**Jurnal Ilmiah Manajemen dan Bisnis**
Volume 11, Number 1, 2026 pp. 94-111
P-ISSN: 2528-2077 E-ISSN : 2528-1208
Open Access: https://journal.undiknas.ac.id/index.php/manajemen/

# From Adoption to Productivity: The Central Role of Optimal Technology Use in The Informal Economy

**Mizan Ikhlasul Rahman[1*], Chairul Sa'roni[1], Sri Hidayah[2], Muhammad Fathur Reza[3]**
[1] Department of Economics and Development Studies, Universitas Lambung Mangkurat, Banjarmasin, Indonesia
[2] Department of Sociology, Universitas Lambung Mangkurat, Banjarmasin, Indonesia
[3] Department of International Business, College of Management, National Dong Hwa University, Hualien, Taiwan

**A R T I C L E I N F O**
***Article history:***
Received: 2026-03-10
Revised: 2026-04-19
Accepted: 2026-06-10
Available Online: 2026-06-30

***Keywords:***
*Informal Economy;*
*Technology Adoption;*
*Optimal Technology Use*

**DOI:**
https://doi.org/10.38043/jimb.v11i1.7610

**A B S T R A C T**

This study examines factors influencing optimal technology use and its relationship with technology adoption and business performance in the informal economy. It highlights the need to explore ways in which technology can maximize productivity and performance. Most studies have documented the discourse on technology adoption and its drivers, while the drivers or factors that facilitate optimal technology use remain comparatively underexplored. Thus, this study fills the gap. This study addresses the question: What factors influence optimal technology use, and how does it mediate the relationship between technology adoption and business performance? It also emphasizes that directly eradicating or formalizing the informal economy is not an ideal solution. Mixed methods were employed in this study. PLS-SEM analysis was conducted using SEMinR in RStudio, based on data from 221 completed questionnaires, providing reliable empirical evidence. Thematic analysis was also applied to qualitative responses to provide additional insights. Quantitative and qualitative evidence confirms significant relationships among technology adoption, technology use, and business performance. All indicators significantly impact their respective constructs, supporting the hypothesized relationships. Optimal use of technology partially mediates the positive and significant impact of adoption on business performance. Key factors, such as technology adoption and user commitment to continuous learning, are essential to optimizing technology use. Practical strategies include allocating adequate resources for ongoing training and skill development and ensuring the technology aligns with operational needs to enhance efficiency.



## 1. INTRODUCTION

The informal economy can be observed as informal economic activities or informal businesses that provide opportunities for people to earn income. These activities operate on a small scale and do not comply with the required regulations by public authorities, mainly paying taxes and providing standardized wages and protection for the employee (Andrews et al., 2011; Chen, 2012; Luque, 2021). The informal economy was initially assumed to be a traditional economic activity before the modernization era. It has been existing and growing due to the inability of the formal economy to provide and absorb employment. Another perspective explains that the informal economy has existed and is growing naturally due to the rational action of individuals in surviving poverty (Blades et al., 2011; Hapsari et al., 2023). Limited state capacity and intervention can also be a cause of the growing informal economy, leading to society's distrust and avoidance of the formal economy (Benjamin et al., 2014; Sharma & Adhikari, 2020; Ulyssea, 2020; Williams, 2023).

The informal economy serves as an economic buffer in a period of uncertainty and instability. Thus, its role is important, providing rationales to further study it and develop or guide it better (Benjamin et al., 2014; Felzensztein et al., 2025). In Indonesia, the informal economy is especially important. Recent data show that a substantial proportion of the workforce is engaged in the informal economy or sector, reaching around 57.7% by 2025 (Badan Pusat Statistik, 2026; Sibagariang et al., 2023). Indeed, there are disadvantages generated by the informal economy, such as tax revenue reduction, unstandardized employment, and limited contribution to economic growth (Blades et al., 2011; Dell'Anno, 2022). However, it has several advantages or positive impacts that are worth considering. Informal economy indirectly incubates potential businesses and entrepreneurs to grow, provides flexibility for people to secure livelihood and earn income, and eventually produces affordable goods and services for society (Benjamin et al., 2014; Gërxhani & Cichocki, 2023; Williams, 2007). This potential long-term impact of the informal economy must be considered (Chen, 2012).

* *Corresponding Author: Mizan Ikhlasul Rahman: mizanrahman@ulm.ac.id*

The discourse and studies on the informal economy have been complemented by policy approaches that both support it and address various issues within it. There are two main policy approaches highlighted from varied studies: 1) the formalization of the informal economy; 2) productivity improvement in the informal economy (Andrews et al., 2011; Chen, 2012; Chen & Carré, 2020; Gërxhani & Cichocki, 2023; Williams, 2023). Essentially, formalization means regulating the informal economy; thus, potential negative impacts from informality, such as labor exploitation by capitalists, tax evasion, and unfair competition, can be reduced and even eradicated. This policy approach, or formalization, may widen socio-spatial disparities as formal employment is limited, and informal employment becomes an option left for people having livelihood and generating income (Ulyssea, 2020). Instead of formalization or disrupting the informal economy with this unfavorable policy, the informal economy needs support to be more productive (Chen, 2012).

Based on the two main policies explained earlier, this study chooses to focus on improving the productivity of the informal economy, rather than relying on a conventional approach to eradicate and transform it directly into the formal economy (Kraemer-Mbula & Wunsch-Vincent, 2016). Specifically, this study aims to understand the role and effect of technology and digitalization in improving the productivity of the informal economy. Several studies explain and argue that technologies with internet connectivity, such as online platforms and digital systems, provide access to larger markets and improve operational efficiency (Ajao et al., 2018; Attaran & Celik, 2023; Khin & Ho, 2019; Shankar et al., 2021). Without these technologies, people or businesses will experience high transaction and operational costs, and reaching a larger market seems impossible (Bhattacharya, 2019; Danquah & Owusu, 2021; Pankomera & van Greunen, 2019; Rangaswamy, 2019; Seetharaman et al., 2019). This focus on enhancing productivity also recognizes the importance of the informal economy in society, as it must be integrated into such an inclusive policy that does not discriminate between formal and informal economies (Kraemer-Mbula & Wunsch-Vincent, 2016).

**Theoretical Frameworks for Technology Adoption and Use**

Technology is becoming increasingly relevant to improving the performance and productivity of the informal economy (Ajao et al., 2018; Danquah & Owusu, 2021; Ebrahim & van den Berg, 2024). As explained earlier, technology enables more effective and efficient operations, optimizes resource utilization, opens new markets, broadens customer reach, and enhances competitiveness. These benefits allow the informal economy to compete with existing and larger enterprises (Garcia-Murillo & Velez-Ospina, 2014; Hyde-Clarke, 2013; Ibidunni et al., 2020; Manyati & Mutsau, 2019; Nguimkeu & Okou, 2021; Pankomera & van Greunen, 2019). This technology comprises both hardware and software. Hardware includes mobile phones, computers, and other physical components that support business operations and activities (Ajao et al., 2018; Danquah & Owusu, 2021; Hyde-Clarke, 2013; Nguimkeu & Okou, 2021; Seetharaman et al., 2019). Software comprises mobile payment applications, social media platforms for business, instant messaging applications, e-commerce platforms, and even bookkeeping and accounting applications (Etim & Daramola, 2023; Garcia-Murillo & Velez-Ospina, 2014; Jacolin et al., 2021; Manyati & Mutsau, 2019; Pankomera & van Greunen, 2019; Seetharaman et al., 2019). The choice of technology can be adapted to the specific activities and tasks in the informal economy (Ibidunni et al., 2020; Nguimkeu & Okou, 2021).

The concept or definition of technology has been evolving along with the development of relevant theories. Technology was only understood as hardware or physical tools that simplify processes and deliver efficiency in completing varied tasks (Chuttur, 2009; Kwarteng et al., 2024; Marangunić & Granić, 2015). Then it has been defined as software, applications, or online services that provide ease for consumers (Yadegari et al., 2024). Despite understanding the importance of technology and its potential benefits, the level of adoption and even use remains low (Al-Emran & Griffy-Brown, 2023; Naushad & Sulphey, 2020; Zolas et al., 2020). As a result, the initial theories and research have been developed to merely observe factors or drivers influencing the adoption and use of technology (Chuttur, 2009; Kwarteng et al., 2024; Lai, 2017; Marangunić & Granić, 2015).

