Natural Resources for Human Health

eISSN: 2583-1194

Original Research

Received 08 May 2026
Revised 23 June 2026
Accepted 09 July 2026

Natural Resources for Human Health 2026, Vol. 6 (12s): 695–707

KEYWORDS:
Adoption, Digital literacy, Effort expectancy, Farmers, Performance expectancy, SEM.

Farmers' Digital Literacy in Technology Adoption: Evidence from Coffee Farms in Central Java, Indonesia

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ABSTRACT:

Coffee is one of Indonesia's major agricultural commodities, providing significant contributions to national income and supporting rural livelihoods. Central Java holds an important position in this sector, but many coffee farmers continue to face persistent challenges, including low productivity, limited market access, and slow adoption of innovation. Digital technology presents opportunities to address these issues, yet its effectiveness relies heavily on farmers' digital literacy. This study investigates how digital literacy influences performance expectancy (PE) and effort expectancy (EE), and how these factors shape the adoption of digital technology among coffee farmers in Central Java. A quantitative survey was conducted between April and June 2024 involving 122 coffee farmers selected using snowball sampling. Data were gathered through structured questionnaires and analyzed using SmartPLS 4 with Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis included outer model testing to assess reliability and validity and inner model testing to evaluate structural relationships. Results show that all constructs—digital literacy, PE, EE, and adoption—achieved strong convergent and discriminant validity, supported by high composite reliability. R-square values indicate that EE had the highest explanatory power ($R^2 = 0.710$), followed by PE ($R^2 = 0.581$), while adoption was moderately explained by the model ($R^2 = 0.436$). Hypothesis testing revealed that digital literacy significantly affected adoption ($t = 3.737$) and strongly influenced EE ($t = 20.329$) and PE ($t = 14.451$). EE also had a significant effect on adoption ($t = 2.338$), whereas PE did not ($t = 0.219$). These findings suggest that ease of use plays a more central role than perceived benefits in farmers' adoption decisions. The study expands the application of UTAUT in agricultural contexts and highlights the importance of practical digital literacy programs and supportive policies to enhance technology adoption and promote sustainable digital transformation in Indonesia's coffee sector.

1. INTRODUCTION

Coffee is one of Indonesia's primary commodities, playing a strategic role in the economy, both as a foreign exchange earner and as a pillar of the welfare of farming communities. For most farmers, coffee is a primary source of income and a significant contributor to the country's foreign exchange earnings. As a leading agricultural commodity, Indonesia's coffee exports reached US$1,136 million [1]. In addition to contributing to the trade balance, coffee exports also play a role in reducing poverty, particularly in rural areas [2]. Indonesia is among the world's largest coffee producers, with a strong presence in the global market. Coffee production on a worldwide scale is increasingly challenged by issues of climate change, sustainability certification, and shifting consumer preferences toward specialty coffee [3] [4] [5]. These dynamics demand that coffee-producing countries, including Indonesia, adopt innovative strategies to remain competitive in the global market.

Regionally, Central Java holds a key position as one of the national coffee production centers. Several regions, such as Temanggung, Banjarnegara, Wonosobo, Batang, and Kendal, are known for producing superior coffee. The coffee sector's contribution in Central Java strengthens the regional economy through job creation and increased incomes, and supports the competitiveness of Indonesian coffee in the international market. However, this sector still faces various challenges, including suboptimal productivity, limited market access, and low innovation in cultivation and marketing.

This situation demands new strategies to increase the competitiveness of Central Javanese coffee, one of which is through the use of digital technology in production and marketing systems. Unfortunately, many farmers lack the skills and knowledge to optimize coffee production, exacerbated by limited access to extension services and training programs [6]. Indonesia, as one of the world's foremost coffee exporters [7], has made digital technology skills among farmers no longer optional but essential, since global market access today is primarily driven by technologies that remove the limits of space and time.

Advances in digital technology have significantly impacted various sectors, including the agricultural industry. The emergence of innovations such as agrotechnological platforms, online marketing platforms, innovative farming applications, and digital-based information services provides new opportunities for farmers to increase the productivity and efficiency of their farming businesses [8]. For coffee farmers, digital technology enables faster and more accurate access to price information, weather forecasts, modern cultivation practices, and market potential. Utilizing online platforms also allows farmers to expand their coffee distribution networks, eliminating dependence on conventional distribution channels, which are often detrimental. Furthermore, digital platforms increase business agility and competitiveness by supporting more effective decision-making and faster responses to market dynamics [9].

