The Relationship between The Artificial Intelligence Marketing Elements and Brand Equity in Online Mobile Shopping: The Mediating Role of Brand Awareness: Applied Study on Egyptian Mobile Shopping Users

submitted by

Amany Atef Elbeheri
Business Management Lecturer
Faculty of Commerce, Tanta University

Wegdan Mahmoud Haggag
Business Management Lecturer
Faculty of Commerce, Tanta University

Raya International Journal of Business Sciences

volume (4), issue (15), october 2025

https://www.rijcs.org/

Publisher

Raya Higher Institute of Management and Foreign Trade in New Damietta

العلاقة بين عناصر التسويق باستخدام الذكاء الاصطناعي وقيمة العلامة التجارية: الدور الوسيط للوعي بالعلامة التجارية: دراسة تطبيقية على مستخدمي الهواتف المحمولة في الشراء في مصر

إعداد

اماني عاطف البحيري

مدرس بقسم إدارة الأعمال

كلية التجارة جامعة طنطا

وجدان محمود حجاج

مدرس بقسم إدارة الأعمال

كلية التجارة جامعة طنطا

مجلة راية الدولية للعلوم التجارية

دورية علمية محكمة

المجلد (٤) ـ العدد (١٥) ـ أكتوبر ٢٠٢٥

https://www.rijcs.org/

معهد راية العالي للإدارة والتجارة الخارجية بدمياط الجديدة

المنشأ بقرار وزير التعليم العالي رقم ٤٨٩٠ بتاريخ ٢٢ أكتوبر ٢٠١٨ بجمهورية مصر العربية

ABSTRACT

The research aimed to investigate how the elements of AI marketing contributes to building brand equity through the mediating role of brand awareness. The study applied on mobile shopping users. Based on an online questionnaire, which was developed and uploaded on google form; 348 mobile shoppers answered this survey. Data was collected and analyzed using Partial Least Squares (PLS), which is one of the structural equation modeling methods. Smart Pls v4 was used to test the model and hypotheses. The research confirmed the significant impact of elements of AI marketing on brand awareness and brand equity. Additionally, the brand awareness was confirmed to having a mediating role between elements of AI marketing and brand equity. The study focused on big data and analytics, machine learning and AI platform as the elements of AI marketing

Keywords: Artificial Intelligent, Big Data and Analytics, Machine Learning, AI Platform, Brand Awareness, Brand Equity, Mobile Shopping.

1. Introduction:

Recent advancements in mobile commerce have significantly transformed consumer behavior, particularly in how individuals engage with and purchase from businesses. Mobile devices have emerged as a dominant platform due to their convenience and accessibility, enabling users to efficiently search for, evaluate, and compare products and services (Lee, 2018). Concurrently, the integration of artificial intelligence (AI) within business operations has introduced innovative approaches for data analysis, allowing firms to extract actionable insights and deliver highly personalized experiences to targeted consumer segments (Latif et al., 2020).

The global market for artificial intelligence (AI) in marketing was valued at approximately \$6.5 billion in 2020 and is projected to reach \$107.4 billion by 2027 (Grand View Research, 2023). In the context of Egypt, AI adoption is progressing rapidly, with 36% of the population reported to have access to AI technologies. The number of AI specialists in Egypt is anticipated to grow substantially, reaching an estimated 30,000 by the year 2030. Consequently, it is projected that

26% of the Egyptian workforce will benefit from AI-driven tools and applications. Additionally, AI is expected to enhance productivity through improved consumption efficiency, potentially contributing to a global GDP increase of up to 14% by 2030. Reflecting this growing interest, the proportion of AI-related academic publications in 2024 has risen significantly, accounting for approximately 6.3% to 17.5% of total research output (Egypt National Artificial Intelligence Strategy, 2025).

In the context of mobile e-commerce in Egypt, mobile sales have experienced a marked increase, accounting for over one-third of all online transactions conducted by Egyptian consumers within the year. Android devices dominate the market, with 95% of users operating on this platform, while iOS users constitute the remaining 5%. By 2024, approximately 2.9% of the population utilized mobile phones for purchasing goods. Notably, a higher proportion of women (3.7%) engaged in mobile-based online shopping compared to men (2.2%) in the same year. Furthermore, around 1.5% of the adult population reported using mobile applications to pay household bills (Galal, 2024).

Artificial intelligence (AI) has played a pivotal role in enhancing the mobile shopping experience by enabling greater personalization and streamlining the overall purchasing process (Vassakis et al., 2018). Through the analysis of extensive user data—including browsing history, purchasing behavior, and demographic information—AI facilitates the delivery of highly tailored product recommendations. These personalized suggestions increase the relevance of offerings and improve the likelihood that users will discover products aligned with their individual preferences and needs (Latif et al., 2020). Moreover, mobile shopping platforms utilize AI to forecast consumer behavior and preferences. By identifying and interpreting shopping patterns, retailers can anticipate customer demands and optimize both inventory management and marketing strategies accordingly (Lee, 2018).

Customer interaction with AI-driven interfaces has been shown to facilitate brand recognition and recall (Ameen et al., 2021; Hollebeek et al., 2014; Sung et al., 2021). AI technologies contribute to the development of brand awareness by enabling the creation of distinctive and engaging brand experiences. Such awareness is considered a key component of brand equity, which is closely associated with enhanced financial performance and competitive advantage in the marketplace. Furthermore, increased brand awareness contributes to higher levels of perceived product quality and customer loyalty (Eslami, 2020; Yoo et al., 2000). By aligning brand messaging with customer expectations, AI supports the reinforcement of brand awareness and the cultivation of brand equity.

Artificial intelligence (AI) equips marketers with powerful tools for real-time analysis of large-scale data, enabling the extraction of valuable insights into consumer behavior, preferences, and purchasing patterns (Liu & Lu, 2023). For instance, AI algorithms can process information from social media content, online reviews, and browsing histories to detect emerging trends, thereby offering marketers actionable intelligence to design more effective and targeted campaigns. Additionally, AI facilitates the implementation of personalized marketing strategies through advanced analysis of individual consumer data. By leveraging machine learning techniques, marketers can deliver highly customized content, offers, and product recommendations that align with users' historical behaviors and interactions (Sheth, 2019).

Personalized marketing strategies enabled by artificial intelligence (AI) significantly support the development of brand awareness, which in turn contributes to strengthening brand equity. According to McKinsey & Company (2020), organizations that implement personalized brand experiences report that approximately 80% of their customers are more likely to make a purchase, driven by brand awareness aligned with individualized preferences and recommendations. This highlights the strategic value of personalization in enhancing brand equity. Recent empirical studies have investigated the influence of AI-driven marketing on various brand-related outcomes, including brand experience and consumer preference (Alkaied et al., 2024; Ho & Chow, 2024), brand image and loyalty (Zhu et al., 2025; Curan, 2024; Weliweriya & Balalle, 2024), and overall brand management (Agersborg et al., 2020). Jelonek et al. (2024) further examine the transformative role of AI and machine learning in brand management, emphasizing the use of AI components—such as big data analytics, machine learning algorithms, and AI platforms—to forecast impacts on brand equity, mediated through enhanced brand awareness. AI technologies encompass a broad array of tools, including predictive analytics, machine learning, and data-driven decision-making systems (Smith, 2020).

A review of the existing literature reveals that many studies tend to conceptualize artificial intelligence (AI) in broad terms, often without disaggregating the specific AI components—such as big data analytics, machine learning models, and AI platforms—that may contribute uniquely to enhancing marketing strategies. Prior research has primarily focused on AI from the perspective of its general applications (Yin & Qin, 2021; Paschen et al., 2019), AI-enabled consumer engagement strategies (Tadimarri et al., 2024), AI-driven marketing efforts (Ho & Chow, 2024), and AI-related marketing activities (El Fawal et al., 2024). However, there remains a notable gap in the application of advanced data analytics, particularly machine learning techniques, for predicting brand equity outcomes derived from the integration of specific AI features.

Existing research on artificial intelligence (AI) has predominantly focused on sectors such as video-on-demand (VOD) services, wireless communications, logistics service providers, and retail banking (El-Nawla & Ibrahim, 2024; Kandeel & Zoghaib, 2024; Ho & Chow, 2024; Switała et al., 2018). In Egypt, notable implementations of AI include companies such as Fawry and Jumia, which have utilized AI technologies to optimize marketing strategies and deliver personalized services tailored to customer needs (Ali et al., 2022). Al-Qazzaz (2024) explored the use of specific AI tools—including predictive analytics, automated email marketing, and AI-powered chat functions—to enhance customer engagement and improve marketing efficiency. Despite these advancements, a gap persists in the integration of core AI components (e.g., big data analytics, machine learning, and AI platforms) into marketing strategies within the Egyptian context, particularly in the mobile commerce sector. There is a critical need for further research that examines how AI can be effectively leveraged to increase engagement among mobile shoppers in Egypt, thereby contributing to greater brand awareness and improved brand equity. The adoption of AI in marketing represents a strategic approach to customizing consumer experiences and shaping the future landscape of Egyptian businesses. This research identifies mobile shopping as a practical domain where AI can significantly enhance the consumer experience.

Based on the above, the research objectives can be presented as follows:

(1) To explore the impact of the elements of AI marketing (Big Data and analytics, machine learning and AI platform) on brand awareness.

(2) To explore the impact of brand awareness on brand equity.

(3) To explore the impact of elements of AI marketing on brand equity.

(4) To investigate the mediation role of brand awareness in the relationship between elements of AI marketing and brand equity.

(5) To provide practical recommendations for online mobile marketers to improve brand equity.

The paper is structured comprising seven sections. Section two presents the theoretical background, and section three details the hypotheses development and proposed model. Section four outlines the research methodology that represents data collection, data analysis and study hypothesis results. Section five displays the discussion. Section six concludes the recommendations. Finally, section seven shows the limitation of the paper.

2. Literature Review:

Customer – Based Brand Equity Model (CBBE):

Brand equity is a fundamental concept closely associated with brand management, as it not only reflects perceptions of product quality but also serves to reduce consumer uncertainty (Hazee et al., 2017). Furthermore, brand equity contributes to value creation by fostering customer trust and enhancing the efficiency and effectiveness of marketing programs (Yoo & Donthu, 2001). The literature generally categorizes brand equity into two main dimensions: financial-based brand equity and consumer-based brand equity (CBBE). Financial-based brand equity primarily concerns the monetary valuation of the brand, while consumer-based brand equity focuses on the brand's impact on consumer responses (Marques et al., 2020). Similarly, Zeugner Roth et al. (2008) describe these dimensions, emphasizing that from a consumer perspective, brand equity encompasses constructs such as perceived quality, brand awareness, brand preference, and loyalty.

