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THE ROLE OF PREDICTIVE ANALYTICS IN INSTAGRAM MARKETING: ANALYSING GEN Z PURCHASING BEHAVIOUR

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ABSTRACT

Predictive analytics' incorporation into marketing plans has revolutionised how companies interact with customers in recent years, especially on social media. Instagram, one of the most powerful digital marketing platforms, has become a vital tool for companies seeking to engage younger consumers. This is particularly true for Generation Z, a group distinguished by its unique buying habits, as well as its digital nativity. To successfully customise their marketing tactics, firms must have a thorough understanding of these behaviours. In this setting, predictive analytics, which determines the likelihood of future events by utilising statistical algorithms, machine learning techniques, and historical data, is essential.

Brands should make sure that their messaging speaks to Gen Z's distinct beliefs and expectations by optimising their Instagram marketing efforts by examining trends in customer behaviour. The purpose of this study is to investigate how predictive analytics may be used for Instagram marketing. Concentrating especially on how Instagram's predictive analytics affects fast fashion firms' customers' purchase decisions. The research approach used in this study is quantitative. Using Google Forms, the survey approach is used to collect primary data. Gen Z (The Centre of Generational Kinetics) respondents who often use social networks are measured using the Likert scale approach, and secondary data is derived from previously published literary works.

Keywords: Artificial Intelligence, Digital Marketing Communication, Gen Z, Instagram Marketing

1. INTRODUCTION:

Artificial intelligence (AI) and predictive analytics (PA) have transformed digital marketing communication by allowing businesses to predict consumer preferences, personalise content, and optimise engagement in real time. Predictive analytics uses statistical modelling, machine learning algorithms, and behavioural data to estimate future consumer activities, including purchase likelihood and reactivity to marketing stimulus (Ahmed et al., 2025; Wedel & Kannan, 2016). Unlike traditional static segmentation, PA enables dynamic, algorithm-based content delivery, allowing marketers to contact consumers at peak relevance.

PA-driven marketing methods are now most commonly implemented on social media platforms. Instagram stands out among these platforms because of its visually engaging layout, algorithmically generated content streams, and incorporation of social commerce tools such as reels, posts that are shoppable posts, and influencer-led campaigns. Instagram's recommendation systems heavily rely on PA to create content based on users' previous interactions, browsing habits, and social relationships, shifting marketing communication from mass messaging to tailored persuasion (Misra et al., 2024). With high interaction rates and an excellent visual appeal, Instagram has evolved as a significant channel for fashion-related consumption, particularly in the fast fashion industry.

The importance of PA-driven Instagram marketing is particularly evident among Generation Z (Gen Z) customers. Gen Z, born during the mid-1990s and early 2010s, is the first generation of totally digital-native consumers to grow up in algorithmically mediated settings. This generation is heavily reliant on social media, has a strong visual preference, and has high expectations for personalised, relevant, and authentic business interactions (Francis & Hoefel, 2018; Shareef et al., 2019). Empirical research reveals that Instagram serves as Gen Z's major medium for discovering brands and fashion guidance, making algorithmically generated material especially significant in determining their purchasing decisions.

Fast fashion offers a theoretically relevant but understudied scenario for investigating the psychological consequences of PA-driven Instagram marketing. Fast fashion firms, known for their short product cycles, trend instability, and impulse-driven buying, are increasingly relying on data-driven insights to predict new trends, personalise suggestions, and encourage frequent purchases (Azuka et al., 2024). While previous research has established the operational and strategic advantages of predictive analytics for fashion retailers, less emphasis has been given to how these algorithmic methods impact consumers' inner psychological assessments—in particular trust—within social media contexts. To fill these gaps, the current study views PA-driven Instagram content as an external stimulus that moulds Gen Z customers' internal psychological responses, particularly trust, which then influences purchasing behaviour. This study, based on the S-O-R Stimulus Organism Response paradigm and backed by the TAM Technology Acceptance Model, goes beyond context-specific applications to present a theoretically grounded description of how predictive analytics works inside algorithmic social commerce environments. By emphasising Indian Gen Z consumers, the study adds region-specific insights to a literature that is dominated by Western perspectives. In doing so, the study increases our understanding of predictive analytics as a technological and psychological driver of consumer behaviour in fast fashion marketing.