Furthermore, using digital tools also strengthens traceability and transparency, which can help coffee producers penetrate premium markets while increasing consumer confidence [10]. Overall, digital technology plays a crucial role in increasing production and marketing efficiency while strengthening the competitiveness of Indonesian coffee globally. Therefore, digital transformation in the agricultural sector can be considered a vital strategy for overcoming coffee farmers' traditional limitations, particularly in Central Java.

In the agricultural context, digital literacy encompasses skills and competencies that enable farmers to use digital technology to improve their farming practices effectively. This includes accessing, managing, interpreting, evaluating, producing, and conveying agricultural information online [11]. Digital literacy extends beyond technical skills in operating devices such as smartphones or computers, but also involves a critical understanding of various digital agricultural applications, online marketing platforms, and agribusiness information services. A high level of digital literacy will influence farmers' capacity to recognize opportunities, maximize the use of technology, and make more informed decisions in producing and marketing agricultural products [12]. Digital literacy may also enable farmers to access and evaluate information related to safe farming practice, appropriate agricultural input use, and occupational risks, which may contribute to safer farming practice and farmer well-being. However, in reality, many traditional coffee farmers still face obstacles such as low digital literacy due to limited formal education, limited access to training programs, or a lack of experience in using digital technology. This condition is a significant challenge because, without improving digital literacy, achieving the optimal implementation of modern agricultural technology is challenging.

Research on technology adoption across diverse contexts frequently identifies Performance Expectancy (PE) and Effort Expectancy (EE) as fundamental dimensions of analysis [13] [14] [15] [16] [17] [18] [19]. Effort Expectancy (EE) is defined as "the degree of ease associated with using a system" [20] . A study by [21] analyzed young people's intention to adopt investment advisor technology using both variables. In a similar technological context, [13] and [18] examined the adoption of digital payment systems, incorporating Performance Expectancy (PE) and Effort Expectancy (EE) along with other factors. The complexity in Fintech tends to reduce user confidence and slow adoption [21] . Therefore, Effort Expectancy (EE) is helpful to capture how users perceive the ease of learning and operating financial technologies, allowing researchers to examine how usability influences adoption intention despite potential technological barriers. Within the healthcare sector, exploring the role of effort expectation (EE) in shaping technology adoption willingness is crucial, particularly given the heavy workload of healthcare professionals [14] [19]. Identifying their expectations in operating these systems ensures they facilitate their work rather than adding to the burden. These demonstrate that analyzing Effort Expectancy (EE) provides valuable insights across diverse contexts, in the sector where users may face even greater unfamiliarity with technology. As Indonesian coffee farmers generally work with minimal exposure to technology, it is essential to conduct studies that examine their expectations regarding its adoption. Such investigations can provide valuable insights into how technology may be designed or introduced to facilitate their farming practices better.

Performance Expectancy (PE) is defined as "the extent to which an individual believes that using a system will help him or her achieve improved job performance" [20]. Performance Expectancy (PE) consistently emphasizes that technology adoption is primarily determined by users' perceptions of its usefulness and their belief that it will effectively support them in attaining their goals. Hence, it helps analyze adoption willingness toward technologies with measurable performance outcomes, such as learning technologies for students [17] and digital voting platforms [16]. Moreover, [15] PE is also relevant to assess adoption in technologies that support individual decision-making, as shown in work on how PE shapes miners' adoption of digital visualization short-interval control systems. Based on previous studies, Performance Expectancy (PE) suggests that individuals are more likely to adopt a technology when it is perceived to enhance productivity. In coffee farming, technology benefits farmers by improving product quality, reducing production costs, and providing broader market opportunities. Thus, exploring how Indonesian coffee farmers perceive technology adoption based on PE becomes relevant and vital.

