Zhongguo Kuangye Daxue Xuebao
Journal of China University of Mining and Technology

2024 | Vol 29 | Issue 4 | Page 146-157
Journal Homepage: https://zkdx.ch/
DOI: 10.1654/zkdx.2024.29.4-13

Sustainable Agricultural Productivity: The Role of Entrepreneurial Orientation in Small Farmers' Adoption of Big Data Devices for Agriculture

Uzairu Muhammad Gwadabe
Faculty of Business and Management, Universiti Sultan Zainal Abidin, Kuala Terengganu, Malaysia

Nalini Arumugam*
Faculty of Bioresources and Food Industry, Universiti Sultan Zainal Abidin, Kuala Terengganu, Malaysia
*Corresponding author

Noor Aina Amirah
Faculty of Business and Management, Universiti Sultan Zainal Abidin, Kuala Terengganu, Malaysia

Abstract
Small farmers in Malaysia face significant productivity challenges due to reliance on traditional farming methods despite the availability of advanced agricultural technologies. This study investigates the factors influencing the intention to adopt Big Data Devices for Agriculture (BDDA), focusing on the mediating role of perceived usefulness in the relationship between Entrepreneurial Orientation (EO)—encompassing innovativeness, proactiveness, and risk-taking—and adoption intention. A 2023 survey of 450 small farmers yielded 310 valid responses, analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicate that innovativeness ($\beta = 0.372$, $p < 0.001$) and proactiveness ($\beta = 0.334$, $p < 0.001$) positively impact the intention to adopt BDDA, while risk-taking ($\beta = -0.133$, $p = 0.008$) has a negative effect. Perceived usefulness significantly influences adoption intention ($\beta = 0.344$, $p < 0.001$) and mediates the relationship between EO and BDDA adoption. The study extends the Technology Acceptance Model (TAM) by illustrating how EO traits affect technology adoption through perceived usefulness. These findings highlight the importance of enhancing perceived usefulness to promote technology adoption for sustainable agriculture among small farmers, offering valuable insights for policymakers and technology developers.

Keywords
Sustainable Agriculture, Technology Adoption, Entrepreneurial Orientation, Big Data Devices, Small Farmers

1. Introduction
Theories such as the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behavior (TPB) (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT) have significantly contributed to understanding technology adoption processes. These models provide validated frameworks for examining how individuals interact with and adopt various technologies (Afsay et al., 2023). Recent research has increasingly focused on understanding the intentions behind technology adoption (Lee, 2018; Min & Jeong, 2019), suggesting that a person's decision to embrace or avoid a particular technology is influenced by perceptions, social pressures, expectations, past experiences, and intentions (Gani et al., 2024; Taherdoost, 2018).

Sustainable agricultural technology adoption has grown remarkably over the past two decades, particularly in developed countries. Wang, Jin, and Mao (2019) defined Big Data Devices for Agriculture (BDDA) as the integration of information technology and agriculture. BDDA holds the potential to significantly increase sustainable agricultural production efficiency (Gwadabe, Arumugam, & Amirah, 2021). Its use transforms and restructures producers' perspectives, promotes environmental consciousness, and fosters a concept of agricultural production that values quality and quantity equally (Amanor, 2024). Industrialization and urbanization exacerbate the labor shortage problem in agriculture, necessitating a shift away from traditional agricultural practices. Consequently, adopting BDDA to optimize agricultural production addresses several issues, including the global food shortage problem.

Despite extensive research on technology adoption, there is limited understanding of the factors influencing small farmers' intentions to adopt advanced agricultural technologies like BDDA in developing countries such as Malaysia. This gap is crucial, given the persistent challenges in productivity due to traditional farming methods. This study seeks to address this gap by examining the role of Entrepreneurial Orientation (EO)—specifically innovativeness, proactiveness, and risk-taking—in shaping small farmers' intentions to adopt BDDA for sustainable agriculture, with perceived usefulness acting as a mediating variable.

Despite extensive agricultural programs and interventions in Malaysia, small farmers still rely on traditional farming techniques, leading to lower productivity, reduced profitability, and a loss of competitive advantage. Although some progress has been made in raising awareness about agricultural technology, BDDA adoption, especially among small farmers, has not yet reached its full potential and remains in the demonstration stage (Li & Li, 2023). In this context, this study identifies a research gap: while much research has been conducted on the use and efficiency of technology in agriculture, less attention has been paid to the factors influencing farmers' intention to adopt agricultural technology (Takahashi et al., 2020).

Understanding the factors influencing farmers' intentions to adopt BDDA is crucial for increasing acceptance and promoting long-term sustainability and benefits (Ahmad et al., 2024). The existing literature highlights the need for a shift in focus toward investigating farmers' behavioral intentions concerning agricultural technology adoption (Cimino et al., 2024; Legris et al., 2003). Based on an extensive literature review, this study posits that small farmers' innovativeness, proactiveness, and risk-taking capacity are vital in determining their intentions to adopt agricultural technology.

This study employs Perceived Usefulness (PU) as a mediating construct between Entrepreneurial Orientation (EO) (innovativeness, proactiveness, and risk-taking) and farmers' intention to adopt BDDA. This approach is based on the idea that small farmers' desire to adopt BDDA may increase proportionally based on their perception of its usefulness. As PU is the underlying assumption of TAM, it is a critical factor in determining whether users will accept a technology. PU refers to users' perceptions of productivity, effectiveness, and the general benefits a technology may offer to improve performance – in essence, the extent to which an individual believes that using a particular technology will enhance the quality of their work.

2. Literature Review

The successful adoption of new technologies, particularly those aimed at promoting sustainability, hinges on a comprehensive understanding of the factors that drive individuals' adoption and use decisions (Gwadabe & Arumugam, 2021). Since the mid-1980s, research in information systems has focused on identifying predictors of technology adoption, contributing to a substantial body of literature (Chickering & Gamson, 1999). Early efforts in this field led to the development of models explaining why individuals adopt or continue using various technologies (Mehrtens et al., 2001). These studies have produced a variety of models aimed at identifying the most critical factors influencing technology adoption, whether new or existing (Gangwar, Date, & Raoot, 2014; Martínez-Román, 2017; Francisco & Swanson, 2018; Liu, Geertshuis, & Grainger, 2020; Yadegari et al., 2024).

