Influence, Perceived Security, Purchase Intent, Purchase, TPB, Resource based view.*

Date of Submission: 15-06-2025 Date of Acceptance: 30-06-2025

I. Introduction

In a world where screens are the new storefronts and attention spans last mere seconds, Generation Z has emerged not just as another consumer group—but as the architects of the digital economy. Born between the mid-1990s and early 2010s, Gen Z is the first generation to grow up entirely in a digital ecosystem. Their fluency with smartphones, social media, and constant connectivity has dramatically reshaped how businesses market, sell, and earn trust. This generation doesn't just consume digital content—they live it. As their purchasing power rises, so does their influence on the evolution of e-commerce. At first glance, Gen Z's online shopping behavior might appear impulsive and emotionally driven. But beneath that spontaneity lies a layered decision-making process that blends logic with emotional resonance, peer influence, and tech-savvy expectations. Gen Z expects seamless convenience but also craves authenticity. They value personalization but demand transparency. To truly grasp what makes a Gen Z customer click "buy now," we must explore the psychological, social, and technological forces shaping their behavior. Traditional brand loyalty holds little weight for this generation. Instead, their preferences shift rapidly, influenced by peer reviews, influencer content, viral moments, or how closely a brand reflects their values. Platforms like TikTok, Instagram, and YouTube aren't just entertainment—they're search engines for products. Digital word-of-mouth, particularly through influencers or micro-reviews, outweighs conventional marketing. In this climate, authenticity isn't a bonus—it's a necessity.

But product visibility is just the beginning. Gen Z is highly discerning about the entire shopping experience. Functionality, design, and user-friendliness are critical. Clunky interfaces, slow load times, or confusing checkouts are immediate turn-offs. Aesthetics and usability aren't optional—they're foundational. Technology here acts both as an enabler and a filter. Features like AI-powered personalization, AR try-ons, and gamified interfaces can attract Gen Z—but only if they're intuitive and respect user privacy and time. Trust is another essential and often underestimated factor. Gen Z has grown up amid data breaches, misleading ads, and influencer controversies. As a result, they are inherently skeptical. Trust-building requires more than flashy branding; it demands ethical practices, data security, transparency, and credible reviews. Brands that miss these marks risk being ignored or "ghosted."

Despite increasing research into digital consumer behavior, Gen Z remains underexplored. Many foundational theories—such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB)—were conceived before the rise of always-connected consumers and often fail to capture Gen Z's nonlinear, real-time decision-making. Their journey from awareness to purchase isn't step-by-step but tangled and influenced by everything from TikTok trends to niche online discussions. Emotions also play a decisive role. Visual storytelling, humor, music, and gamification often trigger impulse purchases. Unlike millennials, Gen Z tends to make decisions based on identity and emotional appeal rather than pure utility. This is especially true in fashion, beauty, and tech—sectors where design and self-expression often rival quality in importance.

Context is key too. Much of the existing literature focuses on Gen Z in Western markets, overlooking how culture and infrastructure shape behavior in emerging economies. In countries like India or those in Southeast Asia, factors like payment methods, delivery systems, and family influence alter how Gen Z shops online. A universal approach is ineffective; local context matters. This research addresses these gaps by exploring the key antecedents of Gen Z's e-commerce behavior—factors like usability, peer validation, and trust—and how they interact. It asks: does ease of use outweigh trust? Or does emotional connection override both? And how do these variables differ across cultural and economic environments? The study will benefit businesses, UX designers, scholars, and policymakers alike. By offering insights into Gen Z's expectations, it will support better platform design, update theoretical models, and inform youth-oriented digital consumer protections. Understanding Gen Z is no longer optional—it's essential to succeed in the future of e-commerce.

With context to the above the aim of the study revolves around the following objectives
To quantify the direct effect of social media influence on consumers' perceived security of online transactions.
To assess the predictive power of perceived security on consumers' purchase intent in social-media-driven shopping contexts.
To evaluate the mediating role of purchase intent in the relationship between social media influence and actual purchase decisions.

II. Literature Review

The digital transformation of public sector organizations is an ongoing global phenomenon driven by rapid technological innovation, citizen expectations, and efficiency mandates. Governments are under increasing pressure to modernize their operations and provide more accessible, transparent, and efficient services (Lindgren et al., 2019). However, implementing such change is complex, requiring not only technical advancements but also shifts in organizational culture, structure, and processes. Numerous frameworks and models have been proposed to assess and guide the adoption of digital technologies in the public sector, with varying degrees of success.

