International Journal of Marketing, Communication and New Media
ISSN: 2182-9306. VOL 13, Nº 25, December 2025

IJMCNM

DOI: https://doi.org/10.54663/2182-9306.2025.v.13.n.281-318

Research Paper

Assessing Gen Z Consumers' Perceptions, Ethical Concerns, and Behavioral Intention Towards AI-Driven Marketing: Case of Anadolu and Woldia University Students.

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ABSTRACT

Nowadays, Artificial Intelligence (AI) has profoundly reshaped business and marketing practices, bringing both opportunities and challenges, particularly concerning ethics and privacy. The main objective of the study is to investigate Generation Z consumers' perception of Ethical concern and behavioural intention towards AI-driven marketing. Particularly, It strives to measure Gen Z awareness level, trust level, perception, attitude, and ethical concern towards AI-driven marketing and its influence on the intention to engage with it. The data was collected from 275 students in Anadolu University, Turkey, and Woldia University, Ethiopia, who are aged between 17 to 30 years, using a convenience sampling technique, using a structured 5-point Likert scale questionnaire mainly. The collected data were analyzed using descriptive and inferential statistics(Multiple regression) on JASP software. The major findings showed that all variables except demographic profile had a statistically significant influence on Gen Z behavioral intention towards AI-driven marketing. Specifically, awareness level, trust level, perception towards AI personalization, and attitude had a positive influence; on the contrary, ethical concern had a weak negative effect. Furthermore, the descriptive statistics revealed that Gen Z has high awareness of AI-driven marketing, a neutral view on its ethics, cautious trust, positive perceptions of personalization, and a generally positive yet careful intent to engage with AI-driven marketing efforts. Finally, the study recommends, to engage Gen Z effectively, organizations should ensure data transparency, use personalized AI marketing, build trustworthy AI systems, and raise awareness about AI benefits to reduce uncertainty.

Keywords: AI-driven marketing, Awareness level, Trust level, Intention, Attitude, personalization, Ethical concern, and Gen Z

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Received on: 2025.08.03
Approved on: 2025.10.18
Evaluated by a double-blind review system

1. INTRODUCTION

New technologies have revolutionized nearly every aspect of human existence, including the ways that firms market products and services to consumers by far (Grewal, Hulland, Kopalle, & Karahanna, 2020). The foremost new-age technology, uniquely disruptive and prominently shaping marketing, is Artificial Intelligence (AI). Its integration is considered as a game-changer, influencing various facets of marketing and reshaping traditional paradigms (Umamaheswari, 2024). Certainly, AI is revolutionizing marketing by advancing personalization, fostering unparalleled efficiency, and providing data-driven insights that enhance consumer engagement (V Kumar, Ashraf, & Nadeem, 2024). AI's powerful data processing capabilities allow marketers to tailor experiences to individual consumers through personalized content and targeted advertisements, and leverage vast datasets on behavior and preferences. For instance, streaming platforms like Netflix, YouTube, and Spotify utilize AI to recommend content based on user interactions, which fosters customer engagement and loyalty by delivering a more personalized experience (Bowden & Mirzaei, 2021; Virender Kumar, Ramachandran, & Kumar, 2021)

Furthermore, AI-driven tools such as predictive modeling and automated messaging refine market segmentation, enabling precise targeting that optimizes marketing efforts and enhances campaign effectiveness (Haleem, Javaid, Qadri, Singh, & Suman, 2022). For instance, chatbots and virtual assistants on platforms streamline customer service by offering immediate, tailored responses, contributing to higher customer satisfaction and positive brand perception (Alhitmi, Mardiah, Al-Sulaiti, & Abbas, 2024).

However, while AI-driven marketing brings considerable benefits, it also brings specific challenges and drawbacks, or ethical concerns that can impact consumer trust and perception. A primary concern centers around data privacy, as an AI-driven marketing environment often requires vast amounts of consumer data to function effectively in targeted advertising and personalized marketing, which presents a major difficulty in maintaining data security (Rosário & Dias, 2023). This reliance raises privacy issues since consumers may feel uncomfortable and worry about how their data is collected and used, potentially leading to mistrust if they feel their information is not being handled transparently (Shankar et al., 2021). Another challenge is the lack of transparency in AI algorithms. Many operate as "black boxes," meaning consumers and even marketers themselves may not fully understand how decisions are made. This can lead to ethical dilemmas if AI's targeting and data use seem overly invasive or manipulative (Paschen, Kietzmann, & Kietzmann, 2019)

Moreover, AI's dependence on data quality means it is only as effective as the input it receives. Falsification of information and inaccurate or biased data can skew outcomes, leading to poor targeting or marketing campaigns, and potentially reinforcing societal or ethical biases (Alhitmi et al., 2024; Choi, Guo, & Luo, 2020). This limitation can harm brand reputation and weaken the efficacy of campaigns (Davenport & Ronanki, 2018). Additionally, AI's increasing role in customer interactions, such as through chatbots and automated responses, may reduce the authenticity of human interactions and result in emotional discomfort. Many consumers still value personal engagement, and an over-reliance on automated responses can diminish customer satisfaction and trust, particularly if the interaction lacks empathy or understanding (Farbod, 2024; Kunz & Wirtz, 2024). AI's extensive tracking capabilities also introduce concerns related to surveillance and hyper-targeting (Siham, Boumadiene, & Abdelhamid, 2024). AI can analyse user behavior across platforms, resulting in tailored advertisements, which can sometimes feel invasive, creating discomfort among consumers who feel the company knows everything about them, and are being monitored and targeted to be influenced (Chen, Chan-Olmsted, Kim, & Sanabria, 2021; Miah, 2024; H. J. Wang et al., 2022).

Despite significant academic research focusing on AI's effectiveness in marketing and the ethical implications surrounding AI, there is limited empirical research addressing how younger generations perceive AI-driven marketing, especially among university students, who are notably active and vulnerable in digital marketing environments. This study seeks to bridge this gap by examining how Gen Z students at Anadolu and Woldia University perceive AI-driven marketing and the ethical issues in practice. Do they really know the value of their personal data? Do they trust AI-driven marketing? By how much? How do they feel about AI-driven marketing (targeted ads, recommendation systems, chatbots, etc.)? So then, how would these influence behavioral intention towards AI-driven marketing? These questions could be answered by collecting and analyzing empirical data.

Likewise, T D. Kumar and Suthar (2024) studied ethical and legal challenges of AI AI-driven marketing area by reviewing the existing literature. Standing from his work, he suggested that future researchers (us) study opinions of all stakeholders engaged in AI-powered marketing using surveys with marketing professionals, customers, and other key stakeholders to know practical difficulties, perceptions, and solutions. This is what the current study is striving for, i.e., to study the perception of Gen Z consumers towards AI-driven marketing practices. Moreover, the current study also strives to understand the interrelationship among variables such as awareness, attitude, trust, perception, intention, and ethical concern in the context of AI-driven marketing among Gen Z users.

1.1 General objectives

To investigate Gen Z consumers' perceptions, ethical concerns, and attitudes towards AI-driven marketing practices, and how these factors, along with awareness and trust, shape their intention to engage with AI-driven marketing efforts.

1.2 Specific objectives

- To assess the level of awareness of AI-driven marketing among Gen Z consumers.
- To examine Gen Z's attitudes toward the personalization aspects of AI-driven marketing.
- To determine the extent to which Gen Z trusts AI-driven marketing practices by brands.
- To explore Gen Z students' privacy and ethical concerns associated with AI-driven marketing.
- To examine how Gen Z's demographic characteristics, awareness level, trust level, attitude, perception, and ethical concerns influence their intention to engage with AI-driven marketing.

1.3 Research questions

1. What is the level of awareness and understanding of AI-driven marketing among Gen Z students in the university?
2. How do Gen Z students perceive the personalization aspects of AI-driven marketing?
3. To what extent do Gen Z students trust AI-driven marketing practices by brands?
4. What privacy and ethical concerns do Gen Z students associate with AI-driven marketing?
5. To what extent do Gen Z's demographic characteristics, awareness level, trust level, attitude, perception, and ethical concerns influence their intention to adopt AI-driven marketing?

2. LITERATURE REVIEW

2.1 Artificial intelligence (AI)

The term artificial intelligence (AI) was introduced by John McCarthy for the first time in 1954 (Cukier, 2019). It is refers to the simulation of human intelligence processes by a machine or computer system, to learn from experience, adjust to new inputs and perform tasks that typically require human intelligence, such as learning, reasoning, problem-solving, language understanding and decision-making (Duan, Edwards, & Dwivedi, 2019; Feng, Park, Pitt, Kietzmann, & Northey, 2021; Russell & Norvig, 2016). In other words, AI "refers to programs, algorithms, systems and machines that demonstrate intelligence"(Haleem et al., 2022; Shankar, 2018), is "manifested by machines that exhibit aspects of human intelligence" (Huang & Rust, 2018), and involves machines mimicking intelligent human behavior (Syam & Sharma, 2018). It relies on several key technologies, such as machine learning, natural language processing, rule-based expert systems, neural networks, deep learning, physical robots, and robotic process automation (T. H. Davenport & Ronanki, 2018).