Consumer-based brand equity (CBBE) is broadly defined as the value a brand creates from the customer's perspective, which may result from either direct or indirect interactions with the brand (Kim et al., 2021). Aaker (1991) conceptualized CBBE as "a set of brand assets and liabilities linked to a brand, its name and symbol, which add to or subtract from the value provided by a product or service to a firm and/or to that firm's consumers." Keller (2008) argued that CBBE influences customer reactions to brand marketing activities. Likewise, Zhang et al. (2021) viewed CBBE as the extent of consumer attachment to a brand, comprising associations and beliefs about the brand. This perspective suggests that customer value creation emerges from consumer perceptions, knowledge, and behaviors (Wang & Sengupta, 2016). According to Ray et al. (2021), consumers exhibit more favorable responses to specific marketing efforts, such as brand promotion, when the brand possesses strong brand equity relative to competitors within the same category.

Brand equity is fundamentally linked to customers' feelings and experiences with a brand. Within the CBBE framework, brand awareness is considered the foundational element for building brand equity. Components of AI marketing——such as big data and analytics (BIGD), machine learning (MALE), and AI platforms (AIP)——have the potential to directly enhance brand awareness, thereby fostering the creation of brand equity. Recent studies (El Fawal et al., 2024; Yuan et al., 2023; Cheng & Jiang, 2022) have employed the CBBE framework to investigate how AI technologies applied in customer service, marketing, and personalization contribute to strengthening brand equity through the development of brand knowledge and awareness.

Artificial Intelligence (AI):

Intelligence can be defined as the capacity to perceive and process data, transforming available information into actionable knowledge, and most importantly, interpreting this knowledge to guide purposeful behavior. Effective adaptation of intelligence involves multiple cognitive processes, including environmental perception, problem-solving strategies, reasoning, learning mechanisms, memory retention, and goal-directed actions (Paschen et al., 2019).

Artificial intelligence (AI) is commonly described as the interdisciplinary field within computer science focused on the design and development of intelligent systems that enhance technological capabilities (Mahto et al., 2022). More specifically, AI encompasses analytical and algorithmic approaches that utilize computational models to address complex problems (Mahto et al., 2022). The discipline aims to embed advanced forms of intelligence into diverse computer systems.

From a rational perspective, an AI system is considered effective if it consistently performs the "right action" based on its current knowledge. This rational view posits that AI operates to optimize outcomes, either by achieving the best possible result or the best expected result under conditions of uncertainty (Sternberg, 2017).

Elements of AI Marketing (ELAI):

Artificial intelligence (AI) marketing represents an emerging and increasingly prominent concept within the contemporary business landscape (Conick, 2017). It can be defined as a strategic approach that leverages advanced technologies and marketing data to enhance the customer experience (Jain & Aggarwal, 2020). AI facilitates the analysis of vast datasets, thereby bridging the gap between data science and practical application—an endeavor that was previously infeasible (Thiraviyam, 2018). Core components of AI marketing include big data and analytics, machine learning algorithms, and AI platform solutions (Wirth, 2018).

Despite these advancements, marketers face challenges in effectively integrating AI into their operational and campaign strategies, particularly given that AI development and implementation tools remain in early stages of maturity (Jarek & Mazurek, 2019). Several researchers, including Gkikas and Theodoridis (2019), Ballamudi (2019), Schwab (2017), Park (2017), and Soni et al. (2020), have emphasized that progress in the digital marketing sector largely stems from the fusion of big data analytics with intelligent system methodologies.

Artificial intelligence (AI) facilitates marketers in achieving enhanced personalization and relevance in their communications, particularly across social media platforms such as Facebook, Instagram, YouTube, and Google Search, which collectively reach billions of users daily. The increasing adoption of AI-driven advertising presents significant opportunities to improve the customization capabilities of marketing tools (Dimitrieska et al., 2018).

Big data, as a critical component of AI, refers to the technological processes involved in the collection, processing, visualization, and analysis of large-scale datasets within timeframes that exceed the capacity of traditional information technologies (Jacobs, 2009). Hrehova (2018) highlights that the strategic value of big data resides in its ability to support informed decision-making processes through continuous monitoring and analysis.

Machine learning is widely recognized by researchers as a fundamental component of artificial intelligence (AI) (Collins et al., 2021; Copeland, 2016; Ongsulee, 2017). It is considered a subset of AI characterized by systems that learn from historical data to predict future outcomes (Koza et al., 1996). Machine learning comprises a range of techniques designed to address complex real-world problems by enabling computer systems to operate autonomously without relying solely on explicit programming instructions (Koza et al., 1996). For example, rather than programming a system with explicit rules to identify customer needs based on specific keywords, machine learning algorithms can be trained on accurately labeled datasets to infer customer intentions from various word combinations.

The evolution of AI has progressed from being a minor technological feature to becoming a critical technological infrastructure. Moreover, AI technologies have assumed a pivotal role within digital business platforms, driving innovation and operational efficiencies (Brynjolfsson et al., 2018; Brynjolfsson & McAfee, 2017; Varian, 2014).

Brand Awareness (BRAW):

Brand awareness (BRAW) is conceptualized as the extent of consumer exposure to a brand (Alba & Hutchinson, 1987). Ross (2006) further characterizes BRAW as the strength of a brand's presence within the consumer's cognitive framework. Additionally, BRAW facilitates consumers' ability to recognize or recall a brand as belonging to a specific product category (Romaniuk et al., 2017). One of the earliest conceptualizations by Rossiter and Percy (1987) defines BRAW as the capacity to identify a brand under varying conditions. Similarly, both Keller (1993) and Aaker

(1991) emphasize that BRAW encompasses two primary components: brand recognition and brand recall. Aaker (1991) specifically defines BRAW as "the ability of the potential buyer to recognize and recall that a brand is a member of a certain product category." Brand awareness is strongly associated with the prominence of a brand in consumers' minds, enabling brand identification and recognition across diverse market contexts (O'Guinn et al., 2009).

Based on the aforementioned definitions, brand awareness (BRAW) can be understood as the consumer's recognition of a brand's existence and its association with a specific product category. Kahneman (2012) posits that the mere appearance of a brand name can trigger brand recognition or the perception of familiarity, often leading consumers to think, "I know this brand." Many advertising strategies leverage this cognitive response by designing messages that emphasize brand visibility and familiarity.

The development of BRAW is a critical phase in the promotion of new products (Foroudi, 2019). Effective brand awareness initiatives typically emphasize product quality and the distinctiveness of the brand relative to competitors. Brands that successfully sustain elevated levels of awareness tend to achieve greater sales performance. Consumers generally demonstrate a preference for well-known brands over unfamiliar alternatives (Bilgin, 2018). Furthermore, in the absence of a strong brand-consumer relationship, customers are more inclined to switch to competing products (Shabbir et al., 2017).

Brand Equity (BREQ):

Brand equity (BREQ) has been a central focus in marketing research and remains a significant concern for many marketing practitioners. Aaker (1996) defines BREQ as "a set of brand assets and liabilities linked to a brand's name and symbol that add to or subtract from the value provided by a product or service to a firm and/or that firm's customers." In contrast, Keller (1993) introduced the concept of consumer-based brand equity (CBBE), offering an alternative perspective that emphasizes the influence of brand knowledge on consumer responses to marketing efforts, thereby focusing on the consumer's viewpoint rather than the company's. Furthermore, Christodoulides and Chernatony (2010) describe BREQ as a collection of consumer perceptions, knowledge, behaviors, and attitudes that enable a brand to command higher profit margins than similar products lacking brand association. Traditionally, BREQ is considered an intangible asset of a brand (Farquhar, 1989) and serves as a critical factor in enhancing product relevance and profitability. More recently, the value of BREQ has been conceptualized as the "added value" generated through the application of artificial intelligence technologies (Farquhar, 1989).

Customer-based brand equity (BREQ) is a multidimensional construct. Keller's (1993) conceptual framework emphasizes brand knowledge, brand image, and brand awareness (BRAW) as fundamental components of customer-based BREQ. In contrast, Aaker (1991) proposed a five-dimensional model comprising brand loyalty, brand associations, BRAW, proprietary brand assets, and perceived quality. Similarly, Lassar et al. (1995) identified five distinct dimensions of BREQ: product performance, perceived value, social image, emotional attachment, and trustworthiness. Ruta and Juozas (2010) also suggested a five-factor model, which includes brand image, perceived quality, brand loyalty, price perception, and BRAW. For the purpose of this study, brand awareness, brand knowledge, and brand image were employed as key indicators for measuring consumer-based brand equity.

3. Conceptual framework and Hypotheses development:

Elements of AI marketing and Brand Awareness:

In recent years, artificial intelligence (AI) has played a pivotal role in enhancing business performance through a range of tools and applications. One of the key contributions of AI lies in its ability to strengthen brand awareness (BRAW), thereby fostering greater customer engagement and loyalty. AI-driven algorithms provide powerful mechanisms for building BRAW by enabling personalized advertising strategies tailored to individual consumer needs and behavioral patterns (Hagan et al., 2021). These algorithms analyze consumer behavior, including personal preferences and historical purchasing data, to develop highly targeted advertisements that effectively enhance BRAW. Furthermore, AI contributes to optimizing the impact of advertising campaigns and improving the overall consumer experience by delivering content that is contextually relevant and engaging (Rajagopal, 2020).

As technological advancements continue to progress, the application of artificial intelligence (AI) in personalized advertising has become increasingly significant. This development enables marketers to deliver highly targeted messages by customizing content according to individual consumer profiles. The deployment of AI algorithms in personalized advertising serves as a powerful strategic tool, contributing to enhanced customer engagement and stronger brand commitment (Varsha et al., 2021).

The utilization of machine learning (MALE) for the generation of tailored content, combined with AI-based analysis of consumer data, supports businesses in fostering deeper customer interaction. This approach facilitates increased conversion rates and traffic, while simultaneously contributing to the enhancement of brand awareness (BRAW) among consumers (Laksamana et al., 2024; Hutter et al., 2013).

