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Exploring small farmers behavioral intention to adopt digital platforms for sustainable and successful agricultural ecosystems

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ABSTRACT

The research study explores the factors influencing small farmers behavioral intention to adopt a pioneering digital platform, whose aim is to establish sustainable and successful business ecosystems within the agricultural sector. To achieve this goal, the authors extend and customize the Unified Theory of Acceptance and Use of Technology model developing a theoretical framework that assesses the impact of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Environmental Uncertainty (EU), and Network Prominence (NP) on the Behavioral Intention (BI) to use the platform. From December 2022 to May 2023, a survey was conducted using a tailor-made questionnaire and gathering 192 valid responses from a sample of Italian small farmers. The empirical analysis confirms positive associations between the independent constructs (EE, PE, SI, EU, NP) and BI. Additionally, the study detects the predominant influence of EU over other constructs on small farmers' intention to adopt the platform. The integration of NP and EU constructs represents a significant contribution to the existing literature, as it offers a novel approach for a deeper understanding of the adoption process. The study's findings determine significant implications for policymakers and platform developers providing valuable insights into driving technology adoption for sustainable and successful ecosystems.

1. Introduction

The agricultural sector plays a crucial role in global food production and sustainability (FAO, 2018), with small farmers being an integral part of this sector. Small farmers make up a significant portion of the agricultural workforce worldwide, contributing to food security and rural development. According to recent statistics (Lowder et al., 2021), small farmers account for approximately 84 % of the world's 608 million farms and produce around a third of the world's food (FAO, 2021). In Europe, Eurostat reports that in 2016, there were approximately 10.3 million farms, of which two third are small in nature (EUROSTAT, 2019). These statistics highlights the importance of understanding the unique challenges and opportunities faced by small farmers, both globally and within specific continents such as Europe. Within this context, a notable challenge faced by small-scale farming pertains to the limited adoption of technological advancements, resulting in relatively low technological penetration (FAO, 2019). This low adoption of digital technologies can be attributed to various factors, including limited access to information and resources (Samii, 2008; Odini, 2014), lack of digital literacy and technical skills among farmers (Odini, 2014; FAO and ZJU, 2021) lack and costs of infrastructure in rural areas (FAO, 2019). However, there is a growing recognition of the potential benefits that digital technologies can bring to create value, including the creation of ecosystems (Parker et al., 2016). In fact, by embracing digital technologies, small farmers can overcome numerous challenges and enhance their productivity, sustainability, and competitiveness (Yigezu et al., 2018). These technologies offer a range of tools and services that enable farmers to connect, share knowledge, access market information, and establish crucial networks within the agricultural community (Omulo and Kumeh, 2020; Chaudhuri and Kendall, 2021; Ortiz-Crespo et al., 2021; Cimino et al., 2023), thus contributing to the creation of collaborative ecosystems among small farmers.

Considering the significance of small farmers, the limited technological penetration in the agricultural sector, and the potential benefits

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of digital technologies in promoting business development through ecosystem creation, it is crucial to examine the factors impacting the adoption of such technologies. In this context, this study aims to investigate the determinants influencing small farmers' adoption of digital technologies with a particular emphasis on digital platforms, whose aim is to establish of sustainable and successful business ecosystems. To achieve this objective, the authors have developed a theoretical framework that expands the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003; Ye et al., 2020) by integrating two additional constructs. The first one, Network Prominence (NP), pertains the network of the farmer, while the second one, Environmental Uncertainty (EU), reflects the influence of the context.

The paper is organized as follows: Section 2 presents the theoretical framework of the study, including a literature review, the authors' developed theoretical model, and the formulation of hypotheses to guide the research. Moving forward, Section 3 proposes the methodology employed, providing a detailed description of the empirical analysis conducted. In Section 4, the obtained results are presented, followed by an in-depth discussion of the main findings in Section 5. Section 6 presents the main implications of the research work, while Section 7 highlights the main limitations and the potential challenges for future research. Finally, in Section 8, the conclusions drawn from the study are outlined.

2. Theory

2.1. Literature review

In today's economy, the concept of a business ecosystem has gained significant attention and recognition (Jacobides et al., 2018; Sun et al., 2023). A business ecosystem represents a dynamic network of interconnected entities (such us organizations, stakeholders, and resources) which collaborate and compete, combining their efforts and competencies, to generate value within a specific industry or market (Moore, 1993; Nalebuff and Brandenburger, 1997; Adner, 2006). The importance of business ecosystems lies in their ability to foster and coordinate innovation (Adner, 2006), stimulate growth (Rong et al., 2015), and ensure long-term sustainability (Lee and Roh, 2023) by leveraging collective capabilities and creating new opportunities for ecosystem participants. In this context, digital technologies play a crucial role in shaping and developing business ecosystems (Parker et al., 2016). These technologies serve often as online infrastructures that facilitate interactions, transactions, and value creation among ecosystem participants. They provide scalable and efficient means for connecting various stakeholders, enabling collaboration, and leveraging data-driven insights (Parker et al., 2016). Digital technologies have been widely employed to create ecosystem orchestration mechanisms, allowing participants to offer complementary products or services (Kapoor, 2018). The application of digital technologies is not limited to traditional industries but also extends to sectors such as agriculture (Engås et al., 2023). Digitalization in agricultural has gained momentum over the past decades, with numerous technologies fast emerging and made available to the academic and farming communities (Mouratiadou et al., 2023). Digital technologies have been extensively employed to tackle diverse challenges in the agricultural sector. These technologies have demonstrated their effectiveness in various areas, including real-time data monitoring and enhancing irrigation efficiency (Bouali et al., 2022), managing efficiently order allocation (Germanos et al., 2023), reducing food waste and improving yield (Van Campenhout et al., 2021), enhancing sustainability in agricultural practices (Mapiye et al., 2021), facilitating credit access (Agyekumhene et al., 2018), optimizing product distribution (Cane and Parra, 2020), and breaking down sociocultural barriers (Agyekumhene et al., 2020). However, despite these advancements, limited efforts have been made to leverage digital technology for the development of ecosystems aimed at enhancing collaboration, interaction, and access to knowledge and information among smallholders and other stakeholders in the agricultural sector. In the following, to the best of authors' knowledge the solely 5 solutions identified in the literature are reviewed. Cimino et al. (2023) develop a digital platform to facilitate interactions between smallholders and buyers, workers and freight transport companies in agri-food ecosystems. Ortiz-Crespo et al. (2021) develop a digital service to facilitate smallholders access to information and knowledge. Chaudhuri and Kendall (2021) emphasize the role of digital solutions in agriculture, supporting collaboration among smallholders and enhancing resilience to climate change. Finally, the concept of collaboration is also addressed by Omulo and Kumeh (2020), who explored the adoption of the SMS-based platform "Wefarm" to support knowledge-sharing among small-scale farmers, enhancing access to information on agricultural production, marketing, and financial services.

