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The hidden power of emotions: How psychological factors influence skill development in smart technology adoption

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ABSTRACT

Working within the theoretical framework set by the Technology Acceptance Model (TAM) literature, this paper clarifies how psychological factors (emotions, attitudes, beliefs, and information-seeking) affect skill development in the context of smart farming technologies. Interviews with multiple stakeholders from the agriculture sectors of three European countries (Belgium, Italy, and the United Kingdom) were used to develop a new conceptual model that attempts to generalize the complex interplay existing between skills and psychological factors in the context of smart technology adoption. This conceptualization provides a systematic view of the correlation between skills and psychological factors, complements the TAM by introducing the new concept of *attitude to learning*, and clarifies how the interplay between cognitive and emotional components influences the decisions to adopt and use smart technologies. In addition to these theoretical contributions, the paper emphasizes the importance of designing policy initiatives that tackle both cognitive and emotional barriers to the adoption of smart technologies, urging decision makers to move away from the simplistic assumption that increasing the digital skills of potential users automatically leads to growth in the adoption and implementation of smart technologies.

1. Introduction

The innovations enabled by smart technologies are triggering profound transformations at both organizational and sectoral levels (Dengler & Matthes, 2018; Fernández-Rovira et al., 2021; Mora et al. 2021). These technologies are increasingly finding applications in diverse geographic and industrial contexts (Mora & Deakin, 2019) and they are gradually spreading beyond urban settings to sustain the development of new productive and organizational models in rural areas, such as climate-smart villages (Groot et al., 2019). Likewise, they are expanding to both industrial and service sectors with the promise of replacing traditional production methods and business models with new paradigms, such as smart agriculture and manufacturing 4.0 (Capello & Lenzi, 2021; Klerkx et al., 2019).

This rapid and intense proliferation in the supply of smart technologies needs to be accompanied by "a reorganization of productive and innovation processes both within and between firms" (Ciarli et al., 2021, p.1). Despite the significant efforts that industry players and policymakers have put in place to support these reorganizations, though, the adoption of smart technologies remains unevenly distributed across sectors and regions (European Commission, 2020a). Obstacles to the adoption of smart technologies are well documented in the literature. For example, high costs and a lack of financial resources have emerged as a major deterrent to the diffusion of industry 4.0 within small and medium-sized enterprises (Agostini & Nosella, 2019; Gastaldi et al., 2022). Moreover, social influences and emotional barriers have been found to play a determinant role in the adoption of smart technologies at the individual level (Bettiga et al., 2020; Vicente, 2021). Great emphasis has also been placed on digital skills as a prerequisite for the adoption and usage of these technologies (Adrian et al., 2005; Ciarli et al., 2021; Janc et al., 2019; Park et al., 2014).

Skills have become central in the academic and policy debate on the diffusion of smart technologies (Helsper & Deursen, 2015). However, this theme is associated with a simplistic assumption that proposes a direct correlation between skill development, adoption, and use: increasing the level of digital skills of a potential user through training

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leads to growth in their adoption and use of smart technologies (Rayna & Striukova, 2021). Most advanced theorizing on this matter, framed in the Technology Acceptance Model (TAM), recognizes the limitation of this assumption, which overlooks the mediating role that psychological factors play in shaping the beliefs and behaviors of potential users in the context of technology adoption (Marangunić & Granić, 2014, Korukonda, 2005). However, the TAM only provides a limited and unsystematic view of the interdependence between skills and psychological factors, leaving a critical gap in the current theoretical and practical discourses on technology adoption, where more organic understanding is missing.

Drawing upon this theoretical context, we raise the following research question: *how do psychological factors influence skill development in smart technology adoption?* This paper helps to unravel this hidden relationship by offering a conceptual framework that is structured upon empirical research conducted in the context of smart farming technologies (SFTs). SFTs encompass a wide range of devices and applications that allow the acquisition, analysis, and usage of data in agriculture. For example, they include data-driven applications for variable-rate irrigation or fertilization, automated feeding systems for intensive farming, satellite-based applications, and on-field sensors for monitoring fields and crops (Balafoutis et al., 2017).

As part of our study, 29 interviews were conducted with multiple stakeholders in the agribusiness industry across three European countries (Belgium, Italy, and the United Kingdom), which we analyzed by applying the methodology developed by Gioia et al. (2012). The findings expand the current theoretical understanding of the relationship between skills and psychological factors in technology adoption by introducing the concept of *attitude to learning*, which complements the *attitude to use* that the TAM builds on. The *attitude to learning* reflects the willingness of non-users to engage with new technology-related knowledge and acts as a mediating factor between skill development and technology adoption, alongside other psychological factors highlighted in the TAM literature (emotions, information-seeking, and beliefs).

Building on these findings, we formulate a model that integrates TAM theory with conceptualizations that explain how different psychological factors trigger and reinforce the acquisition and development of the digital and non-digital skills required to use smart technologies. This theoretical contribution is complemented by relevant implications for policymakers and practitioners, who are provided with useful insights in order to define more effective policies and initiatives for boosting digital literacy and promoting smart technology adoption.

This paper is structured as follows. Section 2 reviews the extant literature on technology acceptance and introduces the theoretical framework that underlies this study. Section 3 details the methodology that we used for data collection and analysis. Section 4 presents the findings of the study, whose theoretical and practical implications are discussed in Section 5. Section 5 also details the limitations of the study and offers recommendations for future research. The paper closes with some final remarks, formulated in Section 6.

2. Technology acceptance model, skill development, and psychological factors

Originally developed by Davis (1986, 1989), the TAM can be used to explain the intention of an individual to use a given technology (Schepers & Wetzels, 2007) by drawing upon the Theory of Reasoned Action (Fishbein & Ajzen, 1975). This theory emphasizes how beliefs lead to a certain behavior. In the TAM, beliefs determining technology adoption are conceptualized in the theoretical constructs of *perceived usefulness* (PU) and *perceived ease of use* (PEOU).

PU is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320), while PEOU can be defined as "the degree to which a person believes that using a particular system would be free of effort" (p. 320). PU directly affects the behavioral intention to use technology, while PEOU influences both PU and such intention. The influence of PU and PEOU on technology acceptance, albeit in different ways, has largely been supported by empirical studies (Chuttur, 2009; Ma & Liu, 2004; Venkatesh & Davis, 2000). Therefore, they are widely considered as appropriate factors for predicting user behavior towards a given technology.

Moreover, the original TAM suggests that PU and PEOU influence the attitude of an individual to use a given technology, which then affects actual usage behavior (Davis 1986, 1989; Ma & Liu, 2004). The determinant *attitude to use* dropped out of subsequent variations of TAM because later studies found that PU and PEOU directly impact the usage behavior, and thus there was no longer a need to consider the mediating factor (Chutter, 2009). Nevertheless, scholars have continued to explore the role that attitudes play in technology adoption. For instance, Hsu and Chiu (2004) explored how attitudes toward the use of Internet services are influenced by social norms, ultimately finding that the attitude towards such services played a significant role in actual usage. In addition, in two separate studies focusing on SFTs, Mohr and Kühl (2021) and Shang et al. (2021) observed that the attitude of farmers toward technology is an important predictor of their intention to use artificial intelligence and digital farming. Conversely, Naspetti et al. (2017) concluded that *attitude to use* is not a significant determinant of the acceptance of innovative production strategies among dairy farmers.

Building on the TAM foundation, subsequent models have emerged to capture how PU and PEOU are influenced by various factors, which can be individual or context-dependent. The reason for considering other factors, in addition to the original PU and PEOU, is to account for social influence and a broader set of cognitive instrumental processes, whose presence influences technology adoption. For example, Venkatesh and Davis (2000) introduced the concepts of job relevance, voluntariness, image, output quality, result demonstrability, experience, and subjective norm – a "person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein & Ajzen, 1975, p. 302). Introducing these factors into the TAM has helped to capture additional insight into how system-wide conditions and technological affordance influence the acceptance of new technologies (Schepers & Wetzels, 2007).

Technological evolution has enabled a more widespread diffusion of technological devices and applications at the individual level, while increasing the interest of scholars in expanding the TAM (Adams et al., 1992; Chatterjee et al., 2021; Irani et al., 2009). Examining this evolution, scholars have emphasized how other psychological factors, beyond beliefs, can affect technology acceptance and user behavior. A relevant strand of literature focuses on the role of emotions (Venkatesh, 2000), such as technophobia and technology-related anxieties (Rosen & Weil, 1995). Most of the research indicates that anxiety influences PEOU through self-efficacy (Brosnan, 1999; Marangunić & Granić, 2014), which is defined as the beliefs of individuals about their ability to perform a specific task by using a technological apparatus (Venkatesh, 2000). This means that, for example, computer self-efficacy will differ from Internet self-efficacy: two types of technology use which involve a different set of tasks, and therefore a different perception of how one may perform these tasks (Roca & Gagné, 2008). However, Partala and Saari (2015) find that emotions may also influence how a user perceives the usefulness of a technology, which may contribute to its direct acceptance or rejection. In a similar manner, technophobia has been related to the acquisition of skills, and it has been suggested that lower skills may lead to higher fear of technology (Korukonda, 2005).

