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E-commerce in Agriculture: A Study on Adoption Intentions and Challenges for Farmers in Pakistan

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Abstract

This study applies an extended Technology Acceptance Model (TAM) to examine how Household Income, Farm Size, and Digital Literacy influence rural farmers' intentions to adopt E-commerce in Pakistan. Based on a quantitative survey of 304 farmers, the study explores the effects of these socioeconomic and technological factors on Perceived Ease of Use, Perceived Usefulness, Attitude, and ultimately, Intention to Adopt E-commerce. Results reveal that higher-income households and those with larger farms are 25–30% more likely to adopt E-commerce, underlining the importance of financial capacity and operational scale. Digital Literacy signif-icantly enhances perceptions of ease and usefulness, which in turn positively shape attitudes and intentions. The model explains a moderate portion of variance (R^2 = 0.23 to 0.31), indicating that additional factors—such as trust in online sys-tems, accessibility, and community support—warrant further study. The findings suggest that targeted digital literacy initiatives and financial support could reduce barriers to adoption, while E-commerce platforms must be simplified and tailored to rural users. This research deepens the understanding of rural digital inclusion and offers guidance for future interventions.

Keywords

E-commerce adoption; digital literacy; Technology Acceptance Model; so-cio-economic factors; agricultural sustainability; rural development; agricultural technology

1. Introduction

Agriculture plays a critical role in the economic growth of emerging nations, including Pakistan, aligning with the United Nations Sustainable Development Goal 2—to end hunger and promote sustainable agriculture (United Nations, 2015). With a population of around 240 million, a substantial portion of Pakistan's citizens are engaged in agriculture. Although 220 million acres are dedicated to agriculture, only 50 million acres are currently under cultivation. The sector contributes about 21% to GDP and supports approximately 44% of the national workforce (World Bank, 2023).

Beyond its economic value, agriculture ensures national food security and provides essential raw materials for Pakistan's industrial sector (Government of Pakistan, 2023). It also plays a significant role in trade, with 70% of exports either directly or indirectly linked to agriculture (Pakistan Bureau of Statistics, 2019).

Importance of E-commerce in Agriculture

E-commerce is transforming global agriculture, allowing farmers to adapt production and marketing strategies more efficiently. Research from countries like China shows that E-commerce platforms can significantly enhance growth in the agro-food sector (Wang et al., 2022). Through real-time access to market prices, weather forecasts, and agricultural best practices, farmers are better equipped to make data-driven decisions (Morepje et al., 2024). This leads to optimised resource use, reduced waste, and increased profitability—key elements for a more sustainable and resilient agricultural sector (Sumets et al., 2022).

Current state in Pakistan

In Pakistan, the E-commerce landscape is evolving, with platforms such as Daraz, Selly.pk, and Mandi Express offering farmers direct access to markets and consumers (Yi et al., 2023; Umer & Tahir, 2023). These digital platforms help bypass traditional supply chains and middlemen, enabling farmers to sell fresh produce like fruits, vegetables, and dairy more profitably.

Despite these opportunities, widespread adoption remains limited. Many farmers still rely on intermediaries to sell their products, which reduces their profit margins and limits their direct interaction with consumers (Ali et al., 2017). Barriers such as poor infrastructure, lack of digital literacy, and mistrust in online systems continue to slow the transition to E-commerce.

Table 1. Digital Market Share by Industry: Pakistan-Specific Data

Industry	Percentage selling	Source
Agriculture (Pakistan)	5-10%	(International trade administration, 2024)
FMCG (Fast-Moving Consumer Goods) (Pakistan)	10-15%	(Statista, 2024)
Fashion (Pakistan)	25-30%	(Statista, 2024)
Travel (Global)	Around 80%	(Statista, 2024)

With increasing internet access, a rise in smartphone usage, and a growing consumer appetite for fresh, locally sourced products, the envi-ronment is becoming more condu-cive for farmers to take advantage of digital platforms (Ejaz, Altay, and Naeem, 2023). As shown in Table 1, the adoption rates for various in-dus-tries highlight the disparity in E-commerce uptake.