Most of these models were developed, among others, from the Theory of Reasoned Action (TRA) and can predict various actions across disciplines and settings. According to TRA, fundamental values influence people's attitudes about adoption. These beliefs may be descriptive, based on personal experience, inferential, or based on information from peers or family members (Mady, 2018). When combined with the individual's assessment of how others will react to the action, this attitude leads to the formation of a behavioral intention (Fishbein, 1980; Kala & Chaubey, 2024). According to TRA, behavioral intention directly affects one's actual behavior.

Among the theories that explain technology adoption, Davis (1989) established the Technology Acceptance Model (TAM), one of the most frequently cited theories of technology adoption in the literature. It is also widely used in various organizational contexts (Oliveira and Martins, 2011). As in TRA, intention is the driving force behind any behavior, including technology adoption. Also, individual attitude toward technology has an impact on the intention. People's attitudes toward technology are shaped by external factors, such as their perceptions and the world around them. In this regard, TAM postulated that attitudes are influenced by perceived ease of use (PEOU) and perceived usefulness (PU) (Davis, 1993). PEOU explains a person's perception of the ease and simplicity of a piece of technology. At the same time, PU refers to the degree to which an individual believes that using a particular technology will improve the effectiveness of their job.

Similarly, the TPB is another theory that explains individual behavior and is widely used to justify the adoption of technologies (Ajzen, 1991). According to TPB, subjective norms, perceived behavioral control, and attitudes shape individuals' intentions toward a behavior (Gwadabe et al., 2022). Hence, the subjective norm is an individual's perception of a particular behavior, which is influenced by the judgment of significant others. Perceived behavioral control is the ease or difficulty an individual perceives when performing a particular behavior. In contrast, an attitude refers to the extent to which an individual has a favorable or unfavorable evaluation of a particular behavior (Ajzen, 1991). Thus, many factors can affect an individual's behavior.

In another initiative, Venkatesh, Morris, Davis, and Davis (2003) tested and combined existing technology acceptance models like TRA, TAM, and TPB to arrive at a different theory, the Unified Theory of Acceptance and Use of Technology (UTAUT). According to the UTAUT theory, performance expectancy, effort expectancy, facilitating conditions, and social influence are the predictive variables that impact behavioral intention, determining actual use. Also, the influence of the predictive variables is moderated by factors such as age, gender, level of experience, and voluntariness. UTAUT's intention is closely tied to one's performance expectancy, which resembles PU in TAM. Effort expectancy is similar to PEOU. However, social influence refers to how much someone perceives that other important people think they should use a particular technology. Social influence is determined subjectively rather than quantitatively. On the other hand, facilitating condition is the degree to which an individual thinks the physical and technical infrastructure exists to support the use of a particular technology (Buraimoh et al., 2023; Panagiotopoulos and Dimitrakopoulos, 2018; Kim, Mirusmonov, and Lee, 2010). UTAUT has been used in various scenarios to understand better how people adopt technologies (Miltgen et al., 2013; Taherdoost, 2018).

Accordingly, this study examines the factors influencing small farmers' intentions to adopt Big Data Devices for Agriculture (BDDA) in Malaysia, mainly focusing on the mediating effect of perceived usefulness on the relationships between innovativeness, proactiveness, risk-taking, and the intention to adopt BDDA.

2.1 Technology Acceptance Model (TAM)

TAM is the most widely used model for understanding the factors influencing users' adoption of novel technologies. The theory comprises many variables, but two of the most significant constructs, perceived usefulness (PU) and perceived ease of use (PEOU) have emerged from previous studies as factors affecting the intention to accept technology. TAM is a framework that describes the cognitive mechanisms among users and how they react to adopting and incorporating a modern piece of technology into their jobs and lives. PU relates to users' perception of technology as beneficial, while PEOU pertains to the perception that using a particular technology requires little or much effort. Users are highly concerned about the efforts involved in using a specific technology. The model provides a theoretical framework for examining the impact of external variables on users' beliefs, attitudes, intentions, and their use of technology. Users can determine how each goal, attitude, and belief fits into the bigger picture by considering a specific goal, action, or scenario. Since TAM's development, numerous research studies have utilized it to establish the reliability, validity, logic, and empirical evidence of different cases and to determine cross-sample invariance. Some studies have applied TAM to examine the adoption of information technology in various contexts (Diop et al., 2019; Kayali and Alaaraj, 2020).

Modifications to the model have addressed additional concerns (Nagy, 2018; Diop et al., 2019). Venkatesh and Davis (2000) proposed the TAM2 hypothesis after identifying and theorizing the broad causes of PU. In line with Davis' contention that attitude only captures users' emotional preferences for information technology and cannot grasp the effects of positive and easy-to-use cognition on behavioral intentions, the attitude was excluded from the TAM model (Mukuze, 2023). According to Venkatesh and Bala (2008), numerous factors influence the adoption and usage of individual-level information technology. They developed TAM as a comprehensive nomological network of the elements affecting individual-level information technology adoption and usage.

2.2 Technological Factors and Intent to Adopt BDDA

The adoption of big data technology has become a crucial factor in the success of many industries, including sustainable agriculture. To understand the factors influencing farmers' intentions to adopt Big Data and Data Analytics (BDDA), it is essential to consider the role of technological factors in this adoption process. According to Rogers' (1983) innovation theory, compatibility, relative advantage, and complexity can affect how a technology is perceived.

In the context of BDDA adoption for sustainable agriculture, the lack of complexity of the technology can determine its simplicity and understandability. This is reflected in the Technology Acceptance Model (TAM), which suggests that a technology's relative advantage and technical complexity can define its usefulness and ease of use (Gangwar et al., 2015). Decision-makers are likely to focus on a technology's usefulness before deciding whether or not to adopt it. They are more likely to embrace it if they perceive it as less complicated (Momani and Jamous, 2017). Consequently, farmers' willingness to use technology decreases if they believe it is difficult to learn and would require excessive time and effort (Zheng et al., 2019).