Skills are also regarded as major factors influencing technology adoption in agriculture. For instance, by focusing on the implementation of drones and precision agriculture, Adrian et al. (2005) and Michels et al. (2021) introduced the concept of *attitude of confidence* to the TAM, which is defined as the extent to which farmers think they can learn a given skill. Their research suggests that this personal trait has a positive impact on both the PEOU of certain technologies and the intention to use smart technologies in the agriculture sector. Attitude of confidence stems from the information systems literature (Adrian et al., 2005), which focuses on more general attitudes toward technologies (Rainer & Miller, 1996). Similarly, after studying the adoption of a new pest management practice, Sharifzadeh et al. (2017) stressed the relationship between skills and self-efficacy, which was used to examine how farmers view their own skills in relation to technology. Self-efficacy is a type of personal assessment whereby individuals are not concerned with the actual skills that they have, but rather with the perception of what they can accomplish with them (Roca & Gagné, 2008).

Information-seeking is another psychological factor considered in the TAM literature. In investigating Internet use, an early study by Shih (2004) analyzed how perceived information-seeking abilities affect the causal relationships between PU, PEOU, and attitudes, but did not directly embed this factor in the TAM. Similarly, in more recent research, information-seeking has been examined as a stand-alone factor in the TAM by Choi (2019), who highlights that information-seeking efforts directly influence both PU and PEOU of innovative tools for online news dissemination.

Overall, these research efforts have revealed the complexity and heterogeneity of psychological factors at stake in the study of technological acceptance, which has spread widely across different applications, contexts, and sectors. However, these factors are examined separately, as outlined in Fig. 1, and research aiming to scrutinize their correlation with the core elements of the TAM – PU and PEOU – is missing. This also applies to skill development; while skills seem linked to psychological factors, such as emotions and attitudes, no organic conceptualization is provided to explain the interrelationships between different psychological factors and skill development.

3. Research design, data collection and analysis

Drawing on Gioia et al. (2012), our methodology follows a three-step approach. The first step involves connecting our research question to an appropriate empirical setting. The second step is the collection of relevant data, which implies the use of semi-structured interviews to gather empirical insights into the subject matter of investigation. The final step is the data analysis, where we adopt a multiple-level and systematic coding approach to the interpretation of interview data.

3.1. Research question and empirical settings

Drawing upon the literature reviewed in Section 2, the research question that forms the basis of this paper is: *how do psychological factors influence skill development in smart technology adoption?* To answer this question, we focused on the agribusiness industry, where both skills and attitudes have emerged as major determinants of smart technology adoption (Da Silveira et al., 2021; Knierim et al., 2019). However, the development of such skills and attitudes remains unclear; hence understanding this process has become a key priority for researchers and policymakers (Ingram et al., 2022).

We chose Belgium, Italy, and the United Kingdom as empirical sites because of these countries are characterized by different levels of digitization and dissimilar structural characteristics of the agribusiness sectors. These differences helped to obtain a sample of interviewees that operate in heterogeneous contextual conditions, matching the variation criterion for case study selection (Seawright & Gerring, 2008).

According to the Digital Economy and Society Index, Italy lags behind other European countries in digital technology usage, whereas the United Kingdom and Belgium both class as leading countries in the penetration of digital technologies. However, the diffusion of digital skills is higher in the United Kingdom compared to Belgium (European Commission, 2020a). As for structural characteristics, the economic size of farms (measured in terms of standard output) is high for Italy, medium for the United Kingdom, and low for Belgium (Eurostat, 2016). Conversely, the average farm size is high for the United Kingdom, while remaining medium and low in Belgium and Italy, respectively (Eurostat, 2018).

3.2. Data collection

The data collection was based on a purposive sampling approach supported by a snowball technique (Johnson & Onwuegbuzie, 2004). We started by purposely identifying three groups of interviewees for each national context. Group 1 consists of SFT users, and they have been identified by screening trade press articles that present case studies of farmers or agribusinesses who have direct experience of SFT adoption in the three regions under investigation. Group 2 includes various knowledge providers operating in the agribusiness sector – i.e., spokespeople of farmers' organizations, agricultural advisors, freelance experts (e.g., agronomists, oenologists, etc.), and representatives of educational institutions (e.g., agricultural colleges, agricultural universities, etc.). These participants were selected by screening the official websites of relevant organizations, trade press articles and consultancy reports on the agribusiness sector. Finally, Group 3 is represented by SFT providers (i.e., manufacturers, dealers and distributors of smart technologies), which were identified among the participants of agricultural fairs, trade associations' members, and additional gray literature.

These groups of actors are representative of the variety of stakeholders involved in the market for smart technologies in the agriculture sector. Groups 1 and 3 represent the demand and supply sides of this market, respectively, whereas the interviewees in Group 2 have a crucial role in disseminating information on SFTs and facilitating the interaction between users and developers of such technologies (Higgins & Briant, 2020; Rijswijk et al., 2019). In addition, the interviewees were selected to account for differences in regional, sectoral (e.g., viticulture, apiculture, etc.), and technological application contexts (e.g., software, robotics, unmanned vehicles, etc.).

In addition, to select our interviewees, we also relied on a snowball sampling technique that helped to enhance the diversity of our sample and recruit stakeholders that would otherwise be difficult to identify (Kirchherr & Charles, 2018). Following this strategy, we identified 96 potential interviewees, who were invited to take part in the study; 29 accepted and were interviewed using a semi-structured interview protocol. The interviewees are distributed across the three countries included in the study and three groups of stakeholders.[1]

As detailed in Appendix A, the interviews lasted between 30 minutes and more than one hour, with an average of 50 minutes per interview, producing a total of 25 hours of discussion and 300 pages of written content. Interviews were conducted online using the following interview protocol. Interviewees in Groups 1 and 2 were initially asked to provide an overview of the digital devices and applications used in their organization or country. Likewise, interviewees in Group 3 were invited to describe the devices and applications they provide to agribusinesses. All participants were then asked to comment on what digital skills are needed to use each device and application by referring to their own knowledge and experience. To facilitate the discussion, the list of digital skills proposed in the DigiComp framework[2] developed by Vuorikari et al. (2016) was adopted, which has also found application in recent academic works (see Rayna & Striukova, 2021). The second part of the interviews focused on the different sources of digital skills available to agribusinesses and the factors facilitating or constraining the acquisition

[1] The breakdown by country and interviewee type is as follows: 7 interviewees in UK (1 in Group 1, 4 in Group 2, 2 in Group 3); 13 in Italy (3 in Group 1, 6 in Group 2, 4 in Group 3) and 9 in Belgium (2 in Group 1, 4 in Group 2, 3 in Group 3).

[2] The DigiComp Framework identifies five types of digital skills: information and data literacy, communication and collaboration, digital content creation, problem solving, and safety. Each category encompasses a wide set of competences: for example, "safety" includes all the skills related to the protection of devices, content, and data in a digital environment; the protection of physical and psychological well-being; and the environmental impact of digital technologies.

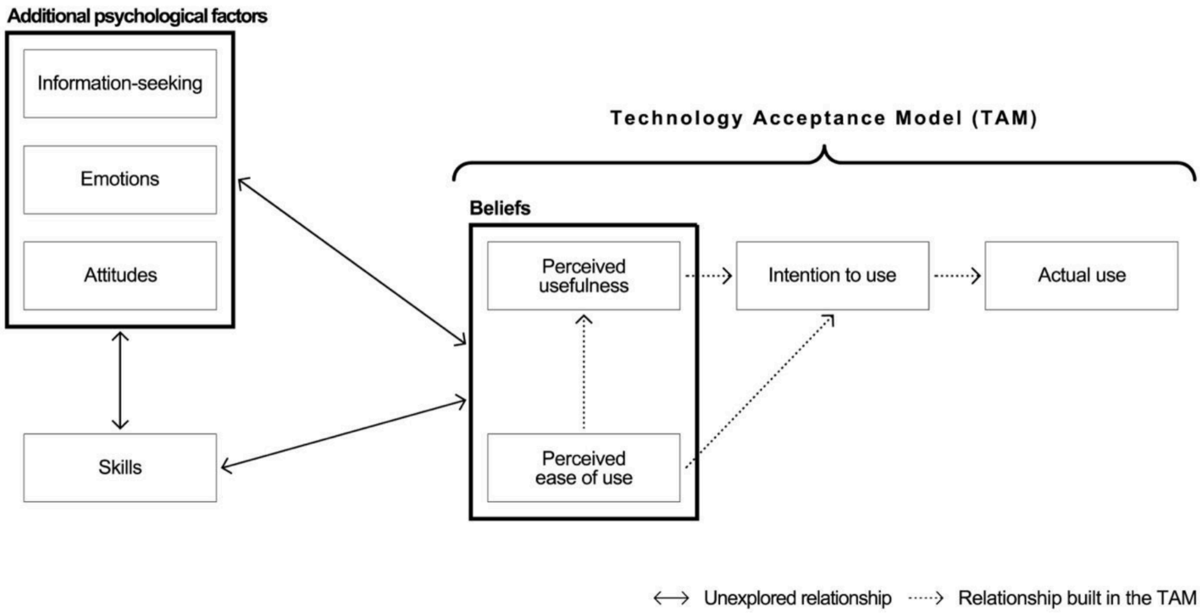

Fig. 1. Technology acceptance model, additional psychological factors, and skills. Elaboration of the authors based on Venkatesh and Davis (1996).

of these skills.