The development of these factors or drivers generates varied perspectives and technological models or frameworks. This development confirms the need to incorporate a broader range of factors and emphasizes contextuality in terms of individual users or collective users, such as organizations and established businesses. Primarily, the technological discourse was examined through the lens of intention, using the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB). Both theories argue that intentions and personal evaluations shape performed behaviors (Marangunić & Granić, 2015; Yadegari et al., 2024). Indeed, while neither theory specifically aligns intentions with technology, these theories set the foundation for understanding the intentions, reasons, and factors behind adopting and using technology (Chuttur, 2009). This foundation contributes to the development of current and well-known theories such as the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), Task-Technology Fit (TTF), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Lai, 2017; Marangunić & Granić, 2015). Each theory explains and emphasizes different factors and drivers in technology adoption and use. TAM explains that the main factors are people's perceptions, such as perceived usefulness and perceived ease of use. Meanwhile, DOI highlights technology's relative advantage and its compatibility as the main factors influencing its adoption and use. The alignment or suitability of technology's capability in completing tasks is also an important factor, as explained in TTF. Furthermore, UTAUT consolidates all the factors or drivers from previous theories. UTAUT refines these factors or drivers, explaining that technology is more likely to be adopted and used when it can improve general performance, deliver advantages, help in completing required tasks, and align with user values and needs (Marangunić & Granić, 2015; Naushad & Sulphey, 2020). Technology also requires a supportive ecosystem to be adopted and used optimally (Kwarteng et al., 2024).

Furthermore, in the post-adoption phase, optimal use of technology is required to achieve maximum potential benefits of higher productivity and efficiency (Khin & Ho, 2019; Kinkel et al., 2022; Martínez-Caro et al., 2020; Shankar et al., 2021; Surya et al., 2021). This optimal use of technology can be performed through varied factors, namely consistent exploration and long-term learning, sufficient organizational and user skills, a supportive environment, or support from technology providers, and the alignment of technology with the expected tasks to complete (Hoang, 2024; Muchenje & Seppänen, 2023). Without clear intentions and objectives, the technology will not be utilized effectively (Chueh & Huang, 2023; Teo & van Schaik, 2012). Moreover, proper timing of technology adoption also enhances its optimal use (Kinkel et al., 2022; Tang et al., 2022). Another piece of evidence emphasizes that technology is more readily adopted when it is fully developed or mature, preventing potential inefficiencies during use (Kinkel et al., 2022). At a minimum, technology must be aligned with market demand and needs (Sagala & Őri, 2024). The link between technology adoption, technology use, and business performance will be explained further, providing relevant evidence and developing hypotheses. Optimal technology use is different from 'normal use', where normal use equals technology adoption without intention to fully integrate it within the system (Martínez-Caro et al., 2020; Surya et al., 2021). Thus, this level of technology integration, or how technology is integrated, is considered an important factor in constructing optimal technology use (Khin & Ho, 2019; Shankar et al., 2021; Tabrizi et al., 2019).

**Linking Technology Adoption, Optimal Use, and Business Performance**

The informal economy, referred to as informal business and informal employment, can either be avoided or supported. The latter, supportive actions, are preferred, as avoiding or eradicating the informal economy is neither proper nor ideal. The informal economy is the main source of income for many people (Deléchat & Medina, 2021; Elvis et al., 2022). If the productivity of the informal economy is improved through supportive environments, there is a probability that it will become a formal economy (Hyde-Clarke, 2013; Ibidunni et al., 2020). The transition into a formal economy can ensure an ideal situation for the main stakeholders, where the government may receive tax payments as regulated, and society can maintain its livelihood better (Bhattacharya, 2019; Danquah & Owusu, 2021; Deléchat & Medina, 2021; Ebrahim & van den Berg, 2024).

Technology utilization can be seen as the main or effective strategy in improving the productivity and performance of the informal economy (Jacolin et al., 2021; Takyi et al., 2022). Technology utilization can be defined as technology adoption and use, while the productivity and performance of the informal economy are observed as business performance (Ibidunni et al., 2020; Martínez-Peláez et al., 2023; Pankomera & van Greunen, 2019). Based on theories and frameworks explained earlier, the initial technological discourse explores factors and drivers influencing technology adoption or not rejecting technology. However, this discourse can be enriched by further understanding factors and drivers influencing optimal use of technology (Manyati & Mutsau, 2019; Nguimkeu & Okou, 2021; Pankomera & van Greunen, 2019; Straub, 2009). There are several hypotheses developed in this study since it includes the factors or drivers of technology adoption, technology use, and business performance.

There are several factors influencing the adoption rate of technology, or Technology Adoption (TA), with the most important factors being Perceived Benefit (PB) and Perceived Usability (PU) (Attaran & Celik, 2023; Blut & Wang, 2020; Nguimkeu & Okou, 2021; Shankar et al., 2021). Theories explain that when these two main factors are observed and realized, the likelihood that a person or group will adopt technology increases. Meanwhile, Technology Use (TU) is influenced by several factors that determine its optimal use, with the most influential factors being Technology Fit (TF) and Commitment (CT) (Khin & Ho, 2019; Manyati & Mutsau, 2019; Martínez-Caro et al., 2020; Nguimkeu & Okou, 2021). If TF aligns with the users' needs, there is a high probability of achieving optimal use. Similarly, CT ensures long-term learning and consistent exploration, thereby improving the optimal use of technology. Moreover, beyond the main theories of technology adoption and use that have been providing and referred to as the framework for technology discourse and research, all factors chosen and considered in this study are justified as foundational cognitive drivers that influence human decision-making in adopting technology (Noerman et al., 2025; Schultz & Kaiser, 2025), and as important contributors to optimal and effective use of technology after adoption (Rahi et al., 2020; Rieg, 2025). Meanwhile, business performance is measured by increased sales or revenue and improved efficiency (Hyde-Clarke, 2013; Ibidunni et al., 2020), where sales increases and efficiency gains are key indicators of business growth (Gunawan et al., 2023; Nayyar et al., 2023). It is also understood that technology must be adopted before it is used, and that its use can mediate the relationship between technology adoption and business performance (Elvis et al., 2022). The hypotheses in this study are outlined as follows:

**Table 1.** Research Hypotheses for Technology Adoption, Technology Use, and Business Performance

| Hypothesis | | |
|---|---|---|
| H1 | : | Perceived Benefit positively influences Technology Adoption. |
| H2 | : | Perceived Usability positively influences Technology Adoption. |
| H3 | : | Technology Fit positively influences Technology Use. |
| H4 | : | Commitment positively influences Technology Use. |
| H5 | : | Technology Adoption is a necessary condition for Technology Use. |
| H6 | : | Technology Use positively impacts Business Performance. |
| H7 | : | Technology Adoption positively impacts Business Performance, partially mediated by Technology Use. |

## 2. METHOD

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) in SEMinR in RStudio. PLS-SEM is chosen because it provides a robust approach for predicting and exploring relationships among variables. PLS-SEM also accommodates the complexity of developed latent constructs (Hair et al., 2019, 2021). Specifically, this study focuses on predicting and exploring relationships between several reflective constructs. These reflective constructs are explained in Table 2 below.

Furthermore, a seven-point Likert scale is used in the questionnaire to measure the indicators. This seven-point range ranges from 1: strongly disagree, highly unlikely, highly unintegrated to 7: strongly agree, highly likely, highly integrated. Each construct comprises multiple indicators to enhance its reliability and validity. Figure 1 illustrates the conceptual model of this study, visualizing the hypothesized relationships between constructs. This conceptual model is developed based on the theoretical framework and research hypotheses. Moreover, this study includes open-ended questions, whose responses are analyzed through thematic analysis in Microsoft Excel. This thematic analysis began with keyword analysis of respondents' answers, followed by coding, theme development, and iterative engagement with the transcripts or data. Such a process aims to ensure the credibility and validity of the analysis, delivering relevant conclusions and explanations regarding the issue, topic, or objective raised in this study (Naeem et al., 2023).