2. LITERATURE REVIEW:

2.1 Predictive Analytics in Digital and Social Media Marketing:

PA has developed as a vital component of modern digital marketing, allowing businesses to translate enormous amounts of consumer data into forward-looking insights that aid in personalisation, targeting, and making informed choices (Wedel & Kannan, 2016). In social media environments, PA is commonly used to forecast audience participation, content virality, and purchase likelihood, hence increasing marketing efficiency and ROI Return on Investment (Ali et al., 2023). PA-powered algorithmic recommendation systems produce customised content streams, radically changing the way consumers interact with companies on sites like Instagram. Despite its broad use, the available literature is primarily technological and firm-centric, focused on the accuracy of prediction, targeted efficiency, and effectiveness of campaigns. Trust, perceived relevance, and emotional involvement are examples of consumer-level psychological responses that have received relatively little study. This constraint is salient in social commerce settings, where algorithmic personalisation directly mediates brand-consumer interactions and purchase behaviour.

2.2 Generation Z and Algorithmic Social Media Consumption:

Gen Z is a distinct consumer demographic marked by strong digital literacy, continual connectivity, and significant interaction with algorithmically curated material. Prior research has consistently shown that Gen Z relies extensively on social media platforms to find knowledge, entertainment, and discover new brands. Their penchant for immediacy, visual interaction, and personalised experiences makes PA-driven marketing content very appealing.

However, new research reveals an essential paradox in Gen Z's interaction with algorithmic customisation. While personalised information increases perceived utility and convenience, Gen Z users are becoming more aware of data-collecting tactics and algorithmic influence (Shareef et al., 2019). This awareness promotes contradictory views, in which relevancy and efficiency coexist with concerns about privacy, manipulation, and surveillance. As a result, trust emerges as a critical psychological mechanism governing the link between predictive analytics-based content and behavioural outcomes, despite being underexplored in empirical research.

2.3 Predictive Analytics in Fast Fashion Marketing:

Fast fashion marketing is distinguished by short trend cycles, rapid product debuts, and a heavy dependence on online platforms to encourage impulse buying. PA is important in this environment because it allows marketers to identify developing micro-trends, *optimise* inventory selections, and provide *personalised* suggestions based on users' browsing patterns and social media interactions (Azuka et al., 2024). A prior study has identified the operational advantages of PA in fast fashion, such as rapidity, responsiveness, and profitability. Nevertheless, the psychological implications of PA-driven marketing in fast fashion remain insufficiently examined. Most studies prioritise firm-level efficiency while overlooking how algorithmic marketing practices shape consumers' perceptions of brand credibility and trustworthiness. Given increasing criticism of fast fashion related to sustainability and ethical consumption, understanding how predictive analytics influences consumer trust is particularly important.

2.4 Ethical Concerns: Privacy, Transparency, and Personalisation Creep:

Recent research in digital marketing and ethical AI has highlighted concerns about the unintended repercussions of predictive analytics-based personalisation. Data privacy, algorithmic transparency, and "personalisation creep," which occurs when marketing messages appear overly personalised and obtrusive, leading to perceptions of snooping rather than service, are all major challenges (Martin & Murphy, 2017). These issues are especially acute for young customers, who are both frequent users of personalised platforms and more sensitive to ethical AI practices (Koneti, 2022). Despite increased interest in ethical AI, such issues are infrequently incorporated into explanatory models of consumer responses to PA-driven marketing communication, especially in fast fashion situations where impulse consumption is common.

2.5 Synthesis of Literature Streams and Positioning of the Study:

Existing research on PA in Instagram marketing focuses on its effectiveness in enhancing targeting accuracy, engagement, and campaign performance, although it is still predominantly business-focused and result-oriented (Wedel & Kannan, 2016). Parallel research on Gen Z highlights the substantial reliance on algorithmically selected social media content, but provides little understanding of the psychological mechanisms by which such content drives consumer behaviour. Similarly, fast fashion research is increasingly acknowledging ethical problems about overconsumption and sustainability, but it rarely investigates how data-driven customisation influences trust among consumers and decision-making.

Despite each of these streams—predictive analytics in Instagram marketing, Gen Z's algorithmic engagement, and fast fashion ethics—developed independently, they are yet insufficiently integrated into a single theoretical framework. To fill this gap, the current study synthesises these strands utilising the S-O-R framework, which is supported by key elements from the TAM. PA-driven Instagram content is seen as a technical stimulus that changes cognitive organismic reactions, including perceived usefulness and ease of use, as well as emotive responses such as trust. These subjective judgments then influence consumer purchase behaviour in the fast fashion sector.