2.1 AI-driven marketing

Artificial Intelligence (AI) holds immense promise and potential for revolutionizing marketing, with anticipation running high for its future applications that would bring a higher level of innovation and efficiency (Capatina et al., 2020; Haleem et al., 2022). Marketers anticipate AI to profoundly impact customer segmentation, personalize experiences, solution or offering design, pricing, promotion, and distribution based on individual data, enhance understanding of consumer behavior, and make predictive analyses based on historical data (Han et al., 2021; Ismagiloiva, Dwivedi, & Rana, 2020; Lai & Yu, 2021). Moreover, AI is poised to map individual customer journeys, optimize experiences, conduct micro-segmentation, and develop predictive models for future behaviors, thus reshaping marketing practices through automation and predictive modeling(Haleem et al., 2022). Marketing data is typically unstructured, sourced from diverse platforms and formats such as social media, behavioral data, app usage, geolocation services, transaction history, and browsing activity. AI leverages this data to cluster customers into groups based on online behavior, preferences, and transactions, enabling data-driven marketing strategies driven by predictive algorithms. The insights derived from this vast pool of unstructured data facilitate personalized product recommendations, targeted advertisements, customized offerings, offering predictive insights and efficiency, primarily in digital marketing spheres (Sharma, Tomar,

& Tadimarri, 2023). AI tools such as recommendation engines and automated chatbots help create more personalized consumer experiences and improve efficiency (T. Davenport, Guha, Grewal, & Bressgott, 2020). In general, when marketers leverage machine learning, data analytics, and automation to create personalized, targeted, and efficient marketing campaigns, we call it AI-driven marketing.

2.2 Behavioral intention towards AI-driven marketing

Behavior is not performed automatically or mindlessly, but follows reasonably and consistently from the behavior-relevant information available to us, where intention is the immediate antecedent of behavior (Ajzen, 1991). Behavioral intention refers to an individual's specific motivation or a plan to engage in a specific behavior in the future (Conner, 2020; Londono, Davies, & Elms, 2017), which can determine people's actual behavior. The theory of reasoned action (TRA) explains that intention is jointly determined by individual attitudes and subjective norms regarding a behavior (Ajzen, 1980), while the theory of planned behaviour (TPB) discloses that it is shaped as a consequence of attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). On the other hand, the theory of the technology acceptance model (TAM) posits that behavioral intention is a function of Perceived usefuln*ess* (the degree to which a technology enhances performance) and perceived ease of use (the degree to which a person believes that using a particular system would be free of effort) (Davis, 1989)

Furthermore, the Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh, Morris, Davis, and Davis (2003) synthesizes elements from eight prominent theories, including the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), suggests that four key constructs affect the Behavioral Intention (BI) to accept technology. These are: Performance Expectancy (PE) (the degree to which an individual believes that the use of the system would enhance his or her job performance), Effort Expectancy (EE): refers to the degree of ease associated with the use of the system, Social Influence (SI): refers to the degree to which an individual perceives that important others believe he or she should use the new system. Facilitating Conditions (FC): The belief that the necessary resources and support to use the technology are available. The model also identifies four moderators that influence the strength of the relationships between the core constructs and behavioral intention or usage behavior: gender, age, experience, and voluntariness of use. Besides these theories, the study of Narteh, Mahmoud, and Amoh (2017) Kesharwani and Singh Bisht (2012), extended the theory of the technology acceptance model (TAM) to determine mobile money and internet banking adoption by adding perceived trust and perceived risk into the model.

The current study strives to examine Gen Z consumers' behavioral intention toward AI-driven marketing. Therefore, this study took relevant variables from each theory of behavioral intention, such as: from TPB, attitude reflecting the Gen Z consumers' positive or negative evaluations of AI-driven marketing. UTAUT contributes perceived performance, representing Gen Z's perception of the benefits and effectiveness of AI-driven personalization, alongside demographic characteristics (gender and age) that influence technology adoption behaviors. Furthermore, perceived trust (capturing confidence in the transparency and reliability of AI platforms), and perceived risk (addressing ethical concerns such as privacy violations and algorithmic bias). Moreover, the current study added knowledge or awareness level of Gen Z consumers to figure out behavioral intention towards AI-driven marketing.

2.3 Privacy and ethical issues of artificial intelligence

The privacy and ethical issues of AI have been considered as serious and urgent issues that businesses, governments, consumers, and others are worried about. One of the prime issues is the violation of privacy, where personal information is frequently collected, processed, and stored by various online platforms. In other words, the issues are misuse, unauthorized, non-transparent collection or access, and distribution of consumers' personal data by business companies (Manikonda et al., 2018) cited in Amil (2024). To make it clear, with AI's powerful data processing capabilities, vast amounts of information, such as browsing habits, purchasing behavior, and even geo-location data, can be collected without clear consumer consent. This can lead to breaches of personal privacy, where individuals' data is used for targeted advertising or personalized marketing without them being fully aware or agreeing to such practices (Wirtz, Kunz, Hartley, & Tarbit, 2023). This shows that privacy concerns in AI-driven marketing are influenced by the extent and manner in which personal data is collected, how it is used, and the security measures in place to protect (Golda et al., 2024), cited in Amil (2024). Therefore, worries about the real and perceived abuse of personal data, such as selling or distributing information without users' agreement, is the other major concern of users nowadays (Crawford & Schultz, 2014).

The other major privacy and ethical issue is the manipulation of consumer behaviour by businesses. AI-based algorithms are often used to analyse customer behaviour and design tailored marketing campaigns for specific segments, which can improve marketing effectiveness.

However, this practice raises ethical concerns, as it may manipulate and exploit vulnerable consumers. Since AI targets individuals based on their psychological profiles and preferences, it enables highly personalized and persuasive marketing that can influence consumers to make purchases or act against their best interests (D. Kumar & Suthar, 2024). Such practices risk undermining consumer autonomy and free will (Zuboff, 2019).

Moreover, another ethical concern in AI-driven marketing is the lack of real human interaction with consumers. While AI-powered chatbots and virtual assistants provide fast and efficient customer service, they cannot replicate the empathy and personal touch of human engagement. This limitation can reduce customer satisfaction, as consumers may feel undervalued, treated insincerely, or even mistreated (D. Kumar & Suthar, 2024).

Furthermore, transparency and explainability are other concerns. AI algorithms often function as "black boxes," making it difficult for consumers to understand how decisions are made. Additionally, customers may be unaware that AI is used to target them with advertisements, and they may not comprehend how the algorithms operate or why they are being targeted, finally erode their trust in the company (Burrell, 2016; Spiekermann, 2015).

More significantly, job displacement has become a key concern. Although AI-driven marketing techniques offer unprecedented efficiency and responsiveness in all sectors of the societies' activity, they pose ethical challenges related to employment loss. Automating tasks traditionally performed by humans can lead to job replacement and aggravate economic inequality (Brynjolfsson & Mitchell, 2017), particularly in roles related to data analysis and customer service. For instance, the advent of AI-powered chatbots and virtual assistants has streamlined customer service but has also led to job losses in these sectors, creating ethical challenges concerning economic sustainability and the responsibility of companies to mitigate the impact on the workforce (Brynjolfsson & McAfee, 2014). Moreover, the advent of AI leads to rising unemployment, which brings lower consumer purchasing power, influencing overall economic growth (Benanav, 2020; Brynjolfsson & McAfee, 2014). In addition, the potential job losses might intensify mental health problems and shift family dynamics (Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017; Godinić & Obrenovic, 2020). Hence, the integration of AI and machine learning in every sector is likely to lead to significant job displacement, particularly for low-skilled and routine jobs (Pandey & Kumar, 2024).

More significantly, job displacement has become a critical ethical concern in AI-driven marketing and beyond. While AI offers unprecedented efficiency and responsiveness, it also threatens employment by automating tasks traditionally performed by humans, particularly in data analysis and customer service (Brynjolfsson & Mitchell, 2017). The rise of AI-powered chatbots and virtual assistants, for example, has streamlined customer service but simultaneously reduced job opportunities, raising questions about economic sustainability and corporate responsibility to mitigate workforce impacts (Brynjolfsson & McAfee, 2014). Such displacement can aggravate economic inequality, lower consumer purchasing power, and slow overall economic growth (Benanav, 2020; Brynjolfsson & McAfee, 2014). Furthermore, widespread unemployment may intensify mental health challenges and disrupt family dynamics(Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017; Godinić & Obrenovic, 2020). Overall, the integration of AI and machine learning is expected to disproportionately affect low-skilled and routine jobs, amplifying social and economic risks (Pandey & Kumar, 2024).