Perceived usefulness is also an influential determinant of technology adoption (Batz et al., 1999). Therefore, to encourage farmers to adopt BDDA, it is essential to communicate the advantages and benefits of the technology clearly and understandably. Additionally, BDDA systems should be designed to be user-friendly and intuitive to reduce the perceived complexity of the technology. By considering the technological factors that influence farmers' intention to adopt BDDA, agricultural industries can facilitate the successful integration of this technology into their operations and enhance overall productivity and efficiency.

2.3 Conceptual Framework

The research framework of this study is schematically represented and interpreted in terms of the relationships between research constructs and their order of influence (Figure 1). The direct connection between innovativeness, proactiveness, and risk-taking with intention establishes the first flow of control. The second flow of the framework forms a link between innovativeness, proactivity, and risk-taking with perceived usefulness. The third flow connects innovativeness, proactiveness, and risk-taking to the intention by meditating on perceived usefulness. This comprehensive research approach enables the evaluation of concepts by examining the relationships between the study's constructs, emphasizing sustainable agricultural outcomes.

The conceptual framework suggests that there are four significant relationships: a direct and positive relationship between innovativeness, proactiveness, and risk-taking on intention; a direct and positive relationship between innovativeness, proactiveness, and risk-taking on perceived usefulness; the influence of perceived usefulness on intention; and, finally, the mediating effect of perceived usefulness on the relationships.

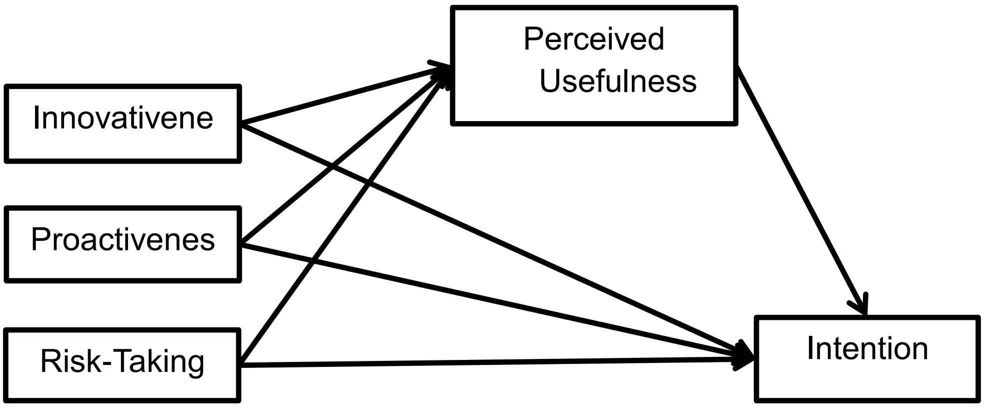

Fig. 1 Research Framework

3. Materials and Methods

An empirical survey was conducted to determine the relationship between the constructs, and a questionnaire was designed explicitly for this purpose. Data was collected through a self-administered questionnaire. The measurement scales for the research model constructs were adapted from previously published studies in the same field. Ten experts assessed the instrument to confirm the validity of the technique and measuring scales and ensure the questions were appropriately worded. The construct items were measured on a 10-point Likert scale, ranging from “strongly disagree” to “strongly agree.” The study included five constructs: perceived usefulness, intention, innovativeness, proactiveness, and risk-taking. Scales were adopted and adjusted from previously published studies.

The process of participation was divided into four stages. The questionnaire was pre-tested on 50 farmers to ensure its appropriateness and suitability in assessing sustainable agricultural practices and to determine whether any changes should be made. In a quantitative study, the reliability of research relies on the instruments used to measure the phenomenon (Golafshani, 2003). In this study, a self-administered questionnaire was used as the instrument for data collection. The questionnaire was initially designed in English and then translated into Malay by a professional native translator to better understand the respondents, who were local farmers, mostly in rural areas. To avoid any form of communication gap and bias, a native Malay speaker and researcher administered the questionnaire to the farmers. The administrator clarified their understanding of the purpose of the study. The research assistant worked closely with the researchers.

3.1 Data Collection and Analysis Procedure

Data was collected using a self-administered questionnaire in the Malaysian states of Johor, Kedah, Kelantan, Pahang, Perak, Selangor, Sabah, and Terengganu. These states were selected due to their significant smallholder farmer populations and varying levels of agricultural technology adoption. A non-probabilistic sampling approach was employed, targeting 384 farmers as the intended sample size. Of 450 distributed questionnaires, 316 were returned, with 310 deemed suitable for analysis. The sample size exceeds the minimum requirements for robust statistical analysis in PLS-SEM, as recommended by Bentler and Chou (1987). All factor loadings were higher than 0.70, indicating that the sample was adequate for evaluating the research model (Guadagnoli and Velicer, 1988). The proposed research model was empirically tested using partial least square structural equation modeling (PLS-SEM). It is suitable for examining cross-sectional data as it employs multiple regression and factor analysis to assess the measurement tool and test hypotheses (Bagozzi and Yi, 2012).

3.2 Measurement Model: Reliability and Validity

The data were analyzed using various techniques, including composite reliability, convergent and discriminant validity, and PLS-SEM with SmartPLS. The study began with exploratory factor analysis (EFA) to reduce the number of items. Items with a factor loading greater than 0.60 were included, while those with a factor loading of less than 0.60 were excluded due to their low factor loading (Gwadabe et al., 2022). The EFA was performed on all items in the model using unrotated principal component analysis. All the variables in the study were adjusted to revolve around a single component. It was found that 44.456% of the variance could be explained, significantly less than the suggested limit of 50% (Yang et al., 2015). All components’ Cronbach’s alpha coefficient was examined, ranging from 0.70 to 0.91. The generally accepted alpha coefficient is 0.70. The factor analysis (CFA) results were confirmed in the second and third tables.