**Table 2.** Constructs, Indicators, and Descriptions

| Constructs | Indicators | Descriptions |
|---|---|---|
| Perceived Benefit (PB) | PB1 | I feel that technology and applications help me reach more customers. |
| | PB2 | I feel that technology and applications make it easier for me to manage my business. |
| Perceived Usability (PU) | PU1 | I find it easy to use a variety of technologies for my business operations. |
| | PU2 | I find it easy to operate hardware technology in my business activities. |
| | PU3 | I am confident in my ability to effectively use the provided technology for my business. |
| Technology Fit (TF) | TF1 | Technology and applications provide significant advantages over traditional tools and methods. |
| | TF2 | The technology and applications I use are fully compatible with my business operations. |
| Commitment (CT) | CT1 | I am willing to invest time and resources into learning and adopting new technologies. |
| | CT2 | I consistently assess whether the technology I use helps me meet my business objectives. |
| Technology Adoption (TA) | TA1 | The likelihood and perceived importance of adopting mobile and online technologies, including smartphones, mobile payment apps, and social media platforms for business activities. |

| | | |
|---|---|---|
| | TA2 | The likelihood and perceived importance of adopting software and hardware technologies, including accounting apps, hardware technology, and e-commerce platforms for business activities. |
| Technology Use (TU) | TU1 | The extent to which digital technologies (smartphones, payment apps, social media, e-commerce, messaging, and accounting tools) are integrated into my daily business processes. |
| | TU2 | The extent to which hardware technology (physical devices) is integrated into my daily business operations. |
| Business Performance (BP) | BP1 | Using technology and applications has contributed to an increase in my sales or revenue. |
| | BP2 | Technology and applications have allowed me to reduce costs or improve operational efficiency. |

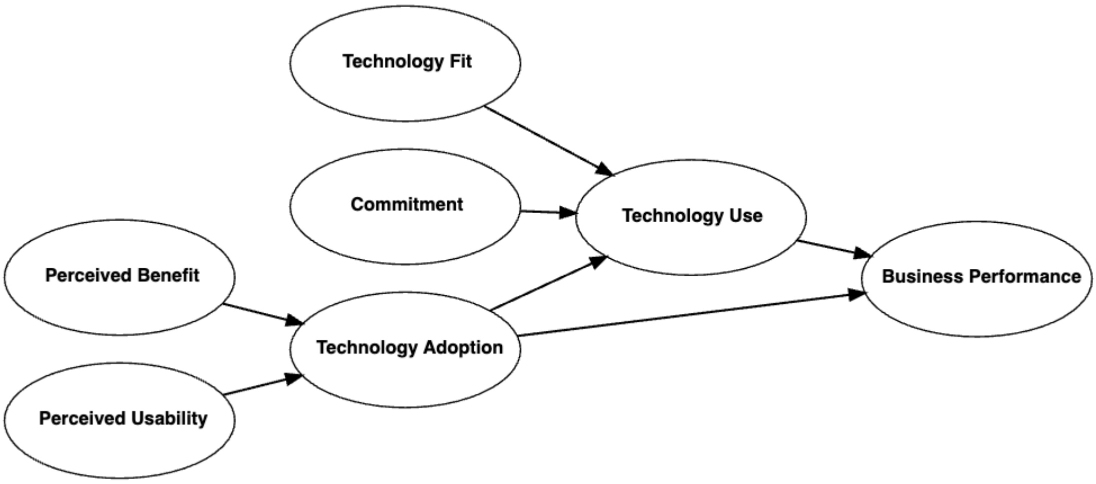


**Figure 1**. Conceptual Model of Constructs

A survey was conducted both online and in person across South Kalimantan over a four-month period (August-November, 2024) to understand the experiences of those running small or informal businesses. This study used purposive sampling to target owners, managers, and employees working in food courts, on the street, or at home (Sarker & AL-Muaalemi, 2022). Sample selection was also based on business scale criteria, measured by revenue or income level and the number of staff, ensuring the sample is relevant to the characteristics of the informal economy or informal sector. All procedures were performed in accordance with standard ethical practices, in which the purposes of the study are explained, and consent is obtained at the beginning. Participation in this study was strictly voluntary, and respondents' privacy was protected. Furthermore, South Kalimantan reflects a mixed economy, with a significant extractive sector and about 53.48% of the workforce engaged in informal work as of August 2025, which is similar to the national average of 57.7%. This makes the region an important setting for studying economic vulnerabilities and hardship (Badan Pusat Statistik, 2026; Handayani et al., 2025). PLS-SEM analysis checked measurement reliability (outer loadings > 0.70, Cronbach's Alpha and CR > 0.70, AVE > 0.50, HTMT < 0.90, Fornell-Larcker criterion). The structural model examined relationships via path coefficients ($p < 0.05$), $R^2$ (0.25, 0.50, 0.75), and effect sizes ($f^2$) (Hair et al., 2019, 2021). Furthermore, in accordance with recent advancements in PLS-SEM guidelines (Hair et al., 2021), traditional goodness-of-fit metrics such as SRMR were not employed because PLS-SEM is a variance-based method designed to maximize explained variance; evaluating its predictive capabilities is prioritized over covariance-based model fit. Then, rather than relying on traditional in-sample $Q^2$ values via blindfolding, out-of-sample predictive power was rigorously assessed using the PLSpredict procedure (Shmueli et al., 2019), comparing the model's Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) against a linear model (LM) benchmark. Additionally, IPMA evaluated predictor importance and performance in relation to technology use. This study also assesses the potential risk of Common Method Bias (CMB) by conducting a collinearity test. Thus, the Variance Inflation Factor (VIF) values were examined using a threshold of 3.3 (VIF < 3.3) (Hair et al., 2021). Qualitative responses were organized into keywords, codes, and themes to understand technology adoption and social impacts beyond the quantitative data (Naeem et al., 2023).

## 3. RESULT AND DISCUSSION

### Descriptive Statistics

A total of 221 valid questionnaires were collected from 231 questionnaires distributed to people involved in small or informal businesses across South Kalimantan, with most data collected through online interactions. These businesses can be found in diverse settings such as food courts, along the streets, or operating out of homes. They are classified as small based on their income levels and the number of staff they employ. The data collected include basic statistics such as the average, variance, kurtosis, and skewness, which are presented in Table 3.

**Table 3.** Descriptive Statistics of Constructs and Indicators

| Constructs | Indicators | Mean | SD | Kurtosis | Skewness |
|---|---|---|---|---|---|
| PB | PB1 | 6.054 | 1.178 | 4.065 | -1.209 |
| | PB2 | 6.027 | 1.198 | 4.080 | -1.244 |
| PU | PU1 | 5.676 | 1.185 | 3.354 | -0.870 |
| | PU2 | 5.430 | 1.418 | 3.639 | -0.865 |
| | PU3 | 5.656 | 1.232 | 2.607 | -0.625 |
| TF | TF1 | 5.629 | 1.300 | 3.288 | -0.795 |
| | TF2 | 5.647 | 1.287 | 3.017 | -0.719 |
| CT | CT1 | 5.412 | 1.361 | 2.745 | -0.578 |
| | CT2 | 5.462 | 1.316 | 3.015 | -0.594 |
| TA | TA1 | 5.919 | 1.132 | 3.581 | -1.029 |
| | TA2 | 5.440 | 1.285 | 3.247 | -0.749 |
| TU | TU1 | 5.458 | 1.246 | 3.062 | -0.660 |
| | TU2 | 5.376 | 1.501 | 3.461 | -0.874 |
| BP | BP1 | 5.801 | 1.178 | 2.519 | -0.697 |
| | BP2 | 5.652 | 1.247 | 3.074 | -0.728 |

The overall scores indicate that most people agree with the statements across various indicators. The results suggest that people tend to have positive feelings about technology and its use.

### Measurement Reliability and Validity

Before assessing the structural relationships, the measurement model was evaluated to ensure the reliability and validity of the reflective constructs. Outer loadings, Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and discriminant validity indices (HTMT and Fornell-Larcker Criterion) were examined according to the thresholds described previously.