Studies on technology adoption are common in education and healthcare because these sectors have a broad user base and are directly linked to fundamental human needs. This makes every technological innovation in these areas gain faster attention and receive more scholarly investigation. In contrast to sectors considered modern and fast-changing, where technology adoption is widely studied, agriculture is often perceived as conservative. Consequently, research on adoption in this field, particularly for specific commodities like coffee, remains limited and is frequently treated as a niche. While prior studies have investigated the willingness to adopt technology from the digital literacy perspective, research incorporating Performance Expectancy (PE) and Effort Expectancy (EE) as moderating variables remains relatively underexplored. This study identifies a novel relationship, showing how digital literacy shapes individuals' PE and EE before ultimately influencing their decision to adopt a technology, particularly among coffee farmers. Therefore, this study aims to analyze the role of digital literacy in influencing performance expectancy and effort expectancy, and investigate the influence of these three factors on digital technology adoption among coffee farmers in Central Java.

2. MATERIALS AND METHODS

2.1 Study area and Context

This research was conducted in the coffee-growing region of Central Java, Indonesia, known as one of the nation's central coffee-producing regions, with Temanggung, Kendal, and Batang as the research locations. These regions were chosen for their significant contribution to coffee production and potential for developing digital-based agricultural technologies. Local governments, research institutions, and agricultural extension workers support farmers by providing information and transferring digital technology related to coffee cultivation and marketing.

2.2 Sampling and Data Collection

This research survey was conducted from April to June 2024 in several coffee-growing regions in Central Java, Indonesia. A snowball sampling technique was used to reach coffee farmers with diverse backgrounds based on location, experience, and business scale, resulting in a sample of 122 respondents. Data collected in this study included farmer demographic characteristics, digital literacy levels, performance expectancy, effort expectancy, and technology adoption levels. Psycho-behavioral constructs were measured using a 3-point Likert scale with categories: 1 = disagree, 2 = undecided, 3 = agree.

Data was collected through face-to-face interviews by trained enumerators using a structured questionnaire. A total of 122 coffee farmers from several regions in Central Java were selected as survey respondents, with a distribution reflecting the diverse conditions of coffee farmers in the area. Instrument reliability was measured using Cronbach's Alpha values from pilot testing, demonstrating good internal consistency before its full implementation in the study. With this design, the researchers produced valid and reliable data to analyze the relationship between digital literacy, performance expectancy, effort expectancy, and technology adoption among coffee farmers.

2.3 Data analysis

Data analysis was conducted using SmartPLS 4 through two main stages: outer model evaluation and inner model evaluation. Outer model evaluation was undertaken to assess the reliability and validity of the indicators in measuring the latent constructs. This stage included examining the Average Variance Extracted (AVE) and square root of AVE (√AVE) values, which were compared with the correlation between constructs to ensure discriminant validity. Composite Reliability (CR) and Cronbach's Alpha values were also analyzed to assess internal consistency, with a threshold of ≥ 0.70 indicating acceptable reliability [22].

Next, inner model evaluation was conducted to test the relationships between latent constructs. The R-square value was used to assess the ability of the independent variables to explain the dependent variable, with criteria of 0.19 (weak), 0.33 (moderate), and 0.67 (strong) [22]. Correlation analysis between constructs was also considered to ensure relationships aligned with the theoretical framework.

The final stage was hypothesis testing through path coefficient analysis using a bootstrapping procedure. A t-statistic value ≥ 1.96 and a p-value ≤ 0.05 were used as the basis for decision-making regarding the significance of the influence between variables [22]. Through this stage, the study identified the direct impact of digital literacy on performance expectancy, effort expectancy, and technology adoption, while also evaluating the extent to which the research model has strong validity and reliability.

3. RESULTS AND DISCUSSION

3.1 Outer model evaluation

An outer model evaluation was conducted to assess the validity and reliability of the constructs used in the study. In the initial stage (Figure 1), several indicators had factor loadings below the threshold of 0.70, particularly for the Performance Expectancy (B1 = 0.695) and Digital Literacy (A4 = 0.673) constructs. Referring to [22] criteria, indicators with loadings below 0.70 can be eliminated to improve convergent validity. Therefore, B1 and A4 were removed from the model.