Table 1 Loading and Internal Consistency Reliability of the Measurement Model

Variables	Loading	CA	CR	AVE
Intention		0.922	0.936	0.649
I1	0.752			
I2	0.784			
I3	0.828			
I4	0.863			
I5	0.86			
I6	0.791			
I7	0.806			
I8	0.75			
Perceived Usefulness		0.924	0.936	0.594
PU1	0.807			
PU2	0.83			
PU3	0.797			
PU4	0.831			
PU5	0.697			
PU6	0.78			
PU7	0.727			
PU8	0.747			
PU9	0.729			
PU10	0.749			
Innovativeness		0.909	0.923	0.522
INN1	0.658			
INN2	0.659			
INN3	0.738			
INN4	0.680			
INN5	0.763			
INN6	0.688			
INN7	0.696			
INN8	0.805			
INN9	0.761			
INN10	0.764			
INN11	0.720			
Proactiveness		0.913	0.929	0.619
PR1	Deleted			
PR2	0.762			
PR3	0.773			
PR4	0.796			
PR5	0.791			
PR6	0.806			
PR7	0.765			
PR8	0.795			
PR9	Deleted			
PR10	0.807			
Risk-Taking		0.885	0.909	0.556
RT1	0.745			
RT2	0.798			
RT3	0.79			
RT4	0.698			
RT5	Deleted			
RT6	0.732			
RT7	0.614			
RT8	0.769			
RT9	0.802			

Table 2 illustrates the reliability and validity of the constructs and the item loadings for each construct. Table 3 presents the structural model's fit criteria. In all instances, the results are consistent with prior findings. The average variance extracted (AVE) is more significant than 0.5, and the composite reliability (CR) is more significant than 0.7. We can conclude that our model fit, reliability, convergence, and discriminant validity were excellent. Table 2 shows several characteristics correlating with each construct's square root of the average variance extracted (AVE). As shown, the AVE of each factor is larger than the sum of the square roots of its corresponding correlation coefficients with the others. Consequently, it exhibited a high degree of discriminant validity.

Table 2 Fornell-Larcker criterion analysis to check discriminant validity

	Innovativeness	Intention	Perceived Usefulness	Proactiveness	Risk-Taking
Innovativeness	0.722				
Intention	0.668	0.805			
Perceived Usefulness	0.613	0.675	0.771		
Proactiveness	0.507	0.677	0.621	0.787	
Risk-Taking	0.602	0.578	0.667	0.632	0.746

Harman's single-factor approach was used to measure common method bias (CMB) (Table 3), which was significant. Therefore, we concluded that no CMB was detected in the study.

Table 3 The Assessment for CMV in Dataset – Harman's One-Factor Solution

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	13.337	44.456	44.456	13.337	44.456	44.456
2	4.093	13.643	58.099	4.093	13.643	58.099
3	1.863	6.209	64.309	1.863	6.209	64.309
4	1.116	3.718	68.027	1.116	3.718	68.027
5	.886	2.954	70.981	.886	2.954	70.981

3.3 Goodness of Fit Index (GoF)

To validate the combined output of the external model and the internal model obtained through these calculations, the Goodness of Fit Index (GoF) test was used. The GoF calculation results indicate that the value of 0.726 reflects an excellent overall combined output, as it exceeds the threshold of 0.36.

$$GoF = \sqrt{AVE \times R^2} = \sqrt{0.649 \times 0.813} = \sqrt{0.528} = 0.726$$

4. Results and Discussion

In this study, the research hypotheses were tested after reviewing the literature and analyzing the reliability and validity of the measurement scales, respectively. For each hypothesis path, PLS-SEM was used to calculate standardized estimates and t-statistics. This enables us to evaluate the significance of each hypothesis path (Table 4 and Figure 2).

In analyzing the intention to adopt BDDA, the study identified two significant antecedents: innovativeness and proactiveness. Both factors positively and significantly influence the intention to adopt BDDA, consistent with findings from similar studies conducted in other contexts (Huang et al., 2017; Hwang et al., 2016; Rahman et al., 2017). The positive relationship between innovativeness and adoption intention ($\beta = 0.372$, $p < 0.001$) underscores the critical role of innovative tendencies in driving technology adoption among small farmers (Lewis et al., 2003; Lu et al., 2003; Rahman et al., 2017). The study found empirical evidence of a positive and statistically significant relationship between proactiveness ($\beta = 0.334$; p-value <0.001) and the intention to use BDDA for sustainable agricultural practices. The result was in line with the findings of several other studies (Bader et al., 2011; Garay et al., 2017; Kujala et al., 2016).

However, risk-taking negatively and significantly impacts the intention to use BDDA ($\beta = -0.133$; p-value = 0.008). Comparable studies have found negative relationships between risk-taking and intention to use (Altinay et al., 2012; Aydemir and Aren, 2017; Mills et al., 2008). Furthermore, this study's findings revealed that the hypothesis that perceived usefulness has a positive impact on the intention to use BDDA is empirically supported ($\beta = 0.344$; $p < 0.001$), which is consistent with previous studies (Burton-Jones and Hubona, 2006; Lin and Filieri, 2015; Mercurio and Hernandez, 2020; Verma et al., 2018). Additionally, the research found that proactiveness positively affects the perceived usefulness of using BDDA ($\beta = 0.51$; $p < 0.001$), which is consistent with the findings of Chang et al. 2005; Pagani, 2004; and Sandberg, 2002. The willingness to take risks positively and significantly affects the perceived usefulness of new technological innovation ($\beta = 0.194$; $p < 0.001$).

Table 4 Summary of Path Coefficients

	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
Innovativeness -> Intention	0.372	0.062	6.000	0.000
Innovativeness -> Perceived Usefulness	0.274	0.052	5.308	0.000
Perceived usefulness -> Intention	0.344	0.066	5.168	0.000
Proactiveness -> Intention	0.334	0.05	6.687	0.000
Proactiveness -> Perceived Usefulness	0.511	0.04	12.925	0.000
Risk-Taking -> Intention	-0.133	0.05	2.642	0.008
Risk-Taking -> Perceived Usefulness	0.194	0.037	5.312	0.000

