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PAPER

Utilization of Data Science Analytics on Mobile Commerce Applications Marketing Strategies: An Example of the Influence of Personalized Offers on the Usage Intentions of Saudi Consumers

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ABSTRACT

The integration of data science plays a vital role in the progression of mobile applications, as it enhances their overall effectiveness and provides users with more benefits. Data science tools have the potential to assist organizations in enhancing their brand marketing endeavors and providing personalized offers, therefore contributing to the overall improvement of consumer acquisition. Consequently, the primary objective of this research was to investigate the influence of the personalized offers aspect on users of mobile commerce applications in Saudi Arabia, in addition to the core elements of the technology acceptance model (TAM). The result of this study indicates that perceived usefulness exhibits the greatest degree of impact in influencing customer attitudes toward usage, with personalized offers following closely. The research further reveals that personalized offers exert a substantial favorable influence on customers' attitudes towards their use. Additionally, the research reveals that personalized offers significantly influence individuals' behavioral intentions concerning the use of m-commerce applications. This research offers significant insights that might inform future academic research in the field. Moreover, it provides app developers and enterprises with novel knowledge and comprehension to devise tactics that enhance the ongoing advancement of mobile commerce applications.

KEYWORDS

data science, m-commerce, apps, personalized offers, Saudi

1 INTRODUCTION

In contemporary society, individuals utilize smartphones for a multitude of purposes beyond interpersonal voice communication. These purposes encompass a

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wide range of activities facilitated by diverse mobile applications, such as electronic mail correspondence, instant messaging, online commerce, Internet exploration, entertainment, and engagement with social media platforms such as Facebook, LinkedIn, and Twitter [1]. The adoption of mobile phones has positively impacted consumer market demand by introducing a new aspect of virtual mobility that aligns with the ongoing trend of geographically extended, faster, and more personalized social interaction [2].

Additionally, smartphones serve as gateways to various Internet of Things (IoT) services, including those related to smart cities, healthcare, and transportation. The field of data science has experienced significant advancements in recent years, particularly with the utilization of computing capabilities in smart mobile phones. This has enabled these devices to operate intelligently and efficiently [3].

The global consumer base is increasingly embracing the utilization of mobile commerce (m-commerce) as a prevalent trend. The rapid and sophisticated advancement of wireless networks and technologies, including 3G, 4G, and LTE, has emerged as a significant topic in the study agenda of information systems (IS), giving rise to the exploration of m-commerce. M-commerce is any sale or purchase carried out through terminal equipment, including personal digital assistants (PDAs) and smartphones, utilizing paid services [2].

Data science is an interdisciplinary subject that focuses on the extraction of useful insights and information from vast amounts of data. It uses a multidisciplinary approach to data analysis, drawing on concepts from mathematics, statistics, artificial intelligence (AI), and computer science [4]. In the context of the creation of mobile apps, data science is a critical factor in enhancing the overall efficacy of applications and providing users with advantages. The utilization of data science can be significant in marketing and developing strategies for acquiring users for mobile applications. Through the analysis of user data and patterns of app usage, developers could discern successful marketing channels and approaches that can be employed to entice and acquire new users [4].

Therefore, analyzing buyer behavior patterns with data science tools can assist in identifying customers who exhibit a higher propensity to establish a long-term connection with the brand. Businesses could effectively promote their brands and personalized offers to specific customers in order to enhance customer acquisition [5].

In the present study, the objective is to investigate and confirm the impact of personalized offers and promotions on users' behavioral intentions to use m-commerce within the specific context of Saudi Arabia. This study concentrates on apps in Saudi Arabia that allow users to purchase products directly from retailers or through intermediary delivery apps such as Noon, Jahez, and Hungerstation. Hence, the present study aims to contribute to the expanding research domain by addressing the subsequent research question: What is the impact of personalized offers generated through data science analytical tools on users' behavioral intention to use m-commerce within Saudi Arabia?

2 LITERATURE REVIEW

A) Mobile commerce

Mobile commerce, also known as m-commerce, pertains to the utilization of wireless electronic commerce for commercial purposes via portable devices such as tablet computers, smartphones, and PDAs. Mobile devices are widely regarded as personal diaries, thereby increasing the number of individuals utilizing such devices [6]. Unlike e-commerce, which mainly relies on desktop computers, m-commerce has expanded the boundaries of consumer limitations, allowing individuals to transcend the constraints of both physical space and temporal constraints [7]. M-commerce encompasses various industries and services, including ticketing, banking, marketing, information services, and retail [8]. In addition, the emergence of food-ordering apps has become a prevalent trend in response to the increasingly busy lifestyles of individuals in contemporary society. Most individuals prefer ordering food online rather than engaging in home cooking or consuming homemade meals, primarily driven by the desire for enhanced taste and a more comprehensive range of culinary options. The emergence and progression of electronic meal-ordering apps have been significantly shaped by the pivotal role played by technology [9].

In contrast to other nations in the Middle East, the rapid proliferation of mobile devices and wireless technologies presents advantageous prospects for consumers to engage in mobile phone-based shopping. The level of internet penetration in Saudi Arabia is significantly high, particularly in comparison to other nations in the Middle East [6]. Moreover, Saudi Arabia is widely recognized as a significant market for m-commerce due to its population's utilization of diverse forms of payment and numerous apps to engage in online shopping activities on a global scale [10].

B) Data science

The term "data science" refers to a wide range of activities, including the analysis of data and the development of automated methods for enhancing the process of developing software applications [11]. App developers may expedite a variety of functions by utilizing predictive data analysis and machine learning models. These models can speed up anything from the collection of data to the interpretation of that data. In addition, big data analytics can gather dispersed data to better comprehend users' actions and preferences from various angles and present an in-depth understanding [11]. The effectiveness of mobile applications is heavily influenced by the user experience they provide. The utilization of data science in app development enables the provision of personalized experiences to users through the analysis of user data and the application of machine learning algorithms [1]. Developers can customize the application to cater to the specific requirements of individual users by comprehending their preferences, behaviors, and previous interactions with the application. This may encompass individualized suggestions, tailored content, and focused marketing initiatives. Using data science techniques, software developers can design a user experience that is captivating and tailored to individual users. This, in turn, has the potential to enhance user satisfaction and promote user retention.

The influence of digital applications on consumer behavior has resulted in a significant increase in the generation and accessibility of data at an unprecedented pace. Integrating big data, AI, and marketing can generate enhanced customer value and numerous benefits for organizations [3]. Big data is a term finance industry experts use to describe a tool that enables organizations to effectively handle and control extensive data sets within a specified time frame. This tool also necessitates adequate storage capacity to accommodate the large volume of data [12]. The defining characteristics of big data include its diverse nature, substantial volume, and rapid velocity. The implementation of big data analytics is currently being observed in various areas of the banking industry. This adoption facilitates providing enhanced services to customers inside and outside the organization. Additionally, it contributes to enhancing both active and inactive security measures within the sector [12].

Marketers and organizations can utilize analytics techniques associated with big data to acquire significant insights about transactions, purchase volumes, and customer credentials [13]. The implementation of personalization strategies enables companies to gain insights into the unique needs and preferences of individual customers, thereby enhancing their ability to provide tailored products and services. This, in turn, leads to increased sales and customer loyalty, ultimately resulting in improved customer acquisition and retention rates [5]. For instance, Walmart employs a data-driven approach when making decisions aimed at customer retention. It utilizes predictive analysis within its intelligent forecasting system to assist managers in estimating consumer preferences for more than 500 million products within its network of stores in the United States. The Walmart grocery application facilitates the process of online grocery shopping, enhancing convenience and efficiency for users. In the year 2020, subsequent to the outbreak of the COVID-19 pandemic, this application exhibited superior performance compared to Amazon, with a notable margin of 20% [14].

It is well acknowledged that Saudi Arabia is a significant market for Internet shopping. People buy things from vendors worldwide and employ various payment methods and applications. Therefore, numerous scholarly investigations have been conducted in the realm of m-commerce within the specific context of Saudi Arabia. For example, a recent study by Khan in 2020 [9] indicates that offers and promotions are one of the most important factors in using an ordering system in Saudi Arabia. In addition, personal opinions affect other related factors. A study by Gull et al. [10] investigated customers' perceptions regarding the security aspects of e-commerce applications in Saudi Arabia. The findings indicate that the presence of privacy hazards has a detrimental effect on the security of mobile applications. In contrast, the implementation of effective privacy policies has a positive influence on security. Individuals possess different perceptions, which are influenced by their sensitivity to the information they encounter. Another study by Wasiq et al. [6] examined factors that influence the adoption and utilization of m-commerce services among customers in Saudi Arabia during the COVID-19 pandemic.

Marketers observe significant outcomes stemming from the implementation of ad personalization, prompting them to persist in allocating resources towards this strategy [5]. Academic studies have corroborated the efficacy of personalized advertisements in fostering favorable effects on various aspects, including attention, attitudes, purchasing behavior, and click-through rates [15]. Despite the many benefits of personalized offers and advertising, certain studies have shown people to have very unfavorable opinions about customized advertisements. According to Boerman et al. study of 1244 Dutch respondents, most consumers dislike tailored ads. Personal information, data, and targeted pricing ads have been shown to decrease perceptions and increase resistance to the context, message, and advertiser. It appears that personalization can transcend boundaries [15]. Therefore, this research aims to understand the influence of personalized offers and promotions through mobile apps on m-commerce in Saudi Arabia.

From a technical point of view, most scholars have conducted investigations about m-commerce, focusing on various factors, including ease-of-use perceived usefulness, security considerations, and trust-related concerns [10] [12] [16]. There need to be more studies regarding the influence of personalized offers or promotions, which could be generated by data science analytical tools, on accepting and using m-commerce apps in the Saudi context, precisely, as well as worldwide.

C) Technology acceptance model

The technology acceptance model (TAM) is a theoretical framework that applies the theory of rational action (TRA) proposed by Fishbein and Ajzen in 1976 [17] to assess the extent to which individuals utilize information technology. This theoretical framework is based on the fundamental premise that all individuals exhibit conscious self-regulation and actively incorporate accessible information into their decision-making processes. According to Fishbein and Ajzen, an individual's intention to engage in a specific behavior could be determined by two key factors [17]. The first factor pertains to the individual's attitude towards the behavior, while the second factor involves the influence of social norms, specifically subjective norms. The technology acceptance model developed by Davis in 1989 [18] has gained significant popularity as a model for understanding users' technology acceptance and usage [19]. In 1989, Davis developed a belief set for the adoption of technology [18], aligning with the recommendation put forth by Fishbein and Ajzen [17]. The belief system comprises two components: perceived usefulness (PU) and perceived ease of use (PEOU). According to Davis [18], the concept of PU refers to an individual's perception of how using a specific information system would improve their job performance. Additionally, Davis defined PEOU as an individual's perception of the level of effort required to use a particular information system [18]. Figure 1 displays a graphical depiction of the components within the technology acceptance model.

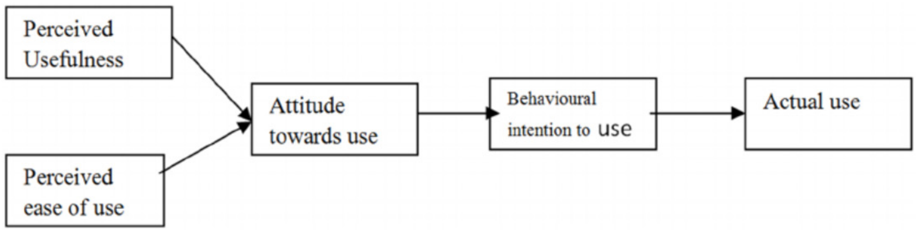

Fig. 1. The TAM model

3 CURRENT RESEARCH

This research has been dedicated since there has yet to be research examining the impact of personalized offers or promotions generated through data science analytical techniques on the acceptance of m-commerce in a general context, specifically within Saudi Arabia. In the domain of m-commerce, numerous recent studies have employed the TAM model as a foundational framework in their investigations and indicated strong and supported results [7], [20], [21], and [22]. As the purpose is to examine the influence of personalized offers and promotions on attitude towards use and behavioral intention to use m-commerce apps in Saudi Arabia, the research model of this study has been developed based on the TAM model, as shown in Figure 2.

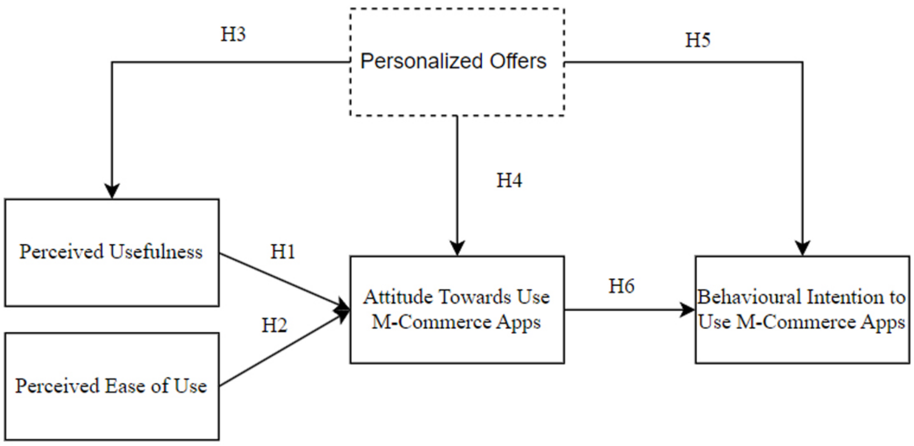

Fig. 2. The research model

4 THEORETICAL FOUNDATION AND HYPOTHESES FORMATION

A) Perceived usefulness

The concept of PU investigates the adoption of information technology from consumers' perspectives and their perceptions of how it can enhance job performance. According to Davis [18], individuals who believe that information technology can improve their performance at work without encountering significant usage challenges are more inclined to adopt the technology. The research conducted by Mollick et al. [7] demonstrates a positive correlation between PU and the intention to utilize mobile commerce from a pragmatic perspective. Mobile commerce businesses should prioritize adequate consideration of PU. It is imperative to establish effective communication channels with telecommunications companies to develop mobile interface environments with streamlined and practical applications. The interface environments should be designed to enable consumers to engage in various levels of mobile commerce activities in a convenient and user-friendly manner. According to a study by Ertz et al. in 2022, there is a positive correlation between the Chinese population's inclination towards mobile shopping (m-shopping) and their perception of its usefulness [21]. Similarly, the research conducted in Indonesia by Indarsin and Ali in 2017 [16] reveals a significant relationship between PU and A partial attitude toward using m-commerce. These findings suggest that a similar trend may be observed in other emerging markets. Therefore, the flowing hypothesis is proposed:

H1: Perceived usefulness positively affects users' intention to use apparel m-commerce.

B) Perceived ease of use

The concept of perceived ease of use (PEU) refers to the subjective perception of the level of effort required when utilizing an information technology system. According to Davis, consumers are more likely to accept information technology if it is easier to use. The research conducted by Chi [23] expanded upon the TAM model by including brand equity and website quality as factors influencing the perception of usefulness and ease of use. This was done to predict the intention of Chinese consumers to engage in apparel m-commerce. The findings indicated that the perception of ease of use significantly impacts consumers' favorable attitudes towards purchasing apparel through m-commerce platforms [23]. In their study, Hsu and Yeh [24] successfully integrated TAM with the decision-making trial and evaluation laboratory (DEMATEL) methodology. This study reveals that the PEU is a significant determinant in adopting m-commerce in Taiwan, thereby contributing to its fulfilment. Therefore, the flowing hypothesis is proposed:

H2: Perceived ease of use positively affects users' intention to use m-commerce apps.

C) Personalized offers

Mobile marketing distinguishes itself from other forms of advertising by utilizing hyper-contextualized, personalized advertising. In essence, marketers can create and distribute mobile targeting content that is both highly relevant and personalized through various mobile channels such as SMS, in-app messaging, and push notifications. This is achieved by considering the immediate customer context, including factors such as location, time, environment, companions, and dynamic competition [25]. According to Anshari et al., numerous organizations tend to adopt a simplified approach to marketing strategies, wherein they prioritize short-term customer relationships without considering the methods of attracting, retaining, and extending these relationships in the long term [26]. Hence, it is imperative to implement personalization and customization strategies in marketing that cater to individual customers' unique needs and preferences. Vassakis et al. [27] identified Google as a prominent born-digital company that utilizes data derived from search engine operations to facilitate digital marketing endeavors. By leveraging this data, Google aims to deliver personalized search experiences to its user base. Additionally, both Google and Facebook engage in data collection practices, thereby creating avenues for tailored and individualized marketing strategies [27]. It's commonly known that Saudi Arabia represents a sizable market for online commerce. Customers use various payment options and software programs when making purchases from merchants in different parts of the world. As a result, several academic studies have been undertaken on m-commerce, focusing on Saudi Arabia. Khan's research from the year 2020 shows, for instance, that discounts and specials are a significant incentive for customers in Saudi Arabia to use an online buying system [9]. Numerous academic studies have provided evidence supporting the effectiveness of personalized promotions in promoting positive outcomes across multiple domains, such as attention, attitudes, purchasing behavior, and click-through rates [15]. Therefore, personalized offers could positively affect both attitudes towards and behavioral intentions to use m-commerce apps. Hence, the following hypotheses were developed:

H3: Personalized offers positively affect perceived usefulness.
H4: Personalized offers positively affect the attitude towards using m-commerce apps.
H5: Personalized offers positively affects users' behavioral intention to use m-commerce apps.

D) Attitude towards use

Attitude pertains to how individuals express their favorable or unfavorable emotions towards something [28]. In this instance, the users' attitude pertains to the extent to which they exhibit either favorable or unfavorable sentiments regarding the usage of m-commerce apps. Numerous scholars have elucidated that there exists a substantial correlation between attitude and behavioral intention [16] [28] [29]. Consequently, the subsequent hypothesis is formulated:

H6: Attitude towards use affects users' intention to use m-commerce apps.

5 RESEARCH METHODOLOGY

The present study utilizes a quantitative approach to gather statistical information from consumers of mobile commerce applications in Saudi Arabia. The study incorporates and modifies established instruments to ensure the appropriateness of the survey items [23] [30]. Table 1 displays the survey construct, matching items, and sources of the items. The survey was first developed in English and later translated into Arabic. To mitigate potential ambiguity in the terminology used, the survey questions underwent a thorough assessment by a qualified translation expert. Subsequently, a pilot study was undertaken to refine the ultimate English/Arabic iteration that was delivered to a group of academics and potential users. A five-point Likert scale is a commonly adopted approach for gauging responses in survey design. This scale ranges from 1, indicating strong disagreement, to 5, indicating strong agreement. A web-based survey was distributed through several social media platforms and WhatsApp groups. To ensure research participants' appropriateness, inclusion and exclusion criteria were established. To be eligible for inclusion in the study, individuals must meet two standards: they must be at least 18 years of age and have prior experience using mobile commerce applications. A total of 385 individuals actively engaged in the survey.

The data analysis comprised a total of 367 replies, following the removal of incomplete responses. The present study utilized the partial least squares (PLS) methodology to examine and confirm the hypothesized linkages within the conceptual model. The PLS methodology is a statistical analytic method that relies on structural equation modeling (SEM) principles [31]. SmartPLS is a widely utilized program for partial least squares structural equation modeling (PLS-SEM) analysis and has been documented by Hair et al. [31]. The utilization of SEM is pertinent to this study as it facilitates the concurrent examination of both formative and reflective components, as supported by Hair et al. [31]. The present study has employed the most recent iteration of the SmartPLS software, namely version 4.

Table 1. Survey based constructs and items

Construct	Measurement Items	Reference
Perceived Ease of Use (PEU)	PE1: Learning how to shop on my mobile device was easy for me. PE2: I found it easy to use mobile shopping apps to do what I wanted to do. PE3: It was easy for me to become skillful at shopping mobile websites. PE4: I found it easy to shop via mobile apps.	Items have been modified to suit the present research context [31].
Perceived Usefulness (PU)	PU1: Shopping on my mobile device improved my performance regarding my shopping tasks. PU2: Shopping on my mobile device improved my productivity. PU3: I find that shopping on my mobile device was more convenient than online shopping via computers. PU4: Shopping on my mobile device enhanced my effectiveness in my shopping tasks.	Items have been modified to suit the context of the present research [31].
Attitude (ATT)	ATT1: I like the idea of using my mobile device to purchase in the next 6 months. ATT2: Using my mobile device to purchase in the next 6 months is a wise idea. ATT3: Using my mobile device to purchase in the next 6 months is a good idea. ATT4: Using my mobile device to purchase in the next 6 months is a positive idea.	Items have been modified to suit the context of the present research [31].
Personalized offers (PO)	PO1: I find it beneficial to receive personalized mobile phone offers. PO2: I appreciate mobile coupons for discounts. PO3: I perceive mobile apps' promotions to be beneficial. PO4: I will use m-commerce apps if they provide personalized offers and promotions.	Self-developed based on Barutçu [4].
Behavioral Intention (BI)	BI1: I intend to use my mobile device to purchase in the next 6 months. BI2: I expect to use my mobile device to purchase in the next 6 months. BI3: It is likely that I will use my mobile device to purchase in the next 6 months. BI4: I will use my mobile device to in the next 6 months.	Items have been modified to suit the context of the present research [30].

6 DATA ANALYSIS

A) Descriptive analysis

The results of the descriptive analysis indicated that 60% of the participants in the study are male, while the remaining 40% are female. The most significant proportion of participants (46%) falls within the age range of 25–34 years, while 31% are aged between 18–24 years, and 16% fall within the 35–44 age group. The participants' educational background is characterized by 50% possessing a bachelor's degree, followed by 19% who possess a high school degree, and 15% possessing a master's degree. The following Table 2 provides a comprehensive depiction of the participant demographics.

Table 2. Demographics of the participants

Variable	Description	Frequency	Percentage
Gender	Male	219	60%
	Female	148	40%
		Total = 367	**Total = 100%**
Age	18–24	115	31%
	25–34	169	46%
	35–44	60	16%
	45–59	17	5%
	60 and above	6	2%
		Total = 367	**Total = 100%**
Educational Level	Less than high school	5	1%
	High school	69	19%
	Diploma	49	13%
	Bachelor	183	50%
	Master	53	15%
	PhD	8	2%
		Total = 367	**Total = 100%**

B) Measurement model assessment

The initial analysis stage involves conducting tests to assess the internal consistency, convergent validity, and discriminant validity of the variables under study [31]. Lambert and Durand in 1991 [32] emphasized the importance of utilizing multiple items to measure a variable. Each item plays a crucial role in the measurement process, and factor loadings provide an indication of the extent to which each scale item, specifically designed to assess a specific parameter, adds to the overall measurement. According to Shevlin and Miles (1998), three distinct threshold values exist. They found that factor loadings under 0.3 are considered low, loadings between 0.5 and 0.7 are considered moderate, and loadings beyond 0.7 are considered high [33]. Factor loadings in the medium range or above are appropriate in this scenario. Table 3 also displays the reliability of the measurement. Previous authors have utilized Cronbach's alpha and composite dependability (CR) to quantify reliability. Internal consistency is calculated using Cronbach's alpha = 0.70 [31]. Average variance extracted (AVE) values of 0.50 and CR values greater than AVE are used to determine convergent validity [31].

Discriminant validity, the second form, is determined by evaluating the square root of each construct's AVE. The AVE value is expected to exceed any correlation observed between the latent variables in each construct [31]. The concept of discriminant validity, as demonstrated in Table 3, indicates that the strength of the correlation between items within a given variable should be greater than the correlation between those items and items from a different variable. Based on the criteria established by Fornell and Larcker in 1981 [34], the bold diagonal values presented in Table 3 are expected to exhibit higher magnitudes than their corresponding values in the associated columns and rows. The presented table demonstrates that the observed values surpass the corresponding values in both the columns and rows, thus providing evidence of discriminant validity.

Table 3. Reliability and validity measurements

	CA	(rho_a)	AVE	ATT	BI	PO	PU	PE
ATT	0.746	0.755	0.568	**0.754**				
BI	0.869	0.874	0.719	0.426	**0.848**			
PO	0.847	0.847	0.686	0.473	0.622	**0.828**		
PU	0.816	0.823	0.646	0.505	0.481	0.484	**0.804**	
PE	0.783	0.795	0.606	0.462	0.492	0.597	0.477	**0.778**

Notes: PU: Perceived usefulness; PE: Perceived ease of use; PO: Personalized offers; ATT: Attitude towards use; BI: Behavior intention.

C) Structural model assessment

1. Path testing

The evaluation of all the hypotheses developed in this study is conducted using the SEM technique. The results presented in Table 4 include the coefficients and significance values. The bootstrapping procedure was employed to assess the significance of the path coefficient. According to Hair et al., SmartPLS has the capability to perform bootstrapping to evaluate the p-value and t-value for assessing the relevance and significance of both the model and experiment [31]. A hypothesis is accepted when its p-value is less than 0.05 and its t-value is more prominent than 1.96, as determined by the directional hypothesis [31]. The outcomes of the path tests and coefficient histograms may be seen in Table 4, Figures 3, and 4.

Table 4. Path testing

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Decision
ATT -> BI	0.170	0.172	0.048	3.509	0.000	Supported
PO -> ATT	0.209	0.212	0.056	3.732	0.000	Supported
PO -> BI	0.541	0.541	0.051	10.652	0.000	Supported
PO -> PU	0.484	0.487	0.048	10.026	0.000	Supported
PU -> ATT	0.314	0.316	0.059	5.326	0.000	Supported
PE -> ATT	0.187	0.188	0.060	3.106	0.002	Supported

Notes: PU: Perceived usefulness; PE: Perceived ease of use; PO: Personalized offers; ATT: Attitude towards use; BI: Behavior intention.

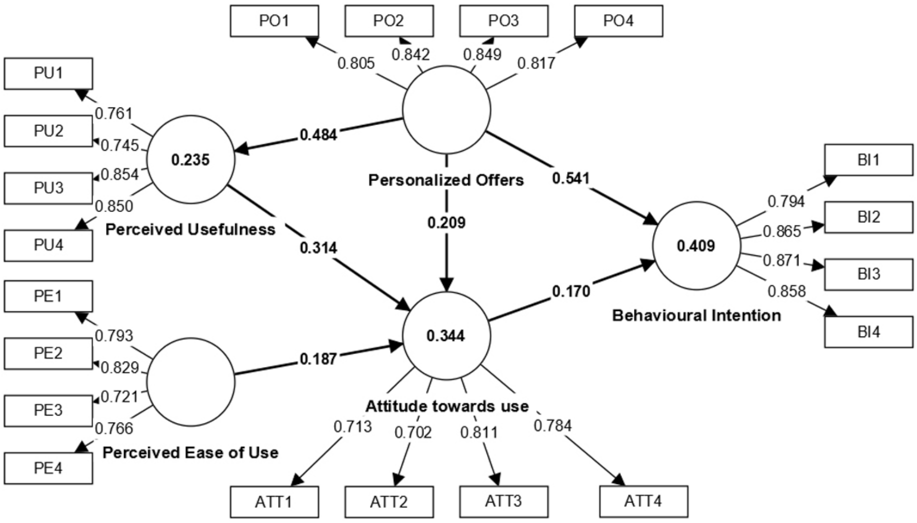

Fig. 3. Measurement tests of the research model

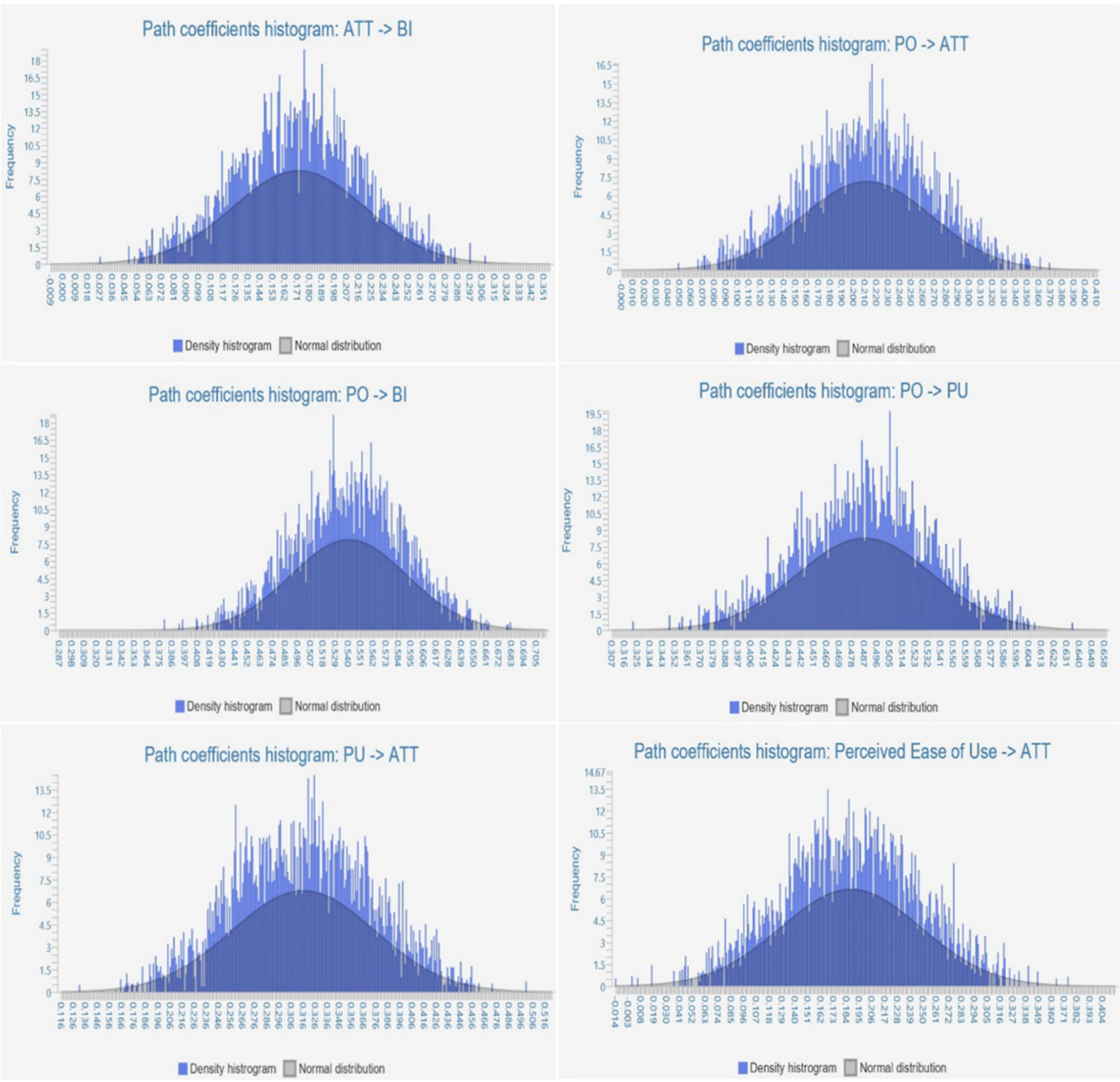

Fig. 4. Path coefficients histograms

2. Coefficient of determination (R^2)

For the coefficient of determination, Chin (1998) suggests a triad of values [35]. In general, R2 values above 0.67 are regarded as very high, those from 0.33 to 0.67 as moderate, and those from 0.19 to 0.33 as insufficient or unsuitable [35]. In this study, the correlation coefficient (R^2) of perceived usefulness is 0.235, attitude towards use is 0.344, behavioral intention is 0.409. Therefore, this investigation yielded just a mediocre outcome.

7 DISCUSSION

Aligned with the research objectives, this study aims to elucidate the impact of personalized offers and promotions generated by data science tools on users' attitudes and behavioral intentions towards using m-commerce apps and their perceived usefulness of such applications in Saudi Arabia. This investigation is grounded in the TAM model. Furthermore, this study aims to investigate further the various factors that influence users' behavioral intentions to adopt mobile commerce applications in Saudi Arabia. According to the findings presented in Table 4 and Figure 3, it can be observed that personalized offers and promotions have the highest level of significance among the variables that strongly impact behavioral intention. This is followed by an attitude towards use. The study results indicate that perceived usefulness is the most significant factor in influencing attitudes toward use. This is followed by personalized offers and promotions, which have a higher significance level than perceived ease of use.

This study's results indicate a significant impact of PU on attitudes towards its use. This is supported by a significance level (P value) of 0.000, less than the conventional threshold of 0.05, and a t-value exceeding 1.96. As a result, the first hypothesis of this study is accepted. This study's results indicate a statistically significant positive impact of PEU on attitude towards use, with a considerable level of 18.7%. This finding is supported by a P value of less than 0.05 and a t-value of 3.106, thereby confirming the second hypothesis.

In addition, the influence of personalized offers on PU is found to be statistically significant. The obtained significance value of 0.000, which is less than the predetermined threshold of 0.05, along with a t-value of 10.026, exceeding the critical value of 1.96, provides evidence to support the acceptance of the third hypothesis in this study. The findings of this study suggest that personalized offers have a notable influence on people's attitudes towards usage. This finding is substantiated by a statistically significant P value of 0.000, which falls below the standard limit of 0.05, and a t-value surpassing 1.96. As a result, both the third and fourth hypotheses of this study are accepted.

Furthermore, the utilization of personalized offers demonstrates a positive and statistically significant effect of 54.1% on behavioral intention. This finding is supported by a p-value of less than 0.05 and a t-value of 10.652, thereby proving the validity of the fifth hypothesis in this research study. The study found that there is a significant positive impact of attitude towards use on behavioral intention, with a 17%. The statistical analysis showed a significance value of $p = 0.000$, less than the threshold of 0.05, and a t-value of 3.509, greater than the critical value of 1.96. Therefore, the sixth hypothesis of this study is accepted.

Based on the findings of the study, it was determined that the factors influencing individuals' attitudes towards the use of m-commerce applications can be ranked in terms of their significance. The order of importance is as follows: perceived usefulness, with a path coefficient of 0.314; personalized offers, with a path coefficient of 0.209; and perceived ease of use, with a path coefficient of 0.187. Furthermore, it has been observed that personalized offers play a significant role in affecting the perceived usefulness of m-commerce apps, as indicated by a path coefficient of 0.484. Based on these findings, it can be concluded that the factors influencing the behavioral intention to use m-commerce apps can be ranked in terms of their significance. The most influential factor is personalized offers, with a path coefficient of 0.451. Following this, attitude towards use is the second most significant factor, with a path coefficient of 0.170.

The findings additionally validate that the suggested factor, personalized offers, exerts a more substantial impact on the behavioral intention to embrace m-commerce applications in Saudi Arabia. The utilization of various data science analytical tools in Saudi m-commerce apps enables the generation of personalized offers and promotions, thereby potentially influencing user behavior and enhancing the overall usefulness of the app. In general, our analysis aligns with previous studies on the acceptance of technology and apps. However, we have also found that the inclusion of personalized offers has an impact on users' behavioral intentions.

The existing study exhibits certain limitations. Initially, the study exclusively utilized a quantitative research approach. The utilization of qualitative or mixed methodologies in studies on the acceptance of m-commerce can result in valuable insights and enhance the credibility of the data collected for studies on m-commerce applications. Furthermore, the study framework failed to incorporate all relevant factors that could potentially influence an individual's inclination to accept and use m-commerce apps.

Furthermore, a significant proportion of the participants in this study were of a younger demographic and originated from a single nation. While these individuals serve as a sample of m-commerce users, it is essential to note that their characteristics may not be applicable to all age groups and cultures. Hence, it is imperative to ascertain the validity of the findings across different age cohorts and cultural contexts.

8 FUTURE WORK

This study examines how personalized offers in m-commerce apps affect user behavior. Future studies might improve our understanding of this phenomenon in numerous ways. Future research may investigate how personalized offers work in different product categories and consumer segments. The effects of customization on customer engagement, purchase intentions, and long-term client loyalty might help explain the efficacy of personalized offers in m-commerce apps. Furthermore, as technological advancements progress quickly and the volume of consumer data expands, future research endeavors might include AI and machine learning algorithms to enhance the customization process. Exploring recommendation systems and predictive analytics to improve the precision and personalization of m-commerce offers could enhance efforts in the field.

Additionally, more research is needed on the ethical implications of personalized offers in Internet commerce. To develop ethical and transparent customization tactics, one must understand client views on privacy, data usage, and confidence in personalized products. Future studies may examine consumer concerns about data privacy, consent, and personalized offer risks. Given the global reach of m-commerce, future research should examine cross-cultural differences in customer responses to personalized offers. Global m-commerce companies operating in different regions may benefit from studying how cultural factors like individualism-collectivism, power distance, and uncertainty avoidance affect consumers' preferences for personalized offers.

9 CONCLUSION

The results of this study carry substantial implications. This study contributes to the existing literature on information systems and mobile technologies by examining various factors influencing the acceptance and utilization of m-commerce applications. In addition, this study investigates the impact of personalized offers and promotions generated with data science analytical tools on users' attitudes and behavioral intentions towards the adoption of mobile commerce applications in the specific setting of Saudi Arabia. The TAM model examines the factors impacting users' behavioral intentions towards utilizing m-commerce applications. The findings show that PU has the highest level of significance for users' attitudes towards usage, followed by personalized offers. The study also finds that personalized offers significantly positively impact users' attitudes towards usage, with a path coefficient of 0.484. The study also finds that personalized offers strongly impact users' behavioral intentions towards using m-commerce apps, with a path coefficient of 0.451.

This research study further provides valuable insights for future academic investigations in the discipline. Additionally, it provides app developers and businesses with novel expertise and understanding to formulate strategies that improve the continued development of m-commerce apps. Incorporating data science is crucial to advancing mobile apps, as it optimizes their overall efficacy and offers users heightened advantages. Developers can identify successful marketing channels and strategies for acquiring new users by analyzing user data and app usage patterns. Data science tools can aid businesses in augmenting their brand promotion efforts and delivering personalized offers, thereby contributing to the overall enhancement of customer acquisition.

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