Study objectives

This study aims to frame the E-commerce use by farmers in Pakistan by framing it under TAM. The specific objectives are:

1. To identify the key factors that influence e-commerce adoption among farmers in Pakistan?
2. To what degree Digital literacy and Socio-Economic factors affects adoption of E-commerce?
3. What measures should be taken to encourage farmers to adopt E-commerce to sell their products?

2. Literature Review

Recent years have seen growing interest in digital technologies transforming traditional agriculture, particularly through e-commerce adoption. Studies highlight e-commerce's potential to improve market access, reduce transaction costs, and enhance supply chain transparency (Lahkani et al., 2020). Farmers benefit from streamlined distribution, timely payments, and direct consumer sales (Dutta et al., 2020), while sustainable practices like organic fertilizer use are encouraged (Su et al., 2021). However, challenges such as low digital literacy, trust deficits, infrastructure gaps, and socioeconomic barriers hinder widespread adoption (Altarturi et al., 2023). In China, farm size and household income significantly influence e-commerce uptake (Song & Yin, 2023), a finding echoed in South Asian agribusiness studies (Shibi & Aithal, 2022). Addressing these barriers is critical to realizing e-commerce's economic and social potential (Yang, 2023).

E-commerce Platforms and Adoption

E-commerce platforms revolutionize agriculture by expanding market reach and promoting sustainability (Bahn et al., 2021). They enable cost reductions, efficient supplier connections, and revenue growth, especially for small-scale farmers (Glaros et al., 2023). Yet, socioeconomic disparities limit access, with rural farmers facing digital literacy gaps and poor infrastructure (Kante et al., 2017). Platform providers can mitigate these issues through user-friendly designs, digital training (Li et al., 2021; Ma et al., 2018), and offline support (Chan et al., 2017). Enhanced digital literacy improves market participation and reduces rural poverty (Zhao et al., 2022), underscoring the need for inclusive interventions.

Technology Acceptance Model (TAM) in Agriculture

TAM effectively explains technology adoption by assessing perceived usefulness, ease of use, and behavioral intention (Marikyan, 2022). In agriculture, these factors determine farmers' willingness to adopt e-commerce (Castiblanco Jimenez et al., 2021). While TAM has been applied in diverse sectors like healthcare and e-learning (Al-Emran et al., 2016), its use in Pakistani agriculture remains limited. Existing studies focus on ICT adoption (Usman et al., 2023; Dimitrovski et al., 2021), leaving gaps in e-commerce-specific research. Bridging this gap could inform policies to accelerate digital transformation.

Socioeconomic Determinants

Household income and farm size critically shape technology adoption. Wealthier households adopt innovations more readily due to better resource access and risk tolerance (Adesina, 1995), while low-income farmers prioritize immediate needs (Acemoglu et al., 2001). Recent data confirms that financial flexibility eases adoption barriers (Cui & Wang, 2023). Similarly, larger farms benefit from economies of scale, distributing fixed costs and absorbing risks (Parvan, 2010). Global studies corroborate these trends, showing higher adoption rates among resource-intensive operations (Smidt, 2021).

Adoption of Agricultural Technology

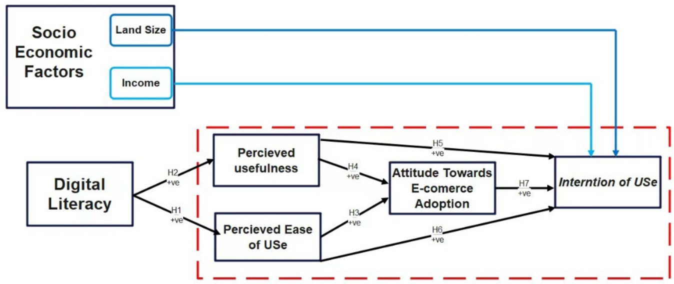
Table 2. Previous studies on Agricultural E-commerce adoption