This research presents a psychologically grounded and ethically informed explanation of how personalisation influences Gen Z consumers' purchasing decisions by emphasising trust as a primary psychological mechanism and addressing ethical concerns such as algorithmic transparency and personalisation creep.

2.6 Theoretical Integration: Stimulus–Organism–Response and TAM:

2.6.1 S-O-R Framework in Algorithmic Marketing

The S-O-R(S-O-R) framework describes how external stimuli influence people's internal cognitive and affective states, which then shape their behavioural reactions (Mehrabian & A. Russell, 1974). Although the paradigm was originally designed for physical surroundings, it has been widely applied to digital and online consumption contexts such as e-commerce and social media (Eroglu et al., 2003; Islam & Rahman, 2017). Stimuli in algorithmic marketing environments are dynamically generated using predictive analytics, rather than being static. Personalised adverts, algorithmic suggestions, and influencer-curated material on Instagram serve as technological stimuli that respond to users' previous behaviour and preferences (Wedel & Kannan, 2016). These inputs shape consumers' internal evaluations by influencing their opinions about relevance, credibility, and emotional resonance.

This study broadens the S-O-R paradigm by conceptualising PA-driven Instagram marketing as an upgraded digital stimulus influencing Gen Z consumers' psychological states before purchasing decisions in the fast-fashion sector.

2.6.2 TAM as a Cognitive Mechanism within S-O-R

According to the Technology Acceptance Model (TAM), people embrace technology based on perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). TAM is commonly used to describe consumer involvement with digital communication platforms and AI-enabled systems (Venkatesh & Davis, 2000; Ma & Liu, 2005). Predictive analytics improves Instagram marketing by offering relevant, timely, and personalised content that lowers information overload, while Instagram's easy UI and integrated shopping capabilities boost PEOU (Ali et al., 2023). Rather than viewing TAM purely as a technological adoption model, this study incorporates PU and PEOU into the organismic component of the S-O-R framework, defining them as cognitive reactions that affect trust and consequent purchase behaviour.

2.6.3 Trust as the Central Organismic Response

Trust is an important emotive reaction in AI-driven marketing contexts, representing consumers' opinions about algorithmic systems' legitimacy, transparency, and compassion (Gefen et al., 2003). While predictive analytics can improve convenience and relevance, excessive or opaque personalisation may raise privacy concerns and perceptions of monitoring, especially among younger consumers (Martin & Murphy, 2017; Koneti, 2022). In fast fashion, where impulsive buying and ethical examination coexist, trust functions as a psychological filter through which algorithmic contents are evaluated. As a result, this study considers trust as a crucial organismic reaction that mediates the link between PA-driven stimuli and customer purchase behaviour.

2.6.4 Integrated Conceptual Model

Drawing on S-O-R and TAM, the proposed conceptual framework asserts that PA-driven Instagram marketing (stimulus) improves PU and PEOU (cognitive responses), which strengthen trust (affective response), ultimately leading to increased purchasing behaviour among Gen Z fast fashion consumers.

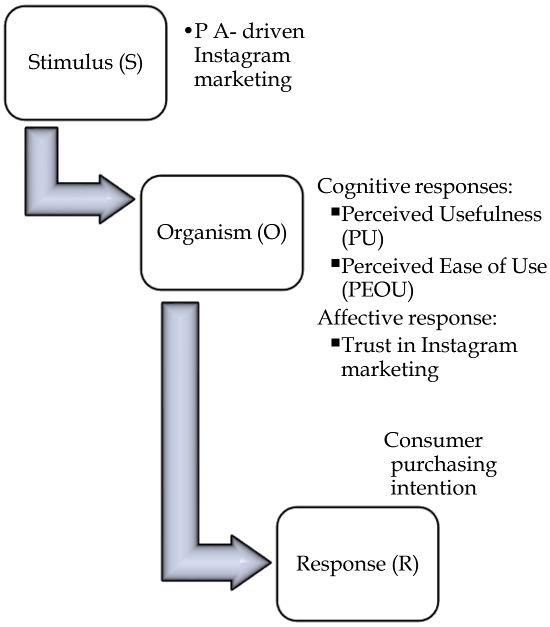

Figure 1: Conceptual Framework based on Stimulus-Organism-Response (S-O-R) Model

The model suggests that predictive analytics improves PU and PEOU, hence increasing confidence in algorithmically selected Instagram posts. Increased trust leads to increased purchasing behaviour across Gen Z fast fashion buyers.