Machine learning algorithms (MALE) are capable of incorporating user demographic information, along with search and browsing histories, to derive insights into consumer behavior. Through the identification of patterns and emerging trends within consumer data, AI systems enable the generation of personalized content that aligns with individual user preferences and interests. This capability enhances the effectiveness of marketing strategies aimed at increasing brand awareness (BRAW) (Sadek et al., 2015). Furthermore, the integration of AI-powered predictive analytics offers businesses a valuable means to detect consumer interests, facilitating the development of more precisely targeted marketing campaigns designed to strengthen brand awareness (Ho & Chow, 2024). The strategic implementation of AI in marketing enables the delivery of customized and relevant messaging, thereby improving the efficiency of BRAW-oriented initiatives (Hutter et al., 2013). Hence, we propose the following hypothesis:

H_1: There is a positive impact of elements of AI marketing on brand awareness.

Brand awareness and brand equity:

Brand awareness (BRAW) is widely recognized as a foundational element in the development of brand equity (BREQ). Aaker (1991) emphasized that BRAW constitutes the initial stage in the formation of BREQ. Empirical studies by Tong and Hawley (2009) as well as

Bakhshizadeh and Aliasghari (2021) identify BRAW as a primary antecedent of brand equity. The transition from BRAW to BREQ occurs through multiple mechanisms: (1) establishing a cognitive brand node within the consumer's memory, (2) fostering a sense of familiarity with the brand, (3) building consumer trust, and (4) offering compelling reasons for brand consideration (Gil et al., 2007; Alhaddad, 2015). Further research conducted by Yasin et al. (2007) and Bernarto et al. (2020) also supports the premise that BRAW significantly contributes to the enhancement of BREQ. Additionally, findings from Mishra and Datta (2011) and Juntunen et al. (2009) demonstrate a positive correlation between brand awareness and brand equity. BRAW plays a critical role in shaping consumer decision-making processes, thereby strengthening BREQ (Dib & Alhaddad, 2014). Elevated levels of BRAW and BREQ present businesses with valuable opportunities to foster greater customer loyalty (Yoo et al., 2000). Hence, we propose the following hypothesis:

H_2: There is a positive impact of brand awareness on brand equity.

AI and brand equity:

In the context of digital transformation, brand equity is increasingly conceptualized as the "added value" generated through artificial intelligence (AI) technologies (Farquhar, 1989). Keller (1993) suggested that AI offers a suite of advanced tools—including predictive analytics, machine learning algorithms (MALE), and social media analytics—that can enhance brand equity (BREQ) by enriching brand knowledge. Additionally, AI enables firms to deliver distinct and personalized value propositions, thereby contributing to higher levels of BREQ (Rajagopal, 2020; Oh et al., 2020).

Empirical research has demonstrated that AI technologies exert a significant impact on the core dimensions of BREQ, specifically brand attitude, customer loyalty, and emotional attachment (Deryl et al., 2023; Ailawadi & Keller, 2004; Oh et al., 2020). The deployment of AI across social media platforms further facilitates the development and reinforcement of a brand's image, which in turn positively influences brand equity (Laksamana et al., 2024; Kuksov et al., 2013). Moreover, organizations increasingly utilize AI-driven big data (BIGD) tools to collect, analyze, and predict consumer perceptions, providing critical insights for strategic brand management (Dwivedi et al., 2023).

The advancement of artificial intelligence (AI) has introduced new opportunities for marketers to foster engagement with consumers. In response, numerous commercial and governmental entities have recognized the strategic significance of AI tools in generating value and expanding their customer reach, which in turn contributes to the enhancement of brand equity (BREQ) (Yu & Yuan, 2019; Reddy et al., 2023). Moreover, Ismail (2017) emphasized that organizations are increasingly adopting AI-driven marketing intelligence systems to facilitate proactive consumer interactions. These interactions play a critical role in strengthening customer loyalty and reinforcing BREQ. Hence, we propose the following hypothesis:

H_3: There is a positive impact of AI on brand equity.

The mediation role of brand awareness:

This study posits that brand awareness (BRAW) functions as a mediating variable in the relationship between artificial intelligence (AI) and brand equity (BREQ). BRAW is conceptualized as a consumer's internal response and behavioral reaction to brand-related stimuli, including product design, packaging, and customization (Koay et al., 2020). These stimuli can be significantly enhanced through AI applications, which serve as catalysts for increasing consumer BRAW. AI-supported marketing strategies have been shown to improve consumer memory, knowledge retention, and emotional engagement, thereby strengthening brand recognition and recall——two key components of BRAW that contribute to the development of brand equity (Beig & Khan, 2018).

Koay et al. (2020) further assert that elevated levels of BRAW are associated with increased brand satisfaction, loyalty, and equity. AI facilitates these outcomes by enhancing the consumer's interaction with the brand and by providing access to detailed, brand-specific information. According to Beig and Khan (2018), brands that employ AI to disseminate content and promote user interaction are more likely to improve BRAW, which, in turn, positively influences BREQ. Empirical findings from Chen and Lin (2019) and Varsha et al. (2021) indicate that AI-driven marketing activities significantly increase consumers' brand awareness, influencing their purchasing decisions. Their studies conclude that favorable consumer experiences with AI-enhanced brand interactions are predictive of higher consumer-based brand equity. Hence, we propose the following hypothesis:

H_4: Brand awareness significantly mediates the relationship between AI and brand equity.

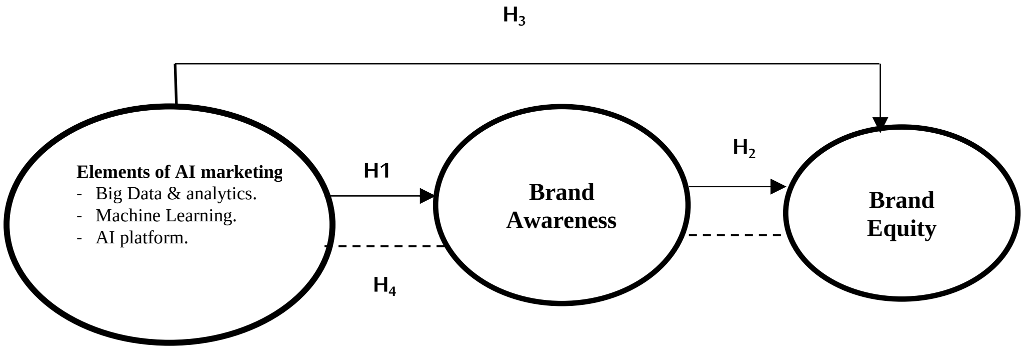

Figure 1: Proposed research model

4. Research Methodology:

Data Collection:

Data were collected through primary sources using a modified questionnaire administered via an online Google Form. The survey link was disseminated across various social media platforms, including Facebook, Instagram, and WhatsApp, to reach a convenience sample of Egyptian mobile shopping users. This method was selected in light of the critical role that mobile phones play in facilitating online shopping, as outlined in the study's introduction.

The questionnaire was made available in both English and Arabic. To ensure accuracy, the English version was translated into Arabic and subsequently back-translated into English. All measurement items were developed and adapted based on insights from the literature review. A panel of experts reviewed the items during a pilot study to evaluate their face and content validity. The questionnaire comprised two primary sections: the first collected demographic and background information of mobile shoppers, while the second, divided into five subsections, assessed the constructs related to the study's hypotheses. Data collection targeted mobile shoppers and was conducted over a four-month period, from December 2024 to March 2025.

450 questionnaires were distributed to the study sample. The members of the sample were selected through a simple random sample. The response rate within the sample reached (85.3%), with (384) mobile shoppers.

Table 1: Descriptive analysis of the study sample characteristic

Age Groups	Sub Variable	Frequency	Percent
Age	29 or younger	226	58.85%
	30 - 49	114	29.69%
	50 or older	44	11.46%
Gender Groups	Sub Variable	frequency	Percent
Gender	Male	203	52.86%
	Female	181	47.14%
Occupation Group	Sub Variable	Frequency	Percent
Occupation	Students	61	15.89%
	Unemployed	40	10.42%
	Private Sector	132	34.38%
	Public Sector	63	16.41%
	Self- employed	88	22.92%

Source: Statistical analysis results

According to table 1, 384 usable responses were collected using questionnaire. Based on the descriptive analysis, most of the respondents were youth, aged 29 or younger at a rate of 58.85%. The male respondents represented 52.86% while 47.14% were female. The majority of the respondents are work in private sector with a rate of 34.38%, 22.92% self-employed, then who work in public sector, with a percentage of 16.41%, then the students, with a rate of 15.89%, finally, unemployed, with a rate of 10.42%.

All the variables were measured using 5-point Likert scale with the same anchors ranged from (1) very strongly disagree to (5) very strongly agree. Big data and analytics as one of elements of AI marketing was measured using a set of six items developed by Abuhamdeh et al. (2023), machine learning scale based on Yin & Qiu (2021) that consists of five items, the third element of AI marketing was AI platform that depends on Lemon & Verhoef (2016) measure, which has five items. Brand awareness scale consists of three items, and brand equity were measured using four items. BRAW and BREQ scales developed by Yoo et al. (2020).

Data Analysis:

To ensure measurement accuracy and model reliability, a set of basic statistical indicators were adopted to assess the quality of the measurement tools. These included internal consistency coefficients (such as Cronbach's alpha and composite reliability), as well as testing for construct validity through average variance extracted (AVE) and item loadings on factors (outer loadings). These indicators were interpreted according to accepted standards in structural modeling using the structural equation modeling method (PLS-SEM).

Table 1 presents the detailed results for each variable separately, indicating the level of evaluation by participants and the validity and reliability of the tools used. This provides a strong statistical basis for testing hypotheses in the next stage of analysis.