Based on the analysis of the state of the art, while digital technologies have demonstrated their potential in supporting smallholders and addressing various challenges in agriculture, there is a need for further research and development to create a robust digital platform that, by effectively and simultaneously connecting smallholders with other stakeholders, enables the development of sustainable and successful business ecosystems. Evaluating the factors that influence the willingness of use this kind of digital platform becomes important in this context and understanding the determinants that shape users' attitudes and intentions towards adopting it can provide valuable insights for platform developers, policymakers, and stakeholders involved in the ecosystem.

2.2. Theoretical framework

To study the intention to adopt digital platforms facilitating the establishment and participation in business ecosystems, in this study the authors decided to use the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT, developed by Venkatesh et al. (2003), is a well-recognized model for the acceptance and use of technology. It integrates eight models of technology adoption within the information technology domain and identifies four key constructs - Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) – that significantly influence users' attitudes and intentions towards adopting (Behavioral Intention – BI) and utilizing (Behavioral Use – BU) technology. Numerous studies have explored its applicability in sectors such as healthcare (Chang et al., 2007; Schaper and Pervan, 2007; Kijsanayotin et al., 2009; Arfi et al., 2021), education (Chauhan and Jaiswal, 2016; Hew and Sharifah Latifah, 2016; Lakhal and Khechine, 2016; Sabah, 2016), banking and finance (Zhou et al., 2010; Im et al., 2011; Martins et al., 2014). Moreover, UTAUT has found relevance and applicability also in the agricultural sector. In the study conducted by Ronaghi and Forouharfar (2020), UTAUT was employed to assess the intention of farmers in Iran to adopt Internet of Things (IoT) technology in smart farming. Furthermore, Michels et al. (2020) examined the intention to use smartphone apps for crop protection among 209 farmers in Germany, while Liang (2012) conducted a study in China's Guizhou province, focusing on the acceptance of last-mile technology among rural farmers in the agricultural context. Consistent with previous researches, these studies found that the key constructs of the UTAUT had a significant influence on farmers' adoption decisions. Additionally, Giua et al. (2022) applied UTAUT to examine the adoption of Smart Farming Technologies (SFTs) in Italy. Another relevant study in the agricultural sector was conducted by Faridi et al. (2020). In their research, the effectiveness of water and soil conservation measures (WSCM) using a combination of the UTAUT and the Initial Trust Model (ITM) has been explored among 538 paddy farmers in Rasht County, Northern Iran. Moreover, other studies have also underscored the importance of enhancing the explanatory capabilities of the UTAUT model within the agricultural domain by incorporating additional constructs. Bezaa et al. (2018) and Molina-Maturano et al. (2021) conducted two separate studies that extended the UTAUT model by integrating constructs related to trust (TR), personal innovativeness in information technology (IN), and mastery approach goals (MAG). Furthermore, researchers such as Li et al. (2020) have proposed modified versions of UTAUT that incorporate additional constructs to further enhance its explanatory power. This modified version includes constructs such as perceived need for technology characteristics (PNTC), perceived benefits (PB) (as perception of the efficacy of facilitating conditions), and the perceived risks (PR) of technology adoption.

The analysis of the state of the art has demonstrated UTAUT model's ability to effectively predict the intention to adopt new technologies, as well as its frequent application in agricultural contexts. Moreover, the literature analysis has also revealed that extending the UTAUT model with additional constructs brings substantial benefits in understanding technology adoption within agricultural contexts. Table 1 presents a comparative analysis between our research and other relevant studies within agricultural contexts, focusing on the intention to adopt a technology. As evident from the data, there are no comparable studies that have tried to examine the factors influencing the intention to adopt an emerging technology, still in the development phase, in the agricultural domain, employing an extended version of the UTAUT model.

In light of this, the authors decide to utilize the UTAUT model as conceptual base for the theoretical framework and to extend it by integrating two additional constructs related to Environmental Uncertainty (EU) and Network Prominence (NP) with the aim of investigating the adoption of digital platforms for sustainable and successful business ecosystems establishment within the agricultural sector. It is noteworthy that such kind of digital platforms, as confirmed by the state-of-the-art analysis, are not yet available in the market. Despite this, the research study has been conducted based on a platform that is currently in the development phase, as part of the European research project named SMALLDERS (Smart Models for Agrifood Local vaLue chain based on Digital technologies for Enabling COVID-19 Resilience and Sustainability). Due to the unique nature of the platform, the authors have finalized the proposed research model by excluding FC and BU variables of the UTAUT model. This decision has been justified by specific rationales. Firstly, FC refers to the availability of resources and support required for technology adoption. Since the digital platform under scrutiny is still in development, it has not been launched, and as such, the relevant facilitating conditions are yet to be established or applicable at this early stage. Secondly, BU in the UTAUT model pertains to the actual engagement and utilization of technology by individuals. Given that the digital platform is not yet operational and lacks users in its current state, examining the behavioral use aspect at this phase would be premature and inconclusive.

By expanding and customizing the UTAUT model through the integration of NP and EU constructs, and by excluding FC and BU variables due to their inapplicability during the platform's developmental phase, this research aligns with the unique context of a digital platform that is not yet in existence and this strategic decision enables the investigation to focus solely on the factors influencing potential users' willingness to adopt a pioneering digital platform aimed at establishing sustainable and successful business ecosystems in the agricultural domain. The insights gained from this investigation hold the potential to inform digital platform developers, policymakers, and stakeholders, facilitating the successful deployment of the platform and its alignment with sustainable business practices. Fig. 1 graphically depicts the proposed research model.

2.3. Hypotheses development

In this section, the authors detail the hypotheses concerning the relationships between the proposed model's constructs and their implications to the behavioral intention (BI) of small farmers in adopting digital platforms, such as the SMALLDERS one.

2.3.1. Performance expectancy (PE)

PE refers to the extent to which an individual believes that utilizing a system or a technology can enhance their task performance and contribute to achieving better outcomes (Venkatesh et al., 2003). PE has been empirically established as a crucial determinant influencing individuals' BI towards technology adoption. This finding has been consistently supported by several scientific studies conducted in the agricultural sector (Liang, 2012; Bezaa et al., 2018; Faridi et al., 2020; Michels et al., 2020; Molina-Maturano et al., 2021; Ronaghi and Forouharfar, 2020; Giua et al., 2022). Therefore, the following hypothesis is proposed:

H1. Performance expectancy has a positive influence on the BI of small farmers to use digital platforms similar to SMALLDERS.