**Table 4.** Outer Loadings of Constructs and Indicators

| | BP | CT | PB | PU | TA | TF | TU |
|---|---|---|---|---|---|---|---|
| BP1 | 0.948 | | | | | | |
| BP2 | 0.932 | | | | | | |
| CT1 | | 0.914 | | | | | |
| CT2 | | 0.928 | | | | | |
| PB1 | | | 0.933 | | | | |
| PB2 | | | 0.944 | | | | |
| PU1 | | | | 0.920 | | | |
| PU2 | | | | 0.851 | | | |
| PU3 | | | | 0.874 | | | |
| TA1 | | | | | 0.923 | | |
| TA2 | | | | | 0.906 | | |
| TF1 | | | | | | 0.879 | |
| TF2 | | | | | | 0.925 | |
| TU1 | | | | | | | 0.935 |
| TU2 | | | | | | | 0.909 |

**Table 5.** Internal Reliability and Validity Metrics

| Constructs | Alpha | rhoC | AVE | rhoA |
|---|---|---|---|---|
| PB | 0.865 | 0.937 | 0.881 | 0.869 |
| PU | 0.858 | 0.913 | 0.779 | 0.865 |
| TF | 0.775 | 0.898 | 0.815 | 0.804 |
| CT | 0.822 | 0.918 | 0.849 | 0.827 |
| TA | 0.805 | 0.911 | 0.837 | 0.810 |
| TU | 0.825 | 0.919 | 0.850 | 0.840 |
| BP | 0.868 | 0.938 | 0.883 | 0.878 |

**Table 6.** Heterotrait-Monotrait Ratio (HTMT) for Discriminant Validity

| Constructs | PB | PU | TF | CT | TA | TU | BP |
|---|---|---|---|---|---|---|---|
| PB | | | | | | | |
| PU | 0.737 | | | | | | |
| TF | 0.762 | 0.700 | | | | | |
| CT | 0.524 | 0.806 | 0.689 | | | | |
| TA | 0.827 | 0.803 | 0.765 | 0.746 | | | |
| TU | 0.618 | 0.824 | 0.741 | 0.832 | 0.838 | | |
| BP | 0.616 | 0.750 | 0.805 | 0.754 | 0.695 | 0.840 | |

**Table 7.** Fornell-Larcker Criterion (FL Criterion) for Discriminant Validity

| Constructs | PB | PU | TF | CT | TA | TU | BP |
|---|---|---|---|---|---|---|---|
| PB | 0.939 | | | | | | |
| PU | 0.641 | 0.882 | | | | | |
| TF | 0.628 | 0.580 | 0.903 | | | | |
| CT | 0.442 | 0.681 | 0.557 | 0.921 | | | |
| TA | 0.697 | 0.669 | 0.611 | 0.604 | 0.915 | | |
| TU | 0.529 | 0.698 | 0.605 | 0.693 | 0.689 | 0.922 | |
| BP | 0.541 | 0.652 | 0.667 | 0.636 | 0.587 | 0.714 | 0.940 |

All the indicators retained in the model show strong reliability, with outer loadings above 0.70, signifying they accurately measure their respective constructs. The Cronbach's Alpha and Composite Reliability values for all constructs are above 0.70, demonstrating consistent internal reliability. Each construct also has an Average Variance Extracted (AVE) above 0.50, indicating that the measures converge well. Discriminant validity is confirmed because the square roots of AVE on the diagonal surpass the correlations between constructs, and all HTMT values stay below 0.90, and meet the stricter threshold of 0.85 (Henseler et al., 2015). However, after employing a 1000-resample bootstrapping procedure to generate 95% confidence intervals, the analysis revealed that the 97.5% upper confidence boundaries for these specific pairs (TU-CT=0.958, TU-TA=0.923, and BP-TU=0.927) exceeded the 0.85 threshold. Although there is some statistical overlap, these constructs were retained as separate variables in the structural model due to their clear conceptual and theoretical documentation shown in the existing literature. The qualitative analysis also confirms that users or respondents view 'adoption' (the initial decision) and 'use' (ongoing engagement) as distinct constructs, supporting their separation despite conservative HTMT bounds. Overall, these results indicate that the measurement model is reliable and valid, making it appropriate for the next phase of structural analysis.

**Common Method Bias (CMB) Assessment**

This assessment aims to test for potential CMB arising from self-reported data, and the VIF values in Table 8 below indicate that the model is free of common method variance. The VIF values for all predictor constructs ranged from 1.696 to 1.905, and all are below the 3.3 threshold. This also ensures that collinearity does not distort the results.

**Table 8.** Inner Variance Inflation Factor (VIF) Values

| Constructs | TA | TU | BP |
|---|---|---|---|
| PB | 1.696 | | |
| PU | 1.696 | | |
| TF | | 1.749 | |
| CT | | 1.728 | |
| TA | | 1.902 | 1.905 |
| TU | | | 1.905 |

**Model Fit**

Following the satisfactory assessment of the measurement model and the assessment of collinearity, the structural model was evaluated to test the hypotheses and examine the relationships among Technology Adoption (TA), Technology Use (TU), and Business Performance (BP), as well as their antecedents. Based on the ($R^2$) values, the model demonstrates moderate to substantial explanatory power, indicating that the independent variables and their indicators effectively explain the endogenous constructs and establish strong connections within the model.

**Table 9.** Coefficient of Determination ($R^2$) and Adjusted $R^2$

| | R-square ($R^2$) | R-square ($R^2$) adjusted |
|---|---|---|
| TA | 0.570 | 0.566 |
| TU | 0.614 | 0.609 |
| BP | 0.527 | 0.522 |

**Table 10.** Path Coefficient, Confidence Intervals, and Significance Levels

| Path | Original Estimate | Bootstrap Mean | Bootstrap SD | T-Statistic | 2.5% CI | 97.5% CI | p-values |
|---|---|---|---|---|---|---|---|
| PB → TA | 0.455 | 0.454 | 0.083 | 5.455 | 0.281 | 0.602 | 0.000 |
| PU → TA | 0.378 | 0.380 | 0.085 | 4.450 | 0.213 | 0.547 | 0.000 |
| TF → TU | 0.180 | 0.186 | 0.069 | 2.604 | 0.053 | 0.318 | 0.000 |
| CT → TU | 0.382 | 0.385 | 0.087 | 4.381 | 0.220 | 0.554 | 0.000 |
| TA → TU | 0.348 | 0.341 | 0.072 | 4.815 | 0.211 | 0.487 | 0.000 |
| TA → BP | 0.181 | 0.183 | 0.078 | 2.318 | 0.029 | 0.331 | 0.026 |
| TU → BP | 0.589 | 0.589 | 0.076 | 7.787 | 0.431 | 0.730 | 0.000 |

**Table 11.** Comparison of Path Coefficients and Indirect Effect between TA, TU, and BP

| Path | Original Estimate | Bootstrap Mean | Bootstrap SD | T-Statistic | 2.5% CI | 97.5% CI | p-values |
|---|---|---|---|---|---|---|---|
| TA → TU | 0.348 | 0.341 | 0.072 | 4.815 | 0.211 | 0.487 | 0.000 |
| TA → BP | 0.181 | 0.183 | 0.078 | 2.318 | 0.029 | 0.331 | 0.026 |
| TU → BP | 0.589 | 0.589 | 0.076 | 7.787 | 0.431 | 0.730 | 0.000 |
| TA → TU → BP | 0.205 | 0.198 | 0.046 | 4.437 | 0.118 | 0.304 | 0.000 |

All seven hypotheses (H1-H7) find support in the data, showing meaningful relationships that range from modest to strong. Notably, when people perceive more benefits and find the technology easier to use, they are more likely to adopt it. Conversely, if they see the technology as complex, they tend to avoid it. This highlights how perceptions of usefulness and simplicity can significantly influence technology adoption. All effects are positive and significant, confirming all hypotheses. Better alignment between technology and tasks and higher user commitment correlate with increased technology use. Technology Adoption (TA) positively predicts TU, supporting H5 and illustrating that adoption is a critical first step before further use. Additionally, TU significantly enhances Business Performance (BP), supporting H6 and showing that greater technology use leads to improved business outcomes.

The partial mediation hypothesis (H7) is also confirmed. The indirect effect of TA on BP via TU is 0.205, which is larger than the direct effect of TA on BP (0.181). The combined (total) effect of TA on BP is 0.386, with the indirect part accounting for 53.1% of this total. This indicates that TA influences BP partially through TU rather than directly. This demonstrates the importance of TU as a mechanism that translates adoption into significant impact, or, in this case, improves business performance (Ghobakhloo et al., 2012; Saghafian et al., 2021). Merely adopting technology can also be impactful, as it is a strategic step toward competing and meeting customer expectations and demands (Sagala & Őri, 2024). Among all path coefficients in the model, the strongest effect is TU on BP, emphasizing the important role of technology use in driving business performance.