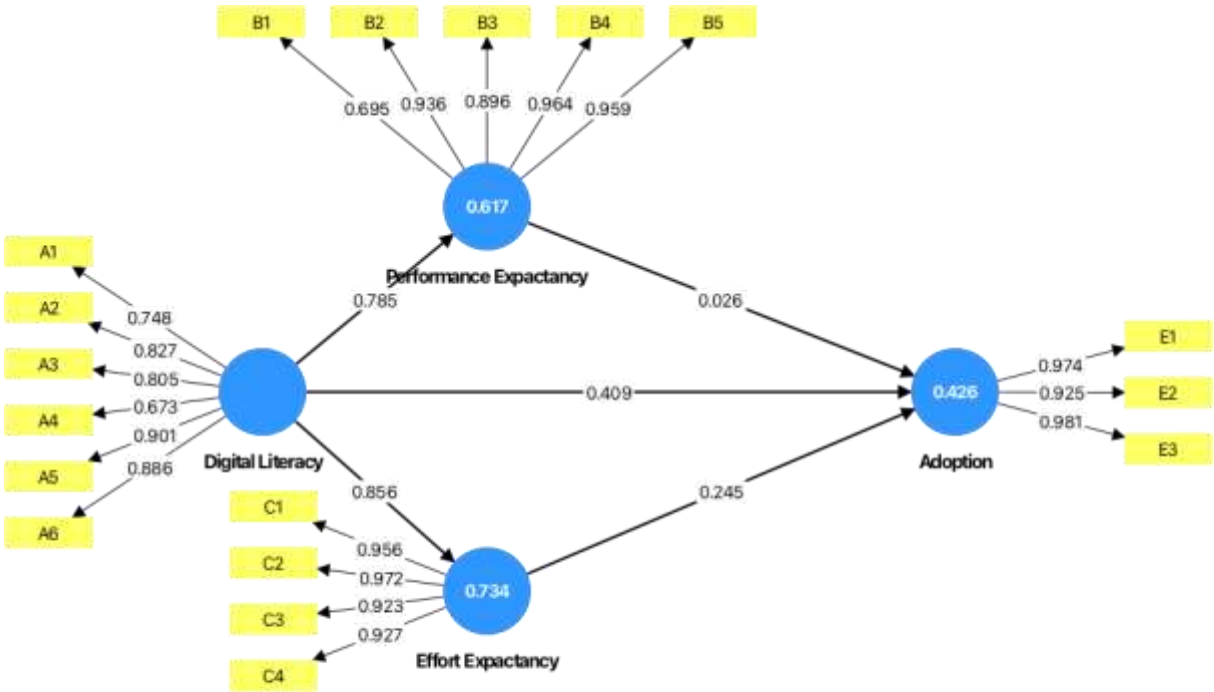

Figure 1. First Level of Path Diagram Before Elimination

After elimination (Figure 2), all remaining indicators showed loading factor values >0.770, confirming that each indicator substantially contributed to the measured construct. The Average Variance Extracted (AVE) value for each construct was also above 0.50, thus meeting the convergent validity criteria. Furthermore, the Composite Reliability (CR) and Cronbach's Alpha (CA) values were recorded above the threshold of 0.70, indicating excellent internal consistency.