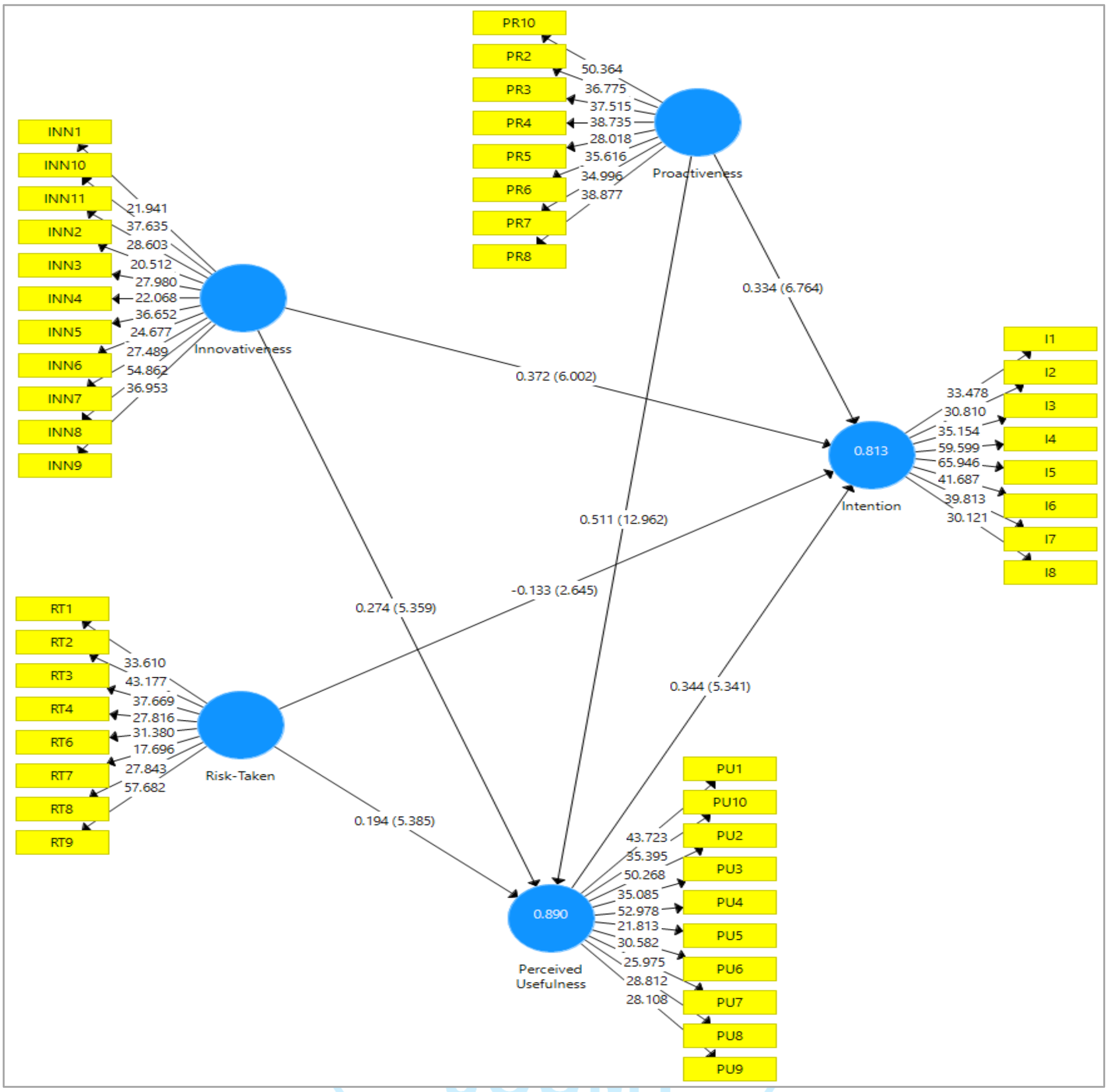

Fig. 2 SmartPLS Standardized Result

The bootstrapping method and indirect effect were employed to determine the mediating relationship. According to Preacher and Hayes (2008), the indirect effect, measured by the 95% boot confidence interval (CI: LL-UL), does not include 0 between the variables in question. The bootstrap results are shown in Table 6.

The study found that the indirect effect (Innovativeness -> Perceived Usefulness -> Intention, β=0.094, t-value=3.510) was statistically significant at p<0.001. A mediating effect was also confirmed, as evidenced by the indirect effect of 0.094, with a 95% confidence interval (LL=0.049, UL=0.155) that does not include 0, indicating support for a mediating effect. Consequently, perceived usefulness was found to mediate between innovativeness and intention in the Malaysian agricultural sectors.

Moreover, the results revealed that the indirect effect (Proactiveness -> Perceived Usefulness -> Intention, β=0.176, t-value=4.639) was statistically significant at p<0.001. A mediation effect was present, as the indirect effect (0.176; 95% Boot CI: LL=0.106, UL=0.255) does not include 0, supporting a mediating effect (Isah et al., 2022). The findings suggested that perceived usefulness mediated proactiveness and intention in the Malaysian agricultural sectors.
The results also showed that the indirect effect (Risk-Taking -> Perceived Usefulness -> Intention, β=0.067, t-value=4.214) was statistically significant at p<0.001 when the bootstrap results were used. The study confirmed a mediating effect since the indirect effect is 0.067, with a 95% Boot CI: LL=0.040, UL=0.103. The absence of 0 within the indirect effect's range indicated support for a mediating effect. The findings suggested that perceived usefulness mediated the relationship between risk-taking and intention in the Malaysian agricultural sectors. In conclusion, the study's findings show that perceived usefulness positively mediates risk-taking and intention in the Malaysian agricultural sectors.

Table 5 Indirect Effect

	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Innovativeness -> Perceived Usefulness -> Intention	0.094	0.027	3.510	0.000
Proactiveness -> Perceived Usefulness -> Intention	0.176	0.038	4.639	0.000
Risk-Taking -> Perceived Usefulness -> Intention	0.067	0.016	4.214	0.000

The R^2 value indicates the extent to which the independent variables explain the variance in the dependent variable. The R^2 estimates are presented in Table 5. The results demonstrate that the independent variables account for a substantial proportion of the variance in the dependent variable. Specifically, Table 5 shows that the independent variables explain 81.3% of the variance in farmers' intentions to adopt AIT. Consequently, the error variance in the intention to use Big Data and Data Analytics (BDDA) accounts for approximately 19% of the differences in intention among farmers. Additionally, Table 5 reveals that 89.0% of the variance in the predictors is explained.

Moreover, the effect size (f^2) of the total number of exogenous latent constructs is considered significant. Additionally, the predictive relevance Q^2 of all exogenous latent constructs in the current study was minor. In conclusion, Hair et al. (2014) suggest that, as a relative measure of predictive relevance, values of 0.02, 0.15, and 0.35 indicate that an exogenous construct has a small, medium, or large predictive relevance for a particular endogenous construct, respectively.

