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Gendered e-commerce adoption among rural Indonesian entrepreneurs: Determinants and income impact

Weni Lidya Sukma*, Kadir Ruslan

BPS-Statistics Indonesia, Indonesia

*Corresponding author: wenilidya@bps.go.id

Abstract

Purpose — This study examines the gendered determinants of e-commerce adoption among rural entrepreneurs in Indonesia and evaluates its impact on income, addressing the gap in rural- and gender-disaggregated evidence in the digital economy literature.
Method — Using nationally representative Sakernas data (2018–2024), this study employs probit models to estimate adoption determinants and applies gender-disaggregated income regressions, Propensity Score Matching, and quantile regression to assess causal and heterogeneous income effects.
Findings — Education and training significantly increase adoption, while age, marital status, and household constraints, particularly for women, reduce participation. E-commerce adoption raises income substantially, with male entrepreneurs gaining higher returns (around 30.8%) than female entrepreneurs (17.5%). Quantile results show stronger equalizing effects among lower-income men, while gains for women are smaller and more evenly distributed.
Implications — The findings highlight the need for gender-sensitive digital inclusion policies that go beyond infrastructure to address capability gaps, time constraints, and structural barriers limiting women's participation and returns in the digital economy.
Originality — This study contributes by integrating gender and rural perspectives using nationally representative data and robust causal methods, offering new evidence on heterogeneous income effects of digital adoption in developing economies.
Keywords: e-commerce; gender; propensity score matching; rural entrepreneurs; sakernas
JEL Classification: J31; J71; O18; O33

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Introduction

E-commerce has become an increasingly important engine of inclusive economic transformation, offering new pathways for entrepreneurship and income generation, particularly in rural settings (Chen and Long, 2024). In developing countries such as Indonesia, where the informal economy and gender disparities persist, digital platforms hold potential to reduce structural barriers faced by rural micro, small, and medium enterprises (MSMEs) (Anatan and Nur, 2023; Yogatama *et al.*, 2025).

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Based on the e-commerce survey conducted by Statistics Indonesia (BPS), the proportion of enterprises adopting e-commerce systems rose from 25.25 percent in 2020 to 41.51 percent in 2023 (BPS, 2021, 2025), indicating a significant acceleration in digital adoption that could further enhance market access, competitiveness, and resilience of rural MSMEs. In rural contexts, e-commerce encompasses a diverse set of activities that link agricultural communities to wider markets. These include the supply of industrial goods to rural households, the sale of farm products to urban consumers, online purchases of agricultural inputs, and the use of digital platforms to deliver services that foster rural development and poverty reduction (Qiu *et al.*, 2024; Zang *et al.*, 2025). However, enterprises in the agricultural sector leveraging e-commerce remain limited, reaching only 3.90 percent in 2023, an increase of merely 0.66 percentage points from 3.24 percent in 2020, suggesting that digital adoption in agriculture lags behind other sectors and may require targeted interventions to unlock its full potential (BPS, 2021, 2025).

This potential is unevenly realized, especially along gender lines (Salyanty, 2023; Yogatama *et al.*, 2025). Women, while increasingly visible in online markets, often face additional challenges in access to technology, time, financing, and formal networks. This raises a critical question: who benefits most from rural digitalization, and under what conditions? E-commerce adoption is defined as the engagement in digital processes of buying, selling, transferring, or exchanging goods, services, and information via networks such as the internet (Rahayu and Day, 2017). Adoption decisions are influenced by multiple factors, including individual characteristics (e.g., gender, age, education, marital status, work hours, and employment status), household attributes (such as family size), and broader contextual conditions like geographic location, digital literacy, prior technological experience, infrastructure availability, and industry specialization (Rogers, 2003; Valarezo, López and Pérez Amaral, 2020; Ariansyah *et al.*, 2021; Purevkhuu and Munkhbold, 2021; Selorm, Selorm and William, 2022; Astuti, Ganefri and Yulastri, 2023; Permani *et al.*, 2025). E-commerce offers new channels for selling and buying goods, accessing services, and engaging with broader markets beyond geographic limitations (Goldfarb and Tucker, 2019; Chen *et al.*, 2022).

Many studies have confirmed its potential to raise incomes in rural areas and reduce income inequality among rural households by empowering traditionally excluded groups, such as small-scale farmers, informal workers, and rural women (Chen *et al.*, 2022; Guan, He and Hu, 2024; Li and He, 2024; Qiu *et al.*, 2025; Zhang, Wu and Cai, 2025). Theoretically, this study analyzes the dynamics of e-commerce adoption and its impact on the earnings of rural entrepreneurs of integrating three primary theoretical pillars. First, Human Capital Theory (Becker, 1964) is utilized to explain how education, training, and work experience function as determinants of productive capacity that influence the probability of technology adoption.

Second, the Diffusion of Innovations Theory (Rogers, 2003) provides a lens to understand how individual attributes such as age, location, and household characteristics act as accelerators or barriers in the digital innovation adoption process. Third, this study adopts a gender and development perspective to examine distinct structural barriers, such as the disproportionate burden of unpaid care work and disparities in access to resources, which often create gaps in economic outcomes between male and female entrepreneurs. The integration of these three theoretical frameworks not only enriches the discussion of the determinants of adoption but also provides an analytical foundation for critically evaluating the gender-differentiated entrepreneurship premium within the digital ecosystem.

While research on e-commerce adoption in Indonesia has grown in recent years, most studies focus on entrepreneurs in urban areas or analyze the country as a whole, overlooking the distinct challenges faced by rural populations. Existing literature tends to emphasize determinants such as education, infrastructure, and digital skills in more developed settings, where access to technology and markets is relatively less constrained. Far fewer studies examine rural entrepreneurs, who operate within different structural and social contexts, including weaker digital infrastructure, limited financial resources, and stronger household-level constraints.

Moreover, gendered analyses in Indonesia rarely disaggregate rural experiences, despite evidence that rural women face unique barriers to adopting and benefiting from e-commerce compared to their urban counterparts. This leaves a critical gap in understanding how gender intersects with rurality to shape both the determinants of e-commerce adoption and its income effects. This gap is particularly evident as rural women entrepreneurs navigate intersecting constraints of limited access to land, finance, markets, digital infrastructure, and patriarchal norms, while leveraging collective organizations, culturally embedded femininity, and low-cost innovation to enable entrepreneurship (Semkunde *et al.*, 2022; Karami *et al.*, 2024; Ti and Khanna, 2025).

This paper examines the gendered determinants and income impacts of e-commerce adoption among rural entrepreneurs in Indonesia. Using recent rounds of the nationally representative labor force survey (Sakernas), we estimate probit models of adoption and income regressions disaggregated by gender and earnings distribution. We ask two central questions: (1) What factors drive e-commerce adoption among rural men and women? and (2) To what extent does adoption improve earnings, and how do these effects vary by gender and across the income distribution?

The contribution of this study is threefold. First, it provides robust empirical evidence on the drivers of digital entrepreneurship in rural areas using a large-scale, nationally representative dataset. Second, it offers a gender-disaggregated analysis of the income returns to e-commerce, revealing how benefits are mediated by education, employment structure, and geography. Third, it applies quantile regression to uncover heterogeneous income effects, highlighting that digital tools may serve as equalizers for some groups while reinforcing advantage for others. By highlighting these patterns, the paper aims to inform the design of gender-sensitive digital policies for inclusive rural development.

Methodology

This study used microdata from the National Labour Force Survey (Sakernas), a biannual household survey conducted by BPS–Statistics Indonesia. We analyzed data from the August rounds between 2018 and 2024, focusing on employers. The pooled cross-sectional dataset includes 693,874 individuals 465,178 male and 228,696 female employers. In this context, "employer" refers to individuals who are self-employed with assistance from unpaid/temporary or paid/permanent labor. A detailed description of the survey variables used was provided in Table 1. Descriptive statistics of those variables by gender were provided in Appendix 1. We utilized econometric models to analyze the factors influencing e-commerce adoption among employers by gender and assess its effect on actual earnings. To strengthen the causal inference of adoption's impact, we also conducted a counterfactual analysis using Propensity Score Matching (PSM) and quantile regression.

Each analysis was performed separately on the same unit of analysis, ensuring that the results of one model did not influence the estimation of subsequent models.