Table 1: Tests Outer loadings, validity, and reliability for study variables

variables	item	Outer loadings	Mean	Std. Deviation	coefficient of variation	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	validty
ELAI	Elements of AI Marketing: (independent variable)	0.717	4.068	0.504	12.40%	0.8577	0.8774	0.8813	0.7029	0.9261
BIGD	Big data and analytics:	0.760	3.925	0.624	15.89%	0.7513	0.7778	0.8261	0.6242	0.8668
BIGD1	Personalized product recommendations are important in online mobile shopping experience.	0.784	3.380	1.192	35.27%					
BIGD2	I am concerned about the privacy of my personal data when using mobile in shopping.	0.811	4.040	0.936	23.17%					
BIGD3	I trust AI-powered virtual assistants for online mobile shopping recommendations.	0.781	4.150	0.794	19.13%					
BIGD4	I am satisfied with the current level of personalization in online mobile shopping.	0.764	4.010	0.900	22.44%					
BIGD5	I believe that big data and AI can improve my online mobile shopping experience.	0.722	4.020	0.856	21.29%					
BIGD6	I am willing to pay a premium for products or services that leverage big data and AI to enhance my online mobile shopping experience.	0.854	3.960	0.923	23.31%					
MALE	Machine learning	0.803	4.195	0.563	13.42%	0.7638	0.7894	0.7887	0.6355	0.8740
MALE1	AI marketing technology recommends me with the best online mobile shopping based on my browsing habits.	0.753	3.750	1.035	27.60%					

variables	item	Outer loadings	Mean	Std. Deviation	coefficient of variation	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	validty
MALE2	AI marketing technology can be used by my online mobile shopping provider to help offer a personalized shopping interface in line with my preferences according to my browsing habits and registration information.	0.849	4.080	0.960	23.53%					
MALE3	AI technology can be used by my online mobile shopping provider read and see to guess what I like.	0.709	4.300	0.816	18.98%					
MALE4	AI technology can be used by my online mobile shopping provider to suggest the best options for the service I can buy.	0.734	4.370	0.787	18.01%					
MALE5	I am willing to buy extra by online mobile shopping when recommended by the AI platform.	0.805	4.470	0.747	16.71%					
AIP	AI platform	0.846	4.083	0.618	15.13%	0.7302	0.7813	0.8181	0.6699	0.8545
AIP1	How has the AI platform improved marketing campaign efficiency in online shopping (e.g., reduced time spent on campaign execution).	0.733	4.380	0.806	18.40%					
AIP2	I feel more engagement in online mobile shopping since depending on AI by my mobile service providers.	0.873	3.990	0.907	22.73%					
AIP3	AI can accurately predicts customer behavior in online mobile shopping compared to traditional analytics.	0.786	3.960	0.922	23.28%					
AIP4	AI process can effectively analyze customer data in real-time.	0.726	4.050	0.861	21.26%					
AIP5	AI platform can handle customer data ethically and comply with privacy regulations.	0.875	4.020	0.945	23.51%					

variables	item	Outer loadings	Mean	Std. Deviation	coefficient of variation	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	validty
BRAW	Brand awareness: (mediator variable)	0.889	4.056	0.724	17.85%	0.7069	0.7117	0.8361	0.6298	0.8408
BRAW1	I am aware of brands in online shopping.	0.819	4.010	0.956	23.84%					
BRAW2	I can recognize specific brand among competing brands in online mobile shopping.	0.780	4.010	0.969	24.16%					
BRAW3	I know what brands in online mobile shopping look like.	0.782	4.150	0.808	19.47%					
BREQ	Brand equity: (dependent variable)	0.932	4.016	0.789	19.65%	0.8268	0.8306	0.8852	0.6589	0.9093
BREQ1	It makes sense to buy specific brand instead of any other brand, even if they are same.	0.834	4.010	0.969	24.16%					
BREQ2	Even if another brand has same features as particular brand, I would prefer to buy this brand.	0.761	4.100	0.916	22.34%					
BREQ3	If there is another brand as good as x I will still prefer to buy this brand.	0.852	3.980	1.017	25.55%					
BREQ4	If another brand is not different from the brand I prefer in any way, it seems smarter to purchase this brand.	0.798	3.980	0.983	24.70%					

Source: based on Smart-Pls v4 output

The table shows the analysis of the results of the elements of artificial intelligence marketing model, the results demonstrated a high level of internal consistency and construct validity for the independent variable (Elements of Artificial Intelligence) (ELAI) and its dimensions, Big Data and Analytics (BIGD), Machine Learning (MALE), and Artificial Intelligence Platform (AIP). Also, table shows result of mediator variable (Brand Awareness) (BRAW), and dependent variable (Brand Equity) (BREQ):

Big Data and Analytics (BIGD)

This dimension consists of six items with averages ranging from (3.38) to (4.15), indicating moderate to high interest among participants in the impact of big data on personalizing the shopping experience. The external loading coefficients for the items reached high values from (0.722) to (0.854), and the variable achieved a good Cronbach's alpha coefficient (0.7513), reflecting adequate internal consistency. The composite reliability reached (0.7778), and the average variance extracted (AVE) exceeded the minimum acceptable limit (0.6242), supporting the validity of this variable in explaining consumer behavior in the digital environment.

Machine Learning (MALE)

The averages for the items associated with this variable ranged from (3.75) to (4.47), with high external loadings from (0.709) to (0.849). The Cronbach's alpha coefficient recorded a value of (0.7638), which is within the acceptable range, indicating good consistency between the items. The composite reliability was (0.7894), while the AVE value reached (0.6355), a strong indicator of the validity of this variable. Accordingly, machine learning is one of the effective factors in enhancing the online shopping experience.

Artificial Intelligence Platform (AIP)

The results of this variable showed high values across all indicators, with item averages ranging between (3.96) and (4.38), with external loadings between (0.726) and (0.875), reflecting a strong correlation between the items and the overall concept of the variable. The Cronbach's alpha coefficient achieved a value of (0.7302), and the composite reliability (0.7813) and average variance extracted (AVE) (0.6699) indicated the strength and stability of this dimension in the model. Therefore, AI platforms can be considered a key factor in improving the shopping experience in terms of efficiency, personalization, and privacy compliance.

Elements of Artificial Intelligence in Marketing (ELAI)

This variable achieved a high mean score of (4.068), reflecting participants' agreement on the importance of AI elements in the e-commerce experience. The items also demonstrated a strong correlation with the variable (external loading = 0.717), and Cronbach's alpha coefficient reached (0.8577), indicating a high level of internal consistency. The composite reliability value reached (0.8774), and the average variance extracted (AVE) value exceeded the acceptable limit of (0.7029), indicating the strength of the factor's variance explanation. Accordingly, the AI elements variable is considered a reliable and robust factor in the model.

Brand Awareness (BRAW)

Brand awareness is a mediating variable in this model. It was measured using three items that reflect consumers' ability to recognize brands during mobile shopping. The average responses ranged from (4.01) to (4.15), indicating a relatively high level of awareness among participants. The items also achieved good external loadings, ranging from (0.780) to (0.819), indicating a correlation between the items and the overall variable. Cronbach's alpha coefficient was (0.7069), which is within the minimum acceptable level for internal consistency, reflecting acceptable reliability. The composite reliability (rho_c) recorded a value of (0.8361), while the average variance extracted (AVE) was (0.6298), which is above the minimum required level (0.5), indicating that the factor can explain a significant amount of the variance within the items. These results demonstrate that the brand awareness variable was measured reliably and statistically valid, strengthening its importance as a mediating variable in the model.

Brand Equity (BREQ)

Brand equity represents the dependent variable in the model and was measured through four items that express consumers' preference for a particular brand even when similar alternatives exist. The item means ranged between (3.98) and (4.10), indicating consumers' positive tendency toward brand differentiation and loyalty. The external loadings of the items were high, ranging from (0.761) to (0.852), reflecting a strong relationship between the items and the variable. This dimension also achieved high internal consistency, with a Cronbach's alpha coefficient of (0.8268) and a composite reliability (rho_c) of (0.8852), both values supporting the reliability of the measurement. Additionally, the average variance extracted (AVE) was (0.6589), which is high and indicates that the variable explains a significant proportion of the variance in its items. These indicators demonstrate that the "brand equity" variable was measured with a high degree of reliability and validity.

Study hypothesis results

To ensure the quality of the structural model and the validity of the hypothesized paths between the variables, a set of statistical tests was conducted, including the Variance Inflation Factor (VIF) to check for multicollinearity, the Standardized Root Mean Error Rate (SRMR) to assess the goodness of fit, the Goodness of Fit Index (NFI), and the Chi-square test. So, table (2) show Structural Model Assessment.

Table 2: Structural Model Assessment

H	Path	VIF	SRMR	Chi-square	NFI
H1	Big data and analytics -> Brand awareness	1.669	0.008	6.962	0.934
	Machine learning -> Brand awareness	1.566			
	AI platform -> Brand awareness	1.892			
H_2	Brand awareness -> Brand equity	1.000	0.006	4.551	0.922
H_3	Big data and analytics -> Brand equity	1.671	0.003	3.790	0.938
	Machine learning -> Brand equity	1.567			
	AI platform -> Brand equity	1.879			
H4	Brand awareness -> Brand equity	1.567	0.004	9.343	0.962
	Elements of AI Marketing -> Brand awareness	1.000			
	Elements of AI Marketing -> Brand equity	1.567			

Source: based on Smart-Pls v4 output

The VIF test results indicate that all values fall within the acceptable limits (less than 5), meaning there is no collinearity problem between the independent variables. The VIF values ranged from (1.000) to (1.892), reflecting adequate independence of the paths in the model. The SRMR values for all paths were very low (ranging from 0.003 to 0.008), well below the acceptable standard limit (0.08), indicating an excellent model fit for the structural model. These results indicate that the differences between the observed matrix and the estimated matrix of the model are very small, enhancing the validity of the model. All paths achieved high NFI ratios ranging from (0.922) to (0.962), all above the acceptable minimum (0.90), indicating a high quality of fit between the hypothesized model and the actual data. This indicator is considered strong support for the validity of the structural model. The Chi-square test statistical values showed varying degrees between the paths, but all of them were within the acceptable range (less than 10), which also supports the validity of the model, and it's fit with the data.

First hypothesis result:

The first hypothesis (H_1) aims to test the impact of elements of AI marketing including (big data and analytics, machine learning and AI platforms) on brand awareness; Therefore, the following figure shows the results of this hypothesis.

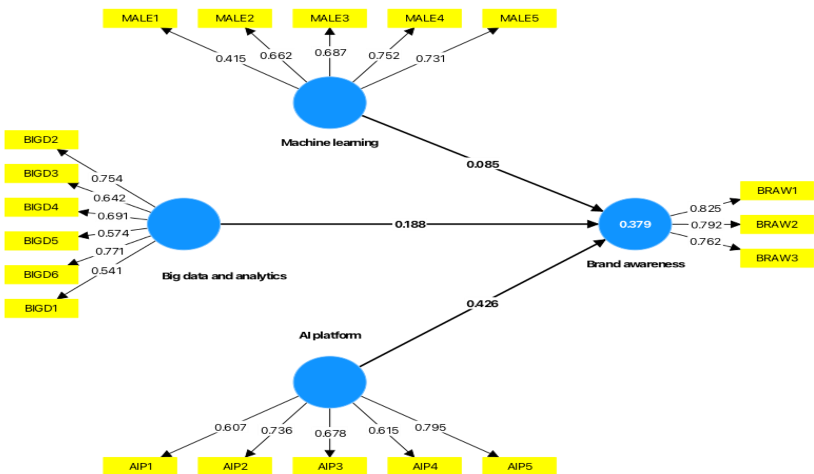

Figure 2: path analysis for hypothesis H_1

Source: from smart-pls v4 output.