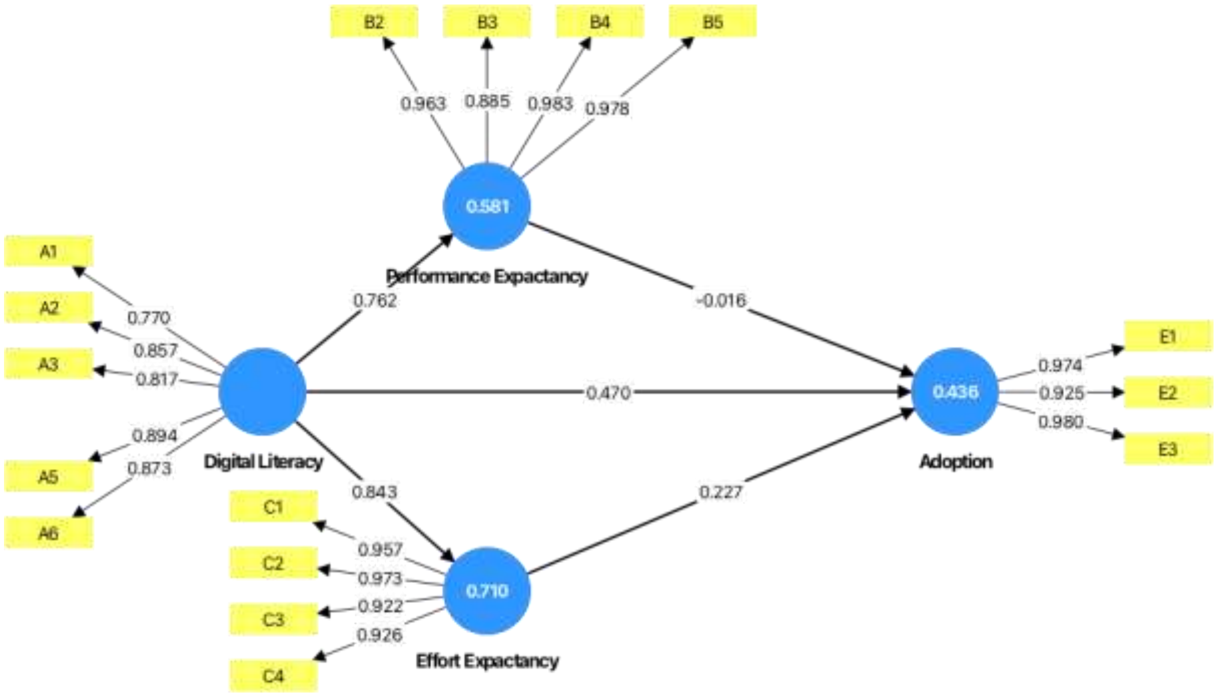

Figure 2. Final Result of Path Diagram

The results of the outer model evaluation demonstrate that indicator reduction is a crucial step in improving the fit of the measurement model. Eliminating indicators with low loading values increases construct stability and produces a more parsimonious model. This finding is consistent with the methodology in the literature, which emphasizes the importance of retaining only indicators with substantive contributions to measuring latent constructs. Conceptually, the guaranteed reliability and validity of the Digital Literacy, Performance Expectancy, Effort Expectancy, and Adoption constructs provide a strong foundation for subsequent structural analysis.

All constructs' Average Variance Extracted (AVE) values were above 0.50, ranging from 0.711 to 0.922. The square root of the AVE for each construct was also greater than 0.84, indicating a high contribution of indicator variance to the latent construct. This confirms that all research constructs have strong convergent validity.

Table 1. AVE values and AVE roots

Latent Variable	Average variance extracted (AVE)	Square root of AVE
Adoption	0,922	0,960
Effort expactancy	0,711	0,843
Digital literacy	0,892	0,945
Effort expactancy	0,908	0,953

Convergent validity is established when the AVE value exceeds 0.50, indicating that the construct explains more than 50% of the variance in its indicators. The high AVE values obtained in this study demonstrate that the Digital Literacy, Effort Expectancy, Performance Expectancy, and Adoption constructs adequately explain their respective indicators. Furthermore, the square root of the AVE for each construct is greater than its correlations with the other constructs, confirming discriminant validity. Therefore, the constructs demonstrate adequate measurement validity and are suitable for use in structural model analysis.

Correlation values between constructs ranged from 0.494 to 0.893. The highest correlation was recorded between Digital Literacy and Effort Expectancy (0.893), while the lowest was between Adoption and Performance Expectancy (0.494). These results indicate a relationship between the constructs, but do not violate the discriminant validity principle because each AVE square root is higher than the corresponding correlation value.

Table 2. Correlation values between construct

Latent Variable	Adoption	Effort expactancy	Digital literacy	Effort expactancy
Adoption	-	-	-	-
Effort expactancy	0,698	-	-	-
Digital literacy	0,633	0,893	-	-
Effort expactancy	0,494	0,804	0,614	-

The relatively high correlation between Digital Literacy and Effort Expectancy confirms that digital literacy plays a key role in influencing farmers' perceptions of the ease of use of technology. However, the relatively lower correlation between Performance Expectancy and Adoption indicates that perceived long-term benefits are not a primary determinant of adoption decisions. These results reinforce the inner model's findings that effort expectancy is more dominant than performance expectancy in the context of technology adoption among coffee farmers.