2.3.2. Effort expectancy (EE)

EE denotes the level of easy associated with the use of a system or a technology (Adner, 2006). The influence of EE on individuals' BI to use a technology has been firmly established through numerous scientific studies in the agricultural domain. The significant impact of EE on the technology intention of use of small farmers underscores its critical role in shaping technology adoption behavior (Liang, 2012; Bezaa et al., 2018; Faridi et al., 2020; Michels et al., 2020; Ronaghi and Forouharfar, 2020; Giua et al., 2022). Thus, the following hypothesis is proposed:

H2. Effort expectancy has a positive influence on the BI of small farmers to use digital platforms similar to SMALLDERS.

2.3.3. Social influence (SI)

SI reflects the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh, 2003). Individuals often rely on their social network, particularly friends and family, when considering the adoption of new technologies and they can be influenced by the perceived social pressure exerted by influential individuals (Molina-Maturano et al., 2021). In the scientific literature, the primary assumption is that SI positively impacts the intention to use technology. However, in the context of the agricultural sector, it is important to note that the influence of SI on BI has yielded mixed results. While some research studies have confirmed a significant relationship between SI and BI (Liang, 2012; Michels et al., 2020; Ronaghi and

Table 1
Comparison between our paper and other similar research works.

Reference	Technology description	Theoretical model		Technology status	
		UTAUT	Extended UTAUT	Available	Under development
Liang (2012)	Information Technology Service	✓		✓	
Faridi et al. (2020)	Water and Soil Conservation Measures	✓		✓	
Ronaghi and Forouharfar (2020)	Internet of Things	✓		✓	
Giua et al. (2022)	Smart Farming Technologies	✓		✓	
Bezaa et al. (2018)	Mobile Short Message Service		✓	✓	
Li et al. (2020)	Precision Agriculture Technologies		✓	✓	
Michels et al. (2020)	Smartphone Apps		✓	✓	
Molina-Maturano et al. (2021)	Agricultural Apps		✓	✓	
Our study	Digital Platform for Agricultural Business Ecosystem		✓		✓

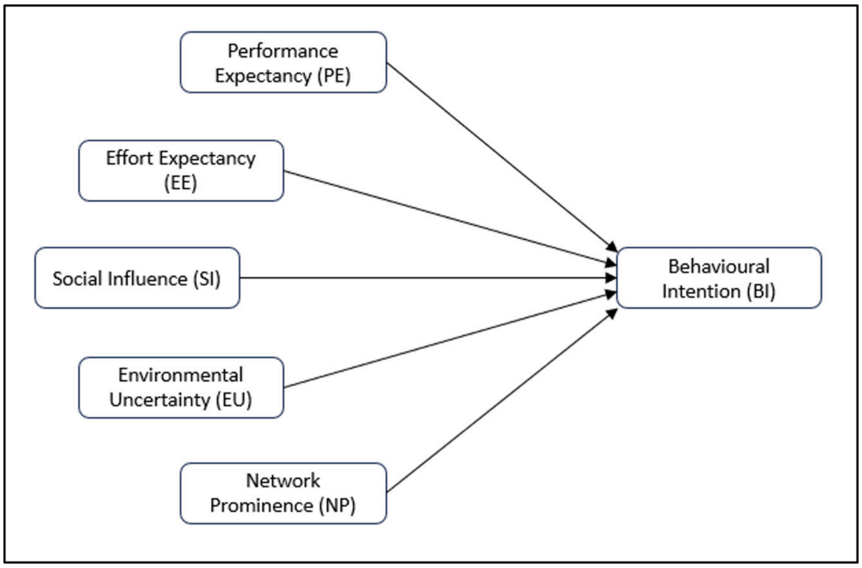

Fig. 1. Research conceptual model.

Forouharfar, 2020; Giua et al., 2022), others have failed to find such a relationship (Bezaa et al., 2018; Faridi et al., 2020; Li et al., 2020; Molina-Maturano et al., 2021). In this research work, the authors have formulated their hypothesis based on the primary assumption prevalent in the literature, which suggests a positive relationship between SI and BI to use the technology.

H3. Social Influence has a positive influence on the BI of small farmers to use digital platforms similar to SMALLDERS.

2.3.4. Environmental uncertainty (EU)

EU mainly refers to the speed and intensity of technological change and market changes in the industry (Lissillour et al., 2023). In a highly uncertain business environment, the influence of consumer demand on product and service preferences becomes more significant. As a result, firms tend to be motivated to actively seek external resources for continuous learning, gaining insights into potential market shifts, and exploring new technological solutions (Slowak, 2008). This proactive approach allows firms to extend the technological innovation cycle (Tatikonda and Montoya-Weiss, 2001) and maintain competitiveness (Srivastava and Frankwick, 2011). Based on this, the following hypothesis is proposed:

H4. Environmental uncertainty has a positive influence on the BI of small farmers to use digital platforms similar to SMALLDERS.

2.3.5. Network prominence (NP)

Network prominence (NP) refers to an organization's capacity to exert influence and achieve favorable outcomes within a network (Wang and Wang, 2020). NP provides firms with access to vital knowledge and diverse information (Powell, 1996), allowing them to stay informed about technological advancements and innovative solutions. In this regard, the authors assume that this enhanced access increases their likelihood of having the intention to use technology, as firms have the necessary information to evaluate technology potential benefits. In addition, NP grants firms a position of authority and power within the supply chain (Patil et al., 2023). This increased power position enhances their ability to negotiate (Nakamura, 2005) and influence resource distribution (Burt, 2004). The authors believe that with greater control and influence, firms are more likely to have the intention to use technology as they can effectively integrate technological solutions into their supply chain operations as well as effectively enhance their competitive advantage. Based on the aforementioned observations, the following hypothesis is proposed:

H5. Network prominence has a positive influence on the BI of small farmers to use digital platforms similar to SMALLDERS.

3. Material and methods

3.1. Research context

This research study has been conducted in Italy, a country where the agricultural sector holds a significant position within the national economy, with over 50 % of the total land surface dedicated to agricultural activities (Marras et al., 2022). The production value of the agricultural sector reached 60.355 million euros in 2021, contributing about 2.2 % to the overall Italian GDP (Marras et al., 2022). Moreover, Italy's agricultural sector is characterized by a notable presence of small farms, with those smaller than 5 ha accounting for a remarkable 73 % of the total agricultural holdings (Caffaro and Cavallo, 2019). The 2022 Seventh General Agricultural Census in Italy (ISTAT, 2022) further confirms this, revealing a total of 1.133.023 agricultural holdings, encompassing a combined land area of approximately 12.5 million hectares. This extensive landscape reflects the significant scale and importance of agriculture in the country, underlining the pivotal role of small farmers within the sector. Within this dynamic agricultural context, characterized by its substantial presence of small farms and its significant contribution to the national economy, this research holds promise in advancing the understanding of digital platforms adoption for business ecosystems establishment among the Italian small farmers. Moreover, the knowledge gained from this study can serve as a model for other agricultural sectors around the world, offering valuable lessons and best practices in the adoption of digital platforms.