Table 1. Description of Research Variables

Variable	Definition
Log (Earning)	The natural logarithm of monthly real earnings. Real earnings per month adjusted for rural inflation
E-commerce	E-commerce adoption in the workplace. E-commerce is defined as the activity of selling or purchasing goods and/or services through digital channels, including email, social media platforms, websites, and marketplace applications. Dummy variable, where 0 for non-adopters (reference category) and 1 for adopters
Female	Gender of an individual. Dummy variable, where 0 is for male (reference category) and 1 is for female
Married	Marital status. Dummy variable, where 0 unmarried (reference category) and 1 married
Household members	Number of household members to which an individual belongs (person)
Household members 15+	Number of household members who are 15 years old and above, in which an individual belongs (person)
Education completed	The highest education level is completed by an individual. Dummy variable, where 1 for no education/elementary school (reference category), 2 for junior high school, 3 for senior high school, 4 for vocational, and 5 for diploma 1/2/3, 5-university
Years of schooling	Years of schooling are calculated by converting the highest educational attainment into years of schooling (years).
Age	Age category of an individual. Dummy variable, where 1 for 15-34 years old (reference category), 2 for 35-44 years old, 3 for 45-54 years old, 4 for 55-64 years old, and for 65 years old and above
Experience	Working experience of an individual (years). It is a potential experience in years, calculated as age minus years of schooling minus 6 years.
Tenure	The length of time an individual has been employed at their current job (years).
Working hours	The average working hours per week (hours).
Full Employment	Employment status of an individual based on average working hours per week. Dummy variable, where 1 is for severely underemployed (reference category), 2 for underemployed, and 3 for fully employed
Trained	Participation of an individual in general work training. Dummy variable, where 0 is for untrained (reference category), and 1 is for trained
Employer	Employment status of employers by type of work. Dummy variable, where 1 for self-employed (reference category); 2 for assisted by unpaid/temporary labour; and 3 for assisted by paid/permanent labour
Formal	Formality status of employment. Dummy variable, where 0 for informal (reference category), and 1for formal
Economic sector	The economic sector of employers' main economic activities. Dummy variable, where 1 is for agriculture (reference category), 2 is for mining, 3 is for manufacturing, and 4 is for services.
Pandemic (temporal dummy)	Pandemic periods. Dummy variable, where 1 for pre-pandemic (2018-2019) (reference category), 2 for pandemic (2020-2022), and 3 for post-pandemic (2023-2024)
Regional Dummy	Regional dummy. This variable serves as one of the control variable, used to account for regional differences that may include variations in culture, infrastructure, geographical conditions, and other related factors. Dummy variable, where 0 is for outside Jawa (reference category) and 1 for Jawa.

To examine the determinants of e-commerce adoption among employers, we estimate a probit model as denoted in Equation (1) below.

$$p(X_i) = pr\left(D_i = 1 \mid X_i\right) = \Phi\left(X_i^{'}\beta\right) \quad (1)$$

where $D_i \in \{0,1\}$ denotes a dummy variable indicating whether the individual i adopts e-commerce in their work or not, as defined by Rainer and Cegielski (2011), X_i denotes observable characteristics influencing the decision of an individual to adopt e-commerce, consisting of individual characteristics, household characteristics, employment characteristics, and temporal and spatial dummy variables; $\Phi(.)$ is the cumulative distribution function (CDF) of the standard normal distribution; and β is a vector of coefficients to be estimated. We assume that the propensity of workers to adopt e-commerce in their work is represented by a latent variable that is a function of observable characteristics and can be denoted as follows

$$D_i^* = X_i^{'}\beta + \varepsilon_i$$
$$D_i = \begin{cases} 1 \; if \; D_i^* > 0 \\ 0 \; otherwise \end{cases} \tag{2}$$

where D_i^* is an unobserved variable representing the propensity to adopt e-commerce and ε_i is a normally distributed error term. Building on the random utility maximization framework by Marschak (1974), Equation (2) posits that an individual adopts e-commerce when their latent utility D_i^* exceeds a certain threshold (normalized to zero), with the observed binary outcome D_i reflecting this decision. We estimated Equation (1) separately for men and women to uncover gender-specific patterns in digital adoption.

This disaggregated analysis acknowledges that gender likely shapes both the motivations and barriers individuals face when deciding to engage in e-commerce. Structural disparities such as unequal access to technology, varying levels of digital literacy, and differences in market integration may also significantly influence adoption probabilities (Valarezo, López and Pérez Amaral, 2020; Ariansyah *et al.*, 2021). By examining gender groups independently, we are better able to identify contextual factors and pinpoint where tailored interventions can effectively support inclusive digital participation among employers in Indonesia.

To gauge the magnitude of the impact of e-commerce adoption on earnings, we estimated the Ordinary Least Squares Regression (OLS) models denoted in Equations (3) and (4) below

$$Y_i = \gamma_0 + \gamma_1 D_i + \textstyle\sum_j \gamma_j X_{ij} + \varepsilon_i \tag{3}$$
$$Y_i = \textstyle\sum_{k=2}^{4} \alpha_k 1(T_i = k) + X'_i\beta + \varepsilon_i \tag{4}$$

where Y_i denotes the real earning adjusted for rural inflation of the ith individual in logarithmic term, D_i denotes e-commerce adoption dummy variable, X_{ij} denotes the j control variables (socio-demographic characteristic, employment characteristics, and temporal and spatial dummy variables) of the ith individual, γ_0 denotes the intercept of the model, γ_1 the regression coefficient of the e-commerce adoption, and ε_i denotes the error term that follow a normal distribution. Since the dependent variable in the logarithmic term, γ_1 can be interpreted as the percentage change of real earning due to participating as adopter. Equation (4) aims to isolate the impact of the gender–e-commerce adoption interaction on individuals' earnings, where T_i is a categorical variable which is the interaction between gender and e-commerce adoption for employer i (1= female non-adopters, 2= if male non-adopters, 3= female adopters, 4= male adopters).

X_i is a vector of the covariate for employer i (intercept is included), β is the vector of corresponding parameters for the covariate, and ε_i is an error term that is assumed to be independently and identically distributed with mean zero and constant variance. Following Halvorsen and Palmquist (1980), the impact estimate was corrected using (e to the gamma sub 1 minus 1) using $\left(e^{\gamma_1} - 1\right) \times 100\%$. We also estimate Equation (3) separately by gender to disaggregate the impact of e-commerce adoption on income, recognizing that the economic returns to adoption may differ between men and women due to underlying gender-specific barriers and opportunities.

This approach enables us to better understand how digital engagement translates into income gains across gender, and to identify whether e-commerce serves as a potential equalizer or reinforces existing income disparities. The causal estimates in Equations (3) and (4) may be biased due to selection on unobserved factors and potential endogeneity, such as reverse causality, where higher earners are more likely to adopt e-commerce (Rosenbaum and Rubin, 1983). Adopters may systematically differ from non-adopters in ways that also affect income, such as digital skills, asset ownership, or access to infrastructure.

To address these issues and improve causal inference, we use Propensity Score Matching (PSM), which creates a statistically comparable group of non-adopters based on their likelihood of adopting e-commerce. To match adopters with comparable non-adopters based on observable characteristics, we estimate propensity scores using a probit model (Equation 1). For robust matching, we apply two algorithms Nearest-Neighbour Matching (n = 5) with Caliper (radius = 0.005) and Kernel Matching.