The Composite Reliability (CR) values for all constructs ranged from 0.909 to 0.968, far exceeding the minimum threshold of 0.70. This indicates that all indicators in this study have high internal consistency in measuring their respective latent constructs.

Table 3. Composite reliability

Latent Variable	Composite reliability
Adoption	0,967
Effort expactancy	0,909
Digital literacy	0,968
Effort expactancy	0,966

Very high composite reliability indicates that each construct can be consistently measured by the indicators used. CR values approaching 1.0 for the Adoption (0.967) and Digital Literacy (0.968) constructs indicate excellent measurement stability and confirm that this research instrument was well-designed. This provides a strong methodological foundation for proceeding to the inner model analysis stage, as the measurement model has been proven reliable.

3.2 Inner Model Evaluation

The R-square value in Table 4 shows that the Adoption construct has a value of 0.436, which means that the exogenous constructs in the model can explain 43.6% of the variation in technology adoption. The Effort Expectancy construct recorded an R^2 value of 0.710, indicating that the predictor variables can explain 71% of its variance. At the same time, the Performance Expectancy construct had an R^2 value of 0.581, indicating the model's explanatory power of 58.1%. Based on the R^2 interpretation criteria by [23], a value of 0.19 is considered weak, 0.33 is moderate, and 0.67 is strong. Thus, the R^2 for Effort Expectancy can be categorized as very strong, Performance Expectancy is classified as mild to strong, while Adoption is at a moderate level.

Table 4. R-square values of construct

Variable	Composite reliability
Adoption	0,436
Effort expactancy	0,710
Effort expactancy	0,581

The obtained R-square value provides an overview of the structural model's predictive power in explaining variation in endogenous constructs. The high R^2 value for the Effort Expectancy construct (0.710) confirms that digital literacy is dominant in shaping farmers' perceptions of the ease of technology use. This is consistent with UTAUT theory, which positions effort expectancy as an essential determinant of adoption intention, especially in the context of farmers with limited prior digital literacy.

Meanwhile, the R^2 value for the Performance Expectancy construct (0.581) indicates that digital literacy also plays a substantial role in shaping perceptions of technology benefits, although not as significantly as its contribution to perceived ease of use. This indicates that farmers are more responsive to the practical aspects of technology use than to potential long-term benefits.

The moderate R^2 value for the Adoption construct (0.436) indicates that although digital literacy, effort expectancy, and performance expectancy play a role in explaining adoption, other external factors also contribute. Factors such as institutional support, access to financing, and social influence from the farming community likely contribute to variations in adoption. These findings broaden empirical insights by emphasizing that interventions to improve digital literacy need to be balanced with supporting policies that strengthen the technology adoption ecosystem in the coffee sector.

The hypothesis testing results in Table 5 show that most relationships between constructs are significant at the 95% confidence level (t-statistic> 1.96; $p < 0.05$). First, Digital Literacy → Adoption has a substantial direct effect with a t-value of 3.737, indicating that digital literacy directly contributes to coffee farmers' decision to adopt technology. Second, Digital Literacy → Effort Expectancy shows a powerful and significant effect ($t = 20.329$), indicating that digital skills substantially increase the perceived ease of use of technology. Third, Digital Literacy → Performance Expectancy is also significant with a t-value of 14.451, confirming that digital literacy increases the perceived benefits of technology among coffee farmers.

Furthermore, the Effort Expectancy → Adoption path is significant with a t-value of 2.338, indicating that technology's perceived ease of use encourages farmers to adopt it. However, contrary to theoretical expectations, the Performance Expectancy → Adoption path was insignificant ($t = 0.219$; $p = 0.827$). This indicates that although farmers are aware of the potential benefits of technology, this factor is not a primary driver in their adoption decisions.