The suggested conceptual framework adds to theory in a variety of ways. First, it broadens the S-O-R framework by reimagining predictive analytics as a dynamic technology stimulus rather than a static environmental indicator. Second, it broadens TAM by incorporating trust and purchasing behaviour, going beyond the adoption of technology to explain how consumers make decisions in AI-mediated marketing contexts. Third, it connects cognitive and affective systems by illustrating how PU and PEOU interact with trust to influence behavioural outcomes. Finally, it places these theoretical discoveries in the ethically sensitive setting of rapid fashion purchasing amongst the Gen Z consumers in emerging nations

3. RESEARCH OBJECTIVES

- To investigate the impact of PA-driven Instagram content on Gen Z purchasing behaviour

- To investigate the influence of predictive analytics on consumer trust towards Instagram marketing

3.1 Purpose and Significance of the Study:

The purpose of this work is to comprehend how algorithms link AI and PA. By forecasting Gen Z's behaviour, emotions, and interests, the study shows how PA influences their purchasing decisions. This helps fast fashion brands understand what their customers want and incorporate that information into their marketing strategies to target particular customers based on their needs. By identifying the potential of PA to influence Gen Z's purchasing behaviour by appealing to their emotions and interests, this study is significant for digital marketing communications.

3.2 Research Gap:

In recent years, AI has become popular with machine learning and data analytics tools, although many studies have focused individually on predictive analytics or CPB. This research contributes valuable insights into the effective role of predictive analytics in the realm of Instagram marketing, particularly as it pertains to engaging the pivotal Gen Z purchasing behaviour for fast fashion brands through Instagram. Even though TAM and Consumer Behaviour Theory have been well researched, little is known about how they might be used in PA-driven social media marketing, especially with Gen Z customers.

4. METHODOLOGY AND DESIGN

4.1 Research Design and Sample:

A quantitative, cross-sectional survey of India's Gen Z Instagram users was conducted. Data were gathered using a standardised questionnaire distributed via Google Forms. A total of 354 valid responses were acquired using convenience sampling.

4.2 Measurement and Reliability Assessment:

The study used a structured questionnaire comprising multi-item constructs. Objective 1 was measured using six MCQ items and Objective 2 using five MCQ items, with all items rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) and adapted from established technology acceptance and digital marketing literature. Internal consistency reliability was assessed using Cronbach's alpha, indicating very high reliability for Objective 1 ($\alpha = 0.999$) and acceptable reliability for Objective 2 ($\alpha = 0.742$). One-way ANOVA was conducted at the item-response level, resulting in 2,124 observations for Objective 1 and 1,770 observations for Objective 2, with corresponding between- and within-groups degrees of freedom as reported in the ANOVA tables. Procedural remedies and Harman's single-factor test indicated no significant common method bias.

5. DATA ANALYSIS AND INTERPRETATION

5.1 Analytical Approach and Findings:

This study used one-way analysis of variance (ANOVA) because the primary goal was to determine whether CPB differed across various levels of exposure to PA-driven Instagram content, rather than modelling direct predictive or causal relationships. The independent measure—perceived exposure to predictive analytics content—was operationalised as a categorical grouping variable, whereas CPB was measured using a continuous composite score. Under these conditions, one-way ANOVA is the best statistical technique for comparing mean differences between more than two independent groups (Kim, 2014). When evaluating linear predictive correlations between continuous data, regression analysis is more suited.

However, the current study focused on group-based variation in behaviour rather than predicting strength or coefficient estimate. Therefore, one-way ANOVA was adopted to enable clearer interpretation of variations in purchase behaviour between exposure groups. This technique is consistent with the descriptive-comparative nature of the research purpose and avoids overstating causal inference.