Using the matched samples, we estimate the impact of e-commerce adoption on real earnings by calculating the Average Treatment Effect on the Treated (ATT), which captures the mean difference in earnings between adopters and their counterfactual outcomes had they not adopted e-commerce; and the Average Treatment Effect (ATE) estimates the average earnings gains that the entire population of employers in Indonesia could realize if they adopted e-commerce.

$$ATT = E\left(Y_{1_i} | D_i = 1, p(X_i)\right) - E\left(Y_{0_i} | D_i = 1, p(X_i)\right) \tag{5}$$

$$ATE = E\left(Y_{1_i} |\, p(X_i)\right) - E\left(Y_{0_i} |\, p(X_i)\right) \tag{6}$$

where Y_{1_i} is the real earnings of an e-commerce adopter and vice versa, Y_{0_i} is the real earnings of an individual for non-adopters. We also estimated equations (5) and (6) by gender. To further assess the robustness of the causal impact, we examine the heterogeneous effects of e-commerce adoption across the earnings distribution using quantile regression. Unlike OLS, which captures average effects, quantile regression estimates conditional impacts at different points of the income distribution, offering a more nuanced view of how adoption affects low-, middle-, and high-income earners. This approach also helps evaluate the potential of rural e-commerce to reduce income inequality among rural households from a gender perspective. The conditional quantile regression for the τ-th quantile of log earnings Y_i given a vector of covariates X_i is specified as:

$$Q_{Y_i}(\tau | X_i) = \gamma_0(\tau) + \gamma_1(\tau) D_i + X_i^{'} \boldsymbol{\gamma}(\tau) + \varepsilon_i(\tau) \tag{7}$$

where $Q_{Y_i}(\tau|X_i)$ is the conditional quantile of the log earnings given X_i; $\tau \in (0,1)$ represents the quantile level ($\tau = 0.1, 0.3, 0.5, 0.7, 0.9$); $\gamma_0(\tau)$ is the model intersept at each quantile; $\gamma_1(\tau)$ denotes the impact of e-commerce adoption at each quantile level; X_i includes independent control variables, and $\gamma(\tau)$ is the vector of quantile-specific parameters of control variables to be estimated; and $\varepsilon_i(\tau)$ is error term at each quantile. Estimating Equation (7) by gender allows the impact of e-commerce adoption to vary across the income distribution, revealing whether gains are concentrated among lower-, middle-, or higher-income earners.

Results and Discussion

To understand the complex dynamics of e-commerce adoption among rural Indonesian entrepreneurs, this study examines a comprehensive set of determinants ranging from human capital capabilities and demographic attributes to structural operational support. Grounded in the Human Capital Theory (Becker, 1964) and the Diffusion of Innovations Theory (Rogers, 2003). This section evaluates how individual attributes and firm-level capacities interact to facilitate or impede digital integration. The following discussion systematically disaggregates these determinants, with particular focus on the gendered nature of adoption, to contextualize the findings within the broader structural realities of rural entrepreneurs in Indonesia.

This analysis addresses critical issues such as gender-based time poverty, organizational scale, and the efficacy of policy interventions, ultimately offering a nuanced understanding of how digital inclusion translates into an entrepreneurship premium across different income distributions. Our study provides empirical evidence from rural Indonesia, a context that is still underexplored in the literature. It also extends previous research by incorporating gender differences into the analysis of digital adoption. Our study highlights that digitalization does not automatically lead to inclusive outcomes.

The full-sample probit estimation reveals a range of demographic, socioeconomic, and structural factors that significantly influence the probability of e-commerce adoption among rural entrepreneurs in Indonesia. Being female is associated with a 0.2 percentage point lower likelihood of adoption compared to males. This persistent gap suggests that gender-based disparities in digital participation are not merely a function of individual choice but are rooted in entrenched structural barriers. This finding is consistent with the gender and development perspective, which highlights unequal access to resources and time constraints faced by women. It also aligns with Priyabadini (2022), suggesting that gender disparities persist even after controlling for socioeconomic characteristics.

Social norms often shape domestic life, relegating women to a disproportionate share of unpaid care work, which creates 'time poverty' and limits the flexibility required to explore and integrate digital tools into business operations (Singh, 2017; Kodithuwakku and De Silva, 2025). These constraints are compounded by unequal access to resources, including digital infrastructure and mobility which are often prioritized for male household members in traditional settings (Priyabadini, 2022). Consequently, the gender gap in e-commerce adoption reflects a 'glass ceiling' effect, where structural inequalities systematically curtail women's capacity to leverage digital technologies, despite their comparable potential for business innovation (Matsinhe and Kabanda, 2019).

Table 2 Estimation Results of the Probit Model for E-commerce Adoption

Variable	Coefficient	dy/dx
Gender (Female)	0.0206**	0.0022**
	(0.0088)	(0.0009)
Marital Status (Married)	0.0052	0.0006
	(0.0112)	(0.0012)
Number of Household Members	-0.0137***	-0.0015***
	(0.0036)	(0.0004)
Number of Household Members 15+	0.0087**	0.0009**
	(0.0037)	(0.0004)
Age		
35-44	-0.2191***	-0.0314***
	(0.0105)	(0.0015)
45-54	-0.4733***	-0.0589***
	(0.0118)	(0.0015)
55-64	-0.7981***	-0.0828***
	(0.0172)	(0.0016)
65+	-1.2159***	-0.0999***
	(0.0301)	(0.0015)
Education		
Junior High School	0.3551***	0.0344***
	(0.0115)	(0.0012)
Senior High School	0.5462***	0.0600***
	(0.0116)	(0.0014)
Vocational	0.5907***	0.0667***
	(0.0164)	(0.0023)
Diploma	0.8662***	0.1155***
	(0.0326)	(0.0063)
University	0.9091***	0.1242***
	(0.0213)	(0.0041)
Training (trained)	0.2961***	0.0363***
	(0.0132)	(0.0018)
Employment status by working hours (full employment)	-0.0154*	-0.0017*
	(0.0090)	(0.0010)
Formality Status (Formal)	0.0052	0.0022**
	(0.0358)	(0.0040)
Worker status		
Assisted by unpaid labour	0.0369***	0.0039***
	(0.0101)	(0.0011)
Assisted by paid labour	0.4385***	0.0573***
	(0.0330)	(0.0052)
Agriculture	-0.7693***	-0.0760***
	(0.0107)	(0.0010)
Regional Dummy (Jawa)	0.3805***	0.0418***
	(0.0087)	(0.0010)
Pandemic Period		
During Pandemic	0.3627***	0.0294***
	(0.0138)	(0.0010)
Post-Pandemic	0.6367***	0.0616***
	(0.0149)	(0.0013)
Constant	-1.8253***	
	(0.0226)	-
Number of Observations	693,874	693,874
Pseudo R-Squared	0.2373	-

Note: Robust standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation
Source: Processed by Author

Household size also acts as a constraint, with individuals from larger households being less likely to adopt. It is likely reflecting limited time and resources.

This is consistent with the literature on household constraints and unpaid work burdens. Notably, the probability of adoption decreases sharply with age entrepreneurs aged 65 and above are 9.9 percentage points less likely to adopt e-commerce than the youngest group, highlighting a pronounced generational digital divide, consistent with the Diffusion of Innovations Theory, which posits that younger individuals are more likely to adopt new technologies.

Education is a strong enabler, where rural entrepreneurs with a university degree are 12.4 percentage points more likely to adopt, and even junior high school completion is associated with a 3.4 percentage point increase compared to the reference category (rural entrepreneurs with no education or only completed elementary school). Our findings support Human Capital Theory (Becker, 1964), where higher education enhances individuals' capacity to adopt new technologies. This result is consistent with Ariansyah et al. (2021), confirming the important role of education in facilitating digital participation.

Participation in training also has a positive and significant effect, increasing the probability of adoption by 3.6 percentage points. It supports the role of skill development in facilitating technology uptake. This is consistent with the human capital framework, where training enhances individuals' readiness to adopt innovation. Employment-related factors provide a nuanced picture: full-time employment reduces the likelihood of adoption, suggesting that time constraints may limit engagement with digital platforms. In contrast, those assisted by paid labor are 5.7 percentage points more likely to adopt, implying that business scale and support structure are important factors. Interestingly, formal employment status has no statistically significant effect.

Sectoral and regional effects are substantial. Entrepreneurs in the agriculture sector are 7.6 percentage points less likely to adopt e-commerce than those in agriculture or other baseline sectors. Being located in Java adds another 4.2 percentage points, highlighting geographic disparities in digital access and market integration. The COVID-19 pandemic also played a catalytic role in the uptake of digital technologies. Entrepreneurs were 2.9 percentage points more likely to adopt during the pandemic and 6.2 points more likely in the post-pandemic period, reflecting the long-term behavioral shifts triggered by the crisis.

Together, these findings emphasize that while e-commerce holds great promise for rural transformation, its adoption remains shaped by deep structural inequalities in gender, education, geography, and labor context. Addressing these barriers requires a multi-dimensional strategy that targets not only infrastructure but also social norms, digital skills, and enterprise support systems.