Table 5. Hypothesis testing results

Path coefficients	Value	T statistics (|O/STDEV|)
Digital Literacy → Adoption	0.000	3.737
Digital Literacy → Effort Expectancy	0.000	20.329
Digital Literacy → Performance Expectancy	0.000	14.451
Effort Expectancy → Adoption	0.000	2.338
Performance Expectancy → Adoption	0.827	0.219

3.4 Discussion

The findings reveal that digital literacy exerts a direct and significant effect on technology adoption, as reflected by a T-statistic of 3.737. This result suggests that strengthening digital literacy among coffee farmers in Central Java increases their readiness to integrate digital tools into farming practices. Digital literacy is thus a critical driver for using digital media and technologies in agriculture, including coffee cultivation. It is a decisive factor in adopting diverse agricultural technologies and practices. By enhancing their digital competence, farmers improve their ability to access and apply information effectively, essential for embracing innovations such as e-commerce platforms that broaden market opportunities [24]. Farmers with higher digital literacy can operate digital tools more efficiently, enabling better decision-making and productivity [25]. Moreover, improved digital literacy equips farmers to understand and manage new technologies' risks, fostering greater confidence in technology adoption [26]. Well-prepared and digitally capable farmers are also better positioned to deal with uncertainty and leverage digital solutions to mitigate risks [27]. Beyond technical skills, digital literacy enhances farmers' social capital by linking them to wider networks through social media and digital platforms, which promotes collaboration and knowledge exchange—key elements in adopting innovative agricultural practices [28] [29].

Additionally, digital literacy expands farmers' access to economic resources and market intelligence. Farmers with stronger digital skills can better interpret market trends, connect to financial services, and use digital marketplaces to sell their produce [30]. Access to such information and resources substantially increases their capacity to adopt digital technologies and reap associated benefits [31]. These insights underscore that digital literacy is not merely a technical skill but a strategic enabler of innovation, resilience, and competitiveness in coffee farming systems.

Digital literacy has also been shown to have a strong influence on two key constructs within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework: effort expectancy (T-statistic 20.329> 1.960) and performance expectancy (T-statistic 14.451> 1.960). Mastery of digital skills directly drives adoption and shapes farmers' perceptions of the ease of use and potential benefits of digital agricultural technologies. Increased digital literacy enables farmers to operate digital devices more effectively, reducing the perceived effort required to interact with the technology. Farmers with higher levels of digital literacy are better prepared to utilize digital platforms in agricultural activities [24]. Therefore, digital literacy training programs and workshops are recommended as a strategic step to bridge the gap and increase adoption readiness. Digital literacy fosters self-confidence and reduces the learning burden, encouraging farmers' willingness to adopt new technologies [25].

Furthermore, digital literacy also influences farmers' expectations regarding the benefits of using digital devices. Farmers with better digital literacy are more likely to rate digital tools as beneficial for improving their farming practices and overall productivity [32]. Adequate digital skills support improved decision-making capacity, resulting in more optimal performance. For example, digital literacy can help farmers adopt conservation tillage practices through enhanced financial literacy and access to agricultural technology services [33].

Furthermore, the results showed that effort expectancy positively and significantly affected technology adoption (T-statistic 2.338> 1.960). This confirms that farmers consider ease of use an important factor when opting for digital media in agricultural activities. In the context of coffee farmers in Central Java, technology that is simple, accessible, and does not require complex technical skills is more readily accepted. In Johor, fruit farmers' attitudes toward post-harvest practices were positively influenced by effort expectations, reinforcing the need for user-friendly technology [34]. Similarly, in implementing digital mobile platforms for farm management, effort expectancy directly influences sustainability usage, highlighting the importance of this factor in both the initial and ongoing implementation phases [35]. In the context of innovative agricultural technology, effort expectations were a significant predictor of adoption intentions among farmers, indicating that ease of use is crucial for technology acceptance [36].

Meanwhile, in contrast to initial expectations, performance expectations did not significantly influence adoption (T-statistic 0.219 <1.960). This suggests that although farmers believe this technology has potential benefits, this perception is not yet strong enough to motivate them to adopt it. This condition may be due to economic circumstances, complexity, socio-cultural circumstances, and limited empirical evidence directly experienced by coffee farmers, such as the financial benefits or productivity increases that are not yet tangible. Farmers may still view digital technology as a complement, rather than an instrument capable of transforming their agricultural performance. Financial constraints, such as high initial costs and limited access to credit, can prevent farmers from adopting new technologies. Even if a technology promises better performance, economic burdens and lack of financial support can be significant barriers [37]. Technology incompatible with existing agricultural practices or perceived as too complex can hinder adoption. Farmers may find it challenging to integrate new technology into their current systems, thus reducing the likelihood of adoption despite high-performance expectations [38]. Social norms and cultural practices can significantly influence adoption decisions. Farmers may rely more on social influence and cultural compatibility than performance expectations. For example, technologies that align with traditional practices or are supported by trusted community members are more likely to be adopted [39].