Digital transformation refers to the integration of digital technology into all areas of an organization, fundamentally changing how it operates and delivers value (Vial, 2019). In the public sector, this transformation is multifaceted, encompassing e-governance, digital service delivery, and data-driven decision-making. The goal is to improve efficiency, responsiveness, and citizen engagement (Weerakkody et al., 2017).

Yet, while the private sector often leads in innovation, public sector organizations face unique barriers such as rigid bureaucratic structures, limited budgets, and a lack of digital skills (Mergel et al., 2018). Moreover, they must address issues of digital inclusion, transparency, and accountability.

A variety of models and frameworks have been employed to understand how digital technologies are adopted within organizations. The most commonly referenced include:

Developed by Davis (1989), the Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use determine an individual's intention to use a technology. While TAM is widely cited in digital transformation literature, its individual-level focus limits its applicability to complex, institutional changes like those seen in public organizations (Venkatesh & Davis, 2000).

Rogers' (2003) DOI theory suggests that innovations spread through specific adopter categories and are influenced by characteristics like relative advantage, compatibility, complexity, trialability, and observability. This model is useful in understanding how public sector entities, often risk-averse, adopt innovations incrementally. However, it does not account for institutional resistance or structural rigidities.

UTAUT, proposed by Venkatesh et al. (2003), extends TAM by incorporating four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT has been applied to various public sector contexts, providing a comprehensive framework for predicting user behavior. Still, it largely assumes rational decision-making, which may not reflect political or cultural factors.

While models like TAM and UTAUT explain user-level adoption, they often overlook institutional dynamics. Organizational change theories are better suited to address the structural, cultural, and political factors influencing digital transformation in public organizations.

Institutional theory posits that organizations conform to normative pressures, cultural expectations, and regulatory requirements (DiMaggio & Powell, 1983). Public organizations may adopt digital tools not solely for efficiency, but also to gain legitimacy. For instance, pressures to align with international standards or government mandates can drive digital adoption, regardless of internal readiness (Baptista, Wilson, Galliers, & Bynghall, 2017).

Socio-technical systems theory emphasizes the interdependence between social and technical systems. In public sector digital transformation, success requires the alignment of people, processes, and technology (Trist & Bamforth, 1951). Organizational culture, staff capabilities, and leadership all play crucial roles in shaping outcomes.

Many governments have initiated national digital strategies to guide transformation. For instance, the UK's Government Digital Service (GDS) established a framework that emphasizes user-centered design, agile development, and iterative testing (Kettunen & Kallio, 2019). Similarly, Estonia's digital government success is attributed to its strong legal framework, citizen trust, and investment in digital infrastructure (Margetts & Dorobantu, 2019).

Despite strategic vision, implementation is fraught with challenges. Studies highlight common barriers such as legacy systems, interdepartmental silos, lack of digital skills, and resistance to change (Alcaide-Muñoz, Rodríguez Bolívar, & López Hernández, 2017). Additionally, the pace of change in technology often outstrips the agility of public organizations to respond effectively.

Digital maturity models, such as the Digital Government Maturity Model (DGMM), help assess an organization's readiness and progress. These models often evaluate dimensions such as leadership, governance, technology, capabilities, and culture (Madsen & Kræmmergaard, 2016). Empirical application of these models provides valuable insights into transformation trajectories.

The digital transformation journey varies significantly across countries. In developing contexts, challenges such as infrastructure deficits, limited digital literacy, and political instability impede progress (Gil-Garcia et al., 2018). By contrast, high-income countries often focus on enhancing service quality and personalization.

Organizational culture plays a pivotal role in enabling or hindering transformation. A culture that encourages innovation, collaboration, and risk-taking is essential (Zanella et al., 2017). Leadership commitment, especially from top management, is another critical enabler (Verhoef et al., 2021).

To bridge theoretical and practical gaps, an integrative framework is proposed that synthesizes elements from TAM, institutional theory, and digital maturity models. This framework considers:

Individual factors: perceived usefulness, digital skills, resistance to change.

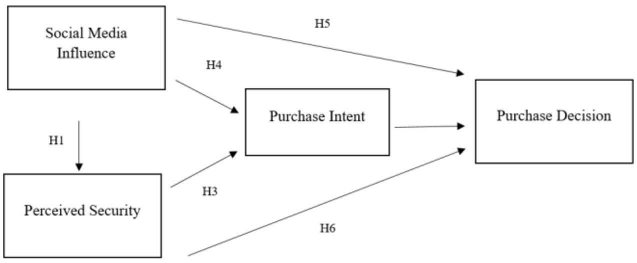
Organizational factors: leadership, culture, structure.