This section examines the determinants of e-commerce adoption among entrepreneurs in Indonesia, with a focus on gender differences. The estimation of the probit model by gender is provided in Table 3. In general, the findings highlight distinct gendered patterns, revealing that while education and training consistently promote adoption, barriers such as age and marital status affect women more severely. These results underscore the need for gender-responsive digital inclusion strategies in the Indonesian context.

The probit regression results for female entrepreneurs reveal clear patterns in the determinants of e-commerce adoption. Education stands out as the most powerful driver, with the likelihood of adopting e-commerce increasing substantially with higher education levels, reaching around a 13.6 percentage-point increase for women with tertiary education. This finding underscores the critical role of cognitive skills, literacy, and exposure to formal learning environments in enabling digital participation.

Training also emerges as a significant enabler for women who have received any form of training, who are 4.4 percentage points more likely to adopt e-commerce, suggesting that targeted skill-building programs can be effective levers for inclusion.

Table 3. Estimation Results of the Probit Model by Gender for E-commerce Adoption

Variable	Male		Female	
	Coefficient	dy/dx	Coefficient	dy/dx
Marital Status (Married)	-0.0304*	-0.0030*	-0.0732***	-0.0091***
	(0.0164)	(0.0016)	(0.0167)	(0.0021)
Number of Household Members	-0.0162***	-0.0016***	-0.0225***	-0.0027***
	(0.0048)	(0.0005)	(0.0059)	(0.0007)
Number of Household Members 15+	0.0081	0.0008	0.0202***	0.0025***
	(0.0050)	(0.0005)	(0.0057)	(0.0007)
Age				
35-44	-0.1176***	-0.0150***	-0.3384***	-0.0572***
	(0.0145)	(0.0019)	(0.0160)	(0.0028)
45-54	-0.3391***	-0.0380***	-0.6778***	-0.0973***
	(0.0158)	(0.0018)	(0.0194)	(0.0028)
55-64	-0.6254***	-0.0591***	-1.1564***	-0.1303***
	(0.0215)	(0.0019)	(0.0303)	(0.0028)
65+	-1.0547***	-0.0772***	-1.5779***	-0.1441***
	(0.0349)	(0.0018)	(0.0625)	(0.0028)
Education				
Junior High School	0.3182***	0.0283***	0.3778***	0.0419***
	(0.0149)	(0.0014)	(0.0185)	(0.0021)
Senior High School	0.4776***	0.0474***	0.5811***	0.0725***
	(0.0148)	(0.0016)	(0.0190)	(0.0026)
Vocational	0.5281***	0.0543***	0.6478***	0.0838***
	(0.0210)	(0.0027)	(0.0263)	(0.0042)
Diploma	0.7780***	0.0940***	0.8572***	0.1235***
	(0.0460)	(0.0081)	(0.0475)	(0.0094)
University	0.8293***	0.1034***	0.9188***	0.1364***
	(0.0275)	(0.0049)	(0.0353)	(0.0071)
Training (trained)	0.2802***	0.0315***	0.3222***	0.0443***
	(0.0176)	(0.0022)	(0.0205)	(0.0032)
Employment status by working hours (full employment)	0.0543***	0.0052***	-0.1489***	-0.0183***
	(0.0120)	(0.0012)	(0.0142)	(0.0018)
Formality Status (Formal)	0.0343	0.0034	0.0039	0.0005
	(0.0405)	(0.0041)	(0.0750)	(0.0091)
Worker status				
Assisted by unpaid labour	0.0557***	0.0053***	-0.0081	-0.0010
	(0.0134)	(0.0013)	(0.0162)	(0.0019)
Assisted by paid labour	0.4571***	0.0552***	0.5285***	0.0800***
	(0.0376)	(0.0055)	(0.0687)	(0.0124)
Economic Sector (Agriculture)				
Mining	0.0006	0.0000	-0.1444	-0.0044
	(0.0454)	(0.0026)	(0.1490)	(0.0041)
Manufacture	0.6540***	0.0635***	0.9385***	0.0707***
	(0.0195)	(0.0025)	(0.0303)	(0.0022)
Services	0.7315***	0.0752***	1.1471***	0.1006***
	(0.0128)	(0.0014)	(0.0275)	(0.0016)
Regional Dummy (Jawa)	0.4264***	0.0432***	0.2813***	0.0344***
	(0.0114)	(0.0013)	(0.0138)	(0.0018)
Pandemic Period				
During Pandemic	0.3274***	0.0240***	0.4240***	0.0396***
	(0.0185)	(0.0012)	(0.0208)	(0.0017)
Post-Pandemic	0.5892***	0.0519***	0.7279***	0.0806***
	(0.0200)	(0.0016)	(0.0224)	(0.0022)

Variable	Male		Female	
	Coefficient	dy/dx	Coefficient	dy/dx
Constant	-2.5905***	-	-2.6618***	-
	(0.0297)		(0.0393)	
Number of Observations	465,178	465,178	228,696	228,696
Pseudo R-Squared	0.2247	-	0.2710	-

Note: Robust standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation
Source: Processed by Author

Conversely, several labor and demographic characteristics serve as barriers for women. Being fully employed is associated with a 1.8-percentage-point decrease in the probability of adoption, which likely suggests significant structural barriers. This aligns with Chatzoglou and Chatzoudes (2016), who posit that resource availability is a fundamental prerequisite for digital adoption. For women, full-time employment can diminish the 'organizational readiness' required to manage digital ventures. Furthermore, this finding is consistent with the behavioral economic perspective proposed by Yang, et al. (2025), where the decision to go online involves risk calculation; for women already burdened by full-time professional commitments, the perceived risk of operational failure in online ventures, compounded by severe time constraints, leads to a more conservative adoption stance compared to their counterparts with greater schedule flexibility.

In contrast, women employers assisted by workers are significantly more likely to adopt e-commerce. These results suggest that more established, resource-rich, or growth-oriented women-led businesses have a greater propensity to leverage digital tools for commerce (Matsinhe and Kabanda, 2019; Hasan, Mustafa Khan and Arif, 2022). Age-related effects are particularly stark. Compared with the youngest age group, older women are significantly less likely to adopt e-commerce, with probabilities dropping by more than 14.4 percentage points in the oldest group. This steep decline illustrates a sharp generational digital divide, where older rural women may face barriers related to digital literacy, confidence, or access to technology (Valarezo, López and Pérez Amaral, 2020; Atanasova and Gerakis, 2023; Thangavel and Chandra, 2024). Household structure and marital status further compound these constraints: being married and having a larger household both reduce the probability of adoption.

It may reflect additional household responsibilities. This is often associated with time constraints highlighted in household and gender-related literature. Having more productive household members (aged 15 and above) slightly increases the likelihood of adoption among females. This can be understood through the lens of intra-household peer effects, where the presence of productive family members facilitates technology adoption by reducing the 'learning cost' and uncertainty associated with new digital tools. As demonstrated by the evidence on smartphone adoption within households, the diffusion of technology is often a social process where early adopters within the home act as catalysts for others (Park and Yeo, 2023).

For male entrepreneurs, these productive members likely serve as 'digital peers' who provide the necessary support for navigating e-commerce interfaces, thereby reinforcing the firm’s operational capacity and readiness to adopt formal digital platforms. Regional and temporal factors also shape digital inclusion. Women living in Java are more likely to adopt e-commerce. Notably, the COVID-19 pandemic also served as a strong external push toward digitalization among female employers.

Adoption probabilities increased by 4.0 percentage points during the pandemic and by 8.1 percentage points after the pandemic, indicating that necessity can drive behavioral change among female employers in the face of disrupted offline markets. Taken together, the results highlight the need for comprehensive and gender-sensitive digital inclusion strategies. Expanding access to education and training is essential, but so too is addressing the structural and social barriers that limit women's ability to adopt and benefit from e-commerce. Policies must focus on supporting older women, those with caregiving responsibilities, and informal entrepreneurs, ensuring that digitalization becomes a truly inclusive pathway for rural economic empowerment.

In Table 3, the probit model for male entrepreneurs indicates that, as with their female counterparts, education and training are the strongest enablers of e-commerce adoption. Men with tertiary education are about 10.3 percentage points more likely to adopt e-commerce than those with no formal education, or only completed elementary school, while even completing lower secondary school increases the probability by over 2.8 percentage points. Participation in training programs is also associated with a significant 3.2 percentage-point increase in the likelihood of adoption, underscoring the importance of human capital in facilitating digital inclusion.