Study Theme	Frameworks Used	Scope & Regions	Key Constructs	Key Findings
Digital Skills & Socioeconomic Factors	TAM, Mobile Adoption (Kante et al., 2017; Dimitrovski et al., 2021)	Mali, Global	Digital skills, perceived benefit, socio-economic traits	Education, motivation, and digital competence strongly influence E-commerce usability. Socio-economic status is a consistent predictor.
Attitudes, Social Norms & Behavioural Intention	TBP, ETBP, Extended TAM (Mayanja et al., 2024; Thi et al., 2024; Aparo et al., 2024)	Uganda, Cambodia, Philippines, Vietnam	Attitude, subjective norms, perceived enjoyment, behavioural control	Adoption is shaped by social pressures, emotional attitude, and demographics (age, gender, mobile ownership).
Structural & Demographic Influences	Adoption Drivers (Song & Wu, 2023)	China	Income, land size, education, health	Health and financial status are critical in adoption decisions; larger landholders show higher participation.
Technology Integration & Platform Design	Sustainability, IoT Integration (Yang et al., 2022; Wang et al., 2022)	China, Global	Platform strategy, trust, tech access	Platform differentiation boosts competitiveness; IoT improves trading efficiency and reduces costs.

Conceptual model and hypotheses

Figure 1 illustrates the extended Technology Acceptance Model (TAM) used in this study. It proposes that Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Attitude significantly influence farmers' Intention to adopt E-commerce. PU reflects users' belief in the platform's practical benefits, while PEOU captures how effortless it feels to use. Digital Literacy (DL) and Socioeconomic Factors—specifically Household Income (HHI) and Farm Size (FS)—are hypothesised to positively affect E-commerce adoption. DL is measured by the farmer's technology knowledge. Attitude is positioned as a mediating variable between PU/PEOU and Intention. HHI and FS are treated as control variables to reflect how wealth and scale influence adoption.

Figure 1. Extended TAM Model



Digital literacy

Research shows digital literacy positively affects Perceived Ease of Use and Perceived Usefulness (Minh et al., 2022; Zhang et al.). Digital literacy helps farmers understand technology's usefulness and ease, leading to these hypotheses:

1. D.L positively relates to Perceived Ease of Use.
2. D.L positively relates to Perceived Useful-ness.

TAM

This study applied the TAM belief–attitude–intention–behavior model to farmers' e-commerce adoption, proposing these hypotheses:

- Perceived ease of use positively influences attitude toward e-commerce adoption.
- Perceived usefulness positively influences attitude toward e-commerce adoption.
- Perceived usefulness positively influences intention to adopt e-commerce.
- Perceived ease of use positively influences intention to use e-commerce.
- Attitude toward technology positively influences intention to adopt e-commerce.

Socio-Economic Factors

When analyzing e-commerce adoption by smallholder farmers, socio-economic factors like Household Income (HHI) and Farm Size (FS) are important control variables. Studies show these influence access to resources, risk tolerance, and scale of operations (Kante et al., 2017; Yang & Zhang, 2023). Though not the primary focus, HHI and FS may shape intentions to adopt e-commerce. Higher income reduces financial barriers, while larger farms may favour efficiency-driven technologies (Dimitrovoski et al., 2021). Including these variables improves the precision of assessing digital literacy and attitudinal factors. Past research also suggests these socio-economic factors indirectly affect technology's value and availability (McCormack et al., 2021; Ping-da et al., 2022). Structural Equation Modeling (SEM) using

AMOS software was used to test the model (Hair et al., 2021). SEM assessed both measurement and structural models. T-tests via SPSS further examined how socio-economic status influences adoption sentiments, highlighting the need to address inequalities in promoting agricultural e-commerce solutions.