5.2 One-way ANOVA Results:

Both research objectives used multi-item constructs measured with MCQ-based indicators, and a one-way ANOVA at the item-response level was used to investigate mean differences among construct indicators. Because each responder answered all questions, the total number of observations exceeded the number of participants, leading to relatively high within-group degrees of freedom. Objective 1 was operationalised using six MCQ items, generating 2,124 item-level observations (354×6), with between-groups df = 5 and within-groups df = 2,118. In Objective

2, five Question items were analysed, yielding 1,770 observations (354 × 5). The between-groups df was 4, and the within-groups df was 1,765. This item-level analytical methodology is appropriate for multi-item constructs and explains the df values presented in the ANOVA findings. Although both ANOVAs revealed significant differences, post hoc tests were not conducted because the study's emphasis was on the overall effect of the marketing stimuli rather than pairwise comparisons between specific groups. These findings imply that various types of PA material have an overall impact on Gen Z consumers' trust and purchasing behaviour, giving a foundation for further interpretation within the S-O-R paradigm."

5.2.1 One-way ANOVA for objective 1

One-way ANOVA findings for objective 1 show that PA content has a substantial influence on brand perception. CPB The findings indicate that there is a statistically significant difference in CPB between one group (F (5,2118) = [2.390], p=0.035). The outcomes of the one-way ANOVA are displayed in the following table:

Table 1: Results demonstrating the Impact of Predictive Analytics content on CPB

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	6.505179	5	1.301036	2.390772	0.035778	2.218322
Within Groups	1152.596	2118	0.544191			
Total	1159.101			2123		

In this case, we reject the null hypothesis since the P-value (0.03) is less than the significance threshold (0.05) and conclude that the nature of Instagram Reels has a statistically significant effect as a marketing platform.

Table 2: Descriptive statistics for CPB

Item	Mean	SD
1	3.42	0.88
2	3.21	0.91
3	3.58	0.84
4	3.46	0.87
5	3.39	0.9
6	3.44	0.86

A one-way ANOVA found statistically significant differences among the six MCQ questions reflecting consumer purchase behaviour. Descriptive statistics demonstrate that mean scores vary only a little, with MCQ3 showing the highest mean and MCQ2 showing the lowest, demonstrating that predictive analytics content characteristics have a different impact. The effect size was $\eta^2 = 0.000004$, indicating a minimal practical effect. This implies that, while item-level variances are statistically significant, all six variables contribute fairly equally to the overall purchase behaviour construct.

For objective 2, Consumer trust in Instagram marketing was statistically impacted, according to the results of a one-way ANOVA. Significant differences between the five groups were found in the study (F (4,1770) = [2.810], p = 0.024). The outcomes of the one-way ANOVA are displayed in the following table:

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	7.507606	4	1.876901	2.810964	0.024255	2.376955
Within Groups	1181.842	1770	0.667707			
Total	1189.35				1774	

Table 3: Results demonstrating the influence of PA on consumer trust toward Instagram marketing

In this case, we reject the null hypothesis since the P-value (0.02) is less than the significance threshold (0.05) and conclude that the nature of Instagram Reels has a statistically significant effect as a marketing platform.

Table 4: Descriptive Statistics for Consumer Trust

Item	Mean	SD
7	3.12	0.82
8	2.98	0.89
9	3.26	0.76
10	3.18	0.8
11	3.01	0.87

For Objective 2, a one-way ANOVA revealed statistically significant differences across all five MCQ questions measuring customer trust. Mean scores differed among indicators, with MCQ9 having the highest trust perception and MCQ8 and MCQ11 having lower values. The measured impact size ($\eta^2 = 0.0066$) indicates that differences in PA-driven content moderately influence customer trust, highlighting its importance as a key psychological response in decision-making.

6. MAJOR FINDINGS AND DISCUSSION

This section contextualises the ANOVA findings within the S-O-R framework and major elements of the TAM, while also recognising significant contextual and ethical boundaries. The study looked at the relationship between predictive analytics, PA-driven Instagram marketing, and Gen Z customers' trust and buying habits in the fast fashion industry. According to the ANOVA results, there were statistically significant differences in consumer purchase behaviour and trust across all types and amounts of exposure to PA-driven Instagram content.

The findings indicate that the type and delivery of predictive analytics-enabled information are linked to changes in customer purchasing behaviour. Gen Z customers are unlikely to respond equally to algorithmic personalisation; rather, their behavioural responses vary depending on how predicted information is packaged and perceived. While PA may improve perceived relevance and effectiveness of decision-making in fast fashion consumption, its impact is limited, implying that its contribution is incremental rather than dominant. This means that predictive analytics interacts with other important factors such as price-sensitiveness, popularity of the brand, trends, and social or peer influence.