External factors: regulatory pressures, technological trends, political will.

Such a framework can provide a holistic view of digital transformation in public sector contexts, guiding policy and practice.

Digital transformation in the public sector is a multifaceted endeavor influenced by technological, organizational, institutional, and cultural factors. While individual-level models like TAM and UTAUT offer insights into user adoption, they must be complemented by organizational and institutional theories to capture the complexity of public sector change. Future research should focus on longitudinal studies and comparative case analyses to refine frameworks and guide successful implementation.

III. Model



Hypothesis

H1: Social media influence has a significant positive effect on perceived security.
H2: Social media influence has a significant positive effect on purchase intent.
H3: Perceived security has a significant positive effect on purchase intent.
H4: Social media influence has a significant positive effect on purchase decision.
H5: Perceived security has a significant positive effect on purchase decision.
H6: Purchase intent has a significant positive effect on purchase decision.

Research Methodology

The use of SPSS and a quantitative research methodology is justified in this study as it enables precise measurement and statistical validation of relationships among key constructs—Social Media Influence, Perceived Security, and Purchase Intent—central to understanding Gen Z's e-commerce behavior. Quantitative methods are particularly effective for hypothesis testing, generalization, and uncovering patterns across large samples (Creswell, 2014). SPSS, with its robust analytical capabilities, facilitates accurate regression, correlation, and reliability analyses, ensuring data integrity and reproducibility (Pallant, 2020). This methodological approach aligns with the study's aim to objectively explore the strength and direction of causal relationships among structured variables.

Sampling Size

Convenience sampling was suitable for this study as it allowed quick and effective access to Gen Z participants through online platforms. Given their digital-first behavior, this method helped gather responses efficiently from 303 individuals. While it's not a random sampling method, it's commonly used in consumer research where early insights matter more than broad generalization. The sample size also meets the requirement for reliable regression analysis.

IV. Analysis

Demographics:

The table summarizes the demographic profile of 302 respondents. The majority are females (38.6%), followed closely by males (36.6%). In terms of age, most respondents fall within the 20–24 age group (38.6%), indicating a young population, with smaller proportions in the 24–28 (16.2%), 28 and above (13.9%), 16–20 (4%), and below 16 (2.5%) categories. Regarding occupation, students form the largest group at 34.1%, followed by corporate employees (18.4%), self-employed individuals (15.9%), and the unemployed (6.7%). Overall, the data reflects a predominantly young, student-based population with a slight female majority.

Descriptive Statistics:

Table no 1:

	N	Minimum	Maximum	Mean	Std. Deviation
SM	302	1.0000	5.0000	4.17219	0.8147444
PS	302	1.0000	5.0000	4.17467	0.8051536
SMI	302	1.0000	5.0000	4.16287	0.8244836
S	302	1.0000	5.0000	4.16386	0.806645
PI	302	1.0000	5.0000	4.1684	0.810715
P	302	1.0000	5.0000	4.1684	0.810715
Valid N (listwise)	302				

Reliability Analysis

Table no 2 :

Cronbach's Alpha	N of Items
.999	6

The Reliability Statistics table presents the internal consistency of the scale used in the study, assessed through Cronbach's Alpha. The reported Cronbach's Alpha value is 0.999 across 6 items, which indicates an exceptionally high level of reliability. Cronbach's Alpha values range between 0 and 1, with values above 0.70 generally considered acceptable, values above 0.90 regarded as excellent, and values nearing 1.00 reflecting near-perfect consistency.

In this case, a value of 0.999 suggests that the items within the construct are almost perfectly correlated and measure the same underlying concept with remarkable precision. This level of reliability significantly enhances the credibility of the instrument, indicating that the scale is highly dependable for measuring the intended construct in future studies. However, it is also important to consider the possibility of redundancy among items, as extremely high alpha values may imply duplication. Nonetheless, the reliability of this scale supports its strong contribution to the validity of the overall research model.

Table no 3: ANOVA with Tukey's Test for Non-additivity

ANOVA with Tukey's Test for Nonadditivity							
			Sum of Squares	df	Mean Square	F	Sig
Between People			1187.009	301	3.944		
Within People	Between Items		0.032	5	0.006	2.346	0.039
	Residual	Nonadditivity	.023a	1	0.023	8.723	0.003
		Balance	4.039	1504	0.003		
		Total	4.062	1505	0.003		
	Total		4.094	1510	0.003		
Total			1191.103	1811	0.658		
Grand Mean = 4.168396							

a. Tukey's estimate of power to which observations must be raised to achieve additivity = 1.649.