3. Methodology

A structured offline questionnaire was administered to 348 active farmers in Southern Punjab, Pakistan—a region selected for its limited digital exposure. This face-to-face approach ensured participation from both affluent and economically disadvantaged farmers. Verbal informed consent was obtained to ensure participants clearly understood the study's aims. Data collection spanned two months, followed by a thorough cleansing process to eliminate incomplete or invalid responses. After this, 304 valid cases were retained for analysis. Data analysis was conducted using SPSS and AMOS, with Structural Equation Modeling (SEM) applied following the methodology by Williams et al. (2009). SEM was used to examine relationships within the proposed model, particularly focusing on how digital literacy, perceptions, and socioeconomic variables influence E-commerce adoption. This rigorous method helped ensure the dataset accurately reflected ground realities and supported the study's aim of identifying key adoption determinants among smallholder farmers.

Table 3. Demographics of the Participants

Sex	Male: 80.3%	Female: 19.7%
Age	18–25: 26.3%	26–35: 25.7%
	36–45: 24.3%	46–55: 17.8%
	56+: 6.3%	–
Education	High School or Below: 14.8%	Diploma: 18.1%
	Bachelors: 34.2%	Masters+: 32.9%
Experience	<5 yrs: 36.8%	5–10 yrs: 20.7%
	11–15 yrs: 21.4%	16–20 yrs: 15.8%
	>20 yrs: 5.3%	–
Farm Size	<10 acres: 11.5%	11–15 acres: 24.3%
	16–20 acres: 33.2%	21–25 acres: 20.7%
	>25 acres: 10.2%	–
HH Income (PKR)	100k–200k: 10.2%	200k–300k: 25.0%
	300k–400k: 30.6%	400k–500k: 22.4%
	>500k: 11.8%	–

Measurements

In the survey, attitudes and perceptions were measured using a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Questions were adapted from pre-vious research to suit the context of e-commerce adoption in agriculture. Since the survey was face to face, no pilot study was conducted; instead, the team clarified questions during interviews. The ques-tionnaire was first prepared in the re-spondents' vernacular language to ensure understanding, then transcribed into Eng-lish for analysis. This approach preserved linguistic and cultural nuances, capturing smallholder farmers' true feelings.

4. Results

Table 4 presents summary statistics of participants' evaluations. Average scores for Digital Literacy (3.17), Perceived Usefulness (3.05), and Perceived Ease of Use (3.06) suggest moderate agreement with e-commerce-related factors. Attitude toward e-commerce acceptance (2.98) and Intention to Use Technology (3.03) were neutral to slightly positive, indicating cautious acceptance. Standard deviations (1.14 to 1.19) reflect moderate variation in responses, likely due to differences in digital exposure, socio-economic status, and resource access. Overall, farmers' impressions of e-commerce adoption were favorable but varied, aligning with findings from similar rural technology acceptance studies.

Table 4. Descriptive Statistics of the data

Descriptive Statistics			
		Mean	Std. Deviation
Digital literacy		3.17	1.14
Perceived Usefulness		3.05	1.15
Perceived Ease of Use		3.06	1.17
Attitude		2.98	1.17
Intention		3.02	1.19

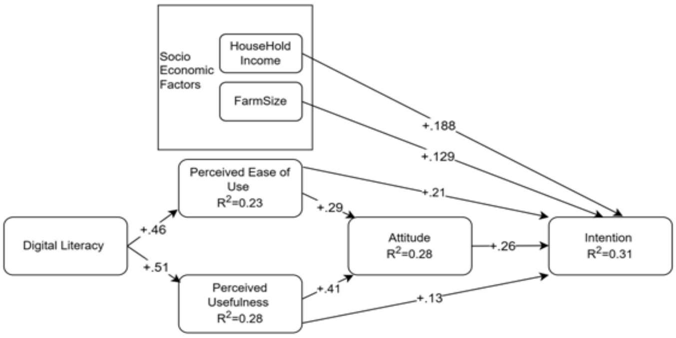
Measurement model

The model fit indices (Table A) indicate an excellent fit: CMIN/DF = 1.059 (ideal between 1 and 3), CFI = 0.997 (>0.95), SRMR = 0.037 (<0.08), RMSEA = 0.014 (acceptable threshold), and PClose = 1.000, confirming goodness of fit. Reliability and validity assessments (Table B) show all constructs with Composite Reliability (CR) ≥ 0.70 and Average Variance Extracted (AVE) > 0.50, supporting reliability and convergent validity. Maximum Shared Variance (MSV) values are less than AVE, ensuring discriminant validity. Max Reliability (MaxR(H)) values align with CR, further validating constructs. Table C displays significant inter-construct correlations and squared AVE values confirming construct distinctiveness. Overall, the measurement model is reliable and valid.