Interviews were recorded and automatically transcribed by two digital applications: Otter.ai for interviews in English and Amberscript for interviews in Italian and French. After processing the conversations with these speech-to-text applications, all written transcriptions were checked for correctness and completeness. Since the study was conducted by a multilingual research team[3] (Martin-Jones et al., 2016), all transcriptions were manually revised in their original language. In addition, the multilingual advantage made it possible to complete the thematic analysis of the interview data without altering the original languages, avoiding any possible variations in the intended meaning, which could have been lost during the translation process.

3.3. Data analysis

Given the significant amount of structured qualitative data, the interview transcripts were analyzed using NVivo as a supporting tool and by applying the following tenets of interpretive research to discern between first order (close to the language of interviewed actors) and higher-ordered categories (Gibbs, 2007; Gioia et al., 2012). By adopting a thematic coding approach, we initially examined the meaning of words and the structure of the sentences, thereby developing a preliminary list of key concepts (first-order coding) that were then aggregated into common themes (second-order coding) and connected to TAM-related aggregate dimensions (third-order coding). All members of the research team were involved in the coding process; based on our respective language skills, we analyzed the interview transcripts independently and elaborated our own list of concepts and themes, linking them to the building blocks of the TAM (see Fig. 1), which functioned as aggregate dimensions. The outcome of the coding was subject to validation by means of multiple open discussions among all researchers. This internal validation process was iterative and resulted in the organized data structure presented in Table 2.

Phrases and terms were coded manually to highlight concepts and patterns of meaning within the data. This first phase produced 406 coded passages. These segments of text include statements on different skills and psychological factors influencing their acquisition. For example, comments on integrating and elaborating existing online material or developing new online content were grouped under the first-order concept *Digital Content Creation*, whereas comments on the informal knowledge shared among peers were grouped under the concept *Word of Mouth*. This initial coding led to the identification of 31 first-order concepts. For each of these concepts, we provide a sample of the most significant coded passages in Appendix B.

Links among these concepts were then established, to develop distinct clusters of themes. These themes characterize the adoption process of SFTs. To provide an example, the first-order concepts related to know-how and abilities that are not specific to the use of digital technologies – such as agronomic knowledge and data interpretation – were grouped into the second-order theme *Non-Digital Skills*. This clustering process resulted in the identification of 11 second-order themes. As represented in Table 1, these thematic clusters were finally grouped into theoretical dimensions corresponding to the TAM components and the additional psychological concepts examined in Section 2 and outlined in Fig. 1. For instance, the second-order themes *Digital Skills* and *Non-Digital Skills* were coded as *Skills,* while *Perceived Usefulness* and *Perceived Ease of Use* were linked to the theoretical dimension *Beliefs.*

4. Findings

This section presents the results of our analysis. Interviewees across the three countries agreed that the beliefs of farmers related to smart agriculture technologies are shaped by their skills, emotions, and personal attitudes. Skills have a direct influence on the PEOU of SFTs, while their PU is affected by the personal attitudes of farmers and the emotions triggered by the technology itself. Information-seeking also plays a pivotal role in the formation of beliefs within the farming community.

4.1. Beliefs

Interviewees confirmed that beliefs about the usefulness and ease of use of SFTs are key in determining the intentions of farmers to adopt these technologies. Such beliefs are shaped by intrinsic characteristics of SFTs (such as the demonstrability and quality of their outcomes), as well as factors that are beyond the control of technology suppliers. Accordingly, in the view of interviewees, “changing the perception of a new technology is almost more important than the technology itself” (I.26).

[3] Within our research team, one member can speak English, French, and Italian, whereas all other researchers can speak either English and French, or English and Italian.

Table 1
Data structure (N = Number of coded passages)

Concepts		Themes	Aggregate dimensions
First Order		Second Order	Third Order
1	Communication and collaboration (n=31)	Digital skills	Skills
2	Digital content creation (n=24)		
3	Information and data literacy (n=20)		
4	Problem solving (n=14)		
5	Safety (n=37)		
6	Agronomic knowledge (n=9)	Non-digital skills	
7	Data interpretation (n=17)		
8	Productivity gains (n=26)	Perceived usefulness	Beliefs
9	Cost saving (n=12)		
10	Environmental benefits (n=13)		
11	User-friendliness (n=27)	Perceived ease of use	
12	Level of automation (n=5)		
13	Convenience of use (n=11)		
14	Curiosity (n=5)	Positive attitudes	Attitudes
15	Willingness to learn (n=6)		
16	Open-mindedness (n=5)		
17	Conservative mindset (n=6)	Negative attitudes	
18	Skepticism (n=3)		
19	Boredom (n=2)	Annoyance	Emotions
20	Lack of time (n=5)		
21	Technophobia (n=4)	Fear	
22	Fear of being replaced (n=4)		
23	Fear of losing control of data (n=12)		
24	Trust in technology (n=7)	Trust	
25	Trust in other people (n=10)		
26	Classroom education (n=29)	Formal information-seeking	Information-seeking
27	Training from tech providers (n=16)		
28	Trade fair (n=13)		
29	Word-of-mouth (n=19)	Informal information-seeking	
30	Peer observation (n=9)		
31	Social media (n=6)		

4.1.1. Perceived usefulness

The PU of smart technologies within the farming community depends on the extent to which agribusinesses believe that “smart technologies bring simplicity and generate many positive outcomes for the management of the business” (I.16). The data analysis clarified that such positive outcomes encompass cost savings and productivity gains, together with environmental benefits. However, their perception is not consistent within the sector.

Some farmers still believe that the benefits of SFTs do not outweigh their costs, and others are simply unaware of the opportunities that technology may offer them. Overall, it was agreed that the PU of smart technologies largely depends on the demonstrability of their outcomes, which farmers learn about from their own experience or the information reported by third parties. However, in some cases, it was highlighted that farmers remain skeptical about the benefits of SFTs even after being thoroughly informed and instructed about their potential uses and outcomes.

4.1.2. Perceived ease of use

The PEOU of SFTs is predominantly determined by the overall know-how required to use these technologies, which in turn depends on how smart technologies are designed and supplied to farmers. Even technology vendors recognized the importance of developing devices and applications that are intuitive and can be used without relying on highly skilled staff or trained operators, because farmers “don’t want something that takes a long time to learn” (I.03).

Furthermore, the PEOU of SFTs is also affected by their convenience when compared to traditional methods and tools. For example, experts noted how going through a large amount of data collected by a drone or satellite could be more time-consuming than observing the same phenomenon directly, while walking in a field. On the other hand, the practicality of smartphone-based applications was emphasized, as these services can be accessed by farmers in multiple locations, even when they are in the fields.

4.2. Skills

The interviewees also confirmed that using smart technologies requires a wide set of competences, including but not limited to digital skills. The latter encompass a wide range of skills in the context of communications, data management, problem solving, content creation, and health and safety protection. All these dimensions were considered to be relevant for agribusinesses, with some differences emerging across various types of SFTs. For example, interviewees noted how coding skills are not required to operate most of the technologies currently available to agribusinesses, but they are going to become increasingly relevant with the diffusion of artificial intelligence. However, it was confirmed that farmers adopting smart technologies must at least have a basic level of digital literacy.

Digital competences are not the sole skills that farmers should develop to use SFTs. Interviewees stressed the importance of analytical skills that allow farmers to read and interpret the data collected by digital devices and applications, and then apply these data to make both operational and strategic decisions. Agronomic knowledge is also deemed necessary to maximize the value that agribusinesses can derive from the data collected and elaborated by smart technologies.