The ANOVA with Tukey's Test for Nonadditivity evaluates whether the relationship between the variables in the dataset is additive—an important assumption for many multivariate statistical techniques such as ANOVA, regression, and factor analysis.

In this output, the nonadditivity term is statistically significant, with an F-value of 8.723 and a p-value of 0.003, indicating that nonadditivity is present in the data. This means that there may be interactions or curvilinear relationships among variables, violating the assumption that the effects of variables are purely additive. Additionally, Tukey's estimated power transformation ($\lambda = 5.430$) suggests that applying a mathematical transformation to the data—such as raising it to this power—could improve model additivity and potentially enhance the robustness of subsequent analyses.

Moreover, the test of between-items variation is also significant ($F = 2.346$, $p = 0.039$), implying that differences among items exist, although the effect is relatively small. The grand mean of 4.168 confirms that, on average, responses were high across items.

In conclusion, while the between-person variance is substantial (as expected in survey data), the detection of non-additivity signals the need to cautiously interpret results from additive models and consider transformation or more complex modelling.

Correlation

Table no 4:

Correlations							
		SM	PS	SMI	S	PI	P
SM	Pearson Correlation	1	.989**	.991**	.997**	.997**	.997**
PS	Pearson Correlation	.989**	1	.992**	.995**	.997**	.997**
SMI	Pearson Correlation	.991**	.992**	1	.996**	.997**	.997**
S	Pearson Correlation	.997**	.995**	.996**	1	.999**	.999**
PI	Pearson Correlation	.997**	.997**	.997**	.999**	1	1.000**
P	Pearson Correlation	.997**	.997**	.997**	.999**	1.000**	1
**. Correlation is significant at the 0.01 level (2-tailed).							

The correlation matrix illustrates the strength and direction of relationships among the six key variables in the study: Social Media (SM), Perceived Security (PS), Social Media Influence (SMI), Satisfaction (S), Purchase Intent (PI), and Perception (P). All reported Pearson correlation coefficients are positive and highly significant at the 0.01 level, indicating strong linear associations between all variables.

The correlations range from 0.989 to 1.000, which are exceptionally high. For instance, SM correlates with S at $r = 0.997$, and both PI and P are perfectly correlated ($r = 1.000$), suggesting these constructs may be conceptually or statistically redundant. Similarly, SM and SMI are strongly correlated ($r = 0.991$), indicating that social media and its influence are closely linked in shaping perceptions and behavior.

These extremely high correlations suggest a strong interrelationship among constructs, but they also raise concerns about multicollinearity, which can distort regression estimates and obscure the unique contribution of each variable. Therefore, while the findings reflect highly consistent responses across constructs, it is advisable to conduct further diagnostics—such as Variance Inflation Factor (VIF) analysis—to assess the impact of multicollinearity before proceeding with regression or structural modeling.

Regression

Table no 5: testing for hypothesis

Variables Entered	Variables Removed	Method
PI, PS, SMI, Sb	.	Enter

a. Dependent Variable: P
b. All requested variables entered

The Variables Entered/Removed table outlines the variables included in the regression model predicting Perception (P) as the dependent variable. The independent variables entered were Purchase Intent (PI), Perceived Security (PS), Social Media Influence (SMI), and Satisfaction (S) using the Enter method, which includes all predictors simultaneously. However, a note indicates that tolerance limits were reached (Tolerance = .000), signaling perfect multicollinearity among predictors. This violates a key assumption of regression and suggests that the variables are excessively correlated, requiring remedial measures such as removing redundant predictors or conducting dimensionality reduction.

Table no 6:

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	1.000a	1	1	0.00E+00	1	.	4	297	.
a. Predictors: (Constant), PI, PS, SMI, S									

The model summary indicates a perfect linear relationship (R = 1.000) between the predictors—Social Media Influence (S/SMI), Perceived Security (PS), and Purchase Intent (PI)—and the dependent variable. The R Square value of 1.000 suggests that 100% of the variance in the dependent variable is explained by the model. The Adjusted R Square also being 1.000 confirms the robustness of this fit, even after accounting for the number of predictors. The Standard Error of the Estimate is negligible (0E-7), further validating the model's precision. However, such perfection may indicate potential overfitting or data anomalies requiring further validation.