3.2. Measurement instruments

In this research work, a survey has been conducted from December 2022 to May 2023 by using a specifically developed questionnaire as primary measurement instrument. The questionnaire has been originally written in English and then the final version was translated into Italian through standard and back translation processes in order to ensure linguistic equivalence and cultural adaptability for the Italian version. The questionnaire consists of three distinct sections, each serving a specific purpose in gathering comprehensive data for the research. Starting with the presentation of the digital platform, the first section aimed to familiarize the surveyed sample with the SMALLDERS platform, providing essential knowledge to enable informed responses. A concise description of the platform's objectives, functionalities, and early-stage user interface drafts was presented. Fig. 2 depicts an example of the web page, reported within this section, displaying the list of activities that end-users can engage in through SMALLDERS platform. For the benefit of greater understanding by the reader, the main features of the SMALLDERS platform are reported below. One of the most innovative aspects of SMALLDERS, which differentiates it from other existing solutions, is the joint presence in a single platform of multiple actors, able to communicate mutually to achieve several benefits: smallholders, citizens (intended as buyers or workers), critical stakeholders (intended as large-scale retail trade operators or large-scale food producers), freight transport companies, policymakers. SMALLDERS can be accessed via web or mobile application. This platform gives the smallholder the opportunity to create and manage an e-commerce channel, with the aim of expanding the customer base, improving perceived product value, and increasing potential revenues. Furthermore, it reduces the unemployment rate and addresses any workforce shortage, through a specific job offer/request module. The direct smallholder-freight transport company connection improves the product shipping process, through the mutual sharing of information, for the benefit of a better level of service offered to the final customer. More specifically, SMALLDERS involves the integration of multiple concepts and technologies such as artificial intelligence (AI), sensors and other IoT components, blockchain, Modeling & Simulation (M&S). AI is aimed at improving the user experience through an appropriate AI-based personal assistant; IoT components mainly aim to acquire data (e.g., humidity, temperature) from the field to improve agricultural practices; blockchain enables supply chain Tracking&Tracing; M&S approaches allow the evaluation of multiple operational scenarios, to identify the most profitable work configuration.

The second section of the questionnaire concerns general information and demographic characteristics of the participating farmers, including gender, age, working experience, and educational level. These details served as contextual factors, aiding in understanding the respondents' backgrounds. Finally, the third section of the survey was dedicated to exploring the constructs depicted in our research conceptual model (see Fig. 1). To ensure correct measurement, the authors derived a total of 20 items from existing literature and tailored them to align it with the specific research setting (see Appendix A for more details). The utilization of Likert scales, ranging from "strongly agree" to "strongly disagree" on a scale of 1 to 5, allowed respondents to express their perceptions and attitudes towards the constructs in question.

3.3. Data collection

Before officially launching the survey, a comprehensive testing phase was conducted to assess the questionnaire's effectiveness and clarity. This involved pilot interviews with 11 farmers from Calabria, a region in Southern Italy. The interviews were conducted via telephone and by using various modalities to ensure a correct questionnaire assessment. Some respondents were assisted by one of the authors during the survey completion, facilitating direct observation of their interpretation of questions and concepts. For other participants, the survey was sent via email, encouraging them to provide feedback and share any additional notes. The results of these pilot interviews enable the authors to improve the formulation of the questions. Once the questionnaire was finalized, it was administered per email to 370 Italian small farmers distributed in the whole country. Each farmer was also contacted by phone with three primary objectives: (1) explaining the research purpose, (2) offering support to address any informational needs or questions regarding the questionnaire, and (3) actively engaging them in the research study to encourage their participation. The average time required to complete the questionnaire was approximately 9–10 min, and no incentives were offered to participants. The response rate was satisfactory, reaching approximately 55 %, resulting in a total of 204 answers. The data were meticulously cleaned to remove repetitive or incoherent responses, leaving 192 valid questionnaires, which formed the foundation of the research analysis. Our dataset adheres to the minimum sample sizes guidelines as recommended by Barclay et al. (1995) and Kock and Hadaya (2018).

3.4. Data analysis

Firstly, the study presents descriptive statistics to provide an overview of the characteristics of the small farmers in the sample. Subsequently, the research employed the Partial Least Squares approach to Structural Equation Modeling (PLS-SEM) to test and validate the proposed research model and hypotheses. PLS-SEM, initially developed by Wold (1975, 1982) and extended by Lohmöller (1989), Bentler and Huang (2014), Dijkstra (2014), and Dijkstra and Henseler (2015), was chosen due to its suitability for small sample sizes (Willaby et al., 2015) and exploratory studies (Hair et al., 2019). Additionally, PLS-SEM is recommended for datasets with a limited number of indicators per latent variable (Hair Jr et al., 2017). For the analysis, the authors utilized

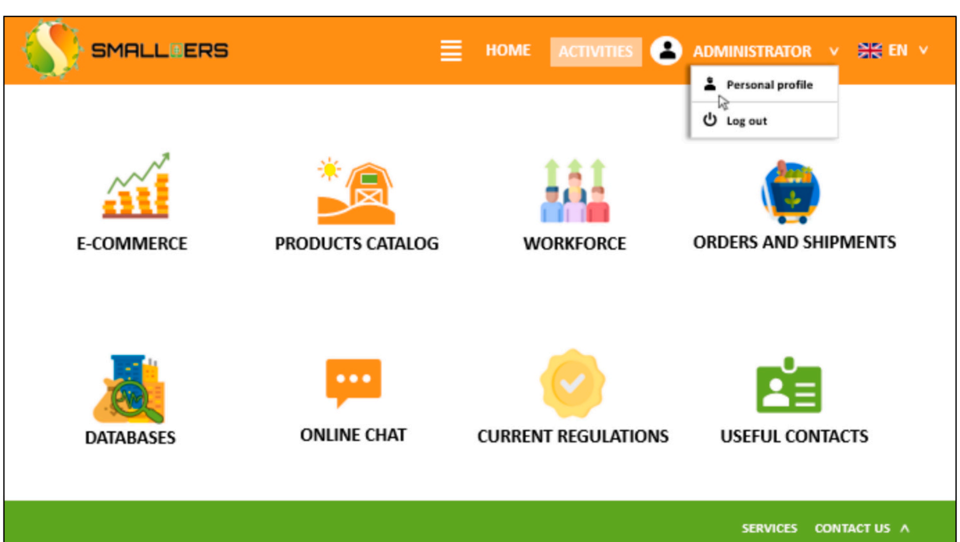

Fig. 2. SMALLDERS activity list web page.