Table 6 Summary of the R^2

	R^2	R^2 Adjusted	f^2	Q^2
Intention	0.813	0.812	0.016	0.521
Perceived Usefulness	0.890	0.889		

5. Conclusions and Recommendations

This study investigated the factors influencing small farmers' intentions to adopt BDDA, focusing on innovativeness, proactiveness, risk-taking, and perceived usefulness. The findings suggest that enhancing perceived usefulness is crucial in promoting BDDA adoption, particularly by leveraging small farmers' innovative and proactive tendencies to achieve sustainable agricultural practices. Policymakers should consider implementing targeted strategies that emphasize the practical benefits of BDDA supported by financial incentives and infrastructure investments to foster sustainable agricultural development.

A model based on the Technology Acceptance Model (TAM) was developed and empirically analyzed using a survey of farmers in Malaysia. The results revealed significant R^2 values for adoption intention and farmers' perceived usefulness, with the model's fitness index being within acceptable limits. The findings indicate that farmers' characteristics of innovativeness, proactiveness, and perceived usefulness play a more significant role in explaining BDDA adoption than risk-taking. Furthermore, the study discovered that perceived usefulness mediates the relationships between innovativeness, proactiveness, risk-taking, and intention to adopt BDDA. Also, the current study contributes to the existing literature by providing empirical evidence that innovativeness, proactiveness, and risk-taking are vital to increasing the adoption of novel technologies, particularly among small farmers.

In an attempt to address the challenges associated with embracing the adoption of BDDA among small farmers in Malaysia, the study proposed the following recommendations:

- To begin, it is suggested that specific strategies and policies be developed to emphasize the benefits of BDDA and address particular concerns of small farmers, particularly regarding the usefulness of BDDA in agriculture. This can be accomplished through knowledge-sharing sessions and awareness programs to show them the practical value of adopting a proactive and innovative agricultural approach.
- It is suggested that small farmers' support mechanisms, such as financial incentives and infrastructure investments, should promote the adoption of BDDA to enhance sustainable agricultural practices. This is a significant step toward encouraging greater entrepreneurialism among agri-food producers.
- Replications of such studies conducted in other developing nations can be beneficial for comparing results and determining generalizability. This will help guide the development of more effective policies and strategies to promote the widespread adoption of technological advances among small farmers in Malaysia.
- Longitudinal studies can shed more light on the shifting importance of factors such as entrepreneurial propensity and perceived usefulness concerning the dynamics of BDDA adoption and sustainability among small farmers in Malaysia.
- It is suggested that more research be conducted to address factors that influence small farmers' adoption and acceptance of new technologies and the characteristics and preferences of the small farmers themselves. This will help ensure that agricultural technologies are developed and deployed to meet the needs and preferences of small farmers by identifying and removing any barriers to technology adoption.

Acknowledgements

I gratefully acknowledge Universiti Sultan Zainal Abidin for their support in the completion of this research

Declaration of Conflict

The authors declare no conflict of interest.

References

1. Afsay, A., Tahriri, A., & Rezaee, Z. (2023). A meta-analysis of factors affecting acceptance of information technology in auditing. *International Journal of Accounting Information Systems*, *49*, 100608.
2. Ahmad, A. U., Abubakar, A. M., Senan, N. A. M., Gwadabe, U. M., Mohammed, B. S., Muhammad, M., ... & Mustapha, U. A. (2024). Examining the Asymmetric Effects of Renewable Energy Use, Financial Development, and Trade Openness on Economic Growth in D-8 Islamic Countries. *International Journal of Energy Economics and Policy*, *14*(4), 125-139.
3. Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.
4. Ajzen, I., & Fishbein, M. (1975). A Bayesian analysis of attribution processes. *Psychological bulletin*, *82*(2), 261.
5. Altinay, L., Madanoglu, M., Daniele, R., & Lashley, C. (2012). The influence of family tradition and psychological traits on entrepreneurial intention. *International Journal of Hospitality Management*, *31*(2), 489-499.
6. Amanor, K. S. (2024). Contradictions between commercializing seeds, empowering smallholder farmers, and promoting biodiversity in Ghana: Seed policy within a historical framework. *Elementa: Science of the Anthropocene*, *12*(1).
7. Aydemir, S. D., & Aren, S. (2017). Do the effects of individual factors on financial risk-taking behavior diversify with financial literacy? *Kybernetes*.
8. Bader, R., Siegmund, O., & Woerndl, W. (2011). A study on user acceptance of proactive in-vehicle recommender systems. *Proceedings of the 3rd International Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI 2011*, 47–54. https://doi.org/10.1145/2381416.2381424
9. Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the academy of marketing science*, *40*(1), 8-34.
10. Batz, F. J., Peters, K. J., & Janssen, W. (1999). The influence of technology characteristics on the rate and speed of adoption. *Agricultural Economics*, *21*(2), 121-130.
11. Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Sociological methods & research*, *16*(1), 78-117.
12. Bioscience Research. *Precision agriculture*, *21*, 08-2021.
13. Buraimoh, O. F., Boor, C. H., & Aladesusi, G. A. (2023). Examining facilitating condition and social influence as determinants of secondary school teachers' behavioural intention to use mobile technologies for instruction. *Indonesian Journal of Educational Research and Technology*, *3*(1), 25-34.
14. Burton-Jones, A., & Hubona, G. S. (2006). The mediation of external variables in the technology acceptance model. *Information and Management*, *43*(6), 706–717. https://doi.org/10.1016/j.im.2006.03.007
15. Chang, S. C., Lin, R. J., Chen, J. H., & Huang, L. H. (2005). Manufacturing flexibility and manufacturing proactiveness: Empirical evidence from the motherboard industry. In *Industrial Management and Data Systems* (Vol. 105, Issue 8, pp. 1115–1132). Emerald Group Publishing Limited. https://doi.org/10.1108/02635570510624482
16. Chickering, A. W., & Gamson, Z. F. (1999). Development and adaptations of the seven principles for good practice in undergraduate education. *New directions for teaching and learning*, *1999*(80), 75-81.
17. Cimino, A., Coniglio, I. M., Corvello, V., Longo, F., Sagawa, J. K., & Solina, V. (2024). Exploring small farmers behavioral intention to adopt digital platforms for sustainable and successful agricultural ecosystems. *Technological Forecasting and Social Change*, *204*, 123436.
18. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008
19. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.
20. Diop, E. B., Zhao, S., & Duy, T. V. (2019). An extension of the technology acceptance model for understanding travelers' adoption of variable message signs. *PLoS one*, *14*(4), e0216007.
21. Effendi, I., Murad, M., Rafiki, A., & Lubis, M. M. (2020). The application of the theory of reasoned action on services of Islamic rural banks in Indonesia. *Journal of Islamic Marketing*.
22. Fishbein, M. (1980). A Theory of Reasoned Action: Some Applications and Implications. In *Nebraska Symposium on Motivation. Nebraska Symposium on Motivation* (Vol. 27, pp. 65-116).
23. Francisco, K., & Swanson, D. (2018). The supply chain has no clothes: Technology adoption of blockchain for supply chain transparency. *Logistics*, *2*(1), 2.
24. Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of enterprise information management*.
25. Gangwar, H., Date, H., & Raoot, A. D. (2014). Review on IT adoption: insights from recent technologies. *Journal of Enterprise Information Management*.