**Effect Size and Out-of-Sample Predictive Power**

Effect size values ($f^2$) for the structural paths range from small ($\geq 0.02$), through medium ($\geq 0.15$), to large ($\geq 0.35$), indicating that the predictors exert effects ranging from small to substantial on their respective endogenous constructs. It can also be highlighted that CT, or commitment to learning, facilitates exploration and experimentation with technology, thereby serving as a catalyst for optimizing its use (Giannakos et al., 2022). Meanwhile, predictive power was assessed using the out-of-sample PLSpredict procedure, showing nuanced results across endogenous constructs. The model exhibits high predictive power for Technology Adoption (TA) and Technology Use (TU), with PLS-SEM out-of-sample RMSE values for the indicators (TA1 = 0.765, TA2 = 1.015, TU1 = 0.753, TU2 = 1.213) lower than those of linear model benchmarks. Meanwhile, Business Performance (BP) shows limited predictive power, with the LM benchmark having a lower error for BP1 (0.805) and an equal error for BP2 (0.983). The PLS-SEM model typically exhibits lower errors than LM for most indicators, indicating a moderate predictive capability. Additionally, the low construct-level overfit metrics (TA = 0.0335, TU = 0.0663, BP = 0.0315) indicate that the model generalizes effectively to unseen data without significant overfitting.

**Table 12.** Effect Size ($f^2$) for Construct Relationship

| | TA | TU | BP |
|---|---|---|---|
| PB | 0.282 | | |
| PU | 0.186 | | |
| TF | | 0.048 | |
| CT | | 0.219 | |
| TA | | 0.168 | 0.037 |
| TU | | | 0.380 |

**Table 13.** Assessment of Out-of-Sample Predictive Power (PLSpredict)

| Constructs | Indicators | PLS-SEM RMSE | LM RMSE |
|---|---|---|---|
| Technology Adoption | TA1 | 0.765 | 0.766 |
| | TA2 | 1.015 | 1.018 |
| Technology Use | TU1 | 0.753 | 0.766 |
| | TU2 | 1.213 | 1.227 |
| Business Performance | BP1 | 0.828 | 0.805 |
| | BP2 | 0.983 | 0.983 |

**Importance-Performance Map Analysis (IPMA)**

The analysis emphasizes the importance and performance of indicators in optimizing technology use (TU). As hypothesized, Technology Adoption (TA) and related indicators are essential for TU. The matrix in Figure 2 below identifies TA and Commitment (CT) as the dominant and important drivers of Technology Use. Specifically, commitment still needs to be supported or encouraged to achieve higher performance, and improvements in user commitment are expected to lead to a significant increase in overall technology use. This matrix also specifically confirms H5.

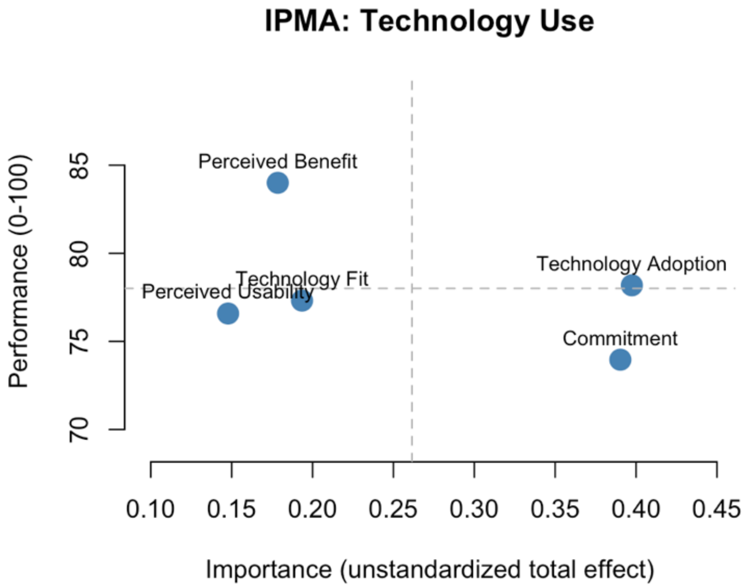


**Figure 2**. Importance-Performance Analysis of Variables Predicting Technology Use (TU)

**Thematic Analysis**

This thematic analysis aims to further develop the empirical evidence presented earlier. The study examined responses to open-ended questions in the questionnaire, focusing on constraints, required support, and feedback from experiences with technology adoption and use. In the process, keywords from responses are highlighted and used to guide the development of codes and themes. Ultimately, the final narrative and conclusions are derived from the entire process (Braun & Clarke, 2021; Douglas, 2017; Naeem et al., 2023). Regarding constraints, respondents were asked about the most significant constraints in adopting and using technology. Table 14 explains the thematic analysis of the responses.

**Table 14**. Constraints in Technology Adoption and Use: A Thematic Analysis

| Response | Keywords | Code | Theme | Conclusion |
|---|---|---|---|---|
| The alignment of technology and applications with business scale and specific needs is necessary. | Technology and applications; Business scale; Specific needs. | ▪ Technology Alignment.<br>▪ Financial Barriers.<br>▪ Skill and Training Gaps.<br>▪ Infrastructure and Adaptation Issues. | ▪ Overcoming Technological Barriers. | Technology must align with the needs and objectives of the business or user and is supported by training and skill development. Thus, barriers are solved, and technology will be used effectively. |
| High costs of premium apps, advertisements, and hardware prevent optimal adoption and use of technology. | High costs; Premium apps; Advertisements; Hardware. | | | |
| Lack of training and technical skills prevent the optimal integration of technology. | Lack of training; Technical skills; Integration of technology. | | ▪ Addressing Financial and Infrastructure Constraints. | Financial and infrastructure constraints are experienced by many users. Technology |

| | | | | |
|---|---|---|---|---|
| Poor infrastructure, such as unstable internet, and limited resources causes inefficient operation. | Poor infrastructure; Internet; Limited resources; Inefficient operation. | | | adoption and use are hindered by these constraints. |
| Some businesses experience resistance to change, satisfied and staying with traditional methods, rejecting modern technology. | Resistance to change; Traditional methods; Modern technology. | | | |

Next, responses regarding possible and required supports for technology adoption and use are analyzed, and Table 15 presents the thematic analysis.

**Table 15**. Required Supports for Technology Adoption and Use: A Thematic Analysis

| Response | Keywords | Code | Theme | Conclusion |
|---|---|---|---|---|
| Social media promotions and content creators widen customer reach and improve brand visibility. | Social media promotions; Content creators; Customer reach; Brand visibility. | ▪ Digital Marketing and Social Media.<br>▪ Training and Skills Development.<br>▪ Technological Infrastructure.<br>▪ Resource Accessibility and Innovation. | ▪ Enhancing Skills and Online Presence. | Social media can improve the presence and reach customers, along with training in improving skills. |
| Training programs and tutorials provide opportunities in improving technical skills and application integration. | Training programs; Tutorials; Technical skills; Application integration. | | | |
| Stable internet and modern devices enhance communication and operational efficiency. | Stable internet; Modern devices; Communication; Operational efficiency. | | ▪ Building Technological and Resource Capacity | Technological and capacity resources are crucial in ensuring the optimal use of technology and sustainable growth. |
| Regular technology upgrades maintain competitiveness. | Technology upgrades; Competitiveness. | | | |
| Resources like open-source tools, funding, and community support empower businesses to adopt new technologies. | Resources; Open-source tools; Funding; Community support; New technologies. | | | |

Respondents also provide feedback based on their experiences with technology. Table 16 presents the thematic analysis of the responses.

**Table 16**. Feedback on Technology Adoption and Use: A Thematic Analysis

| Response | Keywords | Code | Theme | Conclusion |
|---|---|---|---|---|
| Businesses need applications tailored to specific needs, ensuring they are user-friendly and improve workflow efficiency. | Applications tailored to specific needs; User-friendly; Workflow efficiency. | ▪ Customized and Efficient Applications.<br>▪ Customer-Centric Feedback.<br>▪ Trial and Evaluation Features.<br>▪ Supportive Learning and Communities. | ▪ Personalized Tools and Customer Engagement. | Specific needs and objectives can direct or inform the most suitable technology to be used. Feedback from customers is still important. |
| Social media feedback and customer input help refine promotional strategies and enhance customer engagement. | Social media feedback; Customer input; Promotional strategies; Customer engagement. | | | |
| Trial features in applications allow businesses to assess effectiveness before committing to premium subscriptions. | Trial features; Premium subscriptions; Assess effectiveness. | | ▪ Evaluative Practices and Support Systems. | Continuous evaluation and practices improve the utilization of technology; thus, optimal use of technology is achieved. |
| Regular evaluation of technology ensures it aligns with evolving business demands and incorporates customer preferences. | Evaluation of technology; Business demands; Customer preferences. | | | |
| Access to training programs and user communities fosters confidence and enables effective technology adoption. | Training programs; User communities; Confidence; Technology adoption. | | | |

**Hypothesis Discussion**

Based on previous results, all thresholds in the measurement and structural model assessments are met, providing a solid basis for discussing the hypotheses. The previous results indicate that all hypotheses are confirmed. Perceived Benefit (PB) and Perceived Usability (PU) have significant impacts on Technology Adoption (TA) (Allioui & Mourdi, 2023; Blut & Wang, 2020; FakhrHosseini et al., 2024; Shankar et al., 2021). PB and PU have positive impacts, thus when the technology is perceived to have many benefits and is easy to use, it is more likely to be adopted.