Overall, the interviewees downplayed the influence of skills on the adoption and usage of SFTs. Although farmers have often been described as lacking digital skills, interviewees agreed that most of them have some familiarity with digital technologies because they have been using smartphones or computers for personal needs, commercial and managerial activities, or to access e-government services. The experience with these devices and applications has allowed farmers to acquire a minimum level of digital skills and to develop some confidence in the use of smart technologies.

Furthermore, it was recognized that “people in agriculture are great problem solvers” (I.01) and “learning how to use the smart technology is just one of those things that will become part of that problem-solving set” (I.07). What really matters is the willingness and ability to learn about SFTs, which primarily depends on attitudes and information-seeking behaviors.

4.3. Attitudes

The data emphasizes the existence of a “psychological restraint to the use of SFTs” (I.12), which does not necessarily reflect the level of competence and knowledge of farmers. In fact, it was reported that some agribusinesses purposefully decide not to engage with smart technologies, despite possessing some digital skills and being aware of their opportunities. According to the interviewees, this depends on the personal attitudes of farmers towards new knowledge and new technologies

A negative attitude is characterized by a skeptical and conservative mindset that makes farmers reluctant to abandon traditional methods and engage with new technologies. According to some interviewees, such a negative attitude is more likely to be found in small farms and among older farmers. However, others reported that even micro-businesses may display a strong inclination towards smart technologies if their founders or managers are predisposed towards experimenting with innovative methods and tools. Likewise, it was noted that there are “some rather old people that, instead, have a very positive attitude towards technology” (I.12).

Such a positive attitude is primarily associated with personal traits, such as willingness to learn, curiosity, and open-mindedness. At an organizational level, this positive attitude reflects the inclination of the management and workforce towards "look[ing] beyond the organization and open[ing] to what happens in the neighboring firms and to new ideas" (I.10). New entrants in the agribusiness sector are expected to further boost this attitude, since young individuals and first-generation farmers are perceived to be more interested in new technologies and more willing to learn about them.

4.4. Emotions

From the data, it emerged that the attitude of farmers is also shaped by the emotions that they feel towards smart devices and applications. Negative emotions, such as fear and annoyance, generate skepticism and reinforce a conservative mindset. Conversely, positive emotions, such as trust, help farmers to develop an open-minded and curious attitude towards new technologies.

4.4.1. Annoyance

SFTs may generate feelings of annoyance within the farming community. Some agribusinesses experience frustration when they have to deal with multiple devices and applications that are based on different standards and are not interoperable with each other. Due to this interoperability issue, SFTs might be perceived as time-consuming tools, and farmers "have notoriously low thresholds on time wasting" (I.03).

Furthermore, interviewees in Italy and Belgium noted that some farmers, when presented with SFTs, felt as if their expertise was being questioned and underestimated. Consequently, they expressed skepticism on the ability of smart technologies to outperform long-standing methods and defended the superiority of their decisions over those made by automated machines and digital tools.

4.4.2. Fear

This behavior reflects the fact that some agribusinesses "feel almost ousted" (I.11) by smart technologies. STFs are perceived as a threat; there is a fear that digital transformations will replace farmers with machines and result in small independent agribusinesses being acquired by large food-processing companies.

In addition to the fear of losing their jobs and independence, farmers are also scared of losing control of the data collected and generated while using SFTs. An interviewee reported how agribusinesses, when approached by technology suppliers, have shown "a fear of sharing information" or even the "suspicion of being spied on" (I.14). This reflects a more general concern about the intellectual property of data and the risks that data may be monetized by technology suppliers, without any benefits or remuneration for the agribusinesses.

Some interviewees also referred to a generic fear of technology or technophobia. Interviewees in Italy noted that this is not limited to the agribusiness sector but affects the whole society. A technology developer in the UK, instead, suggested that technophobia is primarily linked to the attitude of individuals and how open they are to learning about new technologies.

4.4.3. Trust

Another emotion shaping the attitudes and beliefs of farmers is the trust that they feel towards technology and its suppliers. Agribusinesses do not adopt SFTs because they "do not trust the outcomes deriving from the application of certain technological tools" (I.12). This reflects the fact that the benefits of using smart technologies cannot be seen immediately or experienced directly, and that farmers are often reluctant to use something that has not been tested by others or has not been proven to work in the field. It has also been suggested that such a lack of trust is due to the limited confidence some farmers have in technology and their limited skills.

Trust towards producers of SFTs and other actors in the agriculture sector also emerged as a crucial factor. Interviewees emphasized the role of "trusted advisors" (I.02), such as trade organizations and agronomists, that are recognized as reliable sources of information and contribute "to creating that compelling narrative that helps people to give it a go" (I.01). The creation of strong collaborations between agribusinesses and technology suppliers also emerged as an additional priority to overcome negative attitudes towards smart technologies in the agribusiness sector.

4.5. Information-seeking

Much emphasis was placed on the role that information plays in influencing the skills, attitudes, beliefs, and emotions of the farming community. In the view of the interviewees, knowledge dissemination is crucial to raise awareness among agribusinesses and help them to "overcome the emotional impact that hinders the use of technology" (I.16). Such information can be retrieved by farmers through several formal and informal situations: classroom education, training from technology providers, word-of-mouth, peer observation, and social media.

Interviewees noted how educational institutions are increasingly shifting their focus towards SFTs and integrating digital skills and experiential learning in their curricula. This shift in the focus on the education system is expected to help agribusinesses expand their skillset and address those attitudinal factors that are constraining the adoption of smart technologies in this sector. Nevertheless, their impact in the short term may be limited because of the long time required to develop new curricula and transfer such knowledge from an academic to a practical setting. Furthermore, many farmers cannot benefit from such educational opportunities because they lack the resources and formal titles required to access university courses

Alternatively, training is being provided by farmers unions and other associations promoting SFTs. Farmers unions have been organizing ad-hoc events to raise awareness of smart technologies and put farmers in touch with the developers of these technological solutions. Technology suppliers are also offering training to teach their users how to operate smart devices and applications and to raise awareness of their multiple functionalities and potential benefits.

In general, interviewees agreed that experiential learning is more effective than classroom education, "as it allows [them] to see first-hand the benefits that the technology can provide" (I.10). Accordingly, on-field demonstrations were praised for showing farmers how SFTs work in practice. Likewise, trade and agricultural fairs emerged as opportunities for farmers to learn about smart technologies through direct experience or by exchanging views with exhibitors and others attending these events.

The role of peers was particularly emphasized; given their "sense of community, farmers understand the farmers" (I.01), and they can learn from each other through sharing experiences, advice, and perspectives on the practical applications of smart technologies. Word-of-mouth emerged as the "major channel through which farmers continue to acquire information" (I.09). This information exchange primarily occurs via physical spaces, such as pubs or local markets, that act as knowledge hubs where farmers meet regularly and informally share information about new techniques and solutions. Furthermore, the word-of-mouth from professionals offering services to agribusinesses, such as agronomists and contractors, was particularly valued given their broad expertise and vast network within the farming community.

Social media were also recognized as facilitating such an interaction in the United Kingdom and Belgium. However, their role was questioned by Italian interviewees, who remarked on the importance of in-person interactions and physical proximity, enabling farmers to directly observe how others are using SFTs and benefiting from them. Across the three empirical settings, the observation of neighbors' experience was described as "immediately trigger[ing] the curiosity" (I.03) of farmers and pushing them to trial new technologies.

5. Discussion

The analysis in Section 4 clarifies the role that psychological factors play in skill development in the context of smart technology adoption, evidencing the interplay that exists between skills, emotions, attitudes, and beliefs. While specialized skills are – at least to a certain extent – required to use smart technologies, it has emerged that developing or acquiring these skills is not the major obstacle to the adoption of smart technologies in agriculture. More crucial is overcoming the emotional and attitudinal barriers that shape the beliefs of individuals about SFTs and affect the extent to which they are willing to learn how to operate smart devices and applications.

Drawing upon these findings, we propose a conceptual model (see Section 5.1) that expands the TAM to reflect how skills and psychological factors influence each other and affect the adoption of smart technologies. The theoretical implications of our research are then discussed in Section 5.2, followed by the implications for policymakers and practitioners in Section 5.3. The limitations of this study are discussed in Section 5.4, which also outlines recommendations for future research.

5.1. Integrating psychological factors and skills into the TAM

As shown in Fig. 2, we unpack how emotions, information-seeking, skills, and attitudes influence the beliefs and behaviors of individuals and organizations in the context of digital technology adoption. Consistent with Frijda et al. (2000, p. 5), we comprehend emotions as mental states encompassing “feelings, physiological changes, expressive behavior, and inclinations to act”, while beliefs indicate propositions that individuals consider to be true. Information-seeking refers to the “effort to acquire information in response to a need or gap in knowledge” (Case, 2002, p. 5). We also introduce the concept of *attitude to learning*, which we define as the disposition of an individual or organization towards the exploration and acquisition of new knowledge.