The findings of this study confirm that digital literacy is a crucial foundation for encouraging technology adoption in the agricultural sector. However, ease of use has proven to be more essential than perceived benefits. The practical implication of these results is the need for training and extension programs that focus on improving farmers' digital literacy and emphasize the practical aspects and ease of use of technology [40]. Comprehensive training covering basic to advanced digital skills can increase farmers' confidence in using digital tools, including training in specific applications tailored to their agricultural needs [31].

Furthermore, public policy needs to be directed at creating tangible evidence of the benefits of technology, such as increased access to digital markets or demonstrating direct economic impact. These efforts will strengthen performance expectations and thus play a greater role in encouraging future adoption. Support in the form of subsidies and financial incentives can help reduce barriers to adoption. Government initiatives that combine digital literacy promotion with financial backing are believed to encourage more farmers to utilize digital technology [41].

Furthermore, social support also plays a crucial role. Encouraging farmers to share positive experiences using digital technology can have a ripple effect in their communities [35]. Membership in farmer organizations can serve as a means of knowledge exchange and accelerate collective adoption. Furthermore, farmer-based organizations have the potential to provide strong support networks, helping to strengthen the sustainability of digital technology adoption in the agricultural sector [42].

4. CONCLUSION

This study confirms that digital literacy is a significant factor in driving technology adoption among coffee farmers in Central Java. Outer model analysis results show that all constructs meet convergent validity, discriminant validity, and internal reliability, thus categorizing the research instrument as robust and reliable. The R-square value indicates that Effort Expectancy (R^2 = 0.710) has the highest explanatory power, followed by Performance Expectancy (R^2 = 0.581). In contrast, the Adoption construct has a moderate R^2 value (0.436), indicating the presence of other external factors influencing adoption decisions.

Hypothesis testing revealed that digital literacy influences technology adoption and shapes farmers' perceptions of ease of use (effort expectancy) and benefits (performance expectancy). However, only perceived ease of use proved significant in driving adoption, while perceived benefits played no vital role. These findings suggest that practical and operational factors influence coffee farmers' decisions more than potential long-term benefits.

This study expands the application of the UTAUT framework by emphasizing the dominant role of effort expectancy over performance expectancy in the context of traditional agriculture. Practically, these findings underscore the importance of digital literacy programs geared toward practical skills, tailored training to field needs, and supporting policies that can reduce technical barriers to technology utilization. Collaboration between the government, research institutions, and farmer communities is a strategic step to strengthen sustainable digital transformation in the coffee sector.

The results of this study emphasize the need for digital literacy programs directly relevant to coffee farming activities. The government and relevant stakeholders must provide practical training, such as online marketing platforms, agricultural data management, and simple yet effective digital cultivation technologies. Institutional support in the form of financial incentives, digital device subsidies, and increased rural internet access is also key to reducing adoption barriers. Furthermore, the role of farmer organizations is crucial in strengthening social influence and accelerating collective technology adoption.

ACKNOWLEDGEMENTS

This work is supported by the Concernıng Research Fundıng Grant For Lecturers Of The Faculty of Animal and Agricultural Sciences, Dıponegoro Unıversıty, Fıscal Year 2025 (Project No: 1/UN7.F5/PP/1/2025), Indonesia.

AUTHOR CONTRIBUTIONS

Muhammad Luthfie Fadhilah: Conceptualization, Design, Statistical Analysis, Literature Research.

Irma Fauziah: Conceptualization, Design, Data Collection, Statistical Analysis, Literature Research, Writing—Review & Editing.

Avivah Rahmaningtyas: Design, Data Collection, Literature Research, Writing—Review & Editing.

CONFLICT OF INTEREST

We declare that there is no conflict of interest.

ETHICS STATEMENT

Not applicable in this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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