The previous figure shows that the R^2 value for the dependent variable "brand awareness" was (0.379), meaning that (37.9%) of the variance in brand awareness can be explained by elements of AI marketing including big data and analytics, machine learning and AI platforms. This is an acceptable percentage, given that it is greater than (30%), and supports the validity of the model. In continuation of this, the following table shows the results of the study model parameters.

Table 3: path analysis coefficient for hypothesis H_1

Path	B	T statistics	P values
Big data and analytics -> Brand awareness	0.188	2.768	0.006
Machine learning -> Brand awareness	0.085	2.104	0.020
AI platform -> Brand awareness	0.426	5.867	0.000

Source: from smart-pls v4 output.

Path analysis results showed that the AI platform had the strongest and most statistically significant impact, with an impact coefficient (B) of (0.426), a t-value of (5.867), and strong statistical significance at p = 0.000. This indicates a positive and significant relationship between the use of smart platforms and increased consumer brand awareness. The results also revealed that Big Data and Analytics had a positive and significant impact on consumer awareness, with an impact coefficient of (0.188), a t-value of (2.768), above the critical value (1.96), and a statistical significance at p = (0.006). This reflects the importance of analytical data in enhancing brand recognition in digital competition. Regarding machine learning, the results showed a positive but relatively weak impact, with an impact coefficient of (0.085) and a t-value of (2.104), with an acceptable statistical significance at p = (0.020). Although the impact is smaller compared to other factors, it is still statistically significant, indicating a limited but real role for machine learning in enhancing brand awareness.

The results of hypothesis one support the validity of all three hypothesized relationships, as it was proven that AI platforms, big data, and machine learning each significantly impact brand awareness, the results confirm that practical applications of AI play a pivotal role in enhancing consumer perception of brands in the digital environment.

Second hypothesis result:

The second hypothesis (H_2) aims to test the impact of brand awareness on brand equity; Therefore, the following figure shows the results of this hypothesis.

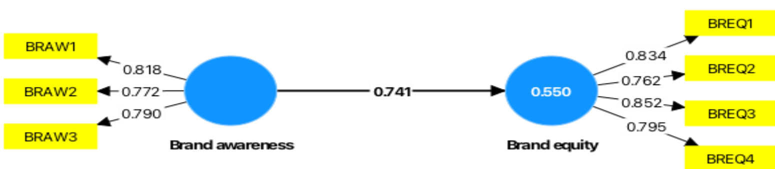

Figure 3: path analysis for hypothesis H_2

Source: from smart-pls v4 output.

The previous figure shows that the R^2 value for the dependent variable "brand Equity" was (0.550), meaning that (55%) of the variance in brand Equity can be explained by brand awareness. This is an acceptable percentage, given that it is greater than (30%), and supports the validity of the model. In continuation of this, the following table shows the results of the study model parameters.

Table 4: path analysis coefficient for hypothesis H_2

Path	B	T statistics	P values
Brand awareness -> Brand equity	0.741	25.369	0.000

Source: from smart-pls v4 output.

The results of the path analysis showed a strong and direct relationship between the two variables. The impact coefficient (B) reached a high value of (0.741), indicating that more than (74%) of the change in brand Equity can be attributed to brand awareness. The t-statistical value reached (25.369), a very high value that far exceeds the minimum acceptable level (1.96), reflecting the strength and stability of the relationship. The statistical significance value (P-value) was (0.000), which is lower than the accepted significance level (0.05), confirming the existence of a strong significant impact for brand awareness on brand equity.

Third hypothesis result:

The third hypothesis (H_3) aims to test the impact of elements of AI marketing including (big data and analytics, machine learning and AI platforms) on brand Equity; Therefore, the following figure shows the results of this hypothesis.

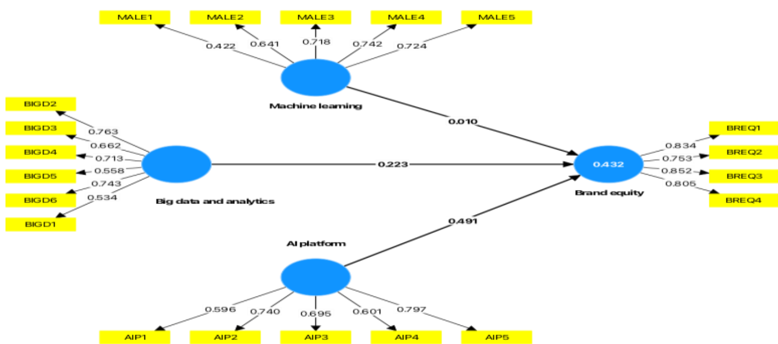

Figure 4: path analysis for hypothesis H_3

Source: from smart-pls v4 output

Figure 4 shows that the R^2 value for the dependent variable "brand Equity" was (0.432), meaning that (43.2%) of the variance in brand Equity can be explained by elements of AI marketing including big data & analytics, machine learning and AI platforms. This is an acceptable percentage, given that it is greater than (30%), and supports the validity of the model. In continuation of this, the following table shows the results of the study model parameters.

Table 5: path analysis coefficient for hypothesis H_3

Path	B	T statistics	P values
Big data and analytics -> Brand equity	0.223	3.660	0.000
Machine learning -> Brand equity	0.010	2.172	0.003
AI platform -> Brand equity	0.491	8.905	0.000

Source: from smart-pls v4 output.

The results showed that the AI platform had the largest and most statistically significant impact on brand equity, with an impact coefficient (B) of (0.491), a high T value of (8.905), and strong statistical significance at p = (0.000). This result indicates that smart platforms powered by AI contribute significantly to enhancing consumers' perceived brand equity. As for big data and analytics, the impact coefficient was (0.223), with a T value of (3.660), and strong statistical significance at p = (0.000), indicating a moderate but significant impact. This reflects that the use of big data to analyze consumer behavior helps improve users' perceptions of brand equity. As for machine learning, the impact was weak in value B = (0.010), but it was nevertheless statistically significant, with a T value of (2.172) at a significance level of p = (0.003). Although the effect was weak, its presence suggests a limited but real role for machine learning in enhancing brand equity, perhaps by improving purchase recommendations or personalizing offers.

Forth hypothesis result:

The forth hypothesis (H_4) aims to test the mediating role of brand awareness on the relationship between elements of AI marketing and brand equity; Therefore, the following figure shows the results of this hypothesis.

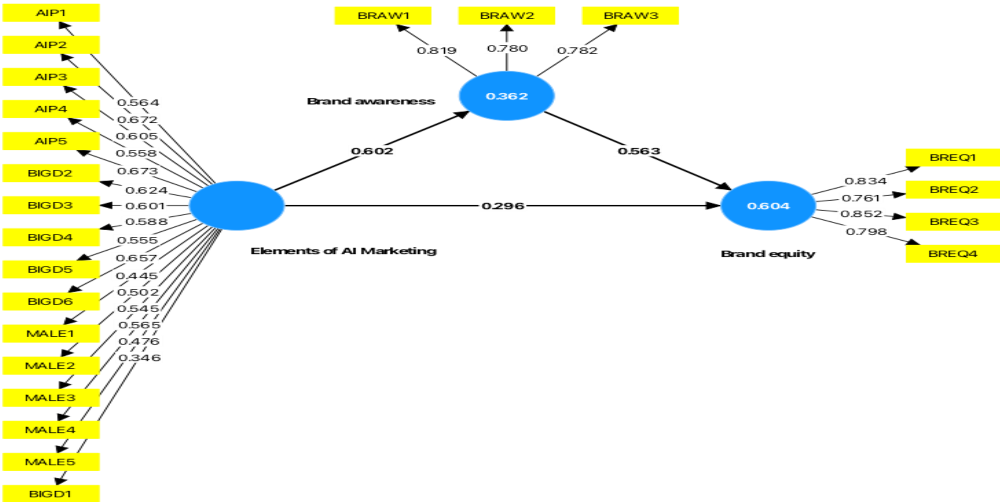

Figure 5: path analysis for hypothesis H_4

Source: from smart-pls v4 output.

The figure also shows that the explanatory values are relatively high, with the R^2 value for brand awareness being (0.362), while the R^2 value for brand equity was (0.604), indicating that AI elements explain more than (60%) of the variance in perceived brand equity a strong indicator of the model's validity, In continuation of this, the following table shows the results of the study model parameters.

Table 6: path analysis coefficient for hypothesis H_4

Path	B	T statistics	P values
Elements of AI Marketing -> Brand awareness	0.602	14.127	0.000
Brand awareness -> Brand equity	0.563	11.120	0.000
Elements of AI Marketing -> Brand equity	0.296	5.560	0.000
indirect effect			
Elements of AI Marketing -> Brand awareness -> Brand equity	0.338	9.755	0.000

Source: from smart-pls v4 output.

The fourth hypothesis (H_4) aims to test whether AI elements in marketing directly and indirectly affect brand equity, via the role of brand awareness as a mediating variable.

The results of the path analysis indicate a direct and significant effect of AI elements on brand equity, with the direct effect coefficient reaching (0.296), a t-statistic of (5.560), and strong statistical significance p = (0.000). This confirms the existence of a direct relationship between the application of AI tools and raising brand equity in the minds of consumers. The results also showed a significant indirect effect via brand awareness, with the indirect effect coefficient for the path: Elements of AI Marketing ⟶ Brand Awareness ⟶ Brand Equity. Reaching (0.338), with a t-statistic of (9.755), and very high statistical significance p = (0.000). This indicates that a significant portion of the impact of AI on perceived brand value is achieved through increased consumer awareness of the brand. In addition, the model demonstrated that the relationship between brand awareness and brand equity is very strong, with an impact coefficient of (0.563), with a t-value of (11.120), and confirmed statistical significance p = (0.000). The relationship between elements of AI marketing and brand awareness was also strong, with an impact coefficient of (0.602), with a t-value of (14.127), the highest in the model.