The *attitude to learning* is a characteristic of individuals or organizations. At an individual level, it reflects personality traits, such as curiosity and propensity to take risks, that are known to make individuals more willing to engage with and acquire new knowledge (Darban & Polites, 2016; Vogl et al., 2019). The *attitude to learning* of an organization is shaped by the personal attitudes of its members, as well as its organizational culture, which may be more or less open to new ideas and supportive of acquiring new knowledge (Ahlgren & Tett, 2010; Hailey & James, 2002).

Although being described as mental dispositions rather than temporary states, attitudes are not static (Frijda et al., 2000). They are affected by emotions, beliefs, and information that contribute to shaping the inclination of an individual or organization towards a specific object. At the same time, psychologists agree that attitudes also have an influence on beliefs, emotions, and behaviors (Albarracín et al., 2005). All these psychological factors, in fact, are considered to be strictly interrelated. For instance, when individuals are exposed to information that is inconsistent with their beliefs or attitudes, they are likely to experience negative emotions (Harmon-Jones et al., 2000). On the other hand, the beliefs and attitudes of individuals determine to what extent they assimilate new knowledge and how they react to external stimuli (Fiedler & Bless, 2000).

Our data evidenced that the *attitude to learning* is what triggers the process underlying technology adoption. Based on the experience of the interviewees, the curiosity and open-mindedness of non-users pushes them to learn about and adopt smart technologies. Such an attitude propels information-seeking (Fig. 2, circle 1), that contributes to shaping emotions and beliefs about the new technologies (circles 2a, 2b). Positive emotions and beliefs reinforce the *attitude to learning* (circles 3a, 3b, 3c), thereby leading to further information-seeking (circle 4) to gain the skills needed to adopt smart technologies (circle 5). The acquisition of such skills also counteracts negative emotions (circle 6) and consolidates positive beliefs (circle 7), thereby leading to the actual usage of new technologies in addition to reinforcing a positive *attitude to learning*.

Despite its centrality in our model, however, the *attitude to learning* is not a *conditio sine qua non* for the adoption of smart technologies. Our findings show that information on smart technologies is not always purposefully sought after, but it can be unconsciously acquired via informal channels and in unstructured circumstances. This benefits the individuals who do not naturally display a proactive *attitude to learning*, as has been discussed in the literature on second language acquisition – see, for example, Krashen (1981) – but it can develop after individuals are exposed to information that contributes to the generation of positive emotions (circle 2a) and positive beliefs (circle 2b).

Information gathered in informal (word-of-mouth, indirect experience through observation of peers) and formal situations (demonstrations, trial events) can alter those negative emotions that hamper the

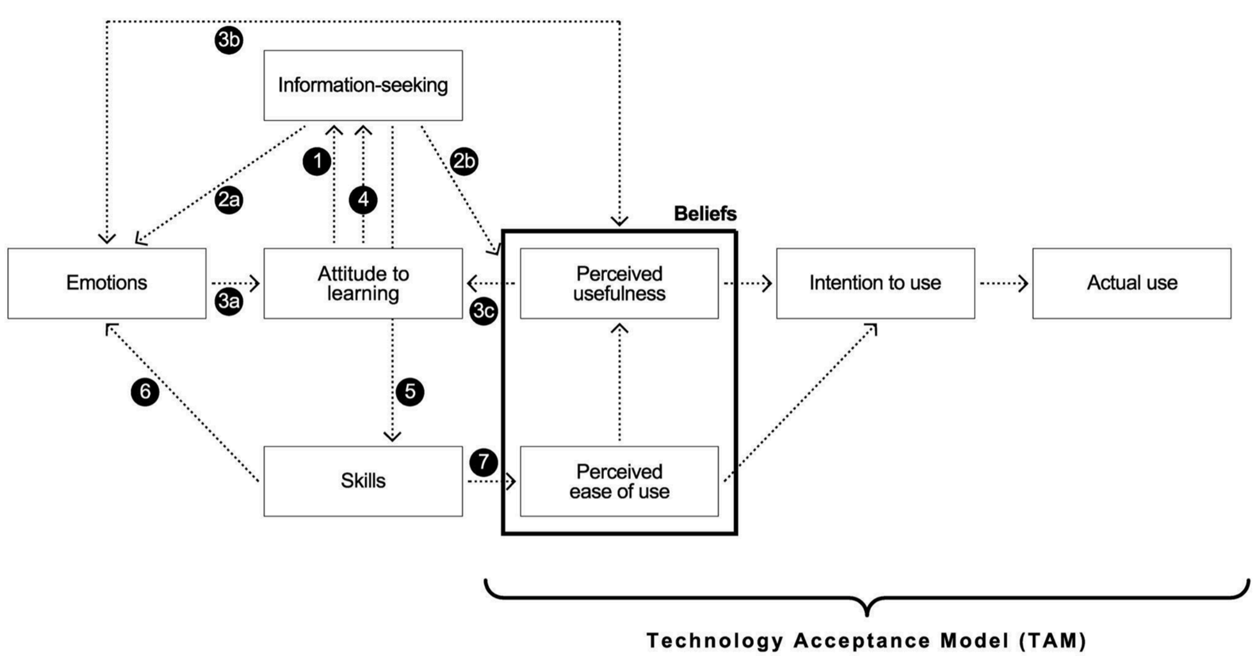

Fig. 2. Integrating psychological factors and skills into the Technology Acceptance Model

adoption of new technologies (circle 2a). The word-of-mouth from peers and advisors or the direct experience of new technologies during trial events and public demonstrations help non-users to overcome their fears or skepticism and develop a sense of trust towards new devices and applications. As observed by Darban and Polites (2016), such positive emotions encourage non-users to learn more about these technologies (circle 3a) and contribute to shaping positive beliefs about their usefulness and ease of use (circle 3b). In fact, non-users are more likely to perceive a new technology to be useful or easy to use once their concerns are addressed and overcome (Partala & Saari, 2015).

Beliefs are also directly shaped by information (circle 2b), which raises awareness in non-users of the usefulness and ease of use of new technologies (Choi, 2019). Non-users develop such awareness through formal (classroom education, trial events) and informal sources (word-of-mouth, direct observation of peers) that provide evidence of the benefits of new technologies and their usability. Gaining this knowledge, mainly through direct or indirect experience, encourages non-users to develop a positive *attitude to learning* (circle 3c). Positive beliefs also contribute to overcoming negative emotions (Partala & Saari, 2015); when they become aware that new technologies are useful and easy to use, this contributes to reducing the feeling of annoyance or mistrust that non-users may experience towards a new device or application (circle 3b).

Once a positive attitude towards innovation is developed or reinforced by positive emotions and beliefs, the non-users will engage in further information-seeking (circle 4) with the purpose, this time, to gain the skills needed to use the new technology (circle 5). Looking at this from a different perspective, it also implies that non-users exposed to information on new technologies are unlikely to develop the related skills if they have not first developed a positive *attitude to learning* that motivates them to invest time and resources in developing new skills, as previously observed by Krashen (1981) with regard to second language acquisition.

Gaining skills reinforces the belief that technologies are easy to use, which in turn affects its *perceived usefulness* (circle 7). In fact, as emerges from the interviews, if a new technology is perceived to be easier to use than an old one, the new one is also perceived to be more useful. These positive beliefs eventually contribute to shaping a positive *attitude to learning*, thereby incentivizing individuals and organizations to continuously engage in information-seeking to expand their skills and take advantage of new and emerging technologies. Furthermore, the acquisition of skills is likely to influence how individuals and organizations feel about technology (circle 6). The increased confidence deriving from a more in-depth knowledge of technology helps to contrast those emotions of fear or annoyance that keep non-users away from it.

5.2. Theoretical implications

The conceptual model in Fig. 2 integrates the TAM to outline how the interplay between psychological factors and skills influences technology adoption and usage. Both skills and psychological factors have already been discussed in the context of technology adoption and in the TAM literature (as highlighted in Section 2). However, such a discussion has largely been unsystematic, focusing on single components (such as emotions and attitudes) rather than providing a comprehensive overview of how psychological factors and skills affect the different steps of the TAM. Furthermore, as noted by Darban and Polites (2016), research on technology acceptance has largely overlooked the role of emotions in the learning process that leads to the acquisition of digital skills.

Our paper bridges this gap by outlining how the process underlying the acquisition of skills and the formation of beliefs leads to the adoption and usage of new technologies. This process elaborates on the empirical findings derived from our analysis, but it is also grounded in existing psychological research. The relationships between the psychological factors formulated in our model are consistent with theories in the field of psychology, where scholars have largely emphasized how different mental states (emotions and attitudes) influence each other and affect beliefs and behaviors (for example, see Albarracín et al., 2005; Fishbein, 1975; Fiedler and Bless, 2000; Frijda et al., 2000). The effects of these interactions have also been widely observed in the context of information sciences and information systems management (Kay, 2008; Savolainen, 2014).