In contrast to women, being fully employed has a positive but modest effect on men, increasing the probability of adoption by 0.5 percentage points. This divergence suggests that male entrepreneurs may face fewer competing domestic responsibilities or possess greater flexibility in balancing formal employment with digital side-ventures. Furthermore, being an employer, with either paid or unpaid workers, correlates positively with e-commerce adoption; men with paid employees are 5.5 percentage points more likely to engage in e-commerce. These results reinforce the theoretical premise that business scale, access to capital, and organizational maturity are essential catalysts for digital engagement (Sulaiman, 2000; Matsinhe and Kabanda, 2019; Kedah, 2023).

However, some demographic constraints also persist. Being married reduces the likelihood of adoption by 0.3 percentage points, and larger household sizes have a small negative effect. The age gradient is also evident among men, with older male entrepreneurs significantly less likely to adopt, a difference of nearly 7.7 percentage points between the oldest and youngest age groups. This again points to a generational digital divide, albeit less severe than what is observed among women.

Geographic and sectoral influences are strong. Men living in Java are 4.3 percentage points more likely, reflecting access to better digital infrastructure and markets. Sectoral variation shows that those in the manufacturing and services sectors experience the highest probabilities of adoption, around 6-8 percentage points higher than the baseline group (agriculture), confirming that those economic sectors are more conducive to digital transformation.

Finally, the COVID-19 pandemic also played a catalytic role; male adoption increased by 2.4 percentage points during the pandemic and by a further 5.2 percentage points afterward, indicating that the crisis triggered significant behavioral shifts even among male entrepreneurs, who may have previously relied more on traditional offline channels. In sum, the findings emphasize the critical role of education, training, and industry affiliation in enabling male entrepreneurs to embrace e-commerce.

While the structural constraints appear less severe for men than for women, policies aimed at digital transformation must still address issues such as age-related digital exclusion and spatial inequality to ensure widespread and inclusive adoption among all segments of rural male entrepreneurs. The estimation results in Table 4 show a strong and statistically significant association between e-commerce adoption and increased income among rural entrepreneurs. In the basic model, the coefficient on ecommerce is 0.3879, implying that adopters earn approximately 47 percent more than non-adopters ($e^{0.3879} - 1$). When controlling for individual, household, employment, and regional characteristics in the controlled model without interaction, the effect remains large and highly significant, although reduced to 0.2176**,** suggesting a 24.3 percent income premium. These findings confirm the substantial economic returns to digital inclusion through e-commerce and highlight its transformative potential for rural labor markets.

Our findings are consistent with the Diffusion of Innovations Theory (Rogers, 2003), which suggests that technology adoption improves efficiency and market access. It also aligns with Chen et al. (2022), who find that digital platforms enhance income in rural areas. This study further shows that the magnitude of these benefits varies across gender. The estimation of the model with gender-adoption interaction, which disaggregates by both gender and adoption status, reveals further heterogeneity. Compared to the female non-adopters, female adopters earn significantly more, with a 62.5 percent income gain. Male adopters benefit the most, with a 113.1 percent gain, while male non-adopters also earn significantly more than female non-adopters (15.2 percent gain).

These results indicate a clear gender gap in both adoption and returns to adoption, reinforcing the double disadvantage faced by rural women: lower rates of adoption and lower returns relative to male peers. This suggests that gender not only affects access to technology but also shapes the economic benefits derived from it. However, the positive and significant effect for female adopters shows that digital platforms can partially close the income gap if access is facilitated. Our findings are consistent with existing gender literature, which highlights structural inequalities in access and economic outcomes. This study adds empirical evidence from rural Indonesia, showing that digital adoption does not fully eliminate gender disparities.

Table 4. OLS Estimation Results of Log Earnings

	Basic Model	Without interaction	With interaction
E-commerce	0.3879*** (0.0094)	0.2176*** (0.0072)	
Gender (Female)		-0.4965*** (0.0054)	
Interaction: Gender and Adoption			
Male-Non-dopter			0.1419*** (0.0104)
Female-Adopter			0.4854*** (0.0056)
Male-Adopter			0.7564*** (0.0115)
Marital Status (Married)		0.0794*** (0.0047)	0.0826*** (0.0047)
Number of Household Members		-0.0190*** (0.0024)	-0.0190*** (0.0024)
Number of Household Members 15+		0.0097*** (0.0022)	0.0098*** (0.0022)

	Basic Model	Without interaction	With interaction
Education			
Junior High School		0.0888***	0.0890***
		(0.0066)	(0.0066)
Senior High School		0.1749***	0.1751***
		(0.0071)	(0.0071)
Vocational		0.1410***	0.1398***
		(0.0084)	(0.0084)
Diploma		0.2788***	0.2816***
		(0.0155)	(0.0155)
University		0.3726***	0.3716***
		(0.0152)	(0.0151)
Experience		0.0263***	0.0259***
		(0.0004)	(0.0004)
Experience squared/100		-0.0427***	-0.0423***
		(0.0006)	(0.0006)
Training (trained)		-0.0264***	-0.0254***
		(0.0070)	(0.0070)
Employment status by working hours (full employment)		0.2752***	0.2749***
		(0.0069)	(0.0069)
Formality Status (Formal)		0.0636***	0.0641***
		(0.0130)	(0.0129)
Worker status			
Assisted by unpaid labour		0.1261***	0.1261***
		(0.0064)	(0.0064)
Assisted by paid labour		0.7812***	0.7772***
		(0.0141)	(0.0140)
Economic Sector			
Mining		0.2444***	0.2448***
		(0.0164)	(0.0164)
Manufacture		-0.0440***	-0.0459***
		(0.0097)	(0.0098)
Services		0.2493***	0.2480***
		(0.0063)	(0.0063)
Regional Dummy (Jawa)		-0.1525***	-0.1533***
		(0.0093)	(0.0093)
Pandemic Period			
During Pandemic		-0.0666***	-0.0661***
		(0.0076)	(0.0076)
Post-Pandemic		0.1225***	0.1230***
		(0.0079)	(0.0079)
Constant	13.9573***	13.4706***	12.9847***
	(0.0064)	(0.0140)	(0.0131)
Number of Observations	693,874	693,874	693,874
R-Squared	0.0117	0.2166	0.2169

Note: Robust standard errors in parentheses (clustered at subdistrict level); ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation

Educational attainment has a strong and consistent positive association with income. Individuals with only secondary education (junior and senior high school) earn modestly more, but returns increase substantially for higher education. Those with upper secondary and tertiary education earn 32.5 percent and 45.0 percent more, respectively, in the model with interactions. Experience has a concave relationship with income: while each additional year of experience increases earnings by about 3 percent, the negative coefficient on the quadratic term of experience suggests diminishing returns over time. Notably, being in full employment (rather than part-time or occasional work) boosts earnings by 31.7 percent, further reinforcing the importance of stable labor engagement in rural areas.

Interestingly, participation in training has a negative impact on earnings, contradicting the predictions of Human Capital Theory, which assumes positive returns to skill acquisition. However, similar findings are reported by McKenzie and Woodruff (2014), suggesting that training programs may be ineffective if they are not aligned with the practical needs of entrepreneurs. This indicates potential inefficiencies in training design in rural contexts. It may happen due to a critical mismatch between training curricula and the practical operational needs of businesses in the field. This inefficacy is likely exacerbated by selection bias, wherein programs are predominantly accessed by entrepreneurs already grappling with deep-rooted structural constraints, thereby limiting the scope for interventions to yield immediate performance improvements (Reid, 1987; McKenzie and Woodruff, 2014). These results suggest that improving the design and delivery of training interventions is crucial for effectively translating digital inclusion into tangible economic gains.

Future policy interventions should shift from generic, 'one-size-fits-all' modules toward personalized, practice-based support systems that specifically target the time poverty, capital constraints, and domestic responsibilities that serve as unique barriers for women entrepreneurs. Our empirical findings indicate that entrepreneurs who employ others, particularly those assisted by paid workers, earn significantly more, yielding income premiums as high as 118.4 percent compared to solo entrepreneurs. This substantial premium reflects the inherent advantages of operational scale, capital ownership, and organizational capacity—factors which have been widely documented as critical drivers of entrepreneurial performance (Sorgner, Fritsch and Kritikos, 2017; Jovanovic, 2019). Sectoral fixed effects also matter: individuals in the mining and services sectors earn roughly 27-28 percent more, suggesting variation in profit margins or market access across sectors.