Tests of the structural model

Structural equation modelling (Table E, Figure 2) reveals Digital Literacy significantly influences Perceived Usefulness (0.529) and Ease of Use (0.484), highlighting digital skills' importance. Perceived Usefulness (0.387) has a stronger effect on Attitude than Ease of Use (0.280), showing benefits weigh more than usability in attitude formation. Attitude (0.285) is the strongest predictor of Intention to Use, ahead of Usefulness and Ease of Use. External factors—Financial Support (FS, 0.149) and Household Income (HHI, 0.221)—also positively affect Intention, with HHI having greater impact. Unstandardized estimates confirm these results (all $p < 0.05$). The model emphasizes digital literacy and perceived benefits shaping attitudes, which alongside usability and external factors, drive adoption intentions.

Figure 2. Structural Model of E-commerce Adoption Intentions: The Mediating Role of Attitude and Digital Literacy



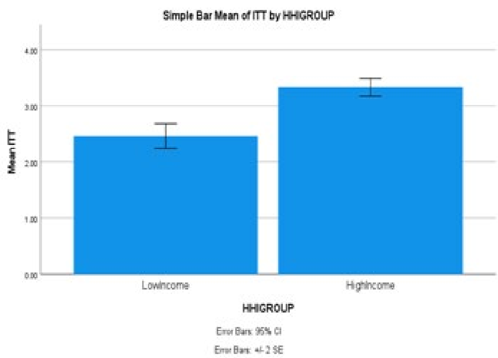
The model's R^2 values show Digital Literacy explains 23% of the variance in Perceived Ease of Use and 28% in Perceived Usefulness, indicating a significant but not exclusive role. Attitude, influenced by Perceived Ease of Use and Usefulness, has an R^2 of 0.28, suggesting moderate influence with other factors likely involved. Intention to use the system has the highest R^2 at 0.31, explained by Attitude, Perceived Usefulness, Perceived Ease of Use, and socioeconomic factors such as Household Income and Farm Size. These moderate R^2 values highlight the need to explore additional variables in future research to better explain these constructs.

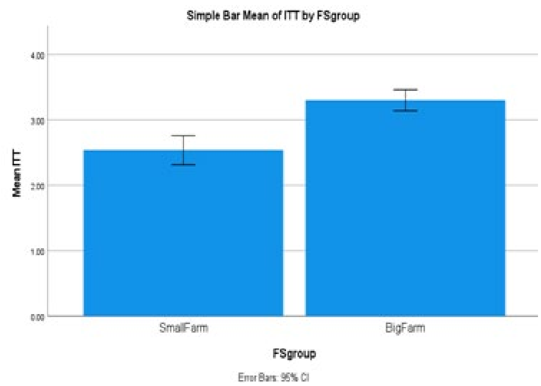
Digital Literacy strongly contributes to Perceived Ease of Use (β = 0.46) and Perceived Usefulness (β = 0.51), demonstrating that digital competence enhances usability and benefits of e-commerce. Regarding Attitude, Perceived Usefulness (β = 0.41) impacts it more than Ease of Use (β = 0.29), indicating users value usefulness over ease for a positive attitude. While both Perceived Usefulness (β = 0.13) and Ease of Use (β = 0.21) affect Intention to adopt e-commerce, Attitude (β = 0.26) is the strongest predictor, emphasizing emotional readiness in adoption. These findings underline the importance of improving digital literacy and perceived value to foster positive attitudes and increase e-commerce adoption intentions.