26. Gani, M. O., Rahman, M. S., Bag, S., & Mia, M. P. (2024). Examining behavioural intention of using smart health care technology among females: dynamics of social influence and perceived usefulness. *Benchmarking: An International Journal*, *31*(2), 330-352.
27. Garay, L., Font, X., & Pereira-Moliner, J. (2017). Understanding sustainability behaviour: The relationship between information acquisition, proactivity and performance. *Tourism Management*, *60*(2017), 418–429. https://doi.org/10.1016/j.tourman.2016.12.017
28. Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The qualitative report*, *8*(4), 597-607.
29. Guadagnoli, E., & Velicer, W. F. (1988). Relation of sample size to the stability of component patterns. *Psychological bulletin*, *103*(2), 265.
30. Gwadabe, U. M., & Arumugam, N. (2021). Adoption of Big Data in Agripreneurship: A Panacea to the Global Food Challenge. *Entrepreneurship and Big Data*, 71-82.
31. Gwadabe, U. M., Arumugam, N., & Amirah, N. A. (2021). An exploratory factor analysis to develop measurement Items for small farmers' proactiveness and risk-taking in precision farming.
32. Gwadabe, U. M., Arumugam, N., & Amirah, N. A. (2022). Exploration And Development of Measurement Items of Innovation for New Technology Adoption Among Small Farmers. *Agricultural Research*, *10*(6), 620-626.
33. Gwadabe, U. M., Arumugam, N., Amirah, N. A. & Isah, S. (2022). The Role of the Theory of Planned Behavior and the Technology Acceptance Model in Determining the Adoption of Innovative Agricultural Technology by Small-Scale Farmers. *Bioscience Research*, 19(SI-1), 263-275.
34. Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European business review*.
35. Huang, R.-T., Tang, T.-W., Lee, Y. P., & Yang, F.-Y. (2017). Does Proactive Personality Matter in Mobile Learning? *Australasian Journal of Educational Technology*, *33*(2), 86–96. https://ajet.org.au/index.php/AJET/article/view/2896/1416
36. Hwang, Y., Al-Arabiat, M., Shin, D. H., & Lee, Y. (2016). Understanding information proactiveness and the content management system adoption in pre-implementation stage. *Computers in Human Behavior*, *64*(2016), 515–523. https://doi.org/10.1016/j.chb.2016.07.025
37. Isah, S., Ibrahim, R. M., Karim, F., & Gwadabe, U. M. (2022). Work Engagement as a Mediator of the Connection Between Compensation and Employee Competence: Evidence from Nigeria. *Journal of Social Economics Research*, *9*(4), 204-218.
38. Kala, D., & Chaubey, D. S. (2024). Exploring the determinants of fashion clothing rental consumption among young Indians using the extended theory of reasoned action. *Global Knowledge, Memory and Communication*.
39. Kayali, M., & Alaaraj, S. (2020). Adoption of Cloud Based E-learning in Developing Countries: A Combination A of DOI, TAM and UTAUT. *Int. J. Contemp. Manag. Inf. Technol*, *1*(1), 1-7.
40. Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in human behavior*, *26*(3), 310-322.
41. Kujala, T., Karvonen, H., & Mäkelä, J. (2016). Context-sensitive distraction warnings - Effects on drivers' visual behavior and acceptance. *International Journal of Human Computer Studies*, *90*(2016), 39–52. https://doi.org/10.1016/j.ijhcs.2016.03.003
42. Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, *5*(1), 2053951718756684.
43. Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & management*, *40*(3), 191-204.
44. Lewis, W., Agarwal, R., & Sambamurthy, V. (2003). Sources of influence on beliefs about information technology use: An empirical study of knowledge workers. *MIS Quarterly: Management Information Systems*, *27*(4), 657–678. https://doi.org/10.2307/30036552
45. Li, K., & Li, Q. (2023). Towards more efficient low-carbon agricultural technology extension in China: identifying lead smallholder farmers and their behavioral determinants. *Environmental Science and Pollution Research*, *30*(10), 27833-27845.
46. Lin, Z., & Filieri, R. (2015). Airline passengers' continuance intention towards online check-in services: The role of personal innovativeness and subjective knowledge. *Transportation Research Part E: Logistics and Transportation Review*, *81*, 158–168. https://doi.org/10.1016/j.tre.2015.07.001
47. Liu, Q., Geertshuis, S., & Grainger, R. (2020). Understanding academics' adoption of learning technologies: A systematic review. *Computers & Education*, *151*, 103857.
48. Lu, J., Yu, C. S., Liu, C., & Yao, J. E. (2003). Technology acceptance model for wireless Internet. *Internet Research*, *13*(3), 206–222. https://doi.org/10.1108/10662240310478222
49. Mady, T. (2018). What makes up intentions to purchase the pioneer? A theory of reasoned action approach in India and the USA. *International Journal of Emerging Markets*.
50. Martínez-Román, J. A., & Romero, I. (2017). Determinants of innovativeness in SMEs: disentangling core innovation and technology adoption capabilities. *Review of Managerial Science*, *11*(3), 543-569.