On the other hand, residing in Java has a negative effect on income (-16.5 percent), which is somewhat counterintuitive given better infrastructure. However, this may reflect higher competition and labor market saturation in more densely populated areas . Moreover, this finding can be explained by several structural factors. Rural Java faces significantly higher population density, which intensifies labor market competition and suppresses wages (BPS, 2023). Additionally, agricultural land is highly fragmented due to generational inheritance, leading to small-scale farming operations (BPS, 2023). This finding suggests that access to infrastructure alone does not guarantee higher economic returns.

Overall, the results demonstrate the strong positive returns to e-commerce adoption among rural entrepreneurs, moderated by gender, education, sector, and geography. Women benefit significantly from adopting e-commerce, but men benefit even more, underscoring the need for targeted interventions that promote both access and capabilities for women. The findings also support policy priorities around digital training, connectivity in rural areas, and the formalization of small enterprises to unlock higher income potential.

The estimation results in Table 5 provide valuable insights into the role of e-commerce in improving entrepreneurs' earnings by gender in Indonesia. For female entrepreneurs, the coefficient on ecommerce is positive and statistically significant in the basic and full models. In the basic model, the coefficient of 0.3252 implies that female adopters of e-commerce platforms earn about 38.4 percent more than non-adopters ($e^{0.3980} - 1$).

When controlling for a comprehensive set of individual, household, and employment characteristics in the full model, the effect remains highly significant, although reduced to 0.1610, indicating a 17.5 percent income premium. This suggests that even after accounting for structural disadvantages, e-commerce adoption offers a substantial uplift in income for rural women entrepreneurs.

Table 5. OLS Estimation Results of Log Earnings by Gender

Variable	Male		Female	
	Basic Model	Full Model	Basic Model	Full Model
E-commerce	0.5182***	0.2686***	0.3252***	0.1610***
	(0.0106)	(0.0093)	(0.0123)	(0.0103)
Marital Status (Married)		0.2276***		-0.0408***
		(0.0052)		(0.0068)
Number of Household Members		-0.0217***		-0.0213***
		(0.0026)		(0.0045)
Number of Household Members 15+		0.0143***		0.0174**
		(0.0024)		(0.0067)
Education				
Junior High School		0.0854***		0.0975***
		(0.0071)		(0.0087)
Senior High School		0.1630***		0.1886***
		(0.0073)		(0.0116)
Vocational		0.1264***		0.1581***
		(0.0082)		(0.0175)
Diploma		0.2366***		0.3464***
		(0.0235)		(0.0273)
University		0.3199***		0.4423***
		(0.0167)		(0.0260)
Experience		0.0197***		0.0317***
		(0.0005)		(0.0008)
Experience squared/100		-0.0356***		-0.0492***
		(0.0008)		(0.0011)
Training (trained)		-0.0254***		-0.0114
		(0.0079)		(0.0119)
Employment status by working hours (full employment)		0.2361***		0.3221***
		(0.0078)		(0.0072)
Formality Status (Formal)		0.0683***		0.0587*
		(0.0178)		(0.0352)
Worker status				
Assisted by unpaid labour		0.0692***		0.2118***
		(0.0081)		(0.0060)
Assisted by paid labour		0.7039***		0.9269***
		(0.0174)		(0.0335)
Regional Dummy (Jawa)		-0.1699***		-0.1155***
		(0.0099)		(0.0101)
Pandemic Period				
During Pandemic		-0.0488***		-0.0979***
		(0.0082)		(0.0097)
Post-Pandemic		0.1511***		0.0752***
		(0.0083)		(0.0113)
Constant	14.1320***	13.4991***	13.6027***	12.9219***
	(0.0057)	(0.0136)	(0.0061)	(0.0192)
Number of Observations	465,178	465,178	228,696	228,696
R-Squared	0.0206	0.1599	0.0102	0.1675

Note: Robust standard errors in parentheses (clustered at subdistrict level); ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation

Interestingly, the marital status variable is negative and significant, suggesting that married women earn approximately 4.2 percent less than their unmarried counterparts, ceteris paribus. This result likely reflects persistent structural barriers, such as the disproportionate burden of unpaid domestic responsibilities and limited mobility, that constrain the capacity of married women to fully leverage digital opportunities (Singh, 2017; Priyabadini, 2022; Kodithuwakku and De Silva, 2025). Education continues to play a transformative role in raising the income of women entrepreneurs. Women with a tertiary education (university degree) earn over 55.6 percent more than those with only primary or no education, emphasizing the compounding effect of formal education in enabling women entrepreneurs to leverage digital tools effectively.

Furthermore, full employment increases income by 53.7 percent, while being an employer with paid workers is associated with a 152.7 percent income gain, reflecting the significant scale effect and entrepreneurial capacity among women who formalize and grow their enterprises. These effects underscore the importance of moving beyond mere access to digital tools toward empowering women to own and grow their businesses. The coefficient for living in Java is negative, consistent with earlier findings. COVID-19 impacts are also evident among women entrepreneurs: income dropped significantly during the pandemic, but a modest recovery was observed afterward. These dynamics highlight the role of e-commerce as a partial stabilizer of income during shocks, particularly for digitally engaged women.

Overall, e-commerce adoption is an effective mechanism for economic empowerment among rural women. However, the full benefits are conditional upon other enabling factors, particularly education, business formality, and employment status. Therefore, policies aimed at promoting rural digital inclusion must go beyond infrastructure alone, integrating gender-sensitive digital literacy programs, enterprise development support, and market access strategies specifically tailored for women entrepreneurs.

The regression results for male entrepreneurs show that e-commerce adoption yields significantly higher returns compared to their female counterparts. In the basic model, the coefficient on ecommerce is 0.5182, suggesting a 67.9 percent increase in income among male adopters relative to non-adopters. Even after controlling for individual, employment, and regional characteristics in the full model, the coefficient remains high at 0.2686, indicating a 30.8 percent income premium. These results are notably larger than those observed in the female subsample, reinforcing the existence of a gender gap in the economic returns to digital adoption. In contrast to the female model, the marital status is positive and significant, indicating that married men earn about 25.6 percent more than their unmarried peers.

This may reflect traditional household structures where men are more likely to be the primary earners, and their labor participation is less constrained by domestic responsibilities (Cohen and Haberfeld, 1991; Hersch and Stratton, 2000). As with women, household size is negatively associated with income, while the number of productive household members is positively correlated, albeit with smaller coefficients. Education remains a significant determinant of men's income. The income premium rises with educational attainment, reaching 37.7 percent for those with tertiary education. Full-time employment is associated with a 26.6 percent increase in income. At the same time, those classified as employers with paid workers enjoy a 102.2 percent income advantage, slightly lower than the 152.7 percent seen in women.

Interestingly, being formally registered also has a greater positive effect for men (7.1 percent) than for women (6.0 percent), likely due to men's greater access to networks, capital, and formal market channels. As with women, the residence location in Java may not confer income advantages once other factors are accounted for. The pandemic effects are also clear: earnings declined during the pandemic but partially rebounded afterward, with a stronger recovery than in the female sample.

Across both genders, e-commerce adoption significantly increases rural income, but the magnitude of the benefit is substantially higher for men. While women see a 17.5 percent income gain from e-commerce (conditional on controls), men see a 30.8 percent gain. Furthermore, structural advantages such as marital status, formalization, and employer status yield greater income boosts for men, pointing to persistent gendered disparities in access to and returns from digital entrepreneurship (Guan, He and Hu, 2024; Zheng, Yu and Fu, 2024).

These findings underline the importance of gender-sensitive digital policy design. Interventions must not only promote access to e-commerce for rural women but also address deeper barriers such as mobility, unpaid work, and financing constraints. Without such attention, digital expansion risks widening existing income gaps, even as it lifts overall earnings. The estimation results from the PSM analysis in Table 6 provide robust evidence that e-commerce adoption significantly increases the earnings of rural entrepreneurs in Indonesia, with notable gender differences in the magnitude of these gains. Across both matching methods, nearest-neighbor and kernel, the ATT and the ATE are positive and statistically significant at the 1 percent level for male, female, and combined samples.