Comparative Sentiment Analysis Based on Socioeconomic Factors (HHI and FS)

Farm Size (FS) and Household Income (HHI) were divided into two groups to simplify comparisons of e-commerce adoption intentions. FS was categorized as "small" (≤15 acres) and "big" (≥16 acres), while HHI was split into "low income" (100,000–300,000) and "high income" (300,001+). This binning approach is common in social sciences to highlight meaningful group differences and ease interpretation. Privitera (2020) explains that categorizing continuous variables by logical thresholds or quantiles is standard in behavioral research to clarify results. DeVellis (2017) adds that grouping around natural cutoffs or midpoints is useful for comparing constructs across "high" and "low" categories, especially with ordinal scales. Our use of these categories aligns with these practices, allowing clearer analysis of socioeconomic influences on e-commerce adoption.

Figure 3. Mean Intention to Adopt E-commerce (ITT) by Socioeconomic Groups





An independent sample T-test was conducted to examine differences in farmers' intentions to adopt e-commerce (ITT) based on socio-economic groups, as shown in Table F. Household Income (HHI) and Farm Size (FS) were divided into "high" and "low" categories. Figure 3 presents bar graphs showing mean ITT across these groups. Farmers in the AHigh-Income group exhibited significantly higher mean ITT than those in the Low-Income group, indicated by non-overlapping error bars. Similarly, the Big Farm group showed a significantly greater mean ITT compared to the Small Farm group. These results highlight that higher household income and larger farm size are associated with stronger intentions to adopt e-commerce in rural settings, underscoring the influence of socioeconomic factors on technology adoption.

5. Discussion

This study shows that e-commerce adoption in rural areas can be effectively explained using an extended TAM model, with an R^2 of 0.31 for Intention to Adopt. Digital Literacy significantly improves Perceived Ease of Use (R^2 = 0.23) and Perceived Usefulness (R^2 = 0.28), indicating that better digital skills help users find the platform easier and more beneficial. This is crucial in rural contexts, where digital literacy enables farmers and entrepreneurs to access broader markets and adopt sustainable practices. Attitude emerged as the strongest predictor of Intention (β = 0.26), reinforcing previous TAM findings that positive beliefs about the system drive adoption. Interestingly, Perceived Usefulness influences both Attitude (β = 0.41) and Intention (β = 0.13), but its direct effect on Intention is weaker than Attitude or Perceived Ease of Use (β = 0.21). This contrasts with typical technology acceptance studies where usefulness is usually paramount. In rural settings, ease of use is more critical, emphasizing the need for simple, hassle-free e-commerce platforms to encourage uptake.

Socioeconomic factors like Household Income (β = 0.188) and Farm Size (β = 0.129) also contribute to Intention, highlighting the importance of contextual influences. Therefore, while digital literacy and perceived benefits are foundational, addressing socioeconomic factors is essential for sustained e-commerce adoption.

5.1. Implications

Implications for Researchers

This study advances understanding of rural e-commerce adoption by highlighting the roles of socioeconomic factors like Household Income and Farm Size alongside Digital Literacy. It shows that models such as TAM need adaptation to reflect rural-specific contexts. Moderate R^2 values suggest future research should explore additional influences such as community support, trust in online transactions, and access perceptions to deepen theory on rural adoption.

Implications for Government policy makers

Findings stress the need for targeted support to low-income households and small farmers. Governments should expand accessible digital literacy programs tailored for rural users with limited tech skills, enhancing perceived ease and usefulness. Financial incentives like subsidies or low-interest loans can help these groups participate in e-commerce. Improving rural internet infrastructure is also crucial. Such efforts promote economic inclusion, enabling rural communities to benefit from broader market access and operational efficiency.

Implications for e-commerce companies

Platforms must be designed to meet rural consumers' needs, emphasizing user-friendly interfaces for novices. Providing localized support and accessible payment options builds confidence among rural users. Marketing campaigns aimed at smallholder farmers should highlight e-commerce's physical and economic benefits and low entry costs, boosting credibility and adoption through word-of-mouth. Addressing digital literacy gaps and rural contexts will help companies enter underserved markets and support equitable digital economies and rural development.