SmartPLS4 software from SmartPLS GmbH (further information about SmartPLS4 can be found at https://www.smartpls.com). The PLS-SEM analysis was conducted in two main steps. In the first step, the measurement model was evaluated to assess the reliability of the constructs used in the study. The second step involved running the structural model and analyzing the results to examine the hypotheses proposed in the theoretical framework and to draw conclusions about hypothesized relationships and their statistical significance. Section 4 presents this study's results, starting with descriptive statistics of the analyzed survey sample (see Section 4.1). Subsequently, it provides the outcomes of the measurement model analysis (see Section 4.2), followed by the results of the structural model analysis (see Section 4.3).

4. Results

4.1. Descriptive statistics

Table 2 presents the demographic characteristics of the small farmers who participated in this study. The survey sample consisted of 70.8 % male and 29.2 % female farmers, indicating a higher representation of male respondents. The age distribution of the surveyed small farmers revealed a relatively balanced profile, with the majority falling within the age groups of 35 to 55 years. Specifically, 23.4 % of the farmers were between the ages of 35 and 45, while 26.6 % fell within the age group of 45 to 55. As concern the work experience, a significant portion of farmers had substantial experience in farming. Precisely, 77,1 % of the respondents reported having at least 5 years' work experience. Finally, in terms of educational background, the survey revealed a considerable proportion of small farmers with higher education qualifications with the majority of individuals holding a bachelor's and/or master's degree (54,7 %).

4.2. Measurement model results

The evaluation of the measurement model follows the guidelines proposed by Hair Jr et al. (2021), encompassing four essential steps to ensure the model assessment. These steps involve evaluating the reliability of model measures at both the indicator level (indicator reliability - STEP 1) and the construct level (internal consistency and reliability - STEP 2). Additionally, the model's validity is thoroughly examined, focusing on each measure's convergent validity (STEP 3) and discriminant validity (STEP 4). The results of these steps are highly positive, reinforcing the reliability and validity of the measurement model. Below, the authors present the details of each step and their corresponding results.

4.2.1. STEP 1 – indicator reliability

The initial step refers to the evaluation of the variance proportion in each indicator that is explained by its corresponding construct, which provides an indication of indicator reliability (Hair Jr et al., 2021). To compute these indicators, the authors calculate the indicator loadings, which measure the strength of the relationship between the indicators and the latent constructs (Jöreskog, 1971; Chin, 1998). The results of this analysis are presented in Table 3, revealing that all the values exceed the recommended threshold of 0.708 (Hair Jr et al., 2021). Therefore, it can be confidently stated that the analysis fulfills the required criteria, signifying the satisfactory measurement of the constructs and providing acceptable indicators reliability.

Table 2
Demographic characteristics of the farmers.

Demographic character		Frequency (n)	Percentage (%)
Gender	Male	136	70,8
	Female	56	29,2
Age	<25	21	10,9
	25–35	39	20,3
	35–45	45	23,4
	45–55	51	26,6
	>55	36	18,8
Work experience	<5	44	22,9
	5–10	51	26,6
	>10	97	50,5
Educational level	Middle school	12	6,3
	High school	75	39,0
	Bachelor degree	56	29,2
	Master degree	49	25,5

4.2.2. STEP 2 - internal consistency and reliability

The second step involves evaluating internal consistency reliability, as extent to which indicators measuring the same construct are associated with each other Hair Jr et al. (2021). To assess internal consistency reliability, the authors utilized three measures: the composite reliability coefficient rhoC (Hair Jr et al., 2017), Cronbach's alpha (Hair Jr et al., 2017), and the reliability coefficient rhoA (Dijkstra, 2014; Dijkstra and Henseler, 2015). It is important to note that Cronbach's alpha represents the lower bound of internal consistency reliability, while the composite reliability rhoC serves as the upper bound (Hair Jr et al., 2021). The reliability coefficient rho_A typically falls between these bounds and can be considered a good representation of a construct's internal consistency reliability (Hair Jr et al., 2021). The analysis results are presented in Table 4, revealing that each value of rho_A falls within the range of 0.7 to 0.9, indicating satisfactory to good levels of internal consistency. Thus, this analysis reinforces the validity and reliability of the measurement model.

4.2.3. STEP 3 – convergent validity

The third step of the analysis entails evaluating the convergent validity of each construct. Convergent validity refers to the extent to which a construct effectively converges and explains the variance of its indicators (Hair Jr et al., 2021). To assess this, the authors utilize the average variance extracted (AVE) metric, which quantifies the amount of variance captured by all indicators within each construct. The results of the AVE analysis are reported in Table 5, and all values exceed the threshold limit of 0.5 (Hair et al., 2022), confirming the validity of the model.

4.2.4. STEP 4 – discriminant validity

Finally, the fourth step aims at assessing the discriminant validity, that measures the degree to which a construct is empirically distinct from other constructs in the structural model (Hair Jr et al., 2021). To evaluate discriminant validity, the authors have employed three

Table 3
Indicator loadings.

	PE	EE	SI	EU	NP	BI
PE-1	0.883					
PE-2	0.847					
PE-3	0.831					
PE-4	0.846					
EE-1		0.808				
EE-2		0.883				
EE-3		0.868				
EE-4		0.900				
SI-1			0.891			
SI-2			0.885			
SI-3			0.852			
EU-1				0.869		
EU-2				0.841		
EU-3				0.768		
NP-1					0.871	
NP-2					0.862	
NP-3					0.814	
BI-1						0.914
BI-2						0.916
BI-3						0.898

Table 4
Internal consistency reliability.

	Cronbach's alpha	Composite reliability (rho_A)	Composite reliability (rho_C)
PE	0.874	0.875	0.914
EE	0.888	0.891	0.923
SI	0.849	0.855	0.908
EU	0.770	0.785	0.867
NP	0.811	0.844	0.886
BI	0.895	0.896	0.935

Table 5
Convergent validity.

	Average variance extracted (AVE)
PE	0.726
EE	0.749
SI	0.768
EU	0.684
NP	0.721
BI	0.827

metrics: Cross-loadings (Hair Jr et al., 2017), Fornell-Larcker (Fornell and Larcker, 1981), and Heterotrait-Monotrait Ratio (HTMT) (Henseler et al., 2015). Tables 6 to 7 present the results for each metric, confirming the positive outcomes regarding the model's discriminant validity (Fornell and Larcker, 1981; Henseler et al., 2015; Hair Jr et al., 2017; Hair Jr et al., 2021). Indeed, the cross-loadings provide confirmation of the model's discriminant validity as the values for each item related to its construct are higher than the values for that item related to other constructs (Hair Jr et al., 2017). The highest values for each item are highlighted in bold in Table 6. Regarding the Fornell–Larcker criterion, the proposed model meets the discriminant validity requirements as the AVE for each construct (see Table 7) is greater than the highest correlation that particular construct has with any other construct in the model (Fornell and Larcker, 1981; Hair Jr et al., 2021). Furthermore, after examining Table 8, it is evident that all HTMT values are below the threshold of 0.9 (Henseler et al., 2015; Hair Jr et al., 2021). This finding firmly establishes the discriminant validity of the model.