For male entrepreneurs, the ATT ranges from IDR 828 thousand to 1.16 million per month, while for female entrepreneurs, it ranges from IDR 321 thousand to 518 thousand. This indicates that men experience approximately twice the income gain from e-commerce adoption as women. The observed difference underscores the structural advantages that men tend to have in rural business contexts, such as greater access to capital, formal markets, and business networks, which allow them to capture larger returns from digital engagement. At the same time, the significant ATT values across all groups confirm that e-commerce has a causal and meaningful impact on income, not merely a correlation due to self-selection. Interestingly, the ATT is consistently higher than the ATE for both genders, suggesting that those who do adopt e-commerce tend to benefit more than the average potential adopter.

Table 6. Estimation results of the Impact of E-commerce on Earnings using PSM

Matching Method	Male		Female		Total	
	ATE	ATT	ATE	ATT	ATE	ATT
- Nearest-Neighbour (5) with Calliper (0.005)	1,096,313***	1,160,745*** (28.22)	525,127***	518,205*** (23.23)	955,681***	860,758*** (26.10)
- Kernel (Bootstrap with 1,000 iterations)	1,027,512***	827,797***	441,162***	320,548***	961,189***	592,873***

Note: ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation; the percentage difference between treated and control groups is in parentheses.

Overall, these results reinforce the role of e-commerce as a transformative tool for rural livelihoods, while also highlighting the importance of targeted, gender-sensitive interventions to ensure that the benefits of digital adoption are equitably distributed. The distribution of propensity score by gender was provided in Appendixes 5 and 5, indicating that there are sufficient comparable individuals in the treatment and control groups, thereby validating the matching procedure and supporting the credibility of the causal estimates derived from the PSM models. Quantile regression results in Table 7 reveal important heterogeneity in the income benefits of e-commerce adoption across the earnings distribution, and these patterns differ markedly between women and men.

Table 7. Estimation results of quantile regression by Gender

Variable	Q10	Q30	Q50	Q70	Q90
Male					
E-commerce	0.4395**	0.3558**	0.2964**	0.2711**	0.2700**
	(0.0173)	(0.0090)	(0.0075)	(0.0089)	(0.0098)
Control variables	yes	yes	yes	yes	yes
Constant	10.5996**	11.5714**	12.3669**	13.0350**	13.8537**
	(0.0319)	(0.0210)	(0.0178)	(0.0170)	(0.0211)
Number of Observations	465,178	465,178	465,178	465,178	465,178
Pseudo R2	0.0699	0.0703	0.0628	0.0634	0.0597
Female					
E-commerce	0.1623**	0.1807**	0.1927**	0.1864**	0.1681**
	(0.0163)	(0.0133)	(0.0117)	(0.0121)	(0.0145)
Control variables	yes	yes	yes	yes	yes
Constant	10.3742**	11.2657**	11.8260**	12.4703**	13.3984**
	(0.0342)	(0.0255)	(0.0248)	(0.0236)	(0.0309)
Number of Observations	228,696	228,696	228,696	228,696	228,696
Pseudo R2	0.0849	0.0725	0.0768	0.0666	0.0580

Note: Robust standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation; the same control variables were applied for all regression equations, consisting of e-commerce adoption, gender, marital status, years of schooling, tenure, training, working hours, and formality status.

For rural male entrepreneurs, the impact of e-commerce adoption is largest at the lower end of the income distribution, with the effect gradually declining across quantiles. At the 10th percentile, the coefficient on ecommerce is 0.4395, implying a wage premium of approximately 55.2 percent. This premium decreases to 31.0 percent at the 90th percentile. The consistently high and statistically significant effects across all quantiles highlight that e-commerce serves as an equalizing force for men, delivering proportionally greater benefits to those who are worse off. This suggests that e-commerce adoption helps mitigate existing income disparities among male entrepreneurs by lifting incomes at the lower end of the distribution. Our finding is supported by Guan, et al. (2024) and Qiu et al. (2025) in rural China, highlighting the uneven benefits of digitalization across income groups.

Among female entrepreneurs, the gains from e-commerce adoption are smaller but more evenly distributed. The coefficient ranges from 0.1623 at the 10th percentile to 0.1681 at the 90th percentile, translating to an income premium of roughly 17–18 percent across the distribution. This pattern contrasts with the male case: females benefit less at the bottom but retain steady returns across quantiles. This flatter distribution suggests that e-commerce primarily reinforces existing economic standing among female entrepreneurs, rather than closing income gaps. These patterns point to a gendered dynamic in how digital tools shape economic outcomes.

For men, e-commerce adoption appears especially beneficial for low-income earners, likely because it helps overcome barriers such as unstable informal employment, limited job opportunities in local markets, or the stigma associated with certain types of in-person labor. In contrast, female entrepreneurs may already operate more established businesses or have better access to capital, resulting in more uniform gains from e-commerce adoption across income levels.

These findings suggest that e-commerce can be a powerful tool for inclusive growth, particularly for low-income men, helping them overcome barriers such as unstable informal work and limited local opportunities. However, effective design and promotion must be gender-sensitive. Policies should prioritize support for low-income women, such as improving access to smartphones, providing targeted digital marketing training, and expanding gender-responsive fintech services. At the same time, efforts to scale men's participation in digital commerce should be accompanied by complementary skills development and business formalization to prevent the deepening of existing inequalities.

Overall, the findings of this study support Human Capital Theory and Diffusion of Innovations Theory in explaining digital adoption and its economic impact in rural areas. At the same time, the results highlight that gender remains a key determinant in both access to and returns from e-commerce. This study contributes to the literature by providing empirical evidence from rural Indonesia that the benefits of digitalization are not evenly distributed among individuals. While this study provides robust evidence on the gendered determinants and impacts of e-commerce adoption among rural entrepreneurs in Indonesia, several limitations should be acknowledged. First, the analysis relies on cross-sectional data from Sakernas, which constrains the ability to capture dynamic changes in adoption behavior or long-term income effects.

Although Propensity Score Matching helps address selection bias, unobserved heterogeneity such as motivation, entrepreneurial skill, or digital literacy may still influence both adoption and income outcomes. Second, the survey's measure of e-commerce adoption is binary and lacks granularity. It does not distinguish between different intensities of use, types of digital platforms, or degrees of integration into online business models. As such, the results may understate variation in how entrepreneurs engage with e-commerce and the corresponding effects on income. Third, the analysis does not explore intra-household dynamics or social constraints (e.g., caregiving responsibilities, gender norms, or access to mobile devices) that may shape women's ability to adopt or benefit from e-commerce.

These dimensions are critical for understanding the full scope of gendered digital exclusion but remain unobservable in the dataset. Fourth, the analysis does not explicitly control for several variables identified in prior studies as determinants of e-commerce adoption, such as the availability of internet-supporting infrastructure and road length as a proxy for market access, due to the unavailability of data disaggregated by rural and urban areas. Should such data become available, future research could extend the analysis to incorporate these factors.

Future research could benefit from panel data to track changes in digital behavior and income trajectories over time. Mixed-methods approaches combining quantitative analysis with qualitative fieldwork would also help uncover the institutional, cultural, and behavioral barriers that shape digital adoption, particularly among marginalized women. Moreover, further studies could examine the role of specific digital tools such as social media marketing, e-payment systems, and online marketplaces in shaping business outcomes across sectors and gender lines.

Finally, policy experiments and impact evaluations of digital literacy programs or financial inclusion initiatives could provide valuable evidence to guide more effective, gender-responsive digital transformation policies in rural areas.

Conclusion

This study provides robust evidence that e-commerce adoption enhances rural entrepreneurs' earnings in Indonesia, but does so unevenly across genders. Women encounter greater barriers related to age, education, marital status, and household responsibilities, and experience smaller income gains than men. While adoption benefits both genders, Propensity Score Matching confirms that male entrepreneurs realize nearly double the monetary returns of their female counterparts. These disparities reflect broader inequalities in resources, networks, and market access.

Policy implications are clear: rural digital transformation must move beyond infrastructure provision to directly address gendered constraints. Interventions should expand women's access to education, digital skills training, and financial capital while supporting enterprise formalization and caregiving infrastructure. In this regard, policies promoting the expansion of Self-Help Groups (SHGs), which enable women to share experiences, provide emotional support, and jointly solve problems, along with the optimization of digital finance, have been shown to enhance women's entrepreneurship in countries such as India and Bangladesh.