Consumer trust in Instagram marketing varied significantly between exposure groups. Higher perceived usefulness and ease of interaction with personalised content were connected with higher trust ratings, which is consistent with TAM's emphasis on cognitive assessments of technology. However, increased exposure to PA-driven content did not result in proportionally better trust levels. This pattern implies that technological efficiency alone may not be sufficient to create affective confidence, emphasising the importance of psychological and ethical factors such as perceived intrusiveness, data privacy concerns, and algorithmic transparency.

When analysed using the S-O-R framework, PA-driven content can be understood as a technical stimulus that modifies internal organismic responses—particularly trust—which are then related to behavioural outcomes such as purchase intention. The low effect sizes indicate this process is dependent on context rather than linear, supporting the notion that PA serves as a supplementary influence within a larger consumer decision-making environment.

From a practical standpoint, the findings highlight the necessity of ethical and transparent customisation in Instagram marketing to Gen Z. Fast fashion firms should strike a balance between relevance-driven targeting and ethical precautions to avoid impressions of monitoring or manipulation. An excessive dependency on algorithmic optimisation without obvious customer value may damage confidence and reduce long-term engagement.

Future research could build on these findings by using longitudinal designs, multivariate modelling, and cross-cultural analyses to investigate the conditional dynamics of algorithms that influence consumer behaviour.

7. CONCLUSION

In the context of digital marketing, this study looked at how PA-driven Instagram content affected CPB. The results show that different types of predictive analytics content cause statistically significant changes in customer purchase-related responses, as indicated by the one-way ANOVA. This implies that predictive analytics does more than just broadcast information; it actively influences the way consumers interpret value and create purchasing intentions. Furthermore, regular interaction with algorithmically selected and personalised information has been shown to increase customer trust and is associated with brands' perceptions, which influences purchase intention.

Predictive analytics helps to make digital communication more engaging and meaningful by prioritising relevant and high-performing material. The study expands on the S-O-R theory via empirically showing how P A-A-driven customisation acts as a stimulus, influencing organismic responses, specifically trust, and, ultimately, purchase behaviour. These findings show predictive analytics as both a technological resource and a strategic communication tool, with implications for long-term customer engagement in competitive digital contexts.

FUTURE SCOPE:
Future research could expand on this topic by expanding theoretical and methodological depth instead of extending to new platforms. According to the S-O-R paradigm, future studies could officially evaluate mediation models, with a focus on customer trust as a means of mediation between P A personalisation and purchase intention. Moderating variables, including privacy concerns, perceived intrusion, and algorithmic openness, can help to improve the model. Longitudinal or experimental designs may improve causal inference, and cross-cultural comparisons may increase generalizability. Employing structural equation modelling would also allow for the simultaneous assessment of measurements and structural linkages, providing further insight into predictive analytics-driven digital communication.

REFERENCES:

Ahmed, S. M. M., Owais, M., Raza, M., Nadeem, Q., & Ahmed, B. (2025). The Impact of AI-Driven Personalization on Consumer Engagement and Brand Loyalty. *Qlantic Journal of Social Sciences*, *6*(1), 311–323. https://doi.org/10.55737/qjss.v-iv.24313

Akbar, M. U., Ibrahim, Nabil, S. J., Iqbal, K. A., & Islam, A. (2024). The Influence of Artificial Intelligence on Consumer Trust in E-Commerce: Opportunities and Ethical Challenges. *European Journal of Theoretical and Applied Sciences*, *2*(6), 250–259. https://doi.org/10.59324/ejtas.2024.2(6).20

Ali, M., Al-Obaydi, A., & Shari, A. (2023). The Impact of Predictive Analytics and AI on Digital Marketing Strategy and ROI. *Studies in Big Data*, *136*, 367–379. https://doi.org/10.1007/978-3-031-42455-7_31

Azuka, P., Ajiga, N. D., Olaoluwa, S., & Ezeigweneme, N. C. (2024). Predictive analytics for market trends using AI: A study in consumer behaviour. *International Journal of Engineering Research Updates*, *7*(1), 036–049. https://doi.org/10.53430/ijeru.2024.7.1.0032