Table 6
Cross-loadings.

	PE	EE	SI	EU	NP	BI
PE-1	**0.883**	0.692	0.688	0.374	−0.021	0.618
PE-2	**0.847**	0.650	0.575	0.371	−0.021	0.603
PE-3	**0.831**	0.637	0.563	0.418	0.023	0.586
PE-4	**0.846**	0.630	0.541	0.332	0.049	0.555
EE-1	0.681	**0.808**	0.625	0.476	0.070	0.595
EE-2	0.679	**0.883**	0.630	0.482	0.176	0.671
EE-3	0.613	**0.868**	0.511	0.483	0.151	0.599
EE-4	0.679	**0.900**	0.593	0.434	0.137	0.638
SI-1	0.533	0.512	**0.891**	0.370	0.100	0.527
SI-2	0.548	0.529	**0.885**	0.394	0.070	0.606
SI-3	0.725	0.726	**0.852**	0.500	0.212	0.664
EU-1	0.404	0.456	0.462	**0.869**	0.085	0.636
EU-2	0.347	0.454	0.350	**0.841**	0.169	0.567
EU-3	0.336	0.436	0.393	**0.768**	0.029	0.487
NP-1	0.027	0.152	0.175	0.095	**0.871**	0.237
NP-2	−0.043	0.044	0.040	0.045	**0.862**	0.131
NP-3	0.014	0.166	0.129	0.138	**0.814**	0.202
BI-1	0.631	0.651	0.651	0.650	0.240	**0.914**
BI-2	0.649	0.661	0.630	0.610	0.255	**0.916**
BI-3	0.614	0.665	0.603	0.613	0.145	**0.898**

The figures in bold in Table 6 represent the cross-loadings values for each item related to its construct.

Table 7
Fornell-Larcker.

	PE	EE	SI	EU	NP	BI
PE	0.852					
EE	0.767	0.865				
SI	0.696	0.682	0.876			
EU	0.439	0.541	0.487	0.827		
NP	0.008	0.156	0.150	0.117	0.849	
BI	0.694	0.724	0.691	0.686	0.236	0.909

Table 8
Heterotrait-Monotrait Ratio (HTMT).

	PE	EE	SI	EU	NP	BI
PE						
EE	0.870					
SI	0.795	0.773				
EU	0.533	0.657	0.592			
NP	0.070	0.167	0.157	0.142		
BI	0.784	0.812	0.783	0.821	0.260	

4.3. *Structural model results*

After confirming the measurement model's reliability and validity, the next step involves evaluating the results of the structural model. Following the systematic assessment procedure proposed by Hair Jr et al. (2021), the authors first address collinearity issues in the structural model (STEP 1). Subsequently, they verify the significance and relevance of the relationships within the structural model (STEP 2). Next, the model's explanatory power is assessed (STEP 3), and finally, the authors proceed to evaluate the model's predictive power (STEP 4). Below, the details of each step and their corresponding results are presented.

4.3.1. *STEP 1 – collinearity issues*

The structural model regressions must be examined for potential collinearity issues. One measure of collinearity is the Variance Inflation Factor (VIF). VIF values above 5 are indicative of probable collinearity issues among predictor constructs (Hair et al., 2011). Table 9 presents the VIF values, and it can be noted that none of these values exceed the threshold limit of 5, thus indicating the absence of collinearity issues in the structural model of this research work.

4.3.2. *STEP 2 – significance and relevance of the structural model relationships*

In the subsequent step, the authors evaluate the significance and relevance of the path coefficients. Table 10 presents the primary results obtained from the PLS-SEM algorithm, confirming that each construct (PE, EE, SI, EU, NP) has an impact on BI. Specifically, the construct EU has the highest impact on BI, with a coefficient value of 0.369, followed by PE with 0.273. The impacts of EE, SI and NP on BI are relatively similar. To assess significance, the authors utilize bootstrapping standard errors as the basis for calculating t-values of path coefficients. Comparing these t-values with the critical values from the standard normal distribution, it can determine whether the coefficients are significantly different from zero. Assuming a significance level of 5 %, a

Table 9
Variance inflation factors (VIFs).

	VIF
PE → BI	2.946
EE → BI	3.041
SI → BI	2.286
EU → BI	1.470
NP → BI	1.079

Table 10
Path coefficients - mean, STDEV, T values, *p* values.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
PE → BI (H1)	0.273	0.273	0.073	3.719	0.000	Supported
EE → BI (H2)	0.166	0.162	0.072	2.308	0.021	Supported
SI → BI (H3)	0.187	0.189	0.059	3.147	0.002	Supported
EU → BI (H4)	0.369	0.370	0.054	6.888	0.000	Supported
NP → BI (H5)	0.137	0.140	0.040	3.444	0.001	Supported

t-value above 1,96 suggests that the indicator weight is statistically significant (Hair Jr et al., 2021). The results of the analysis have confirmed this. Moreover, the authors opted to calculate confidence intervals as an alternative method to test the significance of the path coefficients. Table 11 presents the confidence interval values, confirming that none of them include the value zero. In fact, if a confidence interval does not contain zero, the weight can be considered statistically significant, and the corresponding indicator can be retained (Hair Jr et al., 2021). This reinforces the significance of the structural model.

4.3.3. STEP 3 – model's explanatory power

The next step involves assessing the coefficient of determination (R^2) specifically for the BI construct. R^2 represents the variance explained in each of the endogenous constructs (in this case, BI) and serves as a measure of the model's explanatory power (Shmueli and Koppius, 2011). However, a limitation of R^2 is that its value tends to increase as more explanatory variables are introduced to a model. To address this concern, the authors have decided to use the adjusted R^2 metric (R^2_{adj}), which provides a more conservative estimate of R^2 (Theil, 1961). Table 12 presents the results for both R^2 and R^2_{adj}. Both values are very close to 0.75, indicating that the explanatory power of the model can be considered between moderate and substantial, leaning towards more substantial (as reported in Hair et al. (2011), values of 0.75, 0.5, and 0.25 indicate respectively substantial, moderate, and weak explanatory power). This suggests that a significant portion of the variance in the BI construct is effectively explained by the model's predictor variables.