51. Mehrtens, J., Cragg, P. B., & Mills, A. M. (2001). A model of Internet adoption by SMEs. *Information & management*, *39*(3), 165-176.
52. Mercurio, D. I., & Hernandez, A. A. (2020). Understanding User Acceptance of Information System for Sweet Potato Variety and Disease Classification: An Empirical Examination with an Extended Technology Acceptance Model. *Proceedings - 2020 16th IEEE International Colloquium on Signal Processing and Its Applications, CSPA 2020*, 272–277. https://doi.org/10.1109/CSPA48992.2020.9068527
53. Mills, B., Reyna, V. F., & Estrada, S. (2008). Explaining contradictory relations between risk perception and risk taking. *Psychological science*, *19*(5), 429-433.
54. Miltgen, C. L., Popovič, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the "Big 3" of technology acceptance with privacy context. *Decision support systems*, *56*, 103-114.
55. Min, S., So, K. K. F., & Jeong, M. (2019). Consumer adoption of the Uber mobile application: Insights from diffusion of innovation theory and technology acceptance model. *Journal of Travel & Tourism Marketing*, *36*(7), 770-783.
56. Momani, A. M., & Jamous, M. (2017). The evolution of technology acceptance theories. *International Journal of Contemporary Computer Research (IJCCR)*, *1*(1), 51-58.
57. Mukuze, K. (2023). *Developing a predictive model for human capital analytics adoption in Zimbabwean State Universities* (Doctoral dissertation, Chinhoyi University of Technology).
58. Nagy, J. T. (2018). Evaluation of online video usage and learning satisfaction: An extension of the technology acceptance model. *International Review of Research in Open and Distributed Learning*, *19*(1).
59. Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation*, *14*(1), pp110-121.
60. Pagani, M. (2004). Determinants of adoption of third generation mobile multimedia services. *Journal of Interactive Marketing*, *18*(3), 46–59.
61. Panagiotopoulos, I., & Dimitrakopoulos, G. (2018). An empirical investigation on consumers' intentions towards autonomous driving. *Transportation research part C: emerging technologies*, *95*, 773-784.
62. Preacher, K. J., & Hayes, A. F. (2008). *Assessing mediation in communication research* (pp. 13-54). London: The Sage sourcebook of advanced data analysis methods for communication research.
63. Rahman, S. A., Khadijeh Taghizadeh, S., Ramayah, T., Mohammad, M., & Alam, D. (2017). Technology acceptance among micro-entrepreneurs in a marginalized social strata: The case of social innovation in Bangladesh. *Technological Forecasting & Social Change*, *118*(C), 236–245. https://doi.org/10.1016/j.techfore.2017.01.027
64. Rahman, S. A., Khadijeh Taghizadeh, S., Ramayah, T., Mohammad, M., & Alam, D. (2017). Technology acceptance among micro-entrepreneurs in a marginalized social strata: The case of social innovation in Bangladesh. *Technological Forecasting & Social Change*, *118*(C), 236–245. https://doi.org/10.1016/j.techfore.2017.01.027
65. Recker, J. (2016). Reasoning about Discontinuance of Information System Use. *JITTA: Journal of Information Technology Theory and Application*, *17*(1), 41.
66. Rieple, A., & Snijders, S. (2018). The role of emotions in the choice to adopt, or resist, innovations by Irish dairy farmers. *Journal of Business Research*, *85*, 23-31.
67. Rogers, E. M. (1983). Diffusion of Innovations, A Division of Macmillan Publishing Co. *Inc. Third Edition, The Free Pres, New York*.
68. Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models: A non-linear perspective. *Kybernetes*.
69. Ronquillo, C., Dahinten, V., Bungay, V., & Currie, L. (2019). The Nurse LEADership for Implementing Technologies – Mobile Health Model (Nurse LEAD-IT – mHealth). *Canadian Journal of Nursing Leadership*, *32*(2), 71–84. https://doi.org/10.12927/cjnl.2019.25960
70. Sam, T. H., Wong, W. Y., Gwadabe, Z. L., Balakrishnan, R., Poopalaselvam, R., Adam, A., & Tee, K. S. (2021, May). The adoption of IoT technology in the Malaysian manufacturing industry. In *AIP Conference Proceedings* (Vol. 2355, No. 1, p. 030002). AIP Publishing LLC.
71. Sandberg, B. (2002). Creating the market for disrupSandberg, B. (2002). Creating the market for disruptive innovation: Market proactiveness at the launch stage. Journal of Targeting, Measurement and Analysis for Marketing, 11(2), 184–196. https://doi.org/10.1057/palgrave.jt.5. *Journal of Targeting, Measurement and Analysis for Marketing*, *11*(2), 184–196. https://doi.org/10.1057/palgrave.jt.5740076
72. Siddiqui, H., Raza, F., & Imran, T. (2017). Psychological Empowerment of University Academicians Through Job Crafting in a Challenging Environment. *Global Management Journal for Academic & Corporate Studies*, *7*(2), 151–158.
73. Sun, Y., Wang, N., Guo, X., & Peng, Z. (2013). Understanding the acceptance of mobile health services: a comparison and integration of alternative models. *Journal of electronic commerce research*, *14*(2), 183.
74. Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia manufacturing*, *22*, 960-967.

75. Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia manufacturing*, *22*, 960-967.
76. Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia manufacturing*, *22*, 960-967.
77. Takahashi, K., Muraoka, R., & Otsuka, K. (2020). Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics*, *51*(1), 31-45.
78. Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, *39*(2), 273-315.
79. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.
80. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.
81. Verma, S., Bhattacharyya, S. S., & Kumar, S. (2018). An extension of the technology acceptance model in the big data analytics system implementation environment. *Information Processing and Management*, *54*(5), 791–806. https://doi.org/10.1016/j.ipm.2018.01.004
82. Wang, Y. N., Jin, L., & Mao, H. (2019). Farmer cooperatives' intention to adopt agricultural information technology—Mediating effects of attitude. *Information Systems Frontiers*, *21*(3), 565-580.
83. 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.
84. Zheng, S., Wang, Z., & Wachenheim, C. J. (2019). Technology adoption among farmers in Jilin Province, China: the case of aerial pesticide application. *China Agricultural Economic Review*.