Biondi, J.-E., & McCarthy, B. (2025, September 4). *Future of Fashion Retail: Digital and Omnichannel Imperatives | Deloitte US*. Deloitte. https://www.deloitte.com/us/en/Industries/consumer/articles/future-of-fashion-omnichannel-strategies.html

Consumers Crave More "Natural" Advertising Experiences, finds Kantar US Media Reactions. (2024). Kantar.com. http://kantar.com/north-america/company-news/kantar-us-media-reactions-2024

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

Djafarova, E., & Bowes, T. (2021). "Instagram Made Me Buy it": Gen Z Impulse Purchases in the Fashion Industry. *Journal of Retailing and Consumer Services*, *59*(102345). https://doi.org/10.1016/j.jretconser.2020.102345

Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2003). Empirical testing of a model of online store atmospherics and shopper responses. *Psychology and Marketing*, *20*(2), 139–150. https://doi.org/10.1002/mar.10064

Evanilay, E., Marcellinus Deven Lee, M. D. L., Millenia, M., & Murwani, I. A. (2024). Why Gen Z Still Buy Fast Fashion Although Environmental Awareness is High? *Scholars Journal of Economics, Business and Management*, *11*(09), 268–274. https://doi.org/10.36347/sjebm.2024.v11i09.004

Feng, B. (2024). Research on the Application Effects of Artificial Intelligence in Personalised Marketing. *Journal of Computer and Communications*, *12*(11), 120–129. https://doi.org/10.4236/jcc.2024.1211009

Francis, T., & Hoefel, F. (2018). *"True Gen": Generation Z and Its Implications for Companies*. McKinsey & Company. https://www.mckinsey.com/~/media/McKinsey/Industries/Consumer%20Packaged%20Goods/Our%20Insights/True%20Gen%20Generation%20Z%20and%20its%20implications%20for%20companies/Generation-Z-and-its-implication-for-companies.pdf

GefenDavid, KarahannaElena, & W StraubDetmar. (2003). Trust and TAM in online shopping. *Management Information Systems Quarterly*, *Volume 27,*(Issue 1). https://doi.org/10.5555/2017181.2017185

Grossbart, S., Hampton, R., Rammohan, B., & Lapidus, R. S. (1990). Environmental dispositions and customer response to store atmospherics. *Journal of Business Research*, *21*(3), 225–241. https://doi.org/10.1016/0148-2963(90)90030-h

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*(3), 119–132. https://doi.org/10.1016/j.ijin.2022.08.005

Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Islam, J. U., & Rahman, Z. (2017). The impact of online brand community characteristics on customer engagement: An application of the Stimulus-Organism-Response paradigm. *Telematics and Informatics*, *34*(4), 96–109. https://doi.org/10.1016/j.tele.2017.01.004

Iyanuoluwa, D., Ndubuisi, L., Franca, O., Owolabi, R., Sunday, T., & Adura, R. (2024). AI Driven Predictive Analytics in Retail: A Review of Emerging Trends and Customer Engagement Strategies . *International Journal of Management & Entrepreneurship Research*, *6*(2), 307–321.

Jo Dixon, S. (2025, June 3). *Instagram - statistics & facts*. Statista. https://www.statista.com/topics/1882/instagram/?srsltid=AfmBOopN4QM2dWah0tV5q9i1ZczXOiKdfa7LmR-8Q7tPmbmEq2EyNMhV#topicOverview

Khandelwal, Y., Malhotra, S., Sharma, R., & Sarin, G. (2024a). Artificial Intelligence in Digital Marketing: A Bibliometric Analysis and Future Research Directions. *Abhigyan*, *42*(4). https://doi.org/10.1177/09702385241277358

Khandelwal, Y., Malhotra, S., Sharma, R., & Sarin, G. (2024b). Artificial Intelligence in Digital Marketing: A Bibliometric Analysis and Future Research Directions. *Abhigyan*, *42*(4). https://doi.org/10.1177/09702385241277358

Kim, H.-Y. (2014). Analysis of Variance (ANOVA) Comparing Means of More than Two Groups. *Restorative Dentistry & Endodontics*, *39*(1), 74. https://doi.org/10.5395/rde.2014.39.1.74

Koneti, C. (2022). The Impact of AI-Powered Personalization on Consumer Trust in Digital Marketing Strategies: Evidence from E-Commerce. *Advances in Consumer Research*, *2*(4). https://doi.org/N/A