Building on these well-established debates that have developed outside the TAM literature, our findings can contribute to an explanation of the overlooked interplay between skills, psychological factors, and technology acceptance (Darban & Polites 2016) beyond the empirical setting of this research (as discussed in Section 5.4). As summarized in Section 2, psychological factors are known to influence the acceptance of a wide range of digital technologies, from computers (Davis et al., 1989) to emails (Adams et al., 1992) and broadband (Irani et al., 2009). Whether the nature or intensity of the emotions at stake in technology adoption may vary, there is no doubt that they play a crucial role in shaping beliefs and attitudes of users and non-users.

By introducing psychological factors as antecedents and determinants of skill development in the context of technology adoption, we confirm the crucial role that emotions and information-seeking can play in shaping beliefs and behaviors related to the use of innovation. Consistent with Martin and Briggs (1986), emotion and cognition are conceived as interrelated rather than distinct. Accordingly, beliefs are influenced by what individuals feel and not just what they know, which explains why negative beliefs about technology may persist even when non-users are made aware of their usefulness and ease of use.

This psychological mechanism does not challenge nor diminish the role that knowledge plays in shaping beliefs and behaviors related to technology adoption. As a matter of fact, our empirical data showed that information not only influences individuals and organizations at the cognitive level but also contributes to shaping their emotions, as noted by Sharot and Sunstein (2020). This has important practical implications (discussed in Section 5.3), but also contributes to developing a more precise and in-depth theoretical understanding of how decisions on technology adoption and usage are made.

As to the relationship between skills and emotions, our study confirms that low skills may result in negative feelings towards technology – as previously stated by, among others, Korukonda (2005). However, it should be noted that, compared to earlier studies investigating the adoption of computers and information systems (Brosnan, 1999; Kay, 2008), the influence of skills on emotions seems less prominent in the context of smart technologies. Our analysis suggests that, overall, the design of digital technologies has evolved in a way that has made devices and applications more user-friendly and thus easier to use, thereby requiring a lower level of skill. Furthermore, the increasing diffusion of smartphones and computers for both personal and business purposes has allowed most individuals and organizations to gain at least some familiarity with digital technologies. Consequently, technophobia and other negative emotions associated with the use of smart devices and applications depend less on the level of skill that an individual possesses, but rather reflects more generic concerns about the fairness of digital transformation and the effects that these concerns may have on, for example, job security and data protection.

Furthermore, our study showed that emotions can have an indirect impact on skills, through the *attitude to learning*. The concept of attitude is often discussed in the literature on technology adoption and innovation diffusion. For example, Waarts et al. (2002, p. 415), citing Rogers (1995), observed how "the formation of a favorable or unfavorable attitude towards an innovation precedes the decision to adopt". *Attitude to use* recurs in some studies that apply the TAM as a mediating factor between the intention to use a technology and the actual usage behavior (Chuttur, 2009; Legris et al., 2003; Ma & Liu, 2004).

Our model proposes an alternative approach that focuses on the attitude of individuals towards learning, which also has implications for organizational-level settings. Such an attitude does not directly affect the behaviors of users and non-users but represents a key component in what Grover and Goslar (1993) describe as the initiation phase of innovation diffusion, concerning the collection and evaluation of information. This information directly affects the final behavior, by shaping beliefs and emotions (Sharot & Sunstein, 2020).

To the best of our knowledge, the concept of *attitude to learning* has never been applied in the context of technology acceptance. Previous studies have used similar concepts, such as self-efficacy or attitude of confidence (Adrian et al., 2005; Hsu and Chiu, 2004; Marangunić & Granić, 2014; Roca & Gagné, 2008). However, these constructs describe how non-users perceive themselves as learners, while in our model *attitude to learning* reflects their inclination towards the exploration and acquisition of knowledge. Relatedly, in the previous literature, attitude of confidence is portrayed as an element that shapes PEOU and the intention to use SFTs due to how they perceive their ability (Michels et al., 2021), whereas in our model *attitude to learning* is conceptualized as a preliminary factor that will determine if individuals are willing to seek out information for skill development. The same concept is used in education studies, alongside that of *willingness to learn* (Darban & Polites, 2016; Hamurcu, 2018; Pierce et al., 2007). We echo the findings of this literature here, since *attitude to learning* is seen as a prerequisite to the motivations behind learning a skill (Krashen, 1981; Pierce et al., 2007). Despite a clear-cut definition is missing in the literature, scholars agree that this attitude encompasses cognitive, behavioral, and affective components, and it positively affects those psychological factors that may hamper learning, such as affective filters in second language education (Getie, 2020).

Introducing this concept into the context of technology acceptance contributes to clarifying how the decision to adopt and use a new technology is affected by cognitive and emotional components. In the view of TAM literature, beliefs about technology are shaped by cognitive processes, or the "cognitive responses" of PU and PEOU (Davis, 1986, p. 24). Therefore, non-users decide to adopt a technology when they become fully aware of the benefits that they can derive from it. Even when the role of social pressures is recognized, their influence is still limited to the cognitive level. For example, the subjective norm pushes non-users to adopt technology because of the reputational benefits that they can obtain from it (Chuttur, 2009; Venkatesh & Davis, 2000), without considering the emotions that social pressures also entail.

Our model does not question the relevance of cognition in technology acceptance – which rather found additional support in our empirical data – and its emphasis on the role of information-seeking. However, we acknowledge that cognitive aspects are strictly interconnected with emotional factors. This contributes to better explaining some behaviors regarding technology adoption. For instance, the fact that some individuals and organizations still refuse to adopt a technology, even when they have been made aware of its benefits or advantages.

Having clarified the influence of psychological factors, our findings can also add insight into the role of other factors normally included in the TAM, such as subjective norm and experience. For example, the positive relationship between experience and *perceived usefulness* (Venkatesh & Davis, 2000) can be explained by the fact that the former helps non-users to build a sense of trust towards new technologies. Subjective norms can also be explained in terms of trust; the pressure coming from the peers who are perceived as trustworthy helps non-users to develop positive beliefs towards new technologies.

Furthermore, by outlining the interrelations between psychological factors and technology acceptance, our model recognizes that individuals play a proactive role in the sense-making of technology (Mesgari & Okoli, 2019), and they cannot be seen just as passive recipients, acting in response to utilitarian incentives. In fact, our study suggests that the decision to adopt technology entails a multiplicity of cognitive and emotive instances that are not necessarily intrinsic to that technology. For example, the fears expressed by farmers with regard to data protection are not specific to SFTs but echo wider concerns caused by structural imbalances in the digital economy and in the agriculture sector. Likewise, developing a positive *attitude to learning* within agribusinesses requires a broader cultural shift that goes beyond the agriculture sector to encompass the whole society.

These aspects are largely overlooked in the TAM literature. Our model overcomes some of these limitations by evidencing the complexity of technology adoption as both a cognitive and emotional process, where psychological factors and skills are strictly interrelated and influence each other. Since beliefs about usefulness and ease of use are affected by all these factors, to sustain technology adoption it is fundamental to operate on both levels rather than prioritizing one over the other. This requires a radical change at a system-level, as discussed in the following subsections.

5.3. Practical and policy implications

As part of their global efforts to tackle climate change and support the achievements of Sustainable Development Goals (SDGs), accelerating the diffusion of smart technologies has become a priority for national governments and international organizations. A variety of initiatives are currently in place to support the adoption of these technological solutions, including free training, financial incentives, economic subsidies, and regulatory obligations. The model presented in Section 5.1 can help policymakers and other parties involved in the digital transition of the agribusiness sector (such as educational institutions and trade organizations) to enhance their ongoing interventions and develop new initiatives that better address the barriers to the adoption of SFTs.

As noted above, information-seeking is a crucial component of the psychological and cognitive processes underlying the adoption of technology. Multiple sources of information affect these processes, from classroom education to word-of-mouth, experiential learning, and peer observation. To date, most emphasis has been placed on educational programs and knowledge providers to support the development of digital skills in the agribusiness sector (Rijswijk et al., 2019). Our study confirms the importance of these formal sources of information, but also highlights the key contribution of informal sources, such as word-of-mouth and peer observation, in shaping positive beliefs and generating trust towards SFTs. In other words, formal training and knowledge providers are still necessary to raise awareness and transmit skills around smart technologies, but they appear insufficient to address the psychological restraints to the adoption of these technological solutions.