Summary of results:

The results of the structural model testing showed strong support for all four hypotheses proposed in this study, confirming the validity of the hypothesized model in explaining the impact of AI technologies on both consumer brand awareness and perceived brand equity.

Regarding the first hypothesis (H_1), the results showed that all three elements of AI marketing (big data and analytics, machine learning and AI platform) significantly impact brand awareness, with the AI platform having a clear superior effect. These results indicate that personalized shopping experiences supported by smart technologies contribute to increased consumer awareness of brands within the digital environment.

The second hypothesis (H_2) confirmed a strong and direct relationship between brand awareness and brand equity. It was found that increased awareness significantly contributes to enhancing perceived brand equity, reflecting the importance of building awareness as one of the pillars of brand equity.

Regarding the third hypothesis (H_3), the results demonstrated significant effects of all elements of AI marketing on brand equity. However, the AI platform had the most significant impact, followed by big data and analytics, and then machine learning, with a relatively limited impact. This indicates that investing in technologies that provide direct interaction with consumers enhances brand equity.

Finally, the results of the fourth hypothesis (H_4) support the existence of a direct and indirect impact of AI elements on brand equity, as brand awareness has been shown to play a significant mediating role in this relationship. This finding indicates that elements of AI marketing influence value not only through functional performance but also through shaping consumer cognitive impressions.

5. Discussion

The empirical findings demonstrate a significant influence of Emotionally-Loaded Artificial Intelligence (ELAI) on Building Relationships in the Age of Web (BRAW). Hagan et al. (2021) identified AI as a critical enabler of mobile shopping relationship development, primarily due to its capacity to deliver personalized advertisements, analyze consumer behavior patterns, and address individual needs, thereby enhancing BRAW. This assertion is supported by Rajagopal (2020), who observed that AI contributes to the efficacy of mobile shopping advertising by delivering tailored and engaging content, thereby enriching user experiences and fostering stronger relational ties with consumers. Furthermore, Shaily and Emma (2021) emphasized the utility of ELAI in leveraging consumer data and user profiles to optimize communication strategies. Through such targeted messaging, marketers are better positioned to cultivate BRAW. The establishment of BRAW is considered a foundational step in advancing mobile shopping initiatives. Additionally, Foroudi (2019) affirmed that ELAI serves as an effective tool in facilitating emotional connections between consumers and mobile shopping platforms.

While the results indicated a significant influence of all dimensions of Emotionally-Loaded Artificial Intelligence (ELAI) on Building Relationships in the Age of Web (BRAW), they also identified Artificial Intelligence Personalization (AIP) as having the most substantial and statistically significant impact. Venkatesan and Lecinski (2021) affirmed that AIP is a critical determinant of customer satisfaction and plays a pivotal role in fostering mobile shopping BRAW. This is attributed to AIP's ability to facilitate the acquisition, engagement, and targeting of mobile consumers more effectively. Notably, consumers tend to feel more involved and connected when interacting with AIP-enabled systems. Consequently, marketers can utilize AIP to enhance user engagement and accurately target consumer preferences on mobile shopping platforms. According to Lee (2018), by analyzing consumer shopping behavior and patterns, retailers can forecast preferences and align marketing strategies accordingly for optimal impact. Al-Qazzaz (2024) further supports this perspective, reporting that AI implementation significantly improves customer conversion rates and satisfaction. Moreover, the adoption of AI technologies enhances personalized branding and brand loyalty, thereby enabling Egyptian enterprises to strengthen their competitive positioning in the market. The study concludes that technical integration of AI contributes to the evolution of marketing strategies and serves as a catalyst for business growth in emerging markets such as Egypt.

In line with the second hypothesis, the study results confirmed a strong and statistically significant impact of Building Relationships in the Age of Web (BRAW) on Brand Equity (BREQ). Keller (1993) posited that the development of brand equity is fundamentally rooted in the cultivation of brand knowledge and awareness. The current findings align with those of Dib and Alhaddad (2014), who identified BRAW as a central factor influencing decision-making processes among mobile online shoppers, thereby enhancing BREQ. Similarly, Tong and Hawley (2009) established that BRAW serves as a primary antecedent of BREQ, attributing this relationship to BRAW's capacity to foster brand attachment and cognitive familiarity among consumers. Furthermore, BRAW contributes to the development of brand trust and equips consumers with compelling justifications to favor a particular brand over its competitors. The study by Molinillo et al. (2017) also supports this view, asserting that successful establishment of BRAW in mobile shopping contexts enables marketers to positively influence consumer brand preference. They further emphasized that BRAW plays a pivotal role in delivering perceived value and differentiation within mobile commerce, both of which are instrumental in building mobile shoppers' brand equity—positioned as a critical dimension of BRAW itself.

Furthermore, the empirical data indicated a significant impact of Emotionally-Loaded Artificial Intelligence (ELAI) marketing on Brand Equity (BREQ). Yu and Yuan (2019) emphasized that AI technologies enable marketers to effectively engage with mobile shopping users, thereby expanding their consumer databases and enhancing brand equity. Consistent with these findings, Rajagopal (2020) and Oh et al. (2020) concluded that ELAI facilitates the delivery of differentiated value propositions, which are essential for the development of strong BREQ. Ismail (2017) also identified ELAI as a key driver of BREQ, noting its effectiveness in improving user interaction and fostering brand loyalty in mobile commerce environments. Grewal et al. (2020) further asserted that AI platforms contribute to a deeper understanding of consumer preferences and support the design of engaging marketing campaigns, ultimately enhancing brand equity through improved customer retention. Venkatesan and Lecinski (2021) highlighted AI platforms as one of the most influential components of ELAI in promoting user interaction and engagement within mobile shopping contexts. This conclusion is supported by the current study's findings, which revealed that AI platforms exerted the most substantial and statistically significant influence on the development of mobile shopping users' brand equity.

The findings of the study confirmed the significant mediating role of Building Relationships in the Age of Web (BRAW) in the relationship between Emotionally-Loaded Artificial Intelligence (ELAI) marketing and Brand Equity (BREQ). This relationship was theoretically grounded in the Customer-Based Brand Equity (CBBE) model. According to Yoo and Donthu (2001), brand equity is fundamentally developed through the cultivation of customer awareness and knowledge, which can be achieved by enhancing marketing programs that foster brand recognition. Within this framework, BRAW is conceptualized as a foundational component in the formation of BREQ. The current research supports the use of ELAI marketing strategies—such as big data analytics, machine learning, and AI platforms—as mechanisms to strengthen BRAW, which in turn contributes to the development of brand equity. Beig and Khan (2018) emphasized that AI tools can enhance mobile shoppers' memory retention, elicit positive emotional responses, and facilitate cognitive brand impressions. These outcomes promote brand recall, a core element of BRAW, which subsequently leads to improvements in BREQ. For marketers to effectively build brand equity, strategies must be implemented that enable consumers to easily recognize and recall the brand. However, as noted by Pidhurska (2020), developing brand knowledge and awareness can be resource-intensive. In this context, AI technologies offer an efficient and cost-effective approach to achieving these objectives. Supporting this, Chen and Lin (2019) found that AI-driven marketing initiatives can generate favorable BRAW among mobile shopping users, thereby enhancing consumer-based brand equity.

6. Conclusions and Implications

This study highlights the importance of adapting AI tools for building brand knowledge, awareness and enhancing brand equity. The findings showed that all AI marketing elements affect brand equity, however the most important effecting element on building brand awareness and therefore brand equity was found to be AI platform. AI platform was found to be one the most important AI elements that can leads to customer satisfaction, which can facilitate building mobile shopping brand awareness. Specifically, AI platforms provide marketers with a useful tool that can help them to attain, engage and target mobile shopping customers more easily.

The research concluded that brand awareness is a mediator variable that helps in the achievement of brand equity because of the AI marketing implementation. It can therefore be concluded that AI can be very helpful for marketers if they are considering to establish brand equity.

- The findings from this research can be very helpful to marketers who are looking to improve their business by incorporating AI elements to achieve brand awareness and brand equity for mobile shopping services.
- This research guide marketers to embrace using AI tools which can facilitate building brand awareness and equity.
- By using AI elements, marketers can use customer data to enhance mobile shopping experience. Once that is done, marketers can send customers customized messages to build brand awareness.
- The findings from this research will help the marketers to understand how AI can be used to achieve mobile shopping brand awareness and therefore enhance brand equity.
- Marketers can also use the recommendations made by this research to improve brand awareness for mobile shopping users.
- The research also focused on the advantages of AI implementation which is offering customized advertising and helping customer brand recall and therefore establishing brand equity through reaching more customer segment.

- AI tools used to change the marketing strategies by providing more accurate and personalized, which help marketers to accurately address customers preferences and concerns. Therefore, improving companies brand equity.

7. Research Limitation and Future Research

First, the research does not consider all of AI marketing elements, the research is limited to big data and analytics, machine learning and AI platform. Other AI elements should be investigated by future research such as natural language processing (NLP) and robotics to show their effect on building brand awareness and enhancing brand equity.

Secondly, the research sample came mostly from a specific age who are usually more experienced in using AI and well educated which can limit the generalizability of the research findings. Therefore, future research should consider further age groups to identify if using AI elements in marketing for elder ager segments can be useful in building brand awareness and equity, which can enable more applicability of findings. Thirdly, the research depends on nonprobability connivance sampling technique, border sample need to be considered. Finally, the research practical filed was limited to mobile shopping sectors, future research can consider using AI for marketing other business sectors.

Reference:

Aaker, D. A. (1991). *Managing Brand Equity: Capitalizing on the Value of a Brand Name*. The Free Press, New York.

Aaker, D. A. (1996). Measuring Brand Equity Across Products and Markets. *California Management Review*, 38, 102-120.

Abuhamdeh, M., Qtaish, O., Kanaker, H., Alshanty, A., Yousef, N. & AlAli, A. M. (2023). Leveraging Big Data and AI in Mobile Shopping: A Study in the Context of Jordan. *International Journal of Advanced Computer Science and Applications*, 14(7), 225-232.

Agersborg, C., Mansson, I. & Roth, E. (2020). Brand Management and Artificial Intelligence – A World of Man Plus Machine. *Master's Thesis*, University of Gothenburg.

Ailawadi, K. L., & Keller, K. L. (2004). Understanding Retail Branding: Conceptual Insights and Research Priorities. *Journal of Retailing*, 80(4), 331–342.