Finally, the use of AI for malicious aims(criminal and harmful activities) is increasing, concerning, and existing vulnerabilities and introduces new threats (Blauth, Gstrein, & Zwitter, 2022). AI may be exploited for malicious objectives or destructive goals, such as distributing misinformation and exploiting vulnerable people. This technology can create forgery of videos and images, enabling more realistic material, making it difficult to distinguish between what is real and what is fake. Surprisingly, AI algorithms can produce forgery, deep fakes, password cracking, deception, malware, manipulate media material and disseminate false information and news, which may hurt people and erode faith in institutions (Blauth et al., 2022; D. Kumar & Suthar, 2024; Stoecklin, Jang, & Kirat, 2018; Trieu & Yang, 2018; Westerlund, 2019).

In general, if a user believes his/her information is not being kept safe, the existence of fake, misleading, theft, hacking, invasion of privacy, insecurity, manipulation, little social interaction, etc, then it will reduce the intention and adoption of new technological initiatives (Kirchbuchner, Grosse-Puppendahl, Hastall, Distler, & Kuijper, 2015). Therefore, the following hypothesis (H1).

H1. Higher ethical & privacy concerns about AI-driven marketing negatively influence Gen Z's intention to use it.

2.4 Consumers' perception, awareness, trust, and attitude of consumers towards AI-driven marketing

2.4.1 Consumers' attitude towards AI-driven marketing

Attitude is described as a "psychological tendency, expressed by evaluating a particular entity with some degree of favor or disfavor" (Eagly, 1993). Consumers' attitudes can be defined to be either positive, negative, or neutral regarding a specific object, formed by experiences and the perceived use of it. Attitudes are viewed as consumers' preferences or identification in regard to the object in relation to other alternatives (Amoroso & Lim, 2017). Consumers are a part of different groups that share experiences in products, innovations, values, and views on societal development (Rajagopal, 2022). Thereby, the collective attitude of a consumer group can influence purchases and the view of society in relation to meeting their needs (Rajagopal, 2022).

Forgas, Cooper, and Crano (2011) states that attitude influences our perceptions and provides guidance in human behavior. Positive attitudes can positively impact the purchasing intention, while a negative attitude can hurt their purchasing intention (Smith et al., 2008). Favourable consumer attitudes can lead to higher brand engagement, trust, and loyalty (Kotler & Keller, 2016). So attitude can be viewed as a rational-choice-based evaluation of the consequences of a behavior (Armitage & Conner, 2001). Consumer attitudes toward AI-driven marketing, where trust and ethical practices play a critical role in shaping the overall perception and acceptance of AI tools in marketing.

H2. A positive attitude toward AI-driven marketing significantly increases Gen Z's intention to use AI-driven marketing.

2.4.2 Consumers' awareness level about AI-driven marketing

In this study, awareness refers to the extent to which consumers familiarize themselves, understand, and recognize the application and implications of AI in marketing efforts. It is known that consumer awareness or knowledge influences trust and receptivity toward new technologies. If consumers have a clear understanding of how AI-driven marketing functions, including its data processing and decision-making capabilities, they are more likely to appreciate its benefits, such as personalized experiences and efficiency, or reject it if they perceive irrelevant or dangerous. The study Swaminathan (2003) confirms that consumer behavior depends on their knowledge of the goods of interest. Similarly Gurlitt and Renkl (2010) said users' knowledge level significantly influences their consumption behaviors. However, limited awareness or misconceptions about AI can lead to skepticism or resistance. Younger consumers, specifically Generation Z, are typically more exposed to technology; their understanding of AI's specific applications in marketing might be higher than others.

H3. Higher awareness of AI-driven marketing positively influences Gen Z's intention to use AI-driven marketing.

2.4.3 Consumers' trust level AI AI-driven marketing

Trust is a critical factor influencing consumer acceptance and engagement with marketing strategies and technology adoption success. In the context of AI-driven marketing, trust refers to the confidence and sense of security (Kim, Lee, & Rha, 2017) that consumers have in the fairness, reliability, and ethical handling of data by AI systems. Trust levels can significantly impact consumers' willingness to interact with and respond positively to utilize any technology (Loh, Lee, Tan, Ooi, & Dwivedi, 2021; Narteh et al., 2017). In this sense, AI-powered marketing campaigns. Empirical research indicates that consumer trust in technology (AI-driven marketing) is often shaped by transparency, data security, and perceived control over personal information (Kim et al., 2017). For instance, when consumers believe that AI systems are transparent in how they collect and use data, trust levels increase (Hoff & Bashir, 2015). Conversely, a lack of understanding or negative experiences related to data misuse can lead to diminished trust and reluctance to engage with AI-driven marketing (Smith & McCoy, 2019). Generation Z, known for being tech-savvy and digitally connected, demonstrates a nuanced approach to trust in AI. While they are generally more open to interacting with AI technologies, they also value ethical practices and data protection (Hoyer, Kroschke, Schmitt, Kraume, & Shankar, 2020).

H4. Higher trust level in AI-driven marketing enhances Gen Z's intention to engage with AI-driven marketing.

2.4.4 Consumers' perception of AI-driven personalized marketing

In this study, consumer perception refers to how consumers value or interpret AI-driven personalization, specifically in terms of its perceived usefulness, comfort, and convenience. It reflects consumers' impression that a specific technology enhances their performance and simplifies their tasks (Davis, 1989), which has been considered a key construct in technology adoption. The study by Cai, Cain, and Jeon (2022) on customers' perceptions of AI-enabled voice assistants in hotels revealed that customers associate these technologies with a high level of perceived usefulness and ease of use. Moreover, perceived usefulness was found to have a positive influence on customers' intention to use such technologies.

Kuronen (2023) found that when AI-generated recommendations align with consumers' preferences and needs, they are more likely to have a positive view or value of the marketing effort.

For instance, consumers appreciate personalized product recommendations or advertisements that reflect their browsing history or past purchases. However, his study reveals that it is noteworthy that a significant minority of participants expressed negative attitudes toward AI-generated personalized recommendations. Similarly, Kannan & Li (2017) argued that the success of AI personalization depends on the accuracy of the algorithms. If consumers perceive the personalization to be irrelevant or poorly executed, their trust in the brand diminishes, and they may disengage from the marketing efforts. Research by Shin (2020) found that consumers are more likely to accept AI-driven personalization when they perceive the process as transparent, fair, and trustworthy. While consumers generally appreciate personalized marketing, it can be perceived as intrusive if the frequency of interactions becomes overwhelming. Excessive targeting or poorly timed messages can lead to consumer annoyance, decreasing the effectiveness of the marketing effort. On the other hand, Vashishth, Sharma, Kumar, Chaudhary, and Panwar (2025) found that when AI personalization is done thoughtfully (offering tailored content at the right time or through preferred channels), it can lessen the perception of intrusiveness, leading to improved satisfaction and engagement of consumers.

H5. A favorable perception of AI-driven personalized marketing positively influences Gen Z's intention to use AI-driven marketing.

2.4.5 Demographic characteristics and Behavioral intention towards AI-driven marketing

Demographic data is crucial for companies to understand consumer behavior, including how, who, when, and where consumers search for information. It guides businesses in effectively marketing to their target audience and designing strategic plans to meet future consumer demand. By leveraging demographics, companies can ensure their products and services are directed toward the most relevant and valuable consumer segments (Park, Hong, & Le, 2021). So demographic characteristics could have an influence on behavioural intention to adopt AI technology. According to (Faqih & Jaradat, 2015), gender and age significantly impact mobile technology adoption, findings that are supported by subsequent studies(Chawla & Joshi, 2018; S. Hu, Laxman, & Lee, 2020). Females and males usually differ in their decision-making processes and perceptions, so gender can be regarded as a critical configuration of segmentation and attraction to different types of product (Kara, Kim, Lee, & Uysal, 2018). Similarly, Akram, Hui, Khan, Hashim, and Rasheed (2016) note that societal roles and behavioral expectations associated with gender contribute to these differences. Age also exerts a measurable influence on technology adoption. Research by Yi, Wu, and Tung (2005) highlights that perceptions of and willingness to use technology often differ across age groups. Q. Wang and Sun (2016) report that older individuals are more hesitant to adopt new technologies, a trend attributed to factors such as perceived complexity and a lack of familiarity. Conversely, younger individuals are generally less resistant to innovation, demonstrating a greater propensity to adopt emerging technologies (Malaquias & Hwang, 2019). In the context of AI-driven marketing, these demographic factors are particularly relevant. For instance, younger consumers may exhibit a higher level of behavioral intention to engage with AI-driven marketing due to their familiarity with and openness to digital innovations. Demographic characteristics of consumers in previous studies were used mostly as a moderating variable, but the current study strives to check the direct effect of it on AI-driven marketing usage intention.