Informal sources of information are, by definition, bottom-up and unstructured, hence they cannot be initiated or managed top-down by industry players. However, these actors can still facilitate peer-to-peer exchanges of information, by offering a physical or virtual space for non-users to share views and advice on smart technologies (Meyers et al., 2013). For example, farmers' unions could establish online platforms or organize events where their members can discuss and compare their experiences with SFTs.

From a policy perspective, our findings pave the way for behavioral interventions that use nudges as instruments of policy intervention in the context of smart technology adoption. A nudge enhances the likelihood that an individual will make a particular choice, or behave in a particular way, by intervening in cognitive processes that can be triggered to favor the desired outcome (Thaler & Sunstein, 2008). When it comes to word-of-mouth, nudging strategies should be focused on the design of narratives and story-telling solutions that collect and store relevant information about smart technologies in the form of a story, inducing mental imagery, interest, and narrative transportation in the mind of non-users (Esposito et al., 2021; van Laer et al., 2014). Drawing on Beckman and Barry (2009), we suggest developing stories that describe the uses and usability needs of smart technologies. Moreover, these stories should express meaning-based needs and create emotional connections with the non-users to influence both the cognitive and emotive processes underlying the adoption of these technologies.

Both educational instruments and behavioral interventions should not be limited in time, but rather support the lifelong learning of farmers about both established and emerging smart technologies. In fact, the advent of new devices and applications for agriculture, integrating additional and more complex technologies such as artificial intelligence, is likely to pose new cognitive and emotional challenges (Long et al., 2016). Hence it is crucial that multiple informational instruments remain in place to shape positive beliefs, address negative emotions, and provide the supplementary skills needed to keep up with technological changes.

It is worth emphasizing that the support for information-seeking is not an alternative to financial measures. For some agribusinesses, especially small farms in sectors characterized by low margins, economic incentives and public subsidies remain indispensable to overcome the upfront investment required to implement SFTs (Barnes et al., 2019). However, the effectiveness of such financial support risks to remain limited if it is not accompanied by educational programs and other learning opportunities.

Although derived from a case study on smart technologies in agriculture, the implications of this paper are also relevant in other socio-economic contexts. Our findings can help to improve existing initiatives in support of digital inclusion. These initiatives should be designed to leverage the different attitudes to learning of individuals with limited digital skills and include ad-hoc measures to target the non-users that, albeit possessing the required skills, are reluctant to use smart technologies due to emotional barriers (Darban & Polites, 2016).

Furthermore, the model discussed in Section 5.2 could prove useful to foster the diffusion of smart technologies in other industries. In the professions with a strong sense of community (such as healthcare and legal services), the exchange of information and experiences between peers should be encouraged to generate a shared sense-making of smart technologies that could help to overcome emotional and attitudinal barriers to their adoption. Trade organizations could have a proactive role in this, providing their associates with access to a wide range of both formal and informal sources of information on smart technologies (Gekara et al., 2020).

At a higher level, this paper evidences the need for an update of existing policies in support of digital literacy and a radical shift in the mainstream narrative on digital inclusion. While nowadays their focus is solely on the development of digital skills (European Commission, 2020b), policymakers should recognize that limited engagement with digital technologies also reflects a complex set of psychological factors, exacerbated by limited access to or unavailability of information. This calls for systemic action to support the information-seeking of non-users and help them overcome the emotional and cognitive gaps that cause them to refrain from adopting smart technologies.

5.4. Limitations and recommendations for future research

Despite its rigor, this study has some limitations that call for further research to expand its empirical base and corroborate its theoretical and practical contribution. Despite allowing for an in-depth and meaningful comparison, our data analysis is based on three empirical settings that are solely representative of the European context and the agribusiness sector. Future research should replicate our investigations in other geographic and sectoral contexts to further expand the generalizability of our findings. Replicating this study with a larger sample of participants would also help to achieve a statistical generalization of our conceptual model.

Drawing upon the psychology literature and previous research on technology adoption (Darban & Polites, 2016; Frijda et al., 2000), our model provides a detailed and comprehensive conceptualization of the relationships existing between psychological factors, skill development, and smart technology adoption. Future research, however, is needed to determine the intensity of these relationships and to ascertain how the influence of some factors vary across different geographic and sectoral contexts. Furthermore, the impact of socio-economic variables – such as the age of non-users, the size of their organizations, or the complexity of technology – should be further investigated to understand whether and how they affect the relationships between psychological factors and skills.

6. Conclusions

Our study proposes a new conceptual model that expands the TAM in order to reflect how psychological factors affect the development of digital skills and the adoption of smart technologies. This model has important theoretical implications as it complements the existing literature on technology acceptance by linking digital skills acquisition to the novel concept of *attitude to learning*. Despite being well-established in the research on second language acquisition, this concept has so far been overlooked by scholars in information systems management and related fields. Our paper, therefore, bridges this gap and paves the way for new research on technology acceptance.

Similarly, the findings of this paper expose the critical limitations of the European policies that support digital skills development (see European Commission, 2020b), which is a key prerequisite for enhancing smart technology adoption. As of today, policy measures in this area have primarily focused on boosting the provision of training opportunities, which remain valid instruments but are insufficient to counteract the psychological barriers that we have highlighted. Our findings show that negative emotions and a low *attitude to learning* can compromise the effectiveness of training measures. Therefore, we call for alternative approaches to policy formulation that take into account the linkages between psychological factors and skills development in the framework of smart technology use.

CRediT authorship contribution statement

Paolo Gerli: Conceptualization, Methodology, Investigation, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Jessica Clement:** Methodology, Investigation, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Giovanni Esposito:** Methodology, Investigation, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Luca Mora:** Conceptualization, Methodology, Validation, Visualization, Writing – review & editing, Supervision. **Nathalie Crutzen:** Supervision, 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.

Appendix A. Details on the interview process

Interview Code	Group	Country	Duration
I.01	2	United Kingdom	00:46:00
I.02	2	United Kingdom	00:49:00
I.03	3	United Kingdom	00:49:00
I.04	2	United Kingdom	00:38:00
I.05	3	United Kingdom	00:54:00
I.06	1	United Kingdom	00:46:00
I.07	2	United Kingdom	00:48:00
I.08	2	Italy	01:09:00
I.09	2	Italy	01:14:00
I.10	2	Italy	00:58:00
I.11	3	Italy	00:46:00
I.12	3	Italy	01:07:00
I.13	2	Italy	01:05:00
I.14	3	Italy	00:58:00
I.15	3	Italy	00:44:00
I.16	2	Italy	00:41:00
I.17	2	Italy	01:07:00
I.18	1	Italy	00:32:00
I.19	1	Italy	00:50:00
I.20	1	Italy	01:03:00
I.21	2	Belgium	00:45:00
I.22	1	Belgium	00:25:00
I.23	2	Belgium	00:43:00
I.24	2	Belgium	00:56:00
I.25	2	Belgium	00:45:00
I.26	3	Belgium	00:45:00
I.27	1	Belgium	00:28:00
I.28	3	Belgium	01:05:00
I.29	3	Belgium	00:50:00

Appendix B. Sample of the most significant coded passages

Concepts	
First Order	Representative quotations
Communication and collaboration	"Creating and managing a profile to access online services, yes they do have to do that, it's software as a service. That comes into the web plan aspect of things that I mentioned to you earlier. And that's how they manage their account and their subscription account. And it's also how they manage what tier that account is also on and what features they have access to based on their price bracket. And they can also manage devices through there and share with users like I just mentioned" (I.03)
Digital content creation	"They don't even need to insert the data because the sensor does it automatically: the only data they need to insert are the name of the fields and the type of product they are going to spread" (I.15) "So that online content, I'm sure they're having to do that too, you know, a lot of our businesses have pretty good websites. They need that, you know, retail space [because] they have to look the part" (I.04)
Information and data literacy	"If we are talking about, you know, data literacy, see, yes, we require the level of someone being able to access a website, log in, click through a series of buttons, and, you know, interpret basically what they see, you know, they plot the figures that they see. I mean, we're still trying to make it simpler, because, you know, we realize that while most people understand it, others don't" (I.05) "We include data mining in your training (...) it is fundamental for the farmer to know how to read and interpret the data" (I.10) "Farmers certainly have an understanding of data displayed through digital technologies. I am thinking of weather data, for example. In fact, his skills, he has them at the base" (I.23)
Problem solving	"Fixing technical problems. There can be quite a lot of technical problems, because obviously you're plugging an off the shelf system into custom built kind of software. But we, we have the expertise and know-how to solve these issues with the customer, so we work on a very one to one basis with customers when they have those kinds of issues" (I.03) "Problem solving, as a cross-cutting skill, they need to have it. In relation to technical problems, they rely on customer care, hence, no. But the farmers union is building up these competences to provide a consultancy service" (I.10)
Safety	"Certainly, safety of the digital technologies, data and privacy are two big parts, because we've got all of our customers' and clients' information on there, so we need to be careful there. Protecting the environment, that's what we do anyway. Protecting health and well-being, of course, that's wholly relevant to the smart farming technology" (I.06) "Protection of personal data is something that we are working very, very hard on with farmers". (I.21)
Agronomic knowledge	"Agronomic technical competences are fundamental to understand the need, aren't they?" (I.10) "If you're not a farmer or an agronomist... or someone heavily ingrained in our world, then you're not going to know what you're looking at really as far as the data that is generated" (I.03)
Data interpretation	"Sometimes we run into the issue that, like you have the more basic people that just don't understand what a graph is" (I.05) "We need to try and make sure that the farmers can read the data, because this is the real challenge, that they can read the data and then translate them in business decisions" (I.17)
Productivity gains	"Farmers are not philanthropists (...) therefore, if there is a reduction of the inputs, an increase in the productivity, it's very good! It depends on whether the cost is higher or lower than the return" (I.10) "Data can help farmers to understand soil types that they have at hand to improve productivity of their crops" (I.29)
Cost saving	"Those are the ones who tend to be quite resource hungry. And those are potentially the ones where they can see the benefits of smart technology to drive efficiency through their business" (I.02) "When the farmer sees there is return (...) because when the farmer sees that with the machine it takes an hour, while before it took a day, there is a return indeed!" (I.08)
Environmental benefits	"It's a really environmental focus as well, it's just those farmers that are really looking to improve productivity and decrease, you know, greenhouse gas outputs and to you know, decrease their inputs into their crops and the rest" (I.07) "There is this new thing that we call climate change. That's also a reason why people start looking towards farming technologies" (I.24)
User-friendliness	