4.3.4. STEP 4 – model's predictive power

The evaluation of the structural model is completed by assessing its predictive power. To measure the model's predictive performance for the construct BI, the authors have chosen to use the root-mean-square error (RMSE), as widely accepted metrics for quantifying prediction errors, particularly when the distribution of these errors is symmetric, as is the case for this research study. In interpreting this metric, the authors compare the RMSE values of BI items (BI-1, BI-2, BI-3) calculated using PLS-SEM with the corresponding values obtained from a naïve linear regression model (LM) used as a benchmark (Hair Jr et al., 2021). Table 13 presents a comparison of the RMSE values from both PLS-SEM and LM. All indicators in the PLS-SEM analysis result in lower RMSE values compared to the naïve LM benchmark. This finding demonstrates that the model displays high predictive power (Shmueli et al., 2019), signifying its effectiveness in predicting the construct BI.

5. Discussion

In this section, the authors discuss the main results of this research study, whose aim is to evaluate the factors influencing the willingness of small farmers to use a pioneering digital platform for establishing sustainable and successful business ecosystems. To achieve this, the authors developed a research framework that expands and customizes the UTAUT model by integrating NP and EU constructs while excluding FC and BU variables. The empirical analysis has confirmed all the formulated hypotheses (see Section 2.3), highlighting the impact of each construct on the BI of small farmers to use the digital platform.

Table 11
Path coefficients – confidence intervals.

	Original sample (O)	Sample mean (M)	2.5 %	97.5 %
PE → BI	0.273	0.273	0.129	0.412
EE → BI	0.166	0.162	0.021	0.305
SI → BI	0.187	0.189	0.076	0.307
EU → BI	0.369	0.370	0.271	0.483
NP → BI	0.137	0.140	0.062	0.217

Table 12
R^2 and R^2_{adj}.

	R^2	R^2_{adj}
BI	0.725	0.718

Table 13
RMSE values.

	PLS-SEM_RMSE	LM_RMSE
BI-1	0.644	0.646
BI-2	0.704	0.717
BI-3	0.616	0.619

Firstly, the study findings reveal a positive relationship between PE and BI (H1). It is evident that small farmers are more motivated to adopt the digital platform when they perceive it as valuable and capable of delivering desired outcomes. To effectively enhance platform adoption, it is crucial to align the digital platform's main features with the specific needs of small farmers. By tailoring the platform to address their unique challenges and requirements, it will become more appealing and useful to them, increasing their intention to adopt it.

A positive association between EE ad BI (H2) has been also confirmed by the study. Small farmers who perceive the digital platform as easy to use and navigate are more inclined to adopt it. To capitalize on this insight and enhance platform adoption, making the digital platform more accessible and intuitive for small farmers reduces perceived barriers and encourages a higher adoption rate.

Furthermore, the study has confirmed H3 hypothesis, which establishes a positive association between SI and BI. The results indicate that small farmers' decisions to adopt the digital platform are influenced by social factors such as feedback from trusted individuals within their social networks. To leverage this finding and further enhance platform adoption, fostering a sense of community and social interaction among small farmers could be a valuable strategy.

Additionally, the study highlights the significant impact of EU on BI (H4). The findings underscore that small farmers are more willing to embrace the digital platform when they perceive it as a reliable solution in uncertain and dynamic agricultural environments. To enhance platform adoption, it is crucial for stakeholders to emphasize the platform's adaptability and responsiveness to changing market conditions and environmental challenges. By effectively demonstrating how the platform empowers small farmers to navigate uncertainties and seize emerging opportunities, they can foster a stronger motivation for adoption, ultimately contributing to the establishment of sustainable and successful business ecosystems within the agricultural domain.

Finally, the study confirms hypothesis H5, establishing a positive association between NP and BI of small farmers to use the digital platform. NP plays a crucial role in providing firms with access to vital knowledge and diverse information, enabling them to stay informed about technological advancements and innovative solutions. This enhanced access significantly increases their likelihood of having the intention to use technology, as firms have the necessary information to evaluate the potential benefits that the digital platform can offer. Moreover, the study suggests that with greater control and influence resulting from NP, firms are more inclined to have the intention to use technology. This is due to their enhanced ability to effectively integrate technological solutions into their supply chain operations and, as a result, improve their competitive advantage in the agricultural domain.

6. Implications

In this section, the authors explore the theoretical and practical implications arising from the research study. This work addresses a significant research gap by investigating the adoption of a pioneering digital platform specifically being designed to create sustainable and successful business ecosystems for small farmers. Unlike previous studies that focused on the adoption of existing digital technologies in the agricultural domain, this research stands out for its examination of an innovative digital platform still under development, with the explicit goal of establishing sustainable ecosystems among small farmers. Additionally, while the UTAUT model has been utilized as a theoretical foundation in previous agricultural research studies, this study uniquely customizes this model by integrating the EU and NP constructs. This novel integration allows for a more comprehensive analysis of the factors influencing small farmers' intentions to adopt these innovative digital platforms. The empirical analysis of this study provides robust evidence supporting the reliability and validity of the proposed research model, establishing a robust foundation for future applications of this model in similar contexts. Moreover, the findings yield essential theoretical implications concerning the intention to adopt. It has been observed that environmental uncertainty plays a significant role in shaping small farmers' adoption decisions more than other constructs in the process. In the context of dynamic and ever-changing agricultural environments, small farmers seek digital platforms that foster collaboration, interaction, and knowledge-sharing among stakeholders. The study underscores the pivotal role of such platforms in addressing the challenges posed by uncertain agricultural conditions, ultimately motivating small farmers to adopt and embrace these innovative solutions.

The research study also offers valuable practical implications for various stakeholders within the agricultural domain. Policymakers and platform developers can utilize the insights from this study to design and implement digital platforms that effectively fit to the needs and preferences of small farmers. By understanding the critical role of environmental uncertainty in influencing adoption decisions, policymakers can provide targeted support and incentives to encourage small farmers to embrace these digital solutions.

Moreover, platform designers should also tailor digital platforms features to small farmers' needs, highlighting tangible benefits, and effectively communicating how the platforms addresses their specific challenges. In effect emphasizing the PE aspect, which relates to small farmers perceiving a platform as valuable and capable of delivering desired outcomes, will motivate them to adopt the digital solution.

To further enhance digital platforms adoption, platform designers should focus on creating an easy-to-use and intuitive interface, considering the positive influence of EE on BI. A user-friendly interface that simplifies the platform's functionalities can reduce perceived barriers and encourage a higher adoption rate among small farmers. Creating forums, discussion groups, and networking opportunities where farmers can share their experiences and support each other in adopting the platform is essential, given the positive association between SI and BI. Finally, to capitalize on the influence of NP on the BI and further promote platform adoption, stakeholders should focus on engaging and collaborating with key opinion leaders and influential farmers within the agricultural community. These influential individuals can play a pivotal role in endorsing the digital platform and spreading positive word-of-mouth referrals among their network, fostering a domino effect of adoption.