Al- Quzzaz, M. H. (2024). Utilizing Artificial Intelligence to Enhance Personalized Branding in Startups: A Force on Egyptian Startups. *Journal of Media and Communication Studies*, 24, 24- 46.

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of Consumer Expertise. *Journal of Consumer Research*, 13, 411-454.

Alhaddad. A.A. (2015). The Effect of Advertising Awareness on Brand Equity in Social Media. *International Journal of e-Education, e-Business, e-Management and e-Learning*, 5(2), 73-84.

Ali, M., Ahmed, A. & Hussain, S. (2022). Leveraging Artificial Intelligence in Egyptian Startups: Success Stories and Future Potential. *International Journal of Business and Technology*, 11(3), 125-140.

Alkaied, R., Khattab, S.,Alshaar, I. M., Abu Zaid, M. S. & Al-Bazaiah, S. (2024). The Impact of Artificial Intelligence on Re-purchase Intentions: The Mediation Spproach, *Business Informatics*, 18(3), 86-107.

Ameen, N., Tarhini, A., Reppel, A. & Anand, A. (2021). Customer Experiences in the Age of Artificial Intelligence, *Computers in Human Behavior*, 114,106548.

Bakhshizadeh, E. & Aliasghari, H. (2023, Jan./Mar.).). Customer-Based Brand Equity and Customer Behavioral Intention: Evidence from Insurance Service. *Brazilian Journal of Marketing*. 22(1), 439-468.

Ballamudi, K. R. (2019). Artificial Intelligence: Implication on Management, *Global Disclosure of Economics and Business,* 8(2), 105-118.

Beig, F. A., & Khan, M. F. (2018). Impact of Social Media Marketing on Brand Experience: A Study of Select Apparel Brands on Facebook. Vision, *The Journal of Business Perspective*, 22(3), 264–275.

Bernarto, I., Berlianto, M. P., Meilani, Y. F., Masman, R. R. & Suryawan, I. N. (2020). The Influence of Brand Awareness, Brand Image, and Brand Trust on Brand Loyalty. *Jurnal Manajemen*, 24(3), 412-426.

Bilgin, Y. (2018), The Effect of Social Media Marketing Activities on Brand Awareness, Brand Image and Brand Loyalty. *Business and Management Studies: An International Journal,* 6(1), 128-148.

Brynjolfsson, E., & Mcafee, A. (2017). The Business of Artificial Intelligence. *Harvard Business Review*, 1–20.

Brynjolfsson, E., Rock, D. & Syverson, C. (2018). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. NBER Chapters, in: The Economics of Artificial Intelligence: An Agenda, 23-57, National Bureau of Economic Research, Inc.

Chen, S. C., & Lin, C. P. (2019). Understanding The Effect of Social Media Marketing Activities: The Mediation of Social Identification, Perceived Value, and Satisfaction. *Technological Forecasting and Social Change*, 140, 22–32.

Cheng, Y. & Jiang, H. (2022). Customer–Brand Relationship in the Era of Artificial Intelligence: Understanding the Role of Chatbot Marketing Efforts. *Journal of Product & Brand Management*, 31, 252-264.

Christodoulides, G., & Chernatony, L. (2010). Consumer Based Brand Equity Conceptualization and Measurement. *International Journal of Market Research,* 52, 43-66.

Collins C., Dennehy D., Conboy K. & Mikalef P. (2021) Artificial Intelligence in Information Systems Research: A Systematic Literature Review and Research Agenda. *International Journal of Information Management*, 60, 102383.

Copeland, J. (2016). *Artificial Intelligence: A Philosophical Introduction 1st,* Wiley-Blackwell, England.

Curan, K. (2024). AI and Brand Loyalty: Analyzing the Correlation between AI Customer Service Solutions and Long- Term Consumer Loyalty. Available at SSRN: https://ssrn.com/abstract=5040153 or http://dx.doi.org/10.2139/ssrn.5040153

Deryl. M. D., Verma, S. & Srivastava, V. (2023). How Does AI Drive Branding? Towards an Integrated Theoretical Framework for AI-Driven Branding. *International Journal of Information Management Data Insights*, 3, 100205.

Dib, H., & Alhaddad, A. (2014). The Hierarchical Relationship between Brand Equity Dimensions. *European Scientific Journal*, 10(28), 183-193.

Dimitrieska, S., Stankovska, A. & Efremova, T. (2018). Artificial Intelligence and Marketing. *Entrepreneurship*, 6(2), 298–304.

Dwivedi, R., Nerur, S., & Balijepally, V. (2023). Exploring Artificial Intelligence and Big Data Scholarship in Information Systems: A Citation, Bibliographic Coupling, and Co-word Analysis. *International Journal of Information Management Data Insights, 3*(2), 100-158.

Egypt National Artificial Intelligence Strategy. (2025-2030). *National Council for Artificial Intelligence*, Second Edition.

El Fawal, A., Mawlawi, A, Zakhem, N. B., Baydoun, H., Yassine, D. & Kassably, C. (2024). The Impact of AI Marketing Activities on Consumer-Based Brand Equity: The Mediating Role of Brand Experience. *Journal of Infrastructure, Policy and Development*, 8(7), 3851-3867.

El-Nawla, N. & Ibrahim, H. (2024). AI-Powered 5G Networks: A Roadmap for the Future of Wireless Communications. *Nile Journal of Communication & Computer Science*, 7, 1-14.

Eslami, S. (2020). The Effect of Brand Experience on Brand Equity and Brand Loyalty through The Mediating Role of Brand Awareness, Brand Image and Perceived Quality. *Archives of Pharmacy Practice,* 11(S1), 98-104.

Farquhar, P. H. (1989). Managing Brand Equity. *Marketing Research,* 1(3), 24-33.

Foroudi, P. (2019), Influence of Brand Signature, Brand Awareness, Brand Attitude, and Brand Reputation on Hotel Industry's Brand Performance. *International Journal of Hospitality Management*, 76, 271-285.

Galal, S. (2024). E-Commerce in Egypt- Statistics & facts. Jun 28.

Gil, R. B., Andre´s, E. F., & Salinas, E. M. (2007). Family As A Source of Consumer-Based Band Equity. *Journal of Product and Brand Management,* 16(3), 188-199.

Gkikas, D.C. & Theodoridis, P.K. (2019). Artificial Intelligence (AI) Impact on Digital Marketing Research, *Strategic Innovative Marketing and Tourism*, 1251–1259.

Grand View Research. (2023). Artificial Intelligence in Marketing Market Size, Share & Trends Analysis Report by Offering, By Application (Virtual Assistant, Content Curation), By Deployment, By End Use, By Region, And Segment Forecasts, 2020 - 2027.

Grewal, D., Roggeveen, A., & Nordfält, J. (2020). The Future of Retailing: Technology and the Consumer Experience. *Journal of Retailing,* 96(1), 48–62.

Hagan, J. G., Vanschoenwinkel, B. & Gamfeldt, L. (2021). We should not Necessarily Expect Positive Relationships between Biodiversity and Ecosystem Functioning in Observational Field Data, *Ecology Letters*, 24(12), 2537-2548.

Hazee, S., Vaerenbergh, Y. V., & Armirotto, V. (2017). Co-creating Service Recovery after Service Failure: The Role of Brand Equity. *Journal of Business Research, 74*, 101-109.

Ho, S. P. & Chow, M. Y. (2024). The Role of Artificial Intelligence in Consumers' Brand Preference for Retail Banks in Hong Kong, *Journal of Financial Services Marketing*, 29, 292-305.

Hollebeek, L. D., Glynn, M. S. & Brodie, R. J. (2014). Consumer Brand Engagement in Social Media: Conceptualization, Scale Development and Validation. *Journal of Interactive Marketing*, *Elsevier*, 28(2), 149-165.

Hrehova, S. (2018). Brief Overview of the Concept of Big Data. *3rd EAI International Conference on Management of Manufacturing Systems.*

Hutter, K., Hautz, J., Dennhardt, S., & Füller, J. (2013). The Impact of User Interactions in Social Media on Brand Awareness and Purchase Intention: The Case of MINI on Facebook. *Journal of Product and Brand Management*, 22(5/6), 342–351.

Ismail, A. R. (2017). The Influence of Perceived Social Media Marketing Activities on Brand Loyalty. *Asia Pacific Journal of Marketing and Logistics*, 29(1), 129–144.

Jacobs, C. S. (2009). Management Rewired: *Why Feedback Doesn't Work and Other Surprising Lessons from the Latest Brain Science.* New York: Portfolio Books.

Jain, P. & Aggarwal, K. (2020). Transforming Marketing with Artificial Intelligence, *Int. Res. J. Eng. Technol.* 7(7), 3964–3976.

Jarek, K. & Mazurek, G. (2019). Marketing and Artificial Intelligence. *Central European Business Review*, 8(2), 46-55.

Jelonek, D., Kumar, N. & Paweloszek, I. (2024). Artificial Intelligence Applications in Brand Management. *Silesian University of Technology Publishing House*, 202, 153-170.

Juntunen, M., Juntunen, J., & Juga, J. (2009). Corporate Brand Equity and Loyalty in B2B Markets: A Study among Logistics Service Purchasers. *Journal of Brand Management,* 18(4-5), 300–311.

Kahneman, D. (2012). *Thinking Fast and Slow by Daniel Kahneman*, Farrar, Straus and Giroux: New York.

Kandeel. S. M. & Zoghaib, S. Z. (2024). The Development of VOD Services in Egypt: Examining their Effect on Traditional TV and their possible Future Scenarios Qualitative Research. *Scientific Journal of Radio and Television Research*, 29(2), 47-83.

Keller, K. L. (1993). Conceptualizing, Measuring, and Managing Customer-Based Brand Equity. *Journal of Marketing,* 57(1), 1–22.

Keller, K. L. (2008). *Strategic brand management: building, measuring and managing brand equity* (3 ed.), England: Pearson.

Kim, E. J., Baloglu, S., & Henthorne, T. L. (2021). Signaling Effects of Branded Amenities on Customer-Based Brand Equity. *Journal of Hospitality Marketing & Management*, 30(4), 508-527.

Koay, K. Y., Ong, D. L. T., Khoo, K. L. & Yeoh, H. J. (2020). Perceived Social Media Marketing Activities and Consumer-Based Brand Equity. *Asia Pacific Journal of Marketing and Logistics*, 33(1), 53–72.

Koza, J. R., Bennett III, F. H., Andre, D., & Keane, M. A. (1996). Automated Design of both the Topology and Sizing of Analog Electrical Circuits Using Genetic Programming. *Artificial Intelligence in Engineering*, 10(3), 247-276.