H6. Demographic characteristics significantly influence Gen Z's intention to use AI-driven marketing.

2.5 Conceptual framework of the study

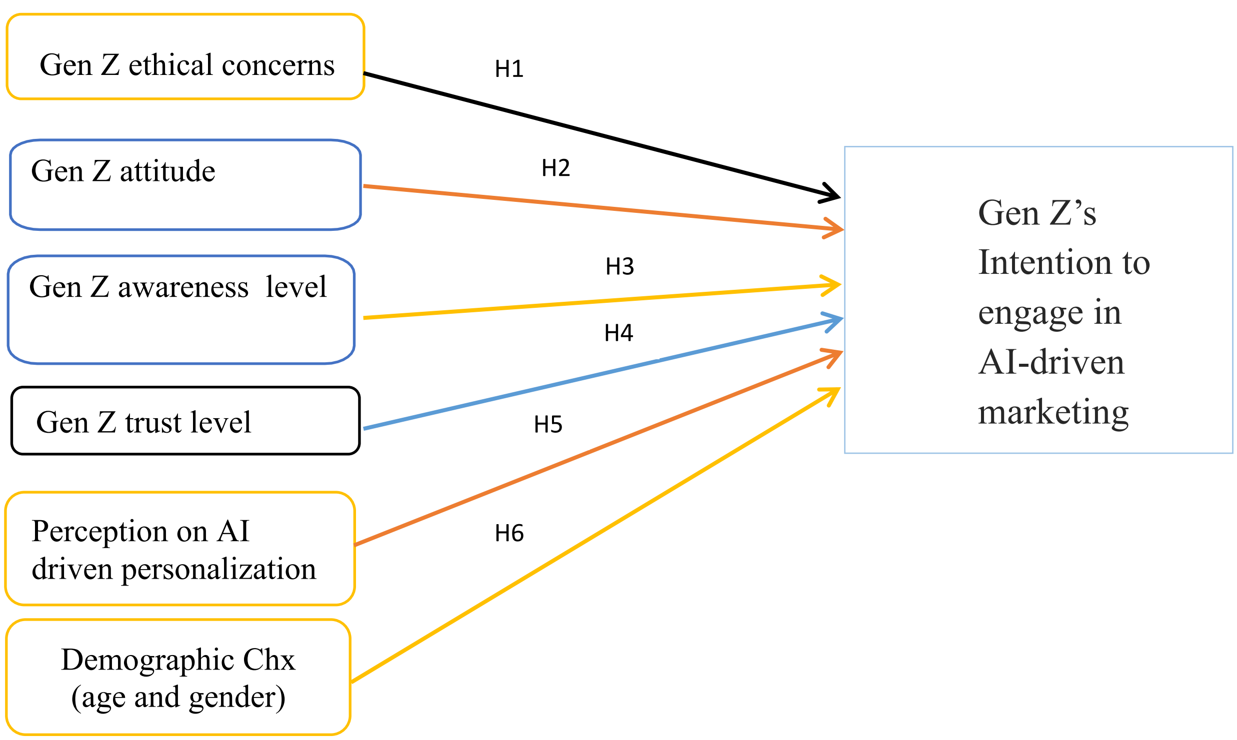

Figure 1. Conceptual framework of the study

3. METHODOLOGY

The study employed a descriptive and explanatory design using a quantitative approach to address the research questions and hypotheses.

The study targeted Gen Z undergraduate and post-graduate students at Anadolu University, Turkey, and Woldia University, Ethiopia. A sample size of 275 students was taken, and the needed data were collected from them.

Data for the study were collected using a structured questionnaire. While demographic characteristics were captured through multiple-choice items, the main part of the questionnaire used was 5-point Likert scale questions to assess Gen Z consumers' attitudes, perceptions, trust level, awareness, ethical concerns, and behavioral intention toward AI-driven marketing. The questionnaire was administered via a Google Form link shared in Telegram and WhatsApp groups, as well as through QR code scanning during face-to-face interactions, but only with Anadolu University students.

3.1 Validity

Factor analysis (CFA) was conducted to check the convergent and discriminant validity of the construct. Moreover, the appropriateness of the questions(content validity) has been verified by instructors, research staff, and academic friends. And these data collection instruments were developed through a direct adoption and customization of instruments used in different prior studies, such as: Alaeddin and Altounjy (2018), Pavlou (2003), Dhagarra, Goswami, and Kumar (2020), Amil (2024), Amoroso and Lim (2017), Suh and Ahn (2022), Xu, Dinev, Smith, and Hart (2008), Dhagarra et al. (2020), Papa, Mital, Pisano, and Del Giudice (2020), Lu, Cai, and Gursoy (2019); (Venkatesh et al., 2003).

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.918**,** indicating meritorious suitability for factor analysis (Kaiser, 1974). Additionally, Bartlett's Test of Sphericity was significant**,** $\chi^2(465) = 4769$, $p < .001$**,** suggesting that the correlation matrix is not an identity matrix and is thus appropriate for factor analysis.

3.1.1 Model fit indices for the confirmatory factor analysis

The measurement model was assessed using confirmatory factor analysis (CFA). Although the chi-square test indicated a significant lack of fit, $\chi^2(289) = 634.400$, $p < .001$, this result is expected given the test's sensitivity to sample size (L. t. Hu & Bentler, 1999; Kline, 2023). Therefore, alternative fit indices were prioritized. The model showed acceptable fit: RMSEA = 0.066 (90%

CI [0.059, 0.073]) and SRMR = 0.063, both within recommended thresholds (≤ 0.08). Incremental indices also supported model adequacy: CFI = 0.904, IFI = 0.905, and RNI = 0.904 (≥ 0.90). TLI was slightly below the cutoff at 0.892. However, the overall pattern of results from key fit indices indicates the model provides an acceptable fit to the data or model's overall adequacy, as indicated in Table 1.

Table 1. Model Fit Indices

Fit Index	Value	Interpretation (General Guidelines)
Chi-square ($\chi 2$)	850.225	Lower values indicate better fit. Sensitive to sample size.
Degrees of Freedom (df)	419	
p-value	< .001	P >.05 for perfect fit; often significant in large samples.
Absolute Fit Indices		
Root Mean Square Error of Approximation (RMSEA)	0.061	P ≤ 0.08 acceptable, ≤0.06 good
RMSEA 90% CI Lower Bound	0.056	
RMSEA 90% CI Upper Bound	0.067	
RMSEA p-value (Close Fit)	0.001	P>.05 for close fit (RMSEA ≤0.05)
Standardized Root Mean Square Residual (SRMR)	0.060	≤ 0.08 good fit
Incremental Fit Indices		
Comparative Fit Index (CFI)	0.905	≥ 0.90 acceptable, ≥0.95 good
Tucker-Lewis Index (TLI)	0.894	≥0.90 acceptable, ≥0.95 good
Bentler-Bonett Non-normed Fit Index (NNFI)	0.894	≥0.90 acceptable, ≥0.95 good
Bollen's Incremental Fit Index (IFI)	0.906	≥ 0.90 acceptable, ≥ 0.95 good
Relative Noncentrality Index (RNI)	0.905	≥ 0.90 acceptable, ≥ 0.95 good

3.1.2 Convergent validity

Convergent validity was assessed through standardized factor loadings, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha. As of Table 2, all standardized factor loadings exceeded 0.60, indicating strong item contributions to their respective constructs(Hair, Risher, Sarstedt, & Ringle, 2019).