Limitations

This study offers key insights but has limitations. The rural-only sample, with varied digital access, may not reflect broader populations. Influential factors like community dynamics, cultural attitudes, and trust in online transactions were not directly measured. Moderate R^2 values suggest other variables are unexplored. Future studies should examine community influence, system design, and personality traits. As the focus was solely on rural adoption, findings may not apply to urban contexts or other technologies. Broader research should include diverse groups, external factors like policy, infrastructure, and cultural norms. Acknowledging these gaps highlights the need for continued exploration in rural E-commerce adoption.

Table 5. Confirmatory Factor Analysis (CFA) Model Fit Indices and Threshold Criteria

Measure	Estimate	Threshold	Interpretation
CMIN	169.373	--	--
DF	160.000	--	--

CMIN/DF	1.059	Between 1 and 3	Excellent
CFI	0.997	>0.95	Excellent
SRMR	0.037	<0.08	Excellent
RMSEA	0.014	<0.06	Excellent
PClose	1.000	>0.05	Excellent

Table 6. Validity Analysis

	CR	AVE	MSV	MaxR(H)
ITT	0.887	0.663	0.249	0.888
ATT	0.890	0.669	0.249	0.891
PEOU	0.880	0.646	0.204	0.880
PU	0.873	0.633	0.247	0.876
DL	0.823	0.541	0.247	0.847

Table 7. Discriminate Validity Analysis: Latent Variable Correlations (Square Roots of AVE on Diagonal

		ITT	ATT	PEOU	PU	DL
ITT		**0.814**				
ATT		0.499***	**0.818**			
PEOU		0.431***	0.429***	**0.804**		
PU		0.397***	0.491***	0.447***	**0.796**	
DL		0.469***	0.401***	0.451***	0.497***	**0.736**

Table 8. Standardized Path Coefficients for E-commerce Adoption Model

VARIABLES		VARIABLES	**Estimate**
Perceived usefulness	<---	Digital literacy	.529
Perceived ease of use	<---	Digital literacy	.484
Attitude	<---	Perceived ease of use	.280
Attitude	<---	Perceived Useful-ness	.387
Intention	<---	Perceived Useful-ness	.135
Intention	<---	Perceived ease of use	.217
Intention	<---	Attitude	.285
Intention	<---	FS	.149
Intention	<---	HHI	.221

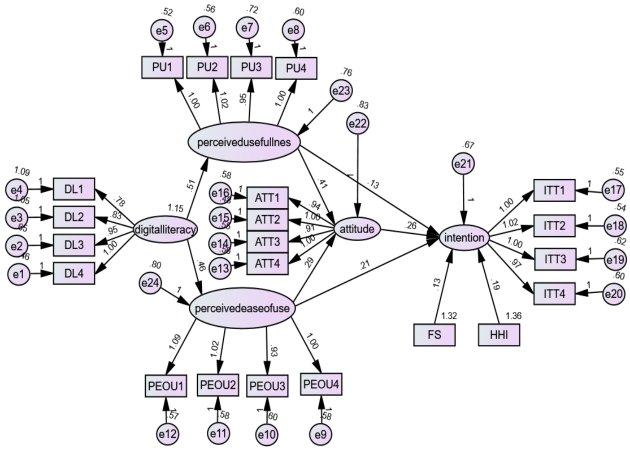
Table 9. Farm Size Group

Variable	t	df	Mean Difference	95% Con-fidence Interval	p-value
Intention to Adopt E-commerce (ITT)	-5.639	302	-0.76587	-1.03314 to -0.49860	< 0.001

Table 10. Household Group

Variable	t	df	Mean Difference	95% Confidence Interval	p-value
Intention to Adopt E-commerce (ITT)	-6.447	302	-0.86854	-1.13366 to -0.60343	< 0.001

Figure 4. Unstandardized Estimates



Disclosure Statement

Authors declare that there are no conflicts of interest regarding the publication of this paper.

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