(continued on next page)

(*continued*)

	"You need to be careful not to go too advanced and too clever. Otherwise, people don't understand the systems. And if you start relying on individuals, that nervous system, then that's not a strong place to be. And the more people that know it, the better and the simpler it is, the better" (I.06)
	"We need to make the technologies more accessible, making the machines simpler and the interfaces more usable, directly without intermediaries. Because intermediaries have a cost" (I.09)
Level of automation	"With newer software, it's much more automated much more intuitive, and it doesn't have the learning curve associated with it really" (I.03)
	"We have made the machine basically autonomous to move in space without the support of a driver. The driver remains compulsory, but only because of the law" (I.15)
Convenience of use	"We had an agritech farm come and talk to us about using drones to take photos of crops and kind of almost use that as a replacement for an agronomist and the drone was capable of taking something like, I think it was like 40,000 photos of the crops in, you know, a 10-minute flight. But, you know, we've kind of got to the point of what would our farmers do with 40,000 photos if they don't have the, you know, the actual software to run and filter the data, and have the technological know-how to, you know, sift through that data and actually make use of it and in a very practical way, sifting through 40,000 photos versus walking in a field with an agronomist, the agronomist is just such an obviously easy way to go" (I.07)
	"Clearly it's a matter of comfort. I can keep a smartphone in my pocket, use it when I need it, even when I am on the tractor or in the field doing some operations and so anytime there has been a massive transition towards the use of the smartphone, there has also been an increment in the use of digital services" (I.17)
Curiosity	"I don't think that to use the app that we are making you need digital skills of a certain type, but in my opinion the curiosity and propensity to use it is correlated perhaps with a positive approach to technology" (I.12)
	"What is fundamental is the cultural operation that is underway, along with the curiosity [of farmers] and the possibility [for them] to interact with generations that are more inclined, […] young people are much more curious than their parents" (I.10)
Willingness to learn	"We just look for people with a bit of, a bit of common sense, of enthusiasm, and willing to learn" (I.06).
	"This has to do with where you're at in your life, and how, how open you are to learning these kinds of new technologies" (I.03)
Open-mindedness	"The problem is not the know-how but the open-mindedness to use it" (I.05)
	"This is very important, this ability of looking forward, this ability to look beyond the organization and [to be] open to what happens in the neighboring firms and to new ideas" (I.10)
Conservative mindset	"Or the smaller farms with one or two farmers on them. They're quite comfortable and set in their ways, they are happy farming the way they are" (I.07)
	"The major limitation is the traditionalism of agriculture. It sounds like a joke, but "I always have done it this way, I always ploughed the field this way because so did my father, my grandfather, and my great grandfather" (I.15)
Skepticism	"One aspect is suspicion, which is given by ignorance" (I.17)
	"There are large firms where the agronomist in charge is more skeptical, as well as micro businesses where the entrepreneur is very much inclined" (I.11)
Boredom	"Farmers like to be in the field and independent in nature [and] don't want to spend time in front of a computer" (I.28)
Lack of time	"They don't want something that takes a long time to learn, they don't have the time for that, farmers have notoriously low thresholds on time wasting" (I.03)
	"At the moment you could have a program for managing the livestock, the irrigation, etc. I could go on and on. All different, built with different standards and conditions. The farmer cannot be bothered to deal with all this" (I.17)
Technophobia	"If you are a technophobe, you are in trouble" (I.06)
	"At some point you get kind of sick of it and you kick yourself out of it and then five years later you're completely out of touch with the newest technologies because you just don't engage with it. Yeah, technophobia is, I think, kind of inevitable" (I.03)
Fear of being replaced	"Farmers fear that they will become employees of big food processing companies or will lose their independence" (I.29)
	"The farmers that for a long time have been working in a certain way... seeing that their work is being transformed, in addition to being skeptical, they feel almost ousted, they have this sensation" (I.11)
Fear of losing control of data	"When we tell them that we use satellite data to analyze the vineyards, we are seen as spies" (I.14)
	"Farmers are quite, quite conscious of who their data belongs to if you know what I mean, or who the data that they've generated belongs to" (I.03)
Trust in technology	"Let's say that in some case the restrain is about the propensity to use technology and therefore the trust towards the outcomes of some technological tools" (I.12)
	"You can promise a lot, but without any proof. It kind of goes back into the technophobia, which also involves trust" (I.03)
	"What I gathered during many meetings with the agribusinesses is that it is not a tangible thing. I mean, if the results cannot be seen or touched, then they do not trust them, for example, the predictive models" (I.11)
Trust in other people	"When your neighbor starts doing it as well, actually he's doing that, [so you think] maybe I'll give that a try as well. It's those, it's those avenues where they can see how it applies to their farm and then people are saying "yes, you should use it" and these people tend to be trusted advisors and other farmers" (I.02)
	"What the government and the tech industry need to do is work with these groups that farmers would trust, that I could go for businesses with trust, and work with them to create that compelling narrative that helps people to give it a go" (I.01)
Classroom education	"We come across like kind of trade organizations that run kind of training programs" (I.05)
	"Everything starts from universities that are increasingly moving from a vertical, sectoral education to a horizontal, transdisciplinary one, combining topics that before were completely separate, and this though curricula that are more and more complex and articulated" (I.13)
	"Schools are trying to work a lot on these topics, that is to make students aware that digital skills are necessary in any job, even a traditional job needs to be reinterpreted through these competences" (I.10)
Training from tech providers	"She is one of the colleagues that follow the customers after the sale, not just to remind them, in specific periods and for specific operators, what they can use the platform for, but also to train them, there are some initial meetings where she shows them the platform and explains to them how it works" (I.11)
	"It'll be the person who made the sale who will be providing you with the advice on what you need to do. And that support package is vital. Otherwise, people won't do it" (I.02)
Trade fair	"It is important to organize demonstrative events to show how the technology works and what are the pros and cons" (I.09)
	"What we've experienced so far also are trade shows and events. You know where you have companies kind of doing demonstrations. These events like that tend to be a great way for operators in the field, to experience new technologies, like I said before, you know, when people start talking about it with their peers, they, that's also the point where they kind of tend to learn the best" (I.05)
Word-of-mouth	"Word-of-mouth is very important, the direct word-of-mouth from the neighbor to the firm, through the associations, and the indirect word-of-mouth through agronomists that attend to more businesses" (I.12)
	"You know farming doesn't happen in isolation, you know it takes a village if you will. And so making sure that every, you know, the contractor, making sure you know that the contractors and those who rent out maybe the combine harvester are really using the most up-to-date technologies and know-how to use them and, you know, because, of course, the machine is really smart but making sure that the data is being analyzed correctly, and all the rest" (I.07)
Peer observation	"They get their smart technology know-how from peers, either in the country or in another country" (I.04)
	"If I see what my neighbors do and he tells me, it's different. Because he told me, and if he told me, if he shows it to me, I believe it" (I.15)

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Social media	"I think there's a great sense of community. And if you could overlay that with electronic communication and create an electronic community of a civil kind, I think that's a huge opportunity" (I.01) "Breeders have discussion forums where they exchange their knowledge and personal experiences, either through Facebook or other existing forums". (I.25)

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