Table 2. Factor loadings

						95% Confidence Interval	
Factor	**Indicator**	**Std. estimate**	**Std. Error**	**z-value**	**p**	**Lower**	**Upper**
Gen Z awareness level	AWL1	0.749	0.036	20.975	< .001	0.679	0.819
	AWL2	0.789	0.033	23.649	< .001	0.723	0.854
	AWL3	0.697	0.039	17.802	< .001	0.620	0.774
	AWL4	0.520	0.051	10.239	< .001	0.420	0.619
Perception to AI driven personalization	AIDP1	0.743	0.032	23.447	< .001	0.681	0.805
	AIDP2	0.731	0.033	22.370	< .001	0.667	0.795
	AIDP3	0.731	0.033	22.373	< .001	0.667	0.795
	AIDP4	0.699	0.035	19.839	< .001	0.630	0.768
	AIDP5	0.680	0.037	18.514	< .001	0.608	0.752
Gen Z trust Level	TL1	0.739	0.031	23.981	< .001	0.679	0.800
	TL2	0.867	0.020	44.173	< .001	0.828	0.905
	TL3	0.848	0.021	39.831	< .001	0.806	0.889
	TL4	0.737	0.031	23.818	< .001	0.677	0.798
	TL5	0.684	0.035	19.346	< .001	0.615	0.754
	TL6	0.644	0.039	16.688	< .001	0.568	0.719
Gen Z attitude	AT1	0.707	0.035	20.479	< .001	0.640	0.775
	AT2	0.700	0.035	19.955	< .001	0.632	0.769
	AT4	0.675	0.037	18.169	< .001	0.602	0.748
	AT5	0.791	0.028	28.645	< .001	0.737	0.845
	AT6	0.729	0.033	22.210	< .001	0.664	0.793
Gen Z concern	UC1	0.705	0.035	19.980	< .001	0.636	0.774
	UC2	0.786	0.029	27.380	< .001	0.729	0.842
	UC3	0.730	0.033	21.970	< .001	0.665	0.795
	UC4	0.748	0.032	23.567	< .001	0.686	0.811
	UC5	0.782	0.029	26.959	< .001	0.725	0.839
	UC_6	0.612	0.042	14.504	< .001	0.530	0.695
Gen Z's intention	UI1	0.758	0.030	25.59	< .001	0.700	0.816
	UI2	0.779	0.028	28.03	< .001	0.724	0.833
	UI3	0.797	0.026	30.46	< .001	0.746	0.849
	UI4	0.706	0.034	20.82	< .001	0.640	0.773
	UI5	0.712	0.033	21.25	< .001	0.646	0.777

3.1.2 Average variance extracted (AVE)

Convergent validity assessed by Average Variance Extracted (AVE), shown in Table 3, shows four out of five constructs had AVE values above the recommended threshold of 0.50 (Fornell & Larcker, 1981), indicating adequate convergent validity. The AVE for Gen Z awareness level was 0.489, slightly below the threshold, but still considered acceptable when supported by strong factor loadings and composite reliability (CR > 0.70) (Hair et al., 2019).

Table 3. Average variance extracted (AVE)

Factor	**AVE**
Gen Z awareness level	0.489
Perception to AIDP	0.514
Gen Z trust Level	0.564
Gen Z attitude	0.520
Gen Z concern	0.538
Gen Z's intention	0.561

3.1.3 Discriminant validity

Discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT). As shown in Table 4, all HTMT values were below the conservative threshold of 0.90, indicating satisfactory discriminant validity among all constructs (Henseler, Ringle, & Sarstedt, 2015).

Table 4. Heterotrait-monotrait ratio

Gen Z awareness level	**Perception to AIDP**	**Gen Z trust Level**	**Gen Z attitude**	**Gen Z concern**	**Gen intention**
1.000					
0.623	1.000				
0.164	0.598	1.000			
0.469	0.877	0.725	1.000		
0.117	0.160	0.192	0.209	1.000	
0.474	0.782	0.662	0.895	0.287	1.000

3.2 Reliability

Reliability of the constructs was evaluated using both Coefficient Omega (ω) and Cronbach's Alpha (α). As it shown in Table 5, all constructs demonstrated good internal consistency, with omega values ranging from 0.792 to 0.886 and alpha values from 0.779 to 0.883, exceeding the commonly accepted threshold of 0.70 (DeVellis, 2003; Nunally & Bernstein, 1994). The overall reliability of the measurement scale was also strong, with ω = 0.923 and α = 0903.

Table 5. Reliability test statistics

	Coefficient ω	Coefficient α
Gen Z awareness level	0.792	0.779
Perception to AIDP	0.843	0.839
Gen Z trust Level	0.886	0.883
Gen Z attitude	0.848	0.841
Gen Z concern	0.874	0.871
Gen Z's intention	0.864	0.865
Total	0.923	0.903

3.3 Ethical considerations

The study was conducted in accordance with ethical standards. Informed consent was obtained from all participants, who were clearly informed of the study's purpose and their voluntary involvement. Data were collected at participants' convenience to encourage honest responses. The researcher ensured ethical handling and analysis of data to maintain accuracy and integrity. The Research Ethics Committee of the University reviewed and approved the study protocol.

3.4 Multiple linear regression analysis method

The data was analyzed using both descriptive statistics, such as frequencies, percentages, central tendencies, and inferential statistics, such as correlation and multiple regression, on the JASP software package.

Under this study, a multiple regression data analysis technique was used, where the dependent variable of the study is Gen Z behavioral intention to adopt AI-driven marketing, and the independent variables of the study are demographic characteristics, awareness level, trust level, attitude, perception of AI-driven personalization, and ethical concerns.

Model Specifications

$$Yi = \beta 0 + \beta 1x1 + \beta 2x2 + \beta 3x3 + \beta 4x4 + \beta 5x5 + \beta 6x6 + ui$$

Where, Yi = Gen Z behavioral intention towards AI-driven marketing β0= the constant or y-intercept, β1… β6 are the slope/coefficient of each x value in the equation, ui= error term X1 = Gen Z ethical concerns, X2= Perception on AI-driven personalization, X3 = Gen Z attitude, X4 = Gen Z trust level, X5 = Gen Z awareness level, and X6 = Demographic Chx (Age and gender).

4. RESULTS AND DISCUSSION

4.1 Descriptive statistics analysis

The dataset consists of 275 Gen Z respondents. In terms of age category, the vast majority of the participants (82.91%) fall within the 18-25 age range, with the largest single group being 22-25 year olds (46.55%), closely followed by 18-21 year olds (36.36%). On the other hand, the gender distribution among respondents is relatively balanced, with males comprising 54.55% (n = 150) and females 45.45% (n = 125).

The study sample consists of a diverse group of students, with Ethiopian nationals comprising the largest segment (38.6%), followed by Turkish nationals (21.32%). The remaining 40% includes international students from over 40 countries, such as Russia, Yemen, Kazakhstan, Indonesia, Egypt, Afghanistan, Somalia, Jordan, Malaysia, Guinea-Bissau, Belarus, Mozambique, Algeria, Cameroon, Uzbekistan, Mali, Azerbaijan, and Tatarstan, and others—all currently studying at Anadolu University in Turkey. In contrast, nearly 95% of the Ethiopian participants are enrolled at Woldia University, Ethiopia. This demographic structure offers a unique blend of global diversity and localized insight, capturing the representation of Generation Z perspectives across different cultural and educational settings.

4.2 Gen Z's Awareness Level Toward (AWL) AI-Driven Marketing

The results indicate that Generation Z respondents show a generally high level of awareness toward AI-driven marketing. For the first three items—AWL1, AWL2, and AWL3—the responses are skewed toward agreement and strong agreement. Specifically, for AWL1, a total of 194 respondents (70.5%) selected either "Agree" (88) or "Strongly Agree" (106), with a mode of 5 and a mean of 3.895, reflecting strong awareness. Similarly, AWL2 and AWL3 follow the same trend: 177 respondents (64.4%) agreed or strongly agreed with AWL2, and 186 respondents (67.6%) did the same for AWL3. This alignment is further supported by the modes of 5 and medians of 4 across these items, signaling a consistent positive tendency.

In contrast, AWL4 shows slightly lower agreement. While it still has a median of 4, the mode drops to 3 (Neutral), and the mean falls to 3.498. Here, the responses are more evenly distributed, with 89 respondents selecting "Neutral," and fewer selecting "Strongly Agree" (58) compared to previous items. Despite this variation, a combined 140 respondents (50.9%) still selected "Agree" or "Strongly Agree" for AWL4, indicating a continued, albeit slightly weaker, awareness.

Overall, the frequency distribution and descriptive statistics together suggest that Generation Z holds a generally strong awareness of AI-driven marketing, though the intensity of that awareness varies slightly depending on the specific aspect being assessed.