7. Limitations and future research

Despite its valuable contributions, this research study has certain limitations that need to be acknowledged. First, the study does not take into consideration the influence of individual factors such as gender, age, work experience, and educational level on the respondents' BI towards adopting the platform. Exploring the potential moderating or independent effects of these individual factors could provide further insights into adoption behavior. Secondly, the study focuses on the specific agricultural domain and a pioneering digital platform being developed to establish sustainable and successful ecosystems. While the findings offer valuable insights for this particular context, their generalizability to different sectors or other types of digital platforms may be limited. Future research endeavors should conduct comparative studies across various sectors and platforms to establish broader applicability. Thirdly, the study is confined to a sample of Italian small farmers. As such, the findings may be influenced by the unique characteristics of the Italian agricultural landscape and the cultural context. To enhance the external validity of the study, further research should be conducted in other national contexts by either replicating the study or considering international samples. Moreover, since the kind of digital platform under investigation is still under development, the study solely focuses on the intention to use the platform. As the platform becomes available in the market, it would be valuable to examine the role of the UTAUT model variable FC in the actual behavior to use the platform. This would provide a more comprehensive understanding of the factors influencing platform adoption and its successful implementation in real-world scenarios. Lastly, it is important to underline the need for future research to assess the impact of additional factors, including financial constraints, access to infrastructure, and digital literacy, on the adoption of this kind of digital platforms among small farmers. Addressing these limitations in future research would definitely contribute to the further extension of knowledge in this field.

8. Conclusions

This research study aims at understanding the factors influencing the willingness of small farmers to adopt a pioneering digital platform for creating sustainable and successful business ecosystems within the agricultural domain. To this end, the authors have extended and customized the UTAUT model with the integration of the NP and EU constructs, and by eliminating the constructs FC and BU. The empirical analysis has confirmed the positive relationships between various constructs (PE, EE, SI, EU and NP) and the BI of small farmers to use the digital platform. Furthermore, the study highlighted the significant impact of EU on small farmers' intention to adopt the digital platform, emphasizing the role of platforms in addressing challenges in dynamic agricultural environments. The findings have both theoretical and practical implications. Theoretically, the study contributes to the literature by offering insights into the adoption of innovative digital platforms and addressing the gaps in the existing research by integrating NP and EU constructs. The study further emphasizes the relevance of considering EU in the decision-making process of small farmers, contributing to the understanding of the role of technology in dynamic agricultural settings. Practically, this research provides valuable insights for stakeholders within the agricultural domain, including policymakers, platform developers, and small farmers themselves. By understanding the critical factors that influence adoption decisions, policymakers can implement targeted support and incentives to encourage small farmers' adoption of digital solutions. Platform developers can leverage the study's findings to design user-friendly interfaces, tailor features to meet small farmers' needs, and foster a sense of community and interaction through networking opportunities. Despite the contributions of this study, it is essential to acknowledge its limitations. The study's focus on the specific agricultural domain and a pioneering digital platform may limit the generalizability of the findings. Future research should explore other sectors and digital platforms to validate the results across diverse contexts. Additionally, the influence of individual factors like gender, age, work experience, and educational level were not considered in this study, offering opportunities for further research to explore their potential influence on platform adoption.

CRediT authorship contribution statement

Antonio Cimino: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ilda Maria Coniglio:** Data curation, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing. **Vincenzo Corvello:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Francesco Longo:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Juliana Keiko Sagawa:** Data curation, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing. **Vittorio Solina:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Research model constructs and items

Construct	Item	Nr.	Source
Performance Expectancy (PE)	*I would find a digital platform like SMALLDERS useful in doing my farm activities*	PE-1	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Zhou et al., 2010; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	Using a digital platform like SMALLDERS would enable me to accomplish tasks more quickly than before in the farm	PE-2	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Zhou et al., 2010; Im et al., 2011; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	Using a digital platform like SMALLDERS would make my farm more productive	PE-3	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Im et al., 2011; Ronaghi and Forouharfar, 2020; Giua et al., 2022; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	If I use a digital platform like SMALLDERS, I think I will increase my chances of increasing my income	PE-4	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Ronaghi and Forouharfar, 2020; Faridi et al., 2020)
Effort Expectancy (EE)	*My first impression of SMALLDERS digital platform could be described as clear, favorable and comprehensible*	EE-1	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Zhou et al., 2010; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	It is applicable to me to become proficient in using a digital platform like SMALLDERS	EE-2	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Zhou and Wang, 2006; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	I think that a digital platform like SMALLDERS would be an easy tool for me to use	EE-3	(Venkatesh et al., 2003; Zhou et al., 2010; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	Learning how to operate with a digital platform like SMALLDERS would be easy for me	EE-4	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Zhou et al., 2010; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Giua et al., 2022; Faridi et al., 2020)
Social Influence (SI)	*The people, who have influence on my behavior, think that I should use a digital platform like SMALLDERS in my farm*	SI-1	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Zhou et al., 2010; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	People, who are important to me, think that I should use a digital platform like SMALLDERS in my farm	SI-2	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Zhou et al., 2010; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	In general, in the farm it would be supported the adoption of a digital platform like SMALLDERS	SI-3	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Giua et al., 2022)
Environmental Uncertainty (EU)	*The market channels and business methods in the agricultural sectors are changing rapidly*	EU-1	(Lissillour et al., 2023)
	The speed of technological change in the agricultural sector is very fast	EU-2	(Lissillour et al., 2023)
	The products and services in the agricultural sector are updated very quickly	EU-3	(Lissillour et al., 2023)

(*continued on next page*)

(*continued*)

Construct	Item	Nr.	Source
Network Prominence (NP)	*My farm plays a central role in actively managing our interorganizational network*	NP-1	(Patil et al., 2023)
	My farm is in a stronger bargaining position than our supply chain partners while negotiating contracts	NP-2	(Patil et al., 2023)
	My farm regularly receives new information, from outside our interorganizational network (such as updates on market dynamics and trends, technological innovations, regulations and norms, industry events, etc.)	NP-3	(Patil et al., 2023)
Behavioral Intention (BI)	*I definitely intend to use a digital platform like SMALLDERS in the future*	BI-1	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)
	I predict I would use a digital platform like SMALLDERS in the future	BI-2	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Im et al., 2011; Martins et al., 2014; Faridi et al., 2020)
	I plan to use SMALLDERS digital platform in the future	BI-3	(Venkatesh et al., 2003; Kijsanayotin et al., 2009; Im et al., 2011; Martins et al., 2014; Ronaghi and Forouharfar, 2020; Michels et al., 2020; Giua et al., 2022; Faridi et al., 2020; Bezaa et al., 2018; Molina-Maturano et al., 2021)

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