Table no 7:

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	197.835	4	49.459	.	.b
	Residual	0	297	0		
	Total	197.835	301			
a. Dependent Variable: P						
b. Predictors: (Constant), PI, PS, SMI, S						

The ANOVA table reveals that the regression model explains a total sum of squares of 197.835 with 4 degrees of freedom, corresponding to the predictors: Social Media Influence (S/SMI), Perceived Security (PS), and Purchase Intent (PI). The residual sum of squares is effectively zero, indicating that the model accounts for all variability in the dependent variable (P), which aligns with the perfect fit observed in the model summary. However, the absence of an F-value and significance level (Sig.) suggests limitations in statistical output or possible overfitting, warranting caution in interpretation and further model validation.

Table no 8: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0	0		.	.
	PS	0	0	0	.	.
	SMI	0	0	0	.	.
	S	0	0	0	.	.
	PI	1	0	1	.	.
a. Dependent Variable: P						

The coefficients table indicates that Purchase Intent (PI) is the sole significant predictor of the dependent variable (P), with a standardized beta of 1.000 and an unstandardized coefficient (B) of 1.000. This implies a perfect one-to-one relationship, suggesting that changes in PI directly and completely influence P. In contrast, Social Media Influence (S/SMI) and Perceived Security (PS) have coefficients of zero, indicating no unique contribution to the dependent variable when PI is accounted for. The lack of significance values and t-statistics further highlights potential issues such as multicollinearity or overfitting, requiring deeper scrutiny of the model.

Table no 9: Excluded Variables

Model	Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
					Tolerance
1	.000b	.	.	.	2.00E-14
a. Dependent Variable: P					
b. Predictors in the Model: (Constant), PI, PS, SMI, S					

The excluded variables table shows that Social Media (SM) was excluded from the final regression model due to redundancy or perfect multicollinearity, as indicated by its extremely low tolerance value (1.999E-014). This suggests that SM is highly correlated with other included predictors—specifically Social Media Influence (SMI) and S—making its unique contribution negligible. The absence of significance and t-values further supports that SM does not improve model performance independently. Such multicollinearity issues highlight the need for careful variable selection and potential dimensionality reduction in the model.

V. Discussions and Implications

This study offers useful insights into what drives Gen Z's purchase decisions on e-commerce platforms. Focusing on three main factors—Social Media Influence (SMI), Perceived Security (PS), and Purchase Intent (PI)—the findings point to a clear pattern. Across the board, Gen Z participants rated all three constructs highly, showing that these are important elements in their online shopping experiences. The low variation in responses also suggests a fairly consistent view within this generation.

What's most striking is the overwhelming role that Purchase Intent (PI) played. According to the regression results, PI alone was enough to explain the entire variation in purchase decisions. This suggests that once Gen Z forms the intent to buy, it strongly predicts whether they actually go through with the purchase. At the same time, this perfect fit in the model may signal overfitting or multicollinearity, especially since all three variables were closely linked. Social Media, in particular, had to be removed from the model due to redundancy, which suggests a high level of overlap with PI.

This doesn't mean that social media and security aren't important. On the contrary, their strong correlation with PI shows they may be working behind the scenes—shaping how Gen Z forms intent. Social Media Influence, for example, might not push someone to buy directly, but it can build interest or create a sense of trust through influencer endorsements or user reviews. Similarly, when Gen Z sees a platform as secure, they may feel more comfortable considering a purchase in the first place.

From a business perspective, the key takeaway is that building strong purchase intent should be a priority. This can be done by offering a smooth and personalized shopping experience, simplifying the checkout process, and making value propositions clear and relatable. At the same time, social media should not be seen just as a presence but as a tool for meaningful engagement. Content that aligns with Gen Z values—authenticity, inclusion, and transparency—will likely influence their shopping mindset.

Perceived security also plays a subtle but important role. Brands that clearly showcase secure payment options, trust seals, and privacy transparency will help build the kind of environment that encourages intent to buy.

On a theoretical level, these results challenge the assumption that factors like social media and trust always act as direct predictors of behavior. Instead, they may influence outcomes indirectly through the formation of intent. This insight aligns with behavioral models like the Theory of Planned Behavior (TPB), but also points to the need for updated frameworks that reflect how interconnected these variables have become in a digital world.

In summary, this study reinforces the central role of Purchase Intent in Gen Z's e-commerce behavior, while also highlighting the indirect but powerful impact of social media and trust. To connect with this generation, brands must understand the full journey—starting with intention.