4.3 Gen Z's Perception Towards AI-Driven Personalization (AIDP)

The overall perception of Gen Z toward AI-driven personalization is moderately favorable, as reflected in both the descriptive statistics and frequency distribution. All items have mean scores above the neutral midpoint of 3, ranging from 3.291 (AIDP1) to 3.484 (AIDP3), suggesting a generally positive orientation. Median and mode values for AIDP2, AIDP3, AIDP4, and AIDP5 are mostly 4, reinforcing this pattern, while AIDP1 and AIDP4 show more neutral central tendencies. The frequency matrix further supports these observations. For example, AIDP3 shows the highest level of support, with 153 respondents agreeing (96 Agree + 57 Strongly Agree) compared to only 54 disagreeing (31 Disagree + 23 Strongly Disagree). Similarly, AIDP2 has 146 in agreement (97 + 49) and 57 in disagreement (38 + 19). AIDP5 and AIDP4 follow this trend, with 137 (90 + 47) and 136 (85 + 51) in agreement, versus 54 (33 + 21) and 70 (37 + 33) in disagreement, respectively. AIDP1, while still leaning positive with 128 in agreement (83 + 45), shows relatively higher neutrality (83 neutral responses) and disagreement (64: 35 Disagree + 29 Strongly Disagree) compared to other items. Overall, the results suggest that Gen Z generally perceives AI-driven personalization in marketing as beneficial, though some reservations are present in the form of neutrality and modest disagreement levels in a few items.

4.4 Gen Z's Trust Level 4.4 Toward AI-Driven Marketing

Indicated in both the descriptive statistics and frequency matrix, Generation Z exhibits a generally neutral but cautious attitude toward AI-driven marketing. Across six trust-related items (TL1 to TL6), the most frequent response (mode) and the middle value (median) are consistently "Neutral" for five out of six items. The average ratings (means) also cluster close to 3 on a 5-point Likert scale, reinforcing this neutrality.

Specifically, TL1 (mean = 2.880) and TL6 (mean = 2.916) indicate a slight tendency toward distrust. For example, in TL1, a combined 105 respondents (38.2%) selected "Disagree" or "Strongly disagree," suggesting skepticism toward that statement. TL2 and TL3 show means slightly above 3, reflecting ambivalence, with a balance between those who agreed, disagreed, or remained neutral. TL4 (mean = 3.305) represents the most positive perception of trust, with 117 respondents (42.5%) agreeing or strongly agreeing, and fewer expressing disagreement. This item signals a modest upward shift in trust. TL5 reveals a more complex pattern—despite a mode of "Agree," the median is "Neutral," and the mean is 3.007. This item had the most polarized responses, with 103 respondents disagreeing ('strongly disagree +disagree response') and 111 agreeing ('strongly agree + agree'), indicating that opinions are divided.

In sum, while Gen Z does not strongly trust or distrust AI in marketing, their views are balanced with subtle shifts of caution or skepticism.

4.5 Gen Z's Attitude Towards (AT) AI-Driven Marketing

The analysis of Gen Z's attitude toward AI-driven marketing based on items AT1, AT2, AT4, AT5, and AT6 shows a moderately positive orientation. Descriptive statistics indicate that the mean values for all five items are above the neutral midpoint (3), ranging from 3.069 (AT4) to 3.404 (AT6). AT1 and AT6 stand out with higher mean scores (3.360 and 3.404, respectively), as well as medians and modes at 4, suggesting a stronger leaning toward agreement. The other items (AT2, AT4, and AT5) have means slightly above 3, with medians mostly at 3, reflecting a more mixed perception.

The frequency matrix reinforces this trend. For AT1, 143 respondents (Agree + Strongly Agree) expressed agreement, compared to only 59 who disagreed, and 73 who remained neutral—showing a clear positive tilt. Similarly, AT6 received 138 agreement responses, outweighing 53 disagreements and 84 neutrals. AT5 also shows stronger support, with 137 in agreement and only 59 in disagreement. AT2 follows the same pattern: 131 agreed while 55 disagreed, though 89 remained neutral, indicating a slightly more reserved stance. In contrast, AT4 reflects more balanced sentiment, with 108 agreements and 83 disagreements, and 84 neutral responses—suggesting greater ambivalence.

In summary, the findings suggest that Gen Z holds a cautiously favorable attitude toward AI-driven marketing, especially on dimensions captured by AT1, AT5, and AT6, which may relate to perceived usefulness or relevance. However, the relatively high levels of neutrality across items—particularly AT2 and AT4—indicate ongoing uncertainty or conditional acceptance, pointing to a need for trust, transparency, and value alignment in AI-driven marketing efforts targeting this cohort.

4.6 Gen Z's Ethical Concerns Towards AI-Driven Marketing

Gen Z demonstrates a predominantly neutral stance toward ethical concerns in AI-driven marketing. Across all six items (UC1–UC6), both the mode and median consistently register at "Neutral" (3.000), indicating it as the most frequent and central response. Mean scores range slightly above the midpoint (3.247 to 3.389), indicating a modest lean toward agreement, but not a strong endorsement. Frequency data further support this interpretation: the "Neutral" category consistently holds the largest share of responses, especially in items like UC6, where 114 out of 275 respondents selected neutrality. While positive ("Agree" and "Strongly agree") and negative ("Disagree" and "Strongly disagree") responses are present, they remain secondary to the dominant neutral pattern. Overall, these findings reveal a cautious and ambivalent attitude among Gen Z—neither rejecting nor fully embracing ethical concerns in AI-driven marketing—which presents an opportunity for marketers to build credibility through transparent and responsible practices.

4.7 Gen Z's Intention Towards AI-Driven Marketing

The analysis of Gen Z's intentions toward AI-driven marketing reveals a generally positive yet cautious outlook. Descriptive statistics show that the median response for all five items (UI1–UI5) is consistently "Neutral" (3.000), indicating a central tendency of ambivalence. The mean scores for all items fall slightly above the neutral midpoint, ranging from 3.258 to 3.335, which suggests a mild inclination toward agreement but not a strong or definitive commitment. The mode is "Neutral" for UI1, UI3, and UI5, while for UI2 and UI4 it shifts to "Agree," indicating that intentions vary slightly depending on the specific issues. At the same time, the frequency matrix in Table 10 reinforces these findings: in each item, the "Positive" category (Agree + Strongly Agree) accounts for the largest share of responses, ranging from 42.5% to 46.9%. However, the "Neutral" segment remains significant—between 30.9% and 35.6%—with UI3 showing "Neutral" as the most frequent single response. These patterns indicate that while Gen Z is generally open to

AI-driven marketing, many still hold back from fully embracing it. Overall, Gen Z appears receptive but not fully committed, presenting marketers with an opportunity to engage this audience further by clearly demonstrating benefits, fostering trust, and addressing underlying hesitations.

4.8 Correlation analysis

The correlation analysis in Table 6 indicates that Gen Z's intention is moderately correlated with awareness level (r = 0.416), strongly correlated with AI-driven personalization (r = 0.668), Gen Z trust level (r = 0.577), and with Gen Z attitude (r = 0.734), all at a statistically significant level ($p < .001$). Gen Z concern shows a weak but significant negative correlation (r = -0.260), suggesting that higher concern is slightly associated with lower intention. In contrast, age (r = 0.062, p = 0.303) and gender (r = -0.051, p = 0.395) exhibit very weak and non-significant correlations, indicating they have little to no association with Gen Z's intention in this study.

Table 6. Correlation statistics

Correlation	**Pearson's r**	**P-value**
	Gen_Z_Intention	
Gen_Z_awareness_level	0.416	< .001
AI_Driven_personalization	0.668	< .001
Gen _Z_Trust_level	0.577	< .001
Gen_Z_Attitude	0.734	< .001
Gen_Z_concern	-0.260	< .001
Age	0.062	0.303
Gender	-0.051	0.395

4.8.1 Multiple Regression

4.8.1.1 Multicollinearity test

The multi-collinearity test in Table 7 shows that there is no multicollinearity problem since it fulfilled the standard, where there are no VIFs more than 10 and tolerance values less than 0.1.

Table 7. Multicollinearity test coefficients

	Tolerance	VIF
Gen_Z_awareness_level	0.808	1.237
AI_Driven_personalization	0.634	1.577
Gen _Z_Trust_level	0.742	1.347
Gen_Z_Attitude	0.612	1.633
Gen_Z_concern	0.939	1.065
Age	0.981	1.020
Gender	0.966	1.035

4.8.1.2 Normality test

To assess whether the residuals met the assumption of normality, a Q-Q plot was examined. As shown in the plot, the residuals closely follow the diagonal reference line, indicating that the observed quantiles align well with the theoretical quantiles of a normal distribution. While minor deviations are observed at the tails, the overall pattern supports the assumption of normality. This suggests that the residuals are approximately normally distributed, and the normality assumption for linear regression is reasonably satisfied.