Kuksov, D., Shachar, R., & Wang, K. (2013). Advertising and Consumers' Communications. *Marketing Science*, 32(2), 294–309.

Laksamana, P., Saripudin, S., Suharyanto, S. & Cahaya, Y. F. (2024). Artificial Intelligence-Driven Brand Strategy: Impact on Awareness, Image, Equity, and Loyalty. *Journal of Infrastructure, Policy and Development*, 8(15), 10084.

Latif, S., Usman, M., Manzoor, S, Qadir, J., Iqbal, W., Tyson, J. & Crowcroft, J. (2020). Leveraging Data Science to Combat COVID-19: A Comprehensive Review. *IEEE Transactions on Artificial Intelligence*, 1(1), 85-103.

Lee, H. L. (2018). Big Data and the Innovation Cycle. *Production and Operations Management*, 27(9), 1642-1646.

Lemon, K. N. & Verhoef, P. C. (2016). Understanding Customer Experience throughout the Customer Journey. *Journal of Marketing*, 80(6), 69-96.

Liu, Y., & Lu, J. (2023). Artificial Intelligence in Marketing: A Review and Agenda for Future Research. *Journal of Interactive Marketing*, 45, 70–81.

Mahto, R. K., Kafle, D., Giri, A., Luintel, S. & Karki, A. (2022). Evaluation of Fully Automated Cephalometric Measurements Obtained from Web-Based Artificial Intelligence Driven Platform. *National Library of Medicine*, 22(1), 132-140.

Marques, C., da Silva, R. V., Davcik, N. S., & Faria, R. T. (2020). The Role of Brand Equity in a new Rebranding Strategy of aPprivate Label Brand. *Journal of Business Research*, 117, 497-507.

McKinsey & Company. (2020). T*he State of Fashion 2021*: In Search of Promise in Perilous Times.

Mishra, P., & Datta, B. (2011). Perpetual Asset Management of Customer-Based Brand Equity-The PAM Evaluator. C*urrent Research Journal of Social Sciences*, 3(1), 34-43.

Molinillo, S., Japutra, A., Nguyen, B., Chen, C.H.S. (2017), Responsible Brands vs Active Brands? An Examination of Brand Personality on Brand Awareness, Brand Trust, and Brand Loyalty. *Marketing Intelligence and Planning,* 35(2), 166-179.

O'Guinn, T. C., Allen, C. T., & Semenik, R. J. (2009). *Advertising and integrated brand promotion* (5th ed.). Mason, OH: South-Western.

Oh, T. T., Keller, K. L., Neslin, S. A., Reibstein, D. J., & Lehmann, D. R. (2020). The Past, Present, and Future of Brand Research. *Marketing Letters,* 31, 151–162.

Ongsulee, P. (2017). Artificial Intelligence, Machine Learning and Deep Learning. *15th International Conference on ICT and Knowledge Engineering (ICT&KE).*

Park, S.C. (2017). The Fourth Industrial Revolution and Implications for Innovative Cluster Policies. *AI & Society*, 33(3), 433-45.

Paschen, J., Kietzmann, J. & Kietzmann, T.C. (2019), Artificial Intelligence (AI) and its Implications for Market Knowledge in B2B Marketing. *Journal of Business and Industrial Marketing*, 34(7), 1410-1419.

Pidhurska, V. (2020), Brand Recognition as one of the Major Goals in the Brand Management. *European Journal of Economics and Management Sciences*, 2, 1-6.

Rajagopal, A. (2020). Analyzing Brand Awareness as a Driver for Determining Brand Value: A Study in Telecommunications Service Marketing, *International Journal of Services and Operations Management*, 37(2), 241-263.

Ray, A., Bala, P. K., Chakraborty, S., & Dasgupta, S. A. (2021). Exploring the Impact of Different Factors on Brand Equity and Intention to take up online Courses from E-Learning Platforms. *Journal of Retailing and Consumer Services*, 59, 102351.

Reddy, K. VV., Sreenivas, T. & Lavanya, G. (2023). Role of AI in Enhancing Brand Equity. *AIP Conference Proceedings*, November 21.

Romaniuk, J., Wight, S., & Faulkner, M. (2017). Brand Awareness: Revisiting an Old metric for a new World. *Journal of Product & Brand Management,* 26(5), 469-476.

Ross, S. D. (2006). A Conceptual Framework for Understanding Spectator-Based Brand Equity. *Journal of Sport Management,* 22-38.

Rossiter, J. R., & Percy, L. (1987). *Advertising and Promotion Management*. McGraw-Hill, New York, NY.

Rūta, R., & Juozas, R. (2010). Brand Equity Integrated Evaluation Model: Consumer-Based Approach. *Economics and Management*, 5(2), 719-725.

Sadek, H., Redding, P., & Tantawi, P. (2015). Investigating the Major Marketing Communication Tools and their Impact on Building Bank Brand Equity in the Egyptian Context a Customer Perspective, *Journal of Business and Retail Management Research,* 10(1), 40-59.

Schwab, K. (2017). *The Fourth Industrial Revolution*. Crown Publishing Group, New York.

Shabbir, M.Q., Khan, A.A. & Khan, S.R. (2017), Brand Loyalty Brand Image and Brand Equity: The Mediating Role of Brand Awareness. *International Journal of Innovation and Applied Studies*, 19(2), 416.

Shaily, S. A. & Emma, N. N. (2021). Integration of Artificial Intelligence Marketing to get Brand Recognition for Social Business. *International Review of Management and Marketing,* 11(4), 29-37.

Sheth, J. (2019). Impact of AI on Marketing. *Journal of the Academy of Marketing Science*, 48(1), 66–88.

Smith, A. (2020). AI in Marketing: Definition, Applications, and Impact. *Marketing News*, 54(3), 18–23.

Soni, N., Sharma, E. K., Singh, N. & Kapoor, A. (2020). Artificial Intelligence in Business: From Research and Innovation to Market Deployment. *Procedia Computer Science*, 167, 2200-2210.

Sternberg, R.J. (2017), *The Nature of Human Intelligence*, Cambridge University Press.

Sung, E. C., Bae, S., Han, D.-I. D., & Kwon, O. (2021). Consumer Engagement via Interactive Artificial Intelligence and Mixed Reality. *International Journal of Information Management*, 60, 102382.

Switala, M., Gamrot, W., Reformat, B. & Bilińska-Reformat, K. (2018). The Influence of Brand Awareness and Brand Image on Brand Equity – an Empirical Study of Logistics Service Providers. *Journal of Economics and Management*, 33(3), 95-119.

Tadimarri, A, Jangoan, S.;, Sharma, K.K. & Gurusamy, A. (2024). AI-Powered Marketing: Transforming Consumer Engagement and Brand Growth, *International Journal for Multidisciplinary Research (IJFMR)*, 6(2), 1011.

Thiraviyam, T. (2018). Artificial Intelligence Marketing. *International Journal of Recent Research Aspects*, Special Issue, 449-452.

Tong, X., & Hawley, J. M. (2009). Creating Brand Equity in the Chinese Clothing Market, the Effect of Selected Marketing Activities on Brand Equity Dimensions. *Journal of Fashion Marketing and Management,* 13(4), 566-581.

Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives*, 28(2), 3-28.

Varsha, P. S., Akter, S., Kumar, A., Gochhait, S. & Patagundi, B. (2021). The Impact of Artificial Intelligence on Branding: A Bibliometric Analysis (1982-2019), *Journal of Global Information Management*, 29(4), 221-246.

Vassakis, K., Petrakis, E. & Kopanakis, I. (2018). Big Data Analytics: Applications, Prospects and Challenges. In book: *Mobile Big Data*, .3-20.

Venkatesan, R., Lecinski, J. (2021), The AI Marketing Canvas: A Five- Stage Road Map to Implementing Artificial Intelligence in Marketing. Palo Alto: Stanford University Press.

Wang, H. D., & Sengupta, S. (2016). Stakeholder Relationships, Brand Equity, Firm Performance: A Resource-Based Perspective. *Journal of Business Research,* 69(12), 5561-5568.

Weliweriya Liyanage, K.P.T.L., & Balalle, H. (2024). Emotionally resonant Branding: the Role of AI in Synthesising Dynamic Brand Images for Artists in the Music Industry. *Open Journal of Applied Sciences*, 14, 2661-2678.

Wirth, N. (2018), Hello Marketing, What Can Artificial Intelligence Help You With? *International Journal of Market Research*, 60(5), 435-438.

Yasin, N. M., Noor, M. N., & Mohamad, O. (2007). Does Image of Country-of-Origin Matter to Brand Equity? *Journal of Product and Brand Management*, 16(1), 38-48.

Yin. J. & Qiu, X. (2021). AI Technology and Online Purchase Intention: Structural Equation Model Based on Perceived Value. *Sustainability*, 13, 56-71.

Yoo, B., & Donthu, N. (2001). Developing and Validating a Multidimensional Consumer-Based Brand Equity Scale. *Journal of Business Research, 52*, 1-14.

Yoo, B., Donthu, N., & Lee, S. (2000). An Examination of Selected Marketing Mix Elements and Brand Equity. *Journal of the Academy of Marketing Science,* 28(2), 195-211.

Yu, X., & Yuan, C. (2019). How Consumers' Brand Experience in Social Media Can Improve Brand Perception and Customer Equity. *Asia Pacific Journal of Marketing and Logistics*, 31(5), 1233–1251.

Yuan, C., Wang, S. & Liu, Y. (2023). AI Service Impacts on Brand Image and Customer Equity: Empirical Evidence from China, *Journal of Brand Management,* 30, 61-76.

Zeugner-Roth, K. P., Diamantopoulos, A., & Montesinos, M. A. (2008). Home Country Image, Country Brand Equity and Consumers' Product Preferences: An Empirical Study. *Management International Review, 48*(5), 577-602.

Zhang, S. N., Li, Y. Q., Liu, C. H., & Ruan, W. Q. (2021). Does Live Performance Play a Critical Role in Building Destination Brand Equity—a Mixed-Method Study of "Impression Dahongpao. *Journal of Retailing and Consumer Services*, 59, 102392.

Zhu, Y., Xin, L., Wang, H. & Park, H. W. (2025). Effects of AI Virtual Anchors on Brand Image and Loyalty: Insights from Perceived Value Theory and SEM-ANN Analysis. *Systems*, 13(2), 79-100.