Furthermore, Technology Fit (TF) and Commitment (CT) also have significant impacts on Technology Use (TU) (Hsieh et al., 2025; Rauniar et al., 2024; Verhoef et al., 2021; Zhang et al., 2025). TF and CT have positive impacts, where better alignment of TF and strong CT accelerates and improves the optimal use of technology. The significant relationships among Technology Adoption, Technology Use, and Business Performance are also confirmed. Technology Adoption is essential for effective Technology Use, which in turn positively impacts Business Performance. Technology Use plays an important role in partially mediating the relationship between Technology Adoption and Business Performance (Y. Li et al., 2020; Shen et al., 2022).

Moreover, it is observed that PB, PU, CT, TA, and TU have strong influences on their respective dependent variables. The results from the thematic analysis are relevant and closely related to these strong relationships. Many users adopt technology as it becomes essential to remain competitive, capture market share, or fulfill the business's needs and objectives. Despite concerns about increased competition driven by the growing use of technology, respondents imply that the benefits of technology still outweigh the drawbacks. In other words, without adopting technology, it becomes more difficult to compete and achieve profitability (Shahadat et al., 2023). The responses also confirm that efficiency and productivity improve with technology adoption and use, further validating its usability and the satisfaction derived from it.

Meanwhile, skill gaps emerge as a crucial factor that can hinder the optimal use of technology. The commitment to continuously learning and exploring technological features, as represented by CT, is highly relevant to addressing these skill gaps (Prokopenko et al., 2024). Collaboration among various stakeholders, including communities and government, is essential to provide a supportive learning environment (Li et al., 2022). Moreover, discussions about reliable devices, better connectivity, and proper digital infrastructure are vital for improving Technology Fit (TF) (Lynn et al., 2022). Improved technology fit ensures that technology functions effectively and meets users' specific needs. The optimal use of technology also requires a range of support mechanisms, such as funding, technical assistance, and feedback. Regular system updates are also necessary to address potential errors and improve user experience.

Although this study provides insights into the discourse on the informal economy and overall technology utilization, it has limitations in generalizing its findings to broader or national contexts because it used a localized sample from South Kalimantan province. The cross-sectional design also prevents the establishment of temporal causality between variables and limits the strength of any causal claims drawn from the findings. Moreover, the model in this study does not account for external factors such as government regulation, digital infrastructure policy, or ecosystem-level support that can influence technology adoption and use. This study also relies on the survey administered by the researcher, which may introduce self-report bias, including reliance on respondents' subjective perceptions and estimates.

**Theoretical Contributions**

To the best of the author's knowledge, existing technological discourse has primarily documented factors driving technology adoption (Verhoef et al., 2021). This study extends the discussion by examining technology use beyond adoption (Hooks et al., 2022), emphasizing that adoption alone does not guarantee optimal use, which is essential for improved business performance (Hooks et al., 2022; Verhoef et al., 2021). The study highlights the mediating role of optimal technology use in the relationship between adoption and performance, identifying key factors such as user commitment, technology fit, and relevant constraints. Among these, user commitment to learning and exploring technological features strongly influences optimal use. The findings show that without optimal use, the impact of adoption on performance is significantly weaker, underscoring the importance of optimal use in realizing technology's full potential. The mixed methods approach also enriches the discourse on optimal technology use by drawing on a sample from South Kalimantan province, a region whose informal economy profile mirrors the national average.

**Practical Contributions**

In practice, these insights emphasize the need for policies and strategies that promote optimal use by fostering a supportive environment and improving digital infrastructure, thereby enhancing accessibility and efficiency. The study, backed by quantitative and qualitative evidence, offers a foundation for effective policy development and future research, advancing understanding of technology use beyond adoption (Verhoef et al., 2021).

## 4. CONCLUSION

In conclusion, this study enriches the technological discourse by examining how optimal use of technology partially mediates the relationship between technology adoption and business performance, and by identifying the factors that influence this optimal use. Conducted within the context of the informal economy, which supports the livelihoods of many, the study highlights the role of technology in enhancing productivity. By improving productivity, an ideal solution emerges where eradicating the informal economy is no longer necessary. However, the model and evidence presented can be further refined, as additional factors may deepen understanding of optimal technology use.

## 5. ACKNOWLEDGEMENT

The authors extend their gratitude to Lembaga Penelitian dan Pengabdian Masyarakat - Universitas Lambung Mangkurat (LPPM ULM) for its support in making this research possible.

## 6. REFERENCES

Ajao, B. F., Oyebisi, T. O., & Aderemi, H. O. (2018). Factors influencing the implementation of e-commerce innovations: The case of the Nigerian informal sector. *African Journal of Science, Technology, Innovation and Development*, *10*(4), 473–481. https://doi.org/10.1080/20421338.2018.1475541

Al-Emran, M., & Griffy-Brown, C. (2023). The role of technology adoption in sustainable development: Overview, opportunities, challenges, and future research agendas. *Technology in Society*, *73*, 102240. https://doi.org/10.1016/j.techsoc.2023.102240

Allioui, H., & Mourdi, Y. (2023). Exploring the Full Potentials of IoT for Better Financial Growth and Stability: A Comprehensive Survey. *Sensors*, *23*(19), 8015. https://doi.org/10.3390/s23198015

Andrews, D., Sánchez, A. C., & Johansson, Å. (2011). *Towards a Better Understanding of the Informal Economy*.

Attaran, M., & Celik, B. G. (2023). Digital Twin: Benefits, use cases, challenges, and opportunities. *Decision Analytics Journal*, *6*, 100165. https://doi.org/10.1016/j.dajour.2023.100165

Badan Pusat Statistik. (2026). *Keadaan Ketenagakerjaan Indonesia November 2025*.

Benjamin, N., Beegle, K., Recanatini, F., & Santini, M. (2014). *Informal Economy and the World Bank* (6888; Policy Research Working Paper).

Bhattacharya, R. (2019). ICT solutions for the informal sector in developing economies: What can one expect? *The Electronic Journal of Information Systems in Developing Countries*, *85*(3). https://doi.org/10.1002/isd2.12075

Blades, D., Ferreira, F. H. G., & Lugo, M. A. (2011). The Informal Economy in Developing Countries: An Introduction. *Review of Income and Wealth*, *57*(s1). https://doi.org/10.1111/j.1475-4991.2011.00457.x

Blut, M., & Wang, C. (2020). Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science*, *48*(4), 649–669. https://doi.org/10.1007/s11747-019-00680-8

Braun, V., & Clarke, V. (2021). Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling and Psychotherapy Research*, *21*(1), 37–47. https://doi.org/10.1002/capr.12360

Chen, M. A. (2012). *The Informal Economy: Definitions, Theories and Policies*.

Chen, M., & Carré, F. (2020). *The Informal Economy Revisited*. Routledge. https://doi.org/10.4324/9780429200724

Chueh, H.-E., & Huang, D.-H. (2023). Usage intention model of digital assessment systems. *Journal of Business Research*, *156*, 113469. https://doi.org/10.1016/j.jbusres.2022.113469

Chuttur, M. Y. (2009). Overview of the Technology Acceptance Model: Origins, Developments, and Future Directions. *Sprouts: Working Papers on Information Systems*, *9*(37). http://sprouts.aisnet.org/9-37

Danquah, M., & Owusu, S. (2021). *Digital technology and productivity of informal enterprises: Empirical evidence from Nigeria*. https://doi.org/10.35188/UNU-WIDER/2021/054-2

Deléchat, C., & Medina, L. (2021). *The Global Informal Workforce: Priorities for Inclusive Growth*. International Monetary Fund.

