

Examining user engagement and experience in agri-tech

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Abstract ***Purpose.** Agricultural technologies (agri-techs) have focused on developing the AI perspective of human-AI interaction rather than human perceptions and responses. A lack of understanding of their employees' behavioral responses when interacting with advanced technologies can lead to unexpected problems in the future. Drawing on the theoretical perspective of advanced user engagement, this paper examines the impact of five different technostressors on user engagement and, consequently, user experience.*

***Design/methodology/approach.** For data collection, 464 participants from the U.S. and Asian (Singaporean) agri-tech sectors were interviewed via an electronic survey.*

***Findings.** The U.S. study showed that techno-overload, techno-complexity, and techno-uncertainty were positively related to user engagement ($t = 2.609$; $t = 6.998$, and $t = 6.013$, respectively), whereas techno-invasion and techno-uncertