Digital Agricultural Marketing: Determinants of Consumer Engagement Intentions in Urmia, Iran

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Abstract

The importance of understanding consumer engagement with digital marketing in agriculture is highlighted by the rapid evolution of digital platforms, which are transforming traditional marketing approaches. This study investigates the factors influencing consumer intentions to engage with digital marketing of agricultural products in Urmia, Iran. Data were collected from 385 respondents through a structured questionnaire and analyzed using a logistic regression model. Results indicate that perceived usefulness, perceived ease of use, trust, information quality, and social influence positively and significantly impact engagement intentions. Demographic factors such as age (negatively), education level, and income (both positively) also play significant roles. Notably, prior online purchase experience emerged as a strong predictor of engagement intention, while price sensitivity showed a marginally significant negative effect. The study contributes to the literature by providing empirical evidence from a developing country context and offering a comprehensive model for understanding consumer behavior in digital agricultural marketing. Implications for marketers include developing user-friendly platforms, prioritizing trust-building mechanisms, and tailoring strategies to different demographic segments.

Keywords: Digital Marketing, Agricultural Products, Consumer Intentions, Urmia

Introduction

Digital marketing in agriculture encompasses online and technology-driven promotional activities, such as social media, content marketing, and e-commerce (Tiago & Veríssimo, 2014; Michaelidou et al., 2011; Yadav & Rahman, 2017). These strategies aim to increase brand awareness, enhance customer engagement, and drive sales of agricultural products (Kutter et al., 2011). The adoption of digital marketing is driven by consumers' growing reliance on digital channels (Dlodlo & Dhurup, 2013). Successful implementation requires an understanding of the unique characteristics and challenges of the agricultural sector, including perishability, seasonality, and producer diversity (King et al., 2010).

Digital marketing in agriculture has evolved significantly over the past decade, driven by advancements in technology and the increasing internet accessibility in rural areas. The integration of digital tools has enabled farmers to access real-time market information, weather forecasts, and best practices, thereby enhancing productivity and profitability (Reddy & Reddy, 2022). Social media platforms such as Facebook and Instagram, along with mobile applications have become pivotal in connecting farmers with consumers. These platforms facilitate direct sales, reducing the dependency on intermediaries and improving margins for farmers (Karle and Mishra, 2022). Additionally, digital marketing strategies have been instrumental in promoting sustainable agricultural practices and educating farmers about innovative techniques (Ijomah et al., 2024). The adoption of digital marketing in agriculture is not only transforming traditional farming practices but also contributing to the overall development of rural economies (Reddy & Reddy, 2022).

Understanding consumer intentions towards digital marketing is crucial in today's rapidly evolving digital landscape (Patel & Chauhan, 2022). As businesses increasingly rely on digital channels to reach and engage their target audience, comprehending the underlying motivations and attitudes of consumers becomes essential for effective strategic development (Haris, 2024). Research indicates that consumer intentions in the digital realm are influenced by a complex interplay of factors, including trust, perceived usefulness, and personal relevance (Cho and Sagynov, 2015). By gaining insights into these intentions, marketers can tailor their approaches to align with consumer expectations, potentially leading to improved engagement rates and higher conversion metrics (Erislan, 2024). Furthermore, a deeper understanding of consumer intentions enables organizations to anticipate shifts in digital behavior, allowing for more agile and responsive marketing strategies in an increasingly competitive online environment (Sunarya et al., 2024).

Despite the growing importance of digital marketing in the agricultural sector, there is limited research on consumers' intentions and attitudes towards these marketing efforts for agricultural products, particularly in the context of Iranian cities. The factors influencing consumer acceptance and engagement with digital marketing of agricultural products remain poorly understood (King et al., 2010). Urmia, the largest city in West Azerbaijan Province, is renowned for its production of apples, grapes, and other agricultural products. Urmia serves as a significant urban market for agricultural goods in northwestern Iran. The city's strategic position near the borders of Turkey and Iraq further enhances its potential as a hub for agricultural trade in the region. Therefore, this study centers on Urmia, which is located in a fertile agricultural region, with an estimated population of approximately 790,000[1] in 2023. This knowledge gap hinders the development of effective digital marketing strategies tailored to the unique characteristics of agricultural products and their consumers in Urmia.

Literature Review

Existing research highlights both the potential benefits and barriers, such as infrastructure constraints and data privacy concerns. Consumer intentions towards digital marketing of agricultural products are influenced by various factors and digital marketing can positively impact agricultural sales. Dlodlo and Dhurup (2013) revealed that small-scale farmers who adopted digital marketing strategies experienced boosted sales and market reach. Furthermore, Lu et al. (2016) found that social media marketing improved brand awareness and customer engagement for organic agricultural products. However, beyond increasing sales and engagement, consumer trust plays a crucial role in shaping online purchasing decisions.

Yadav and Rahman (2017) reported that social media marketing activities positively affected customer equity and purchase intention for agricultural products. Trust has emerged as a critical

[1] Calculated using an annual population growth rate of 1.06% from the 2016 census figure of 736,224 (Statistical Centre of Iran, 2016)

factor in shaping consumer intentions towards the digital marketing of these products. Kang and Namkung (2019) demonstrated that trust in online platforms and sellers significantly influenced consumers' willingness to purchase agricultural products through e-commerce channels. This finding aligns with earlier research by Pavlou and Fygenson (2006), who emphasized the role of trust in reducing perceived risks associated with online transactions. Building on this, various psychological and technological factors further shape consumer trust and purchasing behavior in different regions.

Research in Saudi Arabia emphasizes the impact of social influence, hedonic motives, perceived risk, perceived usefulness, information quality, and perceived ease of use on trust and continuance intention, ultimately leading to sustainable consumer behavior (Zia et al., 2022). Additionally, the performance of e-marketplaces, perceived ease of use, and perceived benefits play a crucial role in influencing consumer purchase intentions for agricultural products online, with website convenience being a significant factor (Kusumawati et al., 2022). Furthermore, in China, factors like perceived interactivity, perceived endorsement, product familiarity, subjective norms, altruistic value, and livestream shopping experience significantly affect consumers' attitudes and purchase intentions towards agricultural products via public-interest livestreaming, especially during the COVID-19 pandemic (Yu and Zhang, 2022). These findings demonstrate that while consumer trust, psychological and technological factors play a vital role, individual preferences, cultural influences, and economic conditions further shape digital purchasing behaviors across different regions.

Studies in Indonesia and India highlight the significance of consumer behavior, subjective norms, demographic variables, time savings, convenience, and promotional attributes in shaping online purchasing intentions for agricultural products (Aulia et al., 2024; Masih et al., 2024). These factors suggest that digital marketing strategies must be tailored to local consumer preferences and market dynamics to enhance engagement and sales.

Researchs in Iran has shed light on the significance of digital agricultural marketing. Sharifpour et al. (2016) highlight the crucial role of social media in shaping consumer perceptions and facilitating direct interactions between consumers and agricultural brands, thereby augmenting engagement intentions. Despite these opportunities, addressing existing barriers it is essential to maximizing the potential of digital agricultural marketing in Iran. Alavion and Taghdisi (2021) introduced the Geographic Model of Planned Behavior (GeoTPB) to analyze the adoption of e-marketing in rural areas. Their study, which encompassed 1,000 villages, successfully predicted 76% of villagers' intentions to adopt e-marketing and identified six distinct rural clusters. Notably, the traditionally less developed southern and southeastern provinces emerged as leading regions for e-marketing adoption, challenging conventional assumptions and providing valuable insights for targeted rural development strategies.

Building on this review, consumer intention to engage with digital marketing for agricultural products is shaped by several key factors. Perceived usefulness and ease of use significantly enhance the likelihood of online purchases, as consumers are more inclined to utilize digital platforms, they deem beneficial and user-friendly. Trust in online platforms and sellers is essential, as it mitigates perceived risks and increases willingness to transact. Furthermore, social influence and social media marketing play a pivotal role in boosting brand awareness and engagement, which further drives purchase intentions. Additionally, the quality of information, website performance, and convenience are crucial in shaping consumer decisions. Subjective norms, demographic variables, and behavioral factors- such as time savings and promotional attributes- also impact online purchasing intentions, highlighting the multifaceted nature of consumer engagement with digital marketing in agriculture. To the best of our knowledge and based on the reviewed literature, this study represents the first investigation within the agricultural sector in Iran. The objective of this research is to examine the key factors influencing the intention to adopt digital marketing for agricultural products in Urmia City.

Methodology

- Research design and Sampling Method

In this study, we employed a quantitative research design to investigate the intentions of consumers in Urmia toward engaging with the digital marketing of agricultural products. Specifically, a cross-sectional survey methodology was employed to collect data from a sample of consumers.

This study utilized a structured questionnaire to gather cross-sectional data on factors influencing digital marketing engagement in agriculture. The questionnaire encompassed three main groups of variables: (1) **Perceptions and Trust**, including perceived usefulness (PU), perceived ease of use (PEOU), trust (TR), information quality (IQ), and social influence (SI); (2) **Demographic and Economic Factors,** comprising age (AGE), education level (EDU), income (INC), and price sensitivity (PS); and (3) **Experience and Behavioral Intention,** covering prior online purchase experience (EXP) and the intention to engage with digital marketing of agricultural products. To ensure a representative sample, we employed a multi-stage sampling technique, selecting regions based on agricultural activity and accessibility, and then randomly choosing participants from lists provided by local agricultural associations. Following data cleaning to address incomplete or inconsistent responses, we analyzed a final sample of 385 valid questionnaires.

The target population for the study was general consumers in Urmia who have the potential to purchase agricultural products. The sample size was determined using the Cochran's formula (1977), which resulted in a sample of 385 respondents.

$$n_0 = \left(Z^2 \times p \times q\right) / e^2 \quad (1)$$

where n_0 is the sample size, Z = 1.96 (95% confidence level), p = 0.5 (most conservative estimate) and e = 0.05 (desired level of precision). This calculation yielded an initial sample size of 385. Cluster random sampling method was used. The city of Urmia is divided into 5 municipal districts, each of which was considered as a cluster.

The structured questionnaire was pilot tested with a small sample of consumers to ensure the clarity and validity of the items. Based on the pilot results, minor revisions were made to the wording of specific questions.

The questionnaire is structured into five distinct sections. Section A collects demographic information, including age, education level, and income level. Section B focuses on participants' online shopping experience, encompassing purchase history and shopping frequency. Section C assesses perceptions and attitudes, measuring constructs such as perceived usefulness, perceived ease of use, trust, information quality, social influence, and price sensitivity. Section D evaluates engagement intention, capturing metrics related to future use likelihood and recommendation intent. Finally, Section E provides space for additional comments, allowing participants to share desired features and express any concerns regarding online shopping platforms.

Data were collected over a 4-week period through face-to-face interviews with respondents in various locations across Urmia, including local markets, grocery stores, and community centers.

In total, 384 valid responses were obtained. Respondents, while not necessarily the designated head of household, were identified as the primary household shoppers.

- Theoretical and Analytical Framework

The theoretical foundation of this study is anchored in the neoclassical microeconomic theory, which posits that economic agents seek to maximize their utility when making decisions. In the context of this research, this theory is applied to understand consumer intentions regarding the digital marketing of agricultural products. Specifically, the study employs the Random Utility Model (RUM) to conceptualize how consumers decide to engage with digital marketing platforms. According to RUM, a consumer's intention to engage with digital marketing is influenced by the utility derived from such engagement.

Consumers are assumed to evaluate the utility (U) of engaging with digital marketing versus not engaging based on factors like perceived usefulness, ease of use, trust, and social influence. The choice to engage with digital marketing is made if the utility from engaging exceeds the utility from not engaging. Formally, a consumer will opt to engage with digital marketing if and only if $Uj > Uk$, where j and k represent digital marketing and an alternative choice, respectively. The consumer utility i (U_i) is decomposed into a deterministic component (V_i), which includes measurable factors, such as perceived benefits and ease of use, and a random component (ε_i), which captures unobservable factors affecting the consumer's decision (Greene, 2019). This theoretical framework guides the empirical analysis, which uses an econometric logit model to estimate the probability of consumer engagement with digital marketing, based on the specified utility components.

$$U_i = V_i + \varepsilon_i \qquad (2)$$

If individual *i*'s utility from choosing a digital purchase exceeds that of a non-digital purchase, the variable *z* will equal one; otherwise, it will equal zero (McFadden, 1974).

$$Z_i = (U_{ij} - U_{ik}) \rightarrow \begin{cases} if\ (U_{ij} - U_{ik}) \geq 0\ then\ Z_i = 1 \\ if\ (U_{ij} - U_{ik}) < 0\ then\ Z_i = 0 \end{cases} \qquad (3)$$

Let U_{ij} denote the utility that consumer *i* derives from selecting digital marketing option (j), and U_{ik} represent the utility from choosing an alternative option. The variable Z_i is defined as the dependent variable that captures the difference in utilities. Specifically, Zi takes a value of one if the difference in utilities is positive, and zero otherwise. Thus, the utility difference model simplifies the choice process into a binary outcome, reflecting whether the digital marketing option is favored over the alternative based on the comparative utility values.

To empirically analyze the factors influencing Z_i, the following logistic regression model is employed (Greene, 2019):

$$\log itP(Z_i = 1) = \alpha + \beta X_i + \varepsilon_i \qquad (4)$$

where, logitP(Z_i = 1) denotes the log odds of Z_i equating to one, thereby indicating a preference for digital marketing option j. X_i represents a vector of control variables that could potentially influence the consumer's choice, encompassing demographic characteristics, prior experience, and other pertinent factors. The terms α and β correspond to the intercept and the coefficient for the control variables, respectively. ε_i signifies the error term, encapsulating unobserved factors that may impact the decision-making process. The Logit model can be estimated using maximum likelihood (MLE) process. The MLE of the logit model involves finding parameter estimates that maximize the likelihood function, which is derived from the probability distribution of the logistic function. This approach ensures that the estimated coefficients best fit the observed data by maximizing the probability of obtaining the observed outcomes, as discussed by McFadden (1974) and Greene (2019).

The marginal effect (ME) measures the change in the probability of Z_i=1 resulting from a one-unit change in X_i. The probability $P(Z_i=1)$ is given by the logistic function:

$$P(Z_i=1) = \frac{1}{1+exp[-(\alpha+\beta X_i)]} \tag{5}$$

To compute the marginal effect of X, we differentiate the probability function with respect to X:

$$ME = \frac{\partial P(Z_i=1)}{\partial X} = P(Z_i=1)\cdot(1-P(Z_i=1))\cdot\beta \tag{6}$$

Standard errors for the marginal effects can be computed using the delta method or bootstrapping techniques. Estimating marginal effects is crucial for evaluating how incremental changes in predictors, such as perceived usefulness or trust, affect consumer engagement. Such insights are instrumental in enabling marketers to refine strategies, thereby enhancing the overall efficacy of digital marketing initiatives.

Table 1 summarizes the dependent and independent variables utilized in this study. Following previous studies, we grouped the explanatory variables into three components: (1) Perceptions and Trust; (2) Demographic and Economic Factors; and (3) Experience. Stata (ver. 17.0, Stata Corp) is used for estimations. To address potential heteroskedasticity arising from measurement errors, model specification inaccuracies, or subpopulation variances, we employed the 'robust' option in Stata to obtain robust standard errors for the logit model estimates. Furthermore, an analysis of variance decomposition of the parameters facilitated the evaluation of multicollinearity among the predictors.

Table 1: Descriptive Statistics of Variables

Variable	Definition of the variables	codes	Mean (SD)
Dependent Variable			
Intention to Engage (Y)	The intention to engage with digital marketing initiatives of agricultural products	Binary (1 = Yes, 0 = No)	0.65 (0.48)
Independent Variables			
-Perceptions and Trust (grouped into Components)			
Perceived Usefulness (PU)	The degree to which a person believes that using digital marketing for agricultural products enhance their purchasing performance.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	3.72 (0.89)
Perceived Ease of Use (PEOU)	The degree to which a person believes that using digital marketing for agricultural products is free of effort.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	3.58 (0.95)
Trust (TR)	The extent to which consumers believe in the reliability and integrity of digital marketing platforms for agricultural products.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	3.41 (1.02)

Variable	Definition of the variables	codes	Mean (SD)
Dependent Variable			
Information Quality (IQ)	The perceived quality of information provided through digital marketing channels for agricultural products.	5-point Likert scale (1 = Very Poor, 5 = Excellent)	3.63 (0.87)
Social Influence (SI)	The degree to which an individual perceives that important others believe they should use digital marketing for purchasing agricultural products.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	3.29 (1.08)
Price Sensitivity (PS)	The degree to which consumers focus on paying low prices for agricultural products.	5-point Likert scale (1 = Not at all sensitive, 5 = Extremely sensitive)	3.85 (0.92)
-Demographic and Economic Factors			
Age	The age of the respondents	Continuous variable (in years)	42.3 (13.7)
Education Level (EDU)	The highest level of education attained by the respondent	Categorical (1 = Primary, 2 = Secondary, 3 = Bachelor's, 4 = Master's, 5 = Doctorate)	2.47 (0.86)
Income (INC)	The monthly income level of the respondent	Categorical (1 = Low, 2 = Medium-Low, 3 = Medium, 4 = Medium-High, 5 = High)	2.81 (1.12)
-Experience with Online Purchasing			
Prior Online Purchase Experience (EXP)	Whether the respondent has previous experience with online purchasing	Binary (1 = Yes, 0 = No)	0.78 (0.41)

Source: Research findings

Findings

- Descriptive Statistics

Table 1 presents the summary statistics for the variables employed in this investigation. The dependent variable, Intention to Engage (Y), indicates that 65% of respondents expressed an intention to engage with digital marketing initiatives for agricultural products, underscoring a strong inclination to interact with such efforts, which is essential for understanding consumer behavior in this context. Among the independent variables, PU and PEOU exhibited mean scores above the midpoint of the scale, indicating that respondents generally find digital marketing of agricultural products useful and easy to navigate, which is essential for user adoption and sustained engagement. TR and IQ demonstrated moderate to positive levels, suggesting that respondents possess a fair to good level of trust and find the information provided reliable and of good quality, both of which enhance user experience and engagement. Notably, PS had the highest mean among the Likert-scale variables, indicating that price is a significant factor for respondents considering engagement with digital marketing for agricultural products. Demographic analysis revealed a mean age of 42.3 years, with respondents' ages ranging from 18 to 75 years, indicating a wide range of age distribution. EDU and INC recorded means near the midpoints of their respective scales, indicating a varied educational background and broad representation of different income levels within the sample, thereby contributing to the robustness of the study's conclusions. Finally, 78% of respondents reported having prior online purchase experience, indicating a high familiarity with online shopping, which may influence their intention to engage with digital marketing of agricultural products by enhancing confidence and reducing perceived risks.

- **Logit Model Results**

To examine the factors influencing consumers' intentions to engage with digital marketing of agricultural products, we estimated a logit model. Table 2 presents the results of this estimation.

Table 2: Estimated Logit Model Results

Variable	Coefficient (p-value)	Marginal Effect (p-value)
Constant	-3.241 (0.000)	-
Perceived Usefulness (PU)	0.652 (0.000)	0.162 (0.000)
Perceived Ease of Use (PEOU)	0.438 (0.000)	0.109 (0.000)
Trust (TR)	0.521 (0.000)	0.129 (0.000)
Information Quality (IQ)	0.375 (0.001)	0.093 (0.001)
Social Influence (SI)	0.289 (0.002)	0.072 (0.002)
Price Sensitivity (PS)	-0.203 (0.053)	-0.050 (0.055)
Age	-0.015 (0.032)	-0.004 (0.046)
Education Level (EDU)	0.241 (0.039)	0.060 (0.039)
Income (INC)	0.185 (0.037)	0.046 (0.037)
Prior Online Purchase Experience (EXP)	0.729 (0.002)	0.181 (0.002)
LR $chi^2(10)$ = 218.73 (0.0000)	Pseudo R^2 = 0.2453	PRP = 76%

Source: Research findings

As shown in table 2, the logistic regression model exhibits strong overall fit, as indicated by the likelihood ratio chi-square test statistic of 218.73, which is highly significant ($p < 0.000$). This result provides compelling evidence for the statistical significance of the model as a whole, suggesting that independent variables collectively explain substantial explanatory power for the variance observed in the dependent variable. The robustness of this finding supports the relevance of the chosen predictors in capturing the underlying dynamics of consumers' intentions to engage with digital marketing of agricultural products.

The model's explanatory power is reflected in the McFadden's Pseudo R^2 value of 0.2453, indicating that approximately 24.53% of the variation in the dependent variable is explained by the predictors. While this value may not account for all variance, it is considered a substantial level of explanatory power for behavioral models in social sciences (McFadden, 1974). This finding highlights the pertinence and efficacy of the selected variables in elucidating the underlying mechanisms driving consumer intentions in this context. Further supporting the model's robustness is the Percentage of Right Prediction (PRP) of 76%. This metric indicates that the model accurately classifies more than three-quarters of the cases, showcasing its strong predictive capability (Wooldridge, 2010). Such a high PRP reinforces the model's utility as a tool for understanding and forecasting consumer behavior specifically within the domain of digital marketing for agricultural products. The model's predictive accuracy also enhances its potential applications in both theoretical frameworks and practical marketing strategies. The following provides an analysis of how each factor influences the intention to engage digital marketing for agricultural products, along with the degree of their effect.

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), consistent with the Technology Acceptance Model (TAM) (Davis, 1986), demonstrate statistically significant positive effects on engagement intentions, with marginal effects showing that a one unit increase in these variables is associated with 16.2% and 10.9% increases in the likelihood of engagement, respectively. The results of the study conducted by Ashraf et al. (2016) are consistent with the findings of our research, demonstrating that PU and PEOU play a crucial role in enhancing the overall user experience; and the study by Al-Gasawneh et al. (2022) demonstrates that these variables exert a positive influence on post-purchase behavior among Jordanian consumers.

Trust (TR), another significant predictor, reveals that higher trust levels increase engagement probability by 12.9%. This result aligns with extant literature emphasizing the pivotal role of trust in digital marketing environments (Gefen et al., 2003), particularly within agriculture where product authenticity is critical. Similarly, Rai and Timalsina (2024) emphasize trust as a central factor in enhancing marketing effectiveness, noting that it fosters consumer engagement and strengthens brand relationships. Also, the study by Otopah et al. (2024) demonstrates that consumer trust moderates the relationship between digital marketing and consumer engagement.

Information Quality (IQ) also exerts a significant positive influence, with a one-unit increase leading to a 9.3% rise in engagement likelihood, all other conditions remain constant, consistent with the Information Systems Success Model (DeLone & McLean 2003). It underscoring the critical role of reliable and pertinent information in shaping consumer decision-making processes within this context. The findings of this research align with the results of the study by Surjandy and Cassandra (2022), which demonstrate that high-quality information positively influences buying decisions by mitigating perceived risks.

Social Influence (SI), aligned with the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), similarly affects engagement, with a marginal effect of 7.2%, all other conditions remain constant, emphasizing the importance of peer influence in the adoption of digital marketing channels. The research conducted by Wang and Huang (2022) elucidates that digital influencers exert a substantial impact on consumer engagement and purchase behavior within online social commerce communities by leveraging diverse forms of social power.

Price Sensitivity (PS) shows a marginally significant negative relationship with engagement, suggesting that highly price-sensitive consumers may be less likely to use digital platforms, even though this effect approaches but does not meet conventional significance levels ($p = 0.053$). This finding contributes to the ongoing discourse on the role of price perceptions in digital marketing engagement (Lichtenstein et al., 1993) and may have implications for pricing strategies in this sector. Also, Hidrobo et al. (2021) demonstrates that farmers in Ghana, though highly price-sensitive, are largely willing to pay a low monthly fee for a digital platforms. The marginal effects analysis reveals an inverse relationship; a unit increase in Price Sensitivity corresponds to a 5% decrease in engagement probability, ceteris paribus. This finding suggests that highly price-sensitive consumers may be less inclined to engage with digital marketing channels for agricultural products.

Demographic variables like age, education, and income also play important roles. Age is negatively associated with engagement, although its effect is relatively small (0.4% decrease per year). This finding aligns with extant literature on digital divide and technology adoption across age groups (Czaja et al., 2006). In contrast, higher education levels and income both positively influence engagement, with marginal effects of 6% and 4.6%, respectively. These results corroborate previous research indicating that higher levels of education and income are associated with increased digital technology adoption and online consumer behavior (Hargittai & Hinnant, 2008). Such findings may have implications for market segmentation and targeted marketing strategies in the agricultural sector.

Prior online purchase experience emerges as a particularly strong predictor, increasing engagement likelihood by 18.1%, ceteris paribus, highlighting the importance of familiarity and prior behavior in shaping future engagement. A phenomenon well-documented in consumer behavior literature (Ajzen, 2002). The magnitude of this effect suggests that consumers with previous online shopping experience are substantially more likely to engage with digital marketing platforms for agricultural products, highlighting the potential value of cross-sector marketing initiatives and the transfer of online shopping behaviors across product categories. The study by Yi et al. (2024) indirectly reflects the influence of prior experiences, as familiarity with a product or service often shapes perceptions of quality and value, thereby affecting satisfaction levels.

Discussion and Conclusion

This study examined the factors influencing consumer intentions to engage with digital marketing of agricultural products in Urmia, Iran, utilizing a logistic regression model to analyze data from 385 respondents. The findings provide valuable insights into the complex interplay of factors shaping consumer behavior in this context, with implications for both theory and practice. The results strongly support the relevance of key constructs from established theoretical frameworks, particularly in the domain of digital agricultural marketing. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) were identified as significant positive predictors of engagement intention. Trust (TR) also emerged as a significant determinant of consumer engagement. In agricultural markets, where product quality and authenticity are paramount concerns, trust-building mechanisms such as transparency in sourcing, product certifications, and consumer reviews, are likely crucial in overcoming consumer hesitations related to product quality in the digital marketplace. Moreover, the significant positive effect of Information Quality (IQ) on engagement, highlighting the critical role of reliable and pertinent information in shaping consumer decision-making processes within this domain.

The positive effect of Social Influence (SI) on engagement emphasizes the importance of social factors in technology adoption. This finding suggests that digital marketing strategies in agriculture should leverage social proof and community engagement to enhance effectiveness. Demographic factors reveal nuanced effects, with engagement intention. Age showed a small but significant negative association with engagement intention. In contrast education level and income demonstrated positive relationships, more educated consumers are more likely to interact with digital marketing platforms for agricultural products. These findings emphasize the need for tailored marketing approaches that account for age-related barriers while leveraging the greater digital readiness of more educated and affluent segments.

A key insight is the strong positive association between Prior Online Purchase Experience and engagement intentions. This suggests that prior familiarity with online shopping significantly enhances the likelihood of engaging with digital agricultural platforms. This finding highlights the potential synergies between general e-commerce experiences and specific engagement with digital agricultural marketing.

For agricultural marketers, the results underscore the importance of designing user-friendly digital platforms that provide clear, tangible value to consumers. Trust-building measures, such as strong security protocols and verified customer reviews, are crucial in an industry where product authenticity and quality are key. Furthermore, digital marketing initiatives should emphasize high-quality, educational content that informs consumers about product origins, farming practices, and sustainability to increase efficacy. Marketers should take advantage of social proof and community involvement. Campaigns must be customized for various demographic groups, taking into account differences in participation across age, income, and educational levels. Addressing price sensitivity is another important consideration. Marketers could experiment creative pricing techniques and unambiguous value communication. Lastly, utilizing customers' past online shopping experiences-possibly by forming alliances with well-known e-commerce platforms-can stimulate interest in agricultural product digital marketing.

This study makes a valuable contribution to the literature by providing empirical evidence on consumer intentions towards digital marketing of agricultural products in a developing country, addressing a notable gap in current research. It integrates multiple theoretical frameworks to percent a comprehensive model of consumer behavior in this specific domain. Notably, the examination of price sensitivity and prior online purchase experience bridges insights from general e-commerce literature with the specific domain of agricultural product marketing.

In conclusion, this study provides valuable insights for practitioners and scholars in the field of digital agricultural marketing. As this domain continues to evolve, ongoing research will be essential to ensure that technological advancements in agricultural marketing contribute positively to broader societal goals while meeting the changing needs and expectations of consumers.

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