KPMG. (2023). *KPMG global tech report 2023: Consumer & retail sector insights*. KPMG. https://kpmg.com/xx/en/our-insights/ai-and-technology/kpmg-global-tech-report-2023-consumer-and-retail-sector-insights.html

Lee, Y.-F., Hwang, G.-J., & Chen, P.-Y. (2022). Impacts of an AI-based chabot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation. *Educational Technology Research and Development*, *70*(5). https://doi.org/10.1007/s11423-022-10142-8

Ma, Q., & Liu, L. (2005, January). *The Technology Acceptance Model*. ResearchGate. https://www.researchgate.net/publication/314410967_The_Technology_Acceptance_Model

Martin, K. D., & Murphy, P. E. (2017). The Role of Data Privacy in Marketing. *Journal of the Academy of Marketing Science*, *45*(2), 135–155. https://doi.org/10.1007/s11747-016-0495-4

Matthew, B., Ahmed, M. R., Ahmed, B., Campbell, L., & Sayad, S. E. (2025). Ethical Implications of AI-Powered Predictive Analytics in Customer Personalization Strategies. *International Journal of Artificial Intelligence (AI) in Business and Management*. https://www.researchgate.net/publication/393506049_Ethical_Implications_of_AI-Powered_Predictive_Analytics_in_Customer_Personalization_Strategies

McKinsey & Company. (2024, November 11). *The State of Fashion 2025: Challenges at every turn*. McKinsey; McKinsey & Company. https://www.mckinsey.com/industries/retail/our-insights/state-of-fashion

Mehrabian , A., & A. Russell, J. (1974, March 15). *An Approach to Environmental Psychology*. MIT Press. https://mitpress.mit.edu/9780262630719/an-approach-to-environmental-psychology/

Misra, R. R., Kapoor, S., & Sanjeev, M. A. (2024, May 22). *The Impact of Personalisation Algorithms on Consumer Engagement and Purchase Behaviour in AI-Enhanced Virtual Shopping Assistants*. Research Square. https://doi.org/10.21203/rs.3.rs-3970797/v1

Naiara Martinicorena-Goñi, & Maria Elena Aramendía-Muneta. (2023). Instagram's Marketing Strategy of the Main Fast Fashion Brands. *Advances in Marketing, Customer Relationship Management, and E-Services Book Series*, 114–141. https://doi.org/10.4018/978-1-6684-8753-2.ch008

Priya Shah. (2024). Machine Learning in Predicting Consumer Behavior in Online Retail. *International Journal for Research Publication and Seminar*, *15*(2), 325–329. https://doi.org/10.36676/jrps.v15.i2.1561

Ramzan, A., Manma Niyazi, Oladele, S., & Ahmad, K. (2025, February). *The Personalization-Privacy Paradox: Understanding Consumer Perspectives*. ResearchGate; unknown. https://www.researchgate.net/publication/388594141_The_Personalization-Privacy_Paradox_Understanding_Consumer_Perspectives

Ruiz-Viñals, C., Pretel-Jiménez, M., Del, L., & Pérez, A. M. (2024). The Influence of Artificial Intelligence on Generation Z's Online Fashion Purchase Intention. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(4), 2813–2827. https://doi.org/10.3390/jtaer19040136

Schaefer, A. (2025, March 21). *How Gen Z uses social media and what that means for brands*. Sprout Social. https://sproutsocial.com/insights/gen-z-social-media/

Shareef, M. A., Mukerji, B., Dwivedi, Y. K., Rana, N. P., & Islam, R. (2019). Social media marketing: Comparative effect of advertisement sources. *Journal of Retailing and Consumer Services*, *46*(1), 58–69. https://doi.org/10.1016/j.jretconser.2017.11.001

Siebecker, M. R. (2024, April 15). *Democracy, Discourse, and the Artificially Intelligent Corporation*. Ssrn.com. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4829917

Tanhaei, H. G., Boozary, P., Sheykhan, S., Rabiee, M., Rahmani, F., & Hosseini, I. (2024). Predictive analytics in customer behaviour: Anticipating trends and preferences. *Results in Control and Optimization*, *17*. https://doi.org/10.1016/j.rico.2024.100462

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://pdfs.semanticscholar.org/2227/17d12ef311906161096bc5e5e325f0bd5fe5.pdf

Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing*, *80*(6), 97–121. https://doi.org/10.1509/jm.15.0413

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