Dell'Anno, R. (2022). Theories and definitions of the informal economy: A survey. *Journal of Economic Surveys*, *36*(5), 1610–1643. https://doi.org/10.1111/joes.12487

Douglas, E. (2017). Beyond the Interpretive: Finding Meaning in Qualitative Data. *ASEE Annual Conference & Exposition Proceedings*. https://doi.org/10.18260/1-2--27658

Ebrahim, A. Q., & van den Berg, C. L. (2024). The barriers to technology adoption among businesses in the informal economy in Cape Town. *South African Journal of Information Management*, *26*(1). https://doi.org/10.4102/sajim.v26i1.1872

Elvis, N. T., Cheng, H., & Providence, B. I. (2022). The Illustrative Understanding on the Informal Sector and Its Influence in Firm Productivity in Sub-Saharan Africa (SSA): Evidence from Cameroon. *Sustainability*, *14*(15), 9789. https://doi.org/10.3390/su14159789

Etim, E., & Daramola, O. (2023). Investigating the E-Readiness of Informal Sector Operators to Utilize Web Technology Portal. *Sustainability*, *15*(4), 3449. https://doi.org/10.3390/su15043449

FakhrHosseini, S., Chan, K., Lee, C., Jeon, M., Son, H., Rudnik, J., & Coughlin, J. (2024). User Adoption of Intelligent Environments: A Review of Technology Adoption Models, Challenges, and Prospects. *International Journal of Human–Computer Interaction*, *40*(4), 986–998. https://doi.org/10.1080/10447318.2022.2118851

Felzensztein, C., Venter, R., & Salloum, C. (2025). Resilient informality and the role of family support in township entrepreneurship. *International Journal of Entrepreneurial Behavior & Research*, 1–22. https://doi.org/10.1108/IJEBR-03-2025-0266

Garcia-Murillo, M., & Velez-Ospina, J. A. (2014). *The impact of ICTs on the informal economy*. https://EconPapers.repec.org/RePEc:zbw:itsb14:106841

Gërxhani, K., & Cichocki, S. (2023). Formal and informal institutions: understanding the shadow economy in transition countries. *Journal of Institutional Economics*, *19*(5), 656–672. https://doi.org/10.1017/S1744137422000522

Ghobakhloo, M., Hong, T. S., Sabouri, M. S., & Zulkifli, N. (2012). Strategies for Successful Information Technology Adoption in Small and Medium-sized Enterprises. *Information*, *3*(1), 36–67. https://doi.org/10.3390/info3010036

Giannakos, M. N., Mikalef, P., & Pappas, I. O. (2022). Systematic Literature Review of E-Learning Capabilities to Enhance Organizational Learning. *Information Systems Frontiers*, *24*(2), 619–635. https://doi.org/10.1007/s10796-020-10097-2

Gunawan, A., Jufrizen, & Pulungan, D. R. (2023). Improving MSME performance through financial literacy, financial technology, and financial inclusion. *International Journal of Applied Economics, Finance and Accounting*, *15*(1), 39–52. https://doi.org/10.33094/ijaefa.v15i1.761

Hagspiel, V., Huisman, K. J. M., & Nunes, C. (2015). Optimal technology adoption when the arrival rate of new technologies changes. *European Journal of Operational Research*, *243*(3), 897–911. https://doi.org/10.1016/j.ejor.2014.12.024

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Handayani, F., Raja, H. S., Nurliana, N., Musyarof, Z., Wiratama, B. F., Damara, D., Assadiqi, G. S., & Hamdani, H. (2025). *Analisis Isu Terkini Provinsi Kalimantan Selatan 2025* (F. Handayani & H. Hamdani, Eds.; Vol. 7). Badan Pusat Statistik Provinsi Kalimantan Selatan.

Hapsari, I. M., Yu, S., Pape, U. J., & Mansour, W. (2023). *Informality in Indonesia: Levels, Trends, and Features* (10586). The World Bank. https://doi.org/10.1596/1813-9450-10586

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hoang, H. (2024). Navigating the Digital Landscape: An Exploration of the Relationship Between Technology-Organization-Environment Factors and Digital Transformation Adoption in SMEs. *Sage Open*, *14*(4). https://doi.org/10.1177/21582440241276198

Hooks, D., Davis, Z., Agrawal, V., & Li, Z. (2022). Exploring factors influencing technology adoption rate at the macro level: A predictive model. *Technology in Society*, *68*, 101826. https://doi.org/10.1016/j.techsoc.2021.101826

Hsieh, M.-C., Pan, H.-C., & Chou, S.-W. (2025). Exploring E-Learners' IT Mindfulness and Its Impact on Post-Adoption Behavior: A Dedication-Constraint Relationship of Commitment in Live Streaming Learning Environments. *International Journal of Human–Computer Interaction*, *41*(17), 11055–11076. https://doi.org/10.1080/10447318.2024.2440637

Hyde-Clarke, N. (2013). The Impact of Mobile Technology on Economic Growth amongst "Survivalists" in the Informal Sector in the Johannesburg CBD, South Africa. *International Journal of Business and Social Science*, *4*(16). www.ijbssnet.com

Ibidunni, A. S., Kolawole, A. I., Olokundun, M. A., & Ogbari, M. E. (2020). Knowledge transfer and innovation performance of small and medium enterprises (SMEs): An informal economy analysis. *Heliyon*, *6*(8), e04740. https://doi.org/10.1016/j.heliyon.2020.e04740

Jacolin, L., Keneck Massil, J., & Noah, A. (2021). Informal sector and mobile financial services in emerging and developing countries: Does financial innovation matter? *The World Economy*, *44*(9), 2703–2737. https://doi.org/10.1111/twec.13093

Khin, S., & Ho, T. C. (2019). Digital technology, digital capability and organizational performance. *International Journal of Innovation Science*, *11*(2), 177–195. https://doi.org/10.1108/IJIS-08-2018-0083

Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. *Technovation*, *110*, 102375. https://doi.org/10.1016/j.technovation.2021.102375

Kraemer-Mbula, E., & Wunsch-Vincent, S. (2016). *The Informal Economy in Developing Nations* (E. Kraemer-Mbula & S. Wunsch-Vincent, Eds.). Cambridge University Press. https://doi.org/10.1017/CBO9781316662076

Kwarteng, M. A., Ntsiful, A., Diego, L. F. P., & Novák, P. (2024). Extending UTAUT with competitive pressure for SMEs digitalization adoption in two European nations: a multi-group analysis. *Aslib Journal of Information Management*, *76*(5), 842–868. https://doi.org/10.1108/AJIM-11-2022-0482

Lai, P. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management*, *14*(1), 21–38. https://doi.org/10.4301/S1807-17752017000100002

Li, L., Zhu, W., Wei, L., & Yang, S. (2022). How can digital collaboration capability boost service innovation? Evidence from the information technology industry. *Technological Forecasting and Social Change*, *182*, 121830. https://doi.org/10.1016/j.techfore.2022.121830

Li, Y., Dai, J., & Cui, L. (2020). The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. *International Journal of Production Economics*, *229*, 107777. https://doi.org/10.1016/j.ijpe.2020.107777

Luque, A. (2021). Analysis of the concept of informal economy through 102 definitions: legality or necessity. *Open Research Europe*, *1*, 134. https://doi.org/10.12688/openreseurope.13990.1

Lynn, T., Rosati, P., Conway, E., Curran, D., Fox, G., & O'Gorman, C. (2022). Infrastructure for digital connectivity. In *Digital towns: Accelerating and measuring the digital transformation of rural societies and economies* (pp. 109–132). Springer.

Manyati, T. K., & Mutsau, M. (2019). Exploring technological adaptation in the informal economy: A case study of innovations in small and medium enterprises (SMEs) in Zimbabwe. *African Journal of Science, Technology, Innovation and Development*, *11*(2), 253–259. https://doi.org/10.1080/20421338.2018.1552650

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

Martínez-Caro, E., Cegarra-Navarro, J. G., & Alfonso-Ruiz, F. J. (2020). Digital technologies and firm performance: The role of digital organisational culture. *Technological Forecasting and Social Change*, *154*, 119962. https://doi.org/10.1016/j.techfore.2020.119962

Martínez-Peláez, R., Ochoa-Brust, A., Rivera, S., Félix, V. G., Ostos, R., Brito, H., Félix, R. A., & Mena, L. J. (2023). Role of Digital Transformation for Achieving Sustainability: Mediated Role of Stakeholders, Key Capabilities, and Technology. *Sustainability*, *15*(14), 11221. https://doi.org/10.3390/su151411221

Muchenje, G., & Seppänen, M. (2023). Unpacking task-technology fit to explore the business value of big data analytics. *International Journal of Information Management*, *69*, 102619. https://doi.org/10.1016/j.ijinfomgt.2022.102619

Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. (2023). A Step-by-Step Process of Thematic Analysis to Develop a Conceptual Model in Qualitative Research. *International Journal of Qualitative Methods*, *22*. https://doi.org/10.1177/16094069231205789

Naushad, M., & Sulphey, M. M. (2020). Prioritizing Technology Adoption Dynamics among SMEs. *TEM Journal*, 983–991. https://doi.org/10.18421/TEM93-21

Nayyar, A., Naved, M., & Rameshwar, R. (2023). *New horizons for industry 4.0 in modern business*. Springer.