To support these efforts, more effective gender-responsive budgeting is required; however, current implementation still faces challenges, including perceptions of adequate budget allocation, uncertainty regarding the effectiveness and efficiency of local budget management, and societal resistance to gender-related concepts. By tailoring policies to the differentiated pathways of men and women, Indonesia can ensure that e-commerce serves not only as a driver of rural income growth but also as a tool for greater economic inclusion and gender equity.

AI declaration

The authors declare that artificial intelligence (AI) tools were used solely to assist in language refinement, grammar checking, and improving the clarity of writing. The use of AI did not influence the research design, data collection, data analysis, interpretation of results, or the development of conclusions. All intellectual contributions, including conceptualization, methodology, analysis, and final content, remain the full responsibility of the authors.

Conflict Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted independently without any financial, commercial, or personal relationships that could be construed as a potential conflict of interest.

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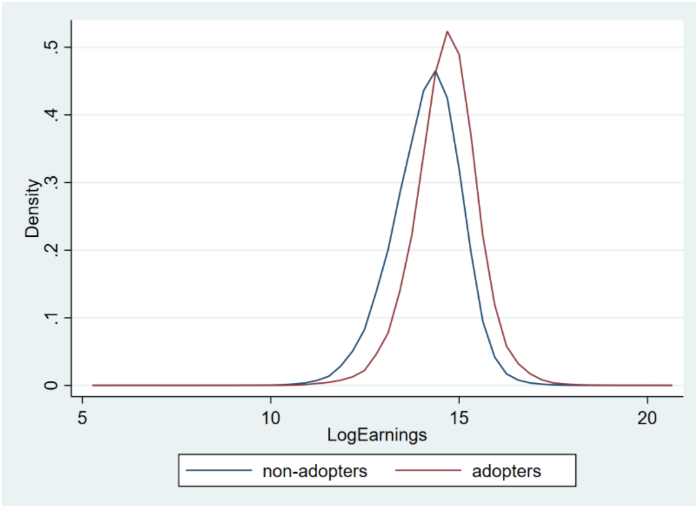
Appendix 1. Distribution of employers by gender and adoption status

Variables	Male			Female		
	Adopters	Non-adopters	Diff	Adopters	Non-adopters	Diff
Continuous variable (mean)						
Earnings (Rp)	3,236,429	1,811,094	1,425,335***	1,716,405	1,128,599	587,806***
Age (years)	39.33	47.27	-7.94***	35.20	47.52	-12.32***
Experience (years)	22.78	33.24	-10.46***	33.79	33.79	0.00***
Tenure (years)	19.01	22.90	-3.90***	18.33	19.59	-1.25***
Working hours (hours)	41.29	33.24	8.05***	37.93	32.23	5.70***
Years of schooling (years)	10.48	8.01	2.47***	10.82	7.72	3.10***
Number of household members	3.94	3.82	0.12***	3.98	3.54	0.43***
Number of household members 15+	2.81	2.83	-0.02***	2.80	2.71	0.09***
Dummy variable (%)						
E-commerce	95.87	4.13	91.74***	93.00	7.00	76.84***
Not Married/ever married	17.08	13.55	3.53***	21.75	14.16	7.59***
Married	82.92	86.45	-3.53***	78.25	85.84	-7.59***
15-34 years old	34.71	18.10	16.61***	50.76	17.20	33.56***
35-44 years old	34.88	25.28	9.60***	30.82	25.32	5.50***
45-54 years old	21.75	26.12	-4.37***	14.89	26.68	-11.79***
55-64 years old	7.32	19.57	-12.25***	3.06	19.83	-16.77***
65+ years old	1.33	10.93	-9.60***	0.46	10.98	-10.52***
No Education/Elementary School	24.36	59.73	-35.37***	19.54	65.40	-45.86***
Junior High School	22.74	18.01	4.73***	24.30	17.34	6.96***
Senior High School	29.84	15.67	14.17***	32.23	12.75	19.48***
Vocational	12.92	4.35	8.57***	11.67	3.48	8.19***
Diploma	2.06	0.55	1.51***	3.51	0.64	2.87***
University	8.08	1.68	6.40***	8.76	1.29	7.47***
Not trained	80.38	93.76	-13.38***	77.59	94.47	-16.88***
Trained	19.62	6.24	13.38***	22.41	5.53	16.88***
Under employment	26.55	40.24	-13.69***	41.02	50.28	-9.26***
Full employment	73.45	59.76	13.69***	58.98	49.72	9.26***
Self employed	55.43	55.87	-0.44***	69.84	68.83	1.01***
Assisted by unpaid workers	28.58	39.67	-11.09***	24.51	29.25	-4.74***
Assisted by paid workers	15.99	4.45	11.54***	5.65	1.92	3.73***
Informal	87.33	96.50	-9.17***	95.31	98.49	-3.19***
Formal	12.67	3.50	9.17***	4.69	1.51	3.19***

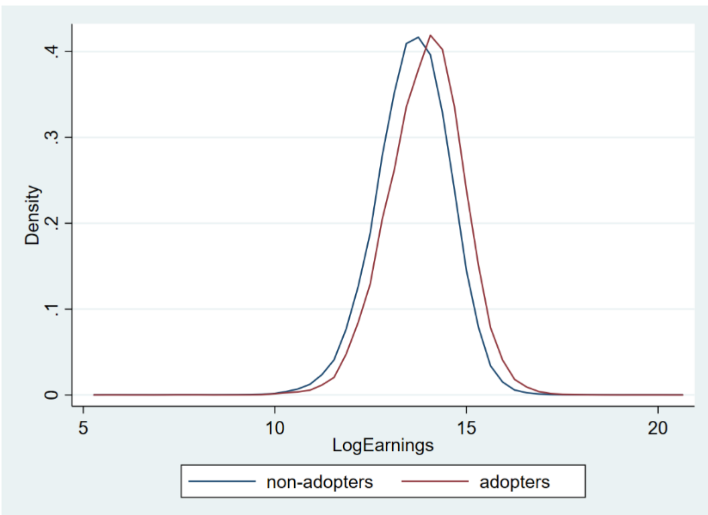
Variables	Male			Female		
	Adopters	Non-adopters	Diff	Adopters	Non-adopters	Diff
Jawa	32.83	15.70	17.12***	27.63	19.26	8.37***
Outside Jawa	67.17	84.30	-17.12***	72.37	80.74	-8.37***

Note: Note: Robust standard errors in parentheses (clustered at subdistrict level); ***p<0.01, **p<0.05, *p<0.1; unweighted

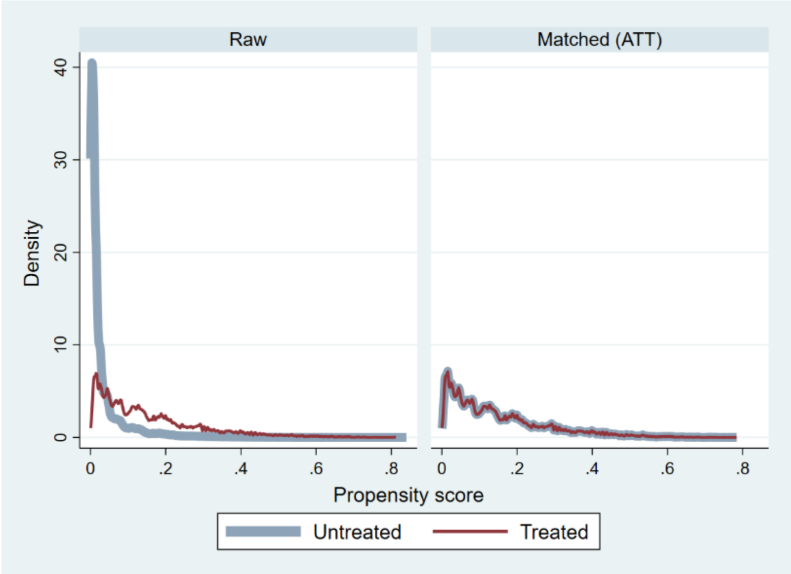
Appendix 2. Log earnings distribution of male employers



Appendix 3. Log earnings distribution of female employers



Appendix 4. Propensity score distribution of male employers



Appendix 5. Propensity score distribution of female employers