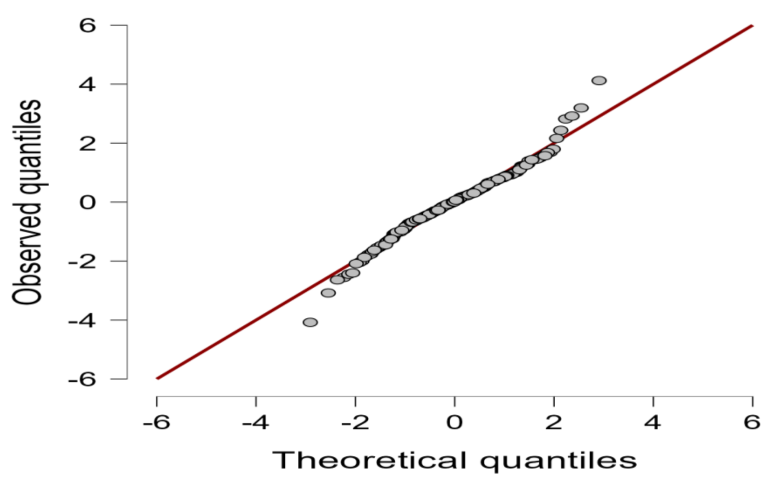

Figure 2. Q-Q plot

4.8.1.3 Test of independence

As indicated in Table 8, the Durbin-Watson statistic is 2.218, which is close to the ideal value of 2, indicating no serious autocorrela**tion** in the residuals.

Table 8. Durbin-Watson statistic

Autocorrelation	Statistic	p
0.101	1.797	0.091
-0.110	2.218	0.079

4.8.1.4 Heteroscedasticity test

The assumption of equal variance of the population error terms (ε), estimated from the sample residuals (e), is essential for the proper application of linear regression. As shown in the scatter plot of residuals versus predicted values, the spread of residuals remains fairly constant across all levels of predicted values, indicating that heteroscedasticity is not present in the data.

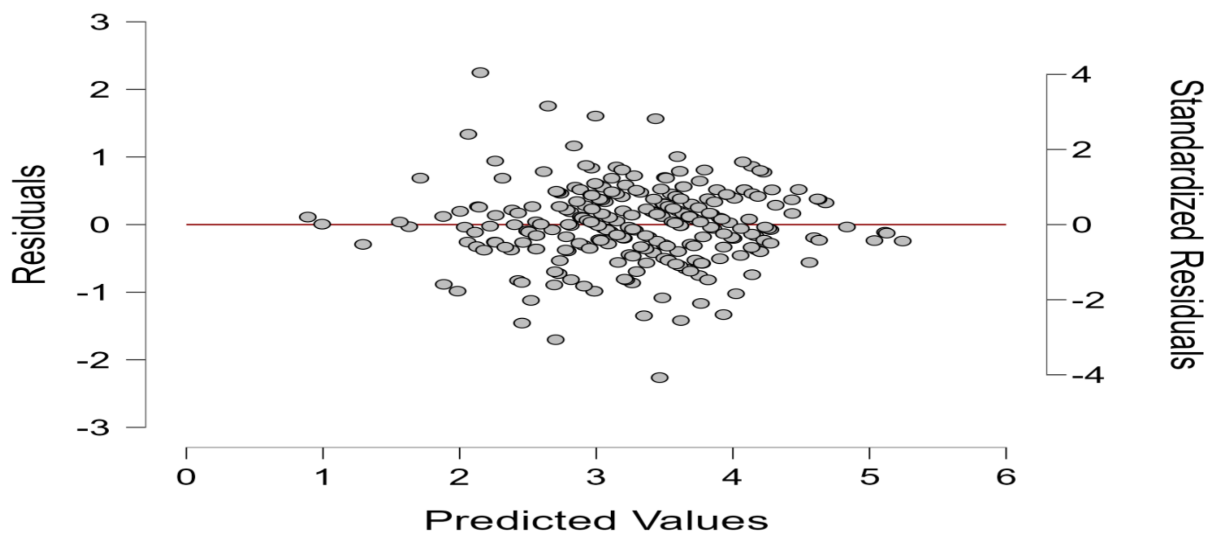

Figure 3. Residuals vs. predicted plot

4.8.2 Regression results

4.8.2.1 Model Summary

The multiple regression model (M_1), which includes Gen Z awareness level, AI-driven personalization, trust level, attitude, concern, age, and gender, explains approximately 62.5% of the variance in Gen Z intention ($R^2 = 0.625$, Adjusted $R^2 = 0.611$), indicating a strong model fit, as shown in Table 9. Also, the standard error of the estimate (RMSE = 0.566) suggests a relatively good prediction accuracy.

Table 9. Model summary

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.907
M_1	0.790	0.625	0.611	0.566

4.8.2.2 *ANOVA*

The ANOVA result in Table 10 shows that the overall regression model (M_1), which includes Gen Z awareness, AI-driven personalization, trust, attitude, concern, age, and gender, is statistically significant ($F(10, 264) = 43.951$, $p < .001$). This indicates that the predictors collectively explain a substantial portion of the variance in Gen Z intention. The regression sum of squares (140.791) notably exceeds the residual sum of squares (84.569), confirming the model's explanatory strength.

Table 10. ANOVA statistics

Model		df	Mean Square	F	p
M_1	Regression	10	14.079	43.951	< .001
	Residual	264	0.320		
	Total	274			

4.8.2.3 Regression Coefficient

The Standardized and unstandardized value in Table 11 below indicates the effect of changes in the independent variables on the dependent variables.

Table 11. Regression Coefficient

Model		Unstandardized	Standard Error	Standardized[a]	t	p
M_0	(Intercept)	3.289	0.055		60.149	< .001
M_1	(Intercept)	0.728	0.387		1.882	0.061
	Gen_Z_awareness_level	0.120	0.051	0.109	2.337	0.020

Model		Unstandardized	Standard Error	Standardized[a]	t	p
	AI_Driven_personalization	0.225	0.058	0.229	3.848	< .001
	Gen _Z_Trust_level	0.121	0.046	0.133	2.611	0.010
	Gen_Z_Attitude	0.464	0.069	0.413	6.701	< .001
	Gen_Z_concern	-0.158	0.043	-0.149	-3.700	< .001
	Age (18-21)	0.022	0.336		0.066	0.947
	Age (22-25)	0.114	0.336		0.341	0.734
	Age (26-28)	0.012	0.351		0.035	0.972
	Age (Over 28)	-0.167	0.362		-0.460	0.646
	Gender (Female)	-0.080	0.071		-1.124	0.262

[a] Standardized coefficients can only be computed for continuous predictors.

4. 9 Gen Z awareness level and behavioral intention towards AI-driven marketing

The regression result indicated in Table 11 reveals a positive and statistically significant relationship between Gen Z's awareness level and their behavioral intention to engage with AI-driven marketing ($\beta = 0.109$, $p = 0.020$). This suggests that as Gen Z consumers gain more awareness about AI-driven marketing practices, such as how these systems work and their benefits, their likelihood of interacting with AI-powered marketing initiatives increases. Awareness plays a critical role in shaping behavioral intention by reducing uncertainty and fostering informed decision-making. Previous studies confirmed that consumers with higher awareness of AI systems are more likely to understand and appreciate the personalized and efficient experiences these technologies offer (Bowden & Mirzaei, 2021). However, awareness also influences behavioral intention through a dual lens: while higher awareness can enhance engagement by showcasing the benefits of AI-driven marketing, it may also increase scrutiny of ethical issues such as data privacy and manipulation (Haleem et al., 2022). Gen Z, known for its digital literacy, often critically evaluates AI systems, balancing their utility against potential ethical concerns. In conclusion, Gen Z's awareness level significantly influences their behavioral intention toward AI-driven marketing.

4.10 Gen Z Perception of AI-Driven Personalization and Behavioral intention towards AI driven marketing

As of Table 11, the regression analysis indicates a positive and statistically significant effect between Gen Z's perception of AI-driven personalization and their behavioral intention toward AI-driven marketing ($\beta = 0.229$, $p < .001$). AI-driven personalization enables marketers to deliver content, advertisements, and product recommendations that align with the individual preferences, habits, and expectations of consumers(Vallabhaneni, Perla, Regalla, & Kumari, 2024; Vashishth, Sharma, Kumar, Chaudhary, & Panwar, 2024) . Hence, the finding shows, when Gen Z perceives these personalized experiences as relevant, useful, and non-intrusive, they are more likely to engage with AI-powered marketing initiatives. Similarly, the previous research by Virender Kumar et al. (2021) found that personalization fosters stronger emotional connections with brands, which can significantly boost purchase intentions. Even a recent study revealed that AI-based personalization significantly improves trust and satisfaction, with satisfaction acting as a significant mediator for purchase intent(Sipos, 2025). Moreover, another related study revealed that AI-driven personalization enhances purchase intention through tailored recommendations that align better with consumer preferences. Therefore, Gen Z's perception of AI-driven personalization would determine intention to engage in the AI-driven marketing practice of brands.