Nguimkeu, P., & Okou, C. (2021). Leveraging digital technologies to boost productivity in the informal sector in Sub-Saharan Africa. *Review of Policy Research*, *38*(6), 707–731. https://doi.org/10.1111/ropr.12441

Noerman, T., Riyadi, Yuliaji, E. S., & Natasha, C. A. M. (2025). The impacts of social influence and hedonic motivation on experience and continuance intention of using AI in SMEs' HRM. *Cogent Business & Management*, *12*(1). https://doi.org/10.1080/23311975.2025.2542422

Pankomera, R., & van Greunen, D. (2019). Opportunities, barriers, and adoption factors of mobile commerce for the informal sector in developing countries in Africa: A systematic review. *The Electronic Journal of Information Systems in Developing Countries*, *85*(5). https://doi.org/10.1002/isd2.12096

Prokopenko, O., Järvis, M., Bielialov, T., Omelyanenko, V., & Malheiro, T. (2024). *The Future of Entrepreneurship: Bridging the Innovation Skills Gap Through Digital Learning* (pp. 206–230). https://doi.org/10.1007/978-3-031-61582-5_18

Rahi, S., Khan, M. M., & Alghizzawi, M. (2020). Extension of technology continuance theory (TCT) with task technology fit (TTF) in the context of Internet banking user continuance intention. *International Journal of Quality & Reliability Management*, *38*(4), 986–1004. https://doi.org/10.1108/IJQRM-03-2020-0074

Rangaswamy, N. (2019). A note on informal economy and ICT. *The Electronic Journal of Information Systems in Developing Countries*, *85*(3). https://doi.org/10.1002/isd2.12083

Rauniar, R., Rawski, G., Cao, Q. R., & Shah, S. (2024). Mediating effect of industry dynamics, absorptive capacity and resource commitment in new digital technology adoption and effective implementation processes. *Journal of Enterprise Information Management*, *37*(3), 928–958. https://doi.org/10.1108/JEIM-06-2022-0190

Rieg, R. (2025). Exploring the determinants and performance effects of digital dashboard use by management accountants. *Journal of Management Control*. https://doi.org/10.1007/s00187-025-00400-0

Sagala, G. H., & Őri, D. (2024). Toward SMEs digital transformation success: a systematic literature review. *Information Systems and E-Business Management*, *22*(4), 667–719. https://doi.org/10.1007/s10257-024-00682-2

Saghafian, M., Laumann, K., & Skogstad, M. R. (2021). Stagewise Overview of Issues Influencing Organizational Technology Adoption and Use. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.630145

Sarker, M., & AL-Muaalemi, M. A. (2022). Sampling techniques for quantitative research. In *Principles of social research methodology* (pp. 221–234). Springer.

Schultz, C. D., & Kaiser, S. (2025). Consumer value dimensions in conversational and mobile commerce. *Journal of Marketing Analytics*, *13*(3), 587–605. https://doi.org/10.1057/s41270-025-00383-w

Seetharaman, P., Cunha, M. A., & Effah, J. (2019). IT for the informal sector in developing countries: A broader perspective. *THE ELECTRONIC JOURNAL OF INFORMATION SYSTEMS IN DEVELOPING COUNTRIES*, *85*(3). https://doi.org/10.1002/isd2.12093

Selim, H. M. (2007). Critical success factors for e-learning acceptance: Confirmatory factor models. *Computers & Education*, *49*(2), 396–413. https://doi.org/10.1016/j.compedu.2005.09.004

Shahadat, M. M. H., Nekmahmud, Md., Ebrahimi, P., & Fekete-Farkas, M. (2023). Digital Technology Adoption in SMEs: What Technological, Environmental and Organizational Factors Influence in Emerging Countries? *Global Business Review*. https://doi.org/10.1177/09721509221137199

Shankar, V., Kalyanam, K., Setia, P., Golmohammadi, A., Tirunillai, S., Douglass, T., Hennessey, J., Bull, J. S., & Waddoups, R. (2021). How Technology is Changing Retail. *Journal of Retailing*, *97*(1), 13–27. https://doi.org/10.1016/j.jretai.2020.10.006

Sharma, B. P., & Adhikari, D. B. (2020). Informal Economy and Poverty Dynamics: A Review. *Quest Journal of Management and Social Sciences*, *2*(1), 130–140. https://doi.org/10.3126/qjmss.v2i1.29028

Shen, L., Zhang, X., & Liu, H. (2022). Digital technology adoption, digital dynamic capability, and digital transformation performance of textile industry: Moderating role of digital innovation orientation. *Managerial and Decision Economics*, *43*(6), 2038–2054. https://doi.org/10.1002/mde.3507

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Sibagariang, F. A., Mauboy, L. M., Erviana, R., & Kartiasih, F. (2023). Gambaran Pekerja Informal dan Faktor-Faktor yang Memengaruhinya di Indonesia Tahun 2022. *Seminar Nasional Official Statistics*, *2023*(1), 151–160. https://doi.org/10.34123/semnasoffstat.v2023i1.1892

Stewart, J. (2007). Local Experts in the Domestication of Information and Communication Technologies. *Information, Communication & Society*, *10*(4), 547–569. https://doi.org/10.1080/13691180701560093

Straub, E. T. (2009). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. *Review of Educational Research*, *79*(2), 625–649. https://doi.org/10.3102/0034654308325896

Surya, B., Menne, F., Sabhan, H., Suriani, S., Abubakar, H., & Idris, M. (2021). Economic Growth, Increasing Productivity of SMEs, and Open Innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 20. https://doi.org/10.3390/joitmc7010020

Tabrizi, B., Lam, E., Girard, K., & Irvin, V. (2019). Digital transformation is not about technology. *Harvard Business Review*, *13*(March), 1–6.

Takyi, G., Okeniyi, J. O., & Samuel, S. E. (2022). Factors and remedies for productivity and efficiency among small-scale informal enterprises: A theoretical perspective. *International Social Science Journal*, *72*(245), 719–735. https://doi.org/10.1111/issj.12359

Tang, W., Wang, T., & Xu, W. (2022). Sooner or Later? The Role of Adoption Timing in New Technology Introduction. *Production and Operations Management*, *31*(4), 1663–1678. https://doi.org/10.1111/poms.13637

Teo, T., & van Schaik, P. (2012). Understanding the Intention to Use Technology by Preservice Teachers: An Empirical Test of Competing Theoretical Models. *International Journal of Human-Computer Interaction*, *28*(3), 178–188. https://doi.org/10.1080/10447318.2011.581892

Ulyssea, G. (2020). Informality: Causes and Consequences for Development. *Annual Review of Economics*, *12*(1), 525–546. https://doi.org/10.1146/annurev-economics-082119-121914

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Williams, C. (2023). *A Modern Guide to the Informal Economy*. Edward Elgar Publishing. https://doi.org/10.4337/9781788975612

Williams, C. C. (2007). Small business and the informal economy: evidence from the UK. *International Journal of Entrepreneurial Behavior & Research*, *13*(6), 349–366. https://doi.org/10.1108/13552550710829160

Yadegari, M., Mohammadi, S., & Masoumi, A. H. (2024). Technology adoption: an analysis of the major models and theories. *Technology Analysis & Strategic Management*, *36*(6), 1096–1110. https://doi.org/10.1080/09537325.2022.2071255

Zhang, L., Shao, Z., Zhao, T., & Chen, K. (KC). (2025). The influences of four dimensions of perceived fit on individuals' utilisation of SPOCs: an extension of the task-technology fit model. *Behaviour & Information Technology*, *44*(3), 611–629. https://doi.org/10.1080/0144929X.2024.2332449

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D., Buffington, C., Goldschlag, N., Foster, L., & Dinlersoz, E. (2020). *Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey*. https://doi.org/10.3386/w28290