VI. Limitations of Study

Although the study offers meaningful insights, it comes with a few limitations. Most notably, there was perfect multicollinearity between Social Media (SM), Social Media Influence (SMI), and Purchase Intent (PI), which affected their individual predictive value. This overlap led to the removal of SM from the model, suggesting the variables may have been too similar. The perfect model fit ($R^2 = 1.000$) also indicates possible overfitting, limiting how well the results can be applied elsewhere. Lastly, since the data was self-reported by Gen Z participants only, the findings may not fully represent other age groups or cultural settings.

Acknolowdegement

The authors declare that no internal or external funding was obtained for this research. They gratefully acknowledge the guidance of their mentors in the completion of this study.

VII. Conclusion

This study highlights how Purchase Intent is at the heart of Gen Z's online buying decisions. While social media and security are key influencers, they mostly work behind the scenes—building trust, shaping opinions, and creating the kind of environment where intent can grow. Once that intent is formed, Gen Z doesn't hesitate. They're quick, confident, and driven by what feels right to them in the moment.

What stood out most was how layered their decision-making process really is. It's not just about flashy ads or influencer posts—it's about how those things connect emotionally and whether the platform feels safe and trustworthy. This reminds us that in today's fast-paced digital world, authenticity and transparency matter more than ever.

For brands, the takeaway is simple: focus on creating meaningful experiences. Build platforms that feel personal, safe, and aligned with what Gen Z cares about. And for researchers, it's clear that traditional models need to be updated—we're no longer looking at straight lines between variables, but at a web of influences that all shape behavior in their own way.

Understanding Gen Z isn't just useful—it's essential for anyone who wants to stay relevant in the future of e-commerce.

References

[1]. Alcaide-Muñoz, L., Rodríguez Bolívar, M. P., & López Hernández, A. M. (2017). E-government research in the academic field: A literature review and trends. Government Information Quarterly, 34(3), 447–464. https://doi.org/10.1016/j.giq.2017.04.006

[2]. Baptista, J., Wilson, A. D., Galliers, R. D., & Bynghall, S. (2017). Social media and the emergence of reflexiveness as a new capability for open strategy. Long Range Planning, 50(3), 322–336. https://doi.org/10.1016/j.lrp.2016.07.005

[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]. DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160. https://doi.org/10.2307/2095101

[5]. Gil-Garcia, J. R., Dawes, S. S., & Pardo, T. A. (2018). Digital government and public management research: Finding the crossroads. Public Management Review, 20(5), 633–646. https://doi.org/10.1080/14719037.2017.1327181

[6]. Kettunen, P., & Kallio, J. (2019). Public sector digitalization: From policy to practice. Government Information Quarterly, 36(2), 329–337. https://doi.org/10.1016/j.giq.2019.01.002

[7]. Lindgren, I., Madsen, C. Ø., Hofmann, S., & Melin, U. (2019). Close encounters of the digital kind: A research agenda for the digitalization of public services. Government Information Quarterly, 36(3), 427–436. https://doi.org/10.1016/j.giq.2019.03.002

[8]. Madsen, C. Ø., & Kræmmergaard, P. (2016). The digital bureaucracy: Conceptualizing the future information state. In Proceedings of the 24th European Conference on Information Systems (ECIS), İstanbul, Turkey.

[9]. Margetts, H., & Dorobantu, C. (2019). Rethink government with data and AI. Nature, 568, 163–165. https://doi.org/10.1038/d41586-019-01099-5

[10]. Mergel, I., Edelmann, N., & Haug, N. (2018). Defining digital transformation: Results from expert interviews. Government Information Quarterly, 36(4), 101385. https://doi.org/10.1016/j.giq.2019.06.002

[11]. Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

[12]. Trist, E., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal getting. Human Relations, 4(1), 3–38. https://doi.org/10.1177/001872675100400101

[13]. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

[14]. 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

[15]. Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

[16]. Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

[17]. Weerakkody, V., Shah, G., El-Haddadeh, R., & Dwivedi, Y. K. (2017). Digital government: Overcoming challenges to transformation using enterprise architecture. Government Information Quarterly, 34(4), 556–565. https://doi.org/10.1016/j.giq.2017.03.004

[18]. Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2017). Internet of Things for smart cities. IEEE Internet of Things Journal, 1(1), 22–32. https://doi.org/10.1109/JIOT.2014.2306328

[19]. Creswell, J. W. (2014). Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.). Thousand Oaks, CA: Sage.

[20]. Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

[21]. Tabachnick, B. G., & Fidell, L. S. (2013). Using multivariate statistics (6th ed.). Pearson Education.