4. 11 Gen Z trust level and Behavioral intention towards AI-driven marketing

As the regression results revealed in Table 11, a positive and statistically significant effect between Gen Z's trust level and their behavioral intention to engage with the AI-driven marketing practice of the brand is confirmed ($\beta = 0.133$, $p = 0.010$). This result is consistent with the literature. When Gen Z trusts that AI-based systems are ethical, transparent, and secure, they are more likely to exhibit favorable behavioral intentions (Hoff & Bashir, 2015), such as engaging with AI-powered recommendations, personalized offers, and interactive advertisements. Similarly, trust levels can significantly impact consumers' willingness to interact with and respond positively to utilize any technology (Loh et al., 2021; Narteh et al., 2017). Moreover, a study by Shankar et al. (2021) supports this, emphasizing that trust in AI systems is built through consistent positive experiences, transparent data usage, and ethical practices. When these systems function transparently and align with user expectations, they foster trust, increasing the likelihood of continued engagement (Virender Kumar et al., 2021). Therefore, in general, trust acts as a foundation for Gen Z's willingness to engage with AI-driven marketing.

4. 12 Gen Z attitude and Behavioral intention towards AI-driven marketing

Once again, the regression result in Table 11 reveals a positive and statistically significant effect of Gen Z's attitude toward AI-driven marketing on their behavioral intention ($\beta = 0.413$, $p < .001$), where it is the strongest predictor. A positive attitude aligns with the theory of planned behavior, which posits that attitudes significantly influence behavioral intentions (Kan & Fabrigar, 2017), especially when the target population views the technology as innovative and beneficial. Positive attitudes influence the purchasing or usage intention positively, while a negative attitude can have a negative influence on their usage or purchasing intention (Smith et al., 2008). Similarly, Kotler and Keller (2016) said that favourable consumer attitudes can lead to higher brand engagement, trust, and loyalty. Additionally, research by Shankar et al. (2021) showed that positive attitudes toward AI's capabilities can significantly increase trust and subsequent usage intention.

4.13 Gen Z ethical concerns and Behavioral intention towards AI-driven marketing

As shown in Table 11, Gen Z's ethical concerns have a negative influence on the behavioral intention of engaging with AI-driven marketing practices of brands ($\beta = -0.149$, $p < .001$). It means ethical concerns, particularly violations of privacy, algorithmic manipulation, and lack of transparency, reducing their willingness to engage with AI-enabled advertisements, recommendations, and platforms. Similarly, a previous study has shown that when users feel their data is being exploited or their autonomy is compromised, their perception of the brand deteriorates, leading to lower behavioral intention(Wirtz, Tarbit, Hartley, & Kunz, 2022). For instance, targeted ads based on invasive data collection may be perceived as intrusive, causing users to avoid interacting with such marketing campaigns (Shankar, 2018)

The regression analysis in Table 11 shows that Gen Z's demographic characteristics, such as age and gender, did not significantly influence behavioral intention toward AI-driven marketing. The collected data from 275 samples suggests that age groups/ categories among Gen Z do not show a significant difference in intention to utilize AI-driven marketing(all $p > 0.05$). However, prior studies had different results. Younger individuals, who have grown up in a digital-first environment, are more open to adopting and interacting with AI technologies (Malaquias & Hwang, 2019). Older groups may exhibit more skepticism or resistance due to concerns about privacy and unfamiliarity with the intricacies of AI systems (Q. Wang & Sun, 2016). Another showed that as consumers are young, they become more cautious about adopting new technologies, including AI-powered marketing initiatives (Haleem et al., 2022). Nonetheless, the current study did not show that; this might be due to age categories in the same generation(Gen Z) are not significantly different since they have grown up more or less in the same technological innovation. Gender also has no significant effect on intention (β = -0.080, p = 0.262), suggesting intention does not differ significantly between males and females in the context of Gen Z. On the contrary, a previous study showed, male consumers often display greater confidence in engaging with new technology, while female consumers are more likely to evaluate ethical concerns, such as privacy and security (Chu, Deng, & Cheng, 2020). This latter influence differs in its intention.

Overall, the results of the correlation and multiple regression analyses provide strong empirical support for the proposed conceptual framework. As summarized in Table 12, most of the hypothesized relationships between Gen Z's cognitive, attitudinal, and perceptual factors and their intention to engage in AI-driven marketing were statistically supported. Specifically, awareness level, attitude, trust, and perception of AI-driven personalization exhibited significant positive effects on behavioral intention, while ethical concerns showed a significant negative effect. In contrast, demographic characteristics such as age and gender did not demonstrate a significant influence on intention. The table below presents a consolidated overview of the hypothesis testing results, indicating whether each hypothesis was supported or not supported.

Table 12. Summary of the hypothesis results

Hypothesis	Relationship	Result
H1	Ethical concerns → Intention	Supported (–)
H2	Attitude → Intention	Supported (+)
H3	Awareness → Intention	Supported (+)
H4	Trust → Intention	Supported (+)
H5	AI personalization → Intention	Supported (+)
H6	Age & Gender → Intention	Not supported

5. CONCLUSION

Based on the descriptive analysis, the study concludes that Generation Z demonstrates a high level of awareness regarding AI-driven marketing, indicating familiarity with its presence and functions. However, their stance on ethical concerns remains predominantly neutral, suggesting uncertainty or limited engagement with the ethical implications of AI in marketing. Trust levels are also cautious. Gen Z neither fully trusts nor completely distrusts AI applications in marketing, reflecting a balanced but hesitant outlook. Despite this caution, their perception of AI-driven personalization is largely positive, with many respondents recognizing its relevance and usefulness. Moreover, their intention to engage with AI-driven marketing is generally favorable, although not absolute, pointing to openness accompanied by careful evaluation.

In contrast, the inferential analysis reveals that all examined variables—except demographic characteristics—significantly influence Gen Z's behavioral intention toward AI-driven marketing. Specifically, ethical concerns, perception of AI-driven personalization, attitude, trust level, and awareness were found to be significant predictors. Positive effects were observed for perception, attitude, trust, and awareness, where higher levels of each corresponded to stronger behavioral intention. Among these, attitude emerged as the most critical driver. Trust also played a major role, indicating that transparent and reliable AI practices enhance consumer confidence and willingness to engage. Awareness contributed by reducing uncertainty and increasing familiarity, thereby promoting greater acceptance. Conversely, ethical concerns negatively influenced behavioral intention, underscoring Gen Z's sensitivity to privacy and data usage. If not addressed transparently, such concerns may deter engagement. On the other hand, demographic factors such as age and gender were found to have no statistically significant effect.

5.1 Recommendations

Based on the study's findings, the following recommendations are proposed:

Enhance transparency in AI-driven marketing: Address ethical concerns by ensuring transparency in how consumer data is collected, stored, and used. Organizations should clearly communicate their data privacy policies and comply with ethical standards to build trust among Gen Z consumers.

Focus on personalization strategies: Given the significant influence of AI-driven personalization on behavioral intention, marketers should leverage AI to create tailored and engaging content. Personalized recommendations, offers, and experiences should be aligned with the preferences of Gen Z to enhance their intention to interact with AI-driven marketing.

Foster trust through reliable AI practices: Organizations must invest in building reliable and trustworthy AI systems by minimizing biases and ensuring consistent performance. Trust-building efforts, such as using secure AI technologies and involving ethical AI audits, can significantly improve consumer acceptance.

Raise awareness about AI marketing: Educate Gen Z consumers about the benefits and workings of AI-driven marketing to reduce uncertainty and promote positive perceptions. Campaigns or educational programs can bridge the knowledge gap and encourage informed engagement with AI technologies.

5.2 Further research area

Future studies could expand on the current research by exploring the mediating and moderating roles of the studied variables. For instance, researchers could investigate how awareness moderates the influence of personalization on Gen Z's behavioral intention. Incorporating additional variables, such as digital literacy, cultural differences, or the role of AI transparency, would enrich the understanding of factors influencing AI-driven marketing acceptance. Furthermore, studies could extend the scope to include other generational cohorts, such as Millennials or Baby Boomers, to understand intergenerational differences in AI adoption. Comparative studies between Gen Z and Millennial consumers could reveal unique behavioral patterns and provide insights into generational shifts in marketing perceptions. Cross-country comparisons could also examine how cultural and regional factors shape perceptions of AI-driven marketing.

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How to cite this article:

Dessie, T. S. (2025). Assessing Gen Z Consumers' Perceptions, Ethical Concerns, and Behavioral Intention Towards AI-Driven Marketing: Case of Anadolu and Woldia University Students. *International Journal of Marketing, Communication and New Media*, *Vol 13, Nº 25*, pp. 281-318. https://doi.org/10.54663/2182-9306.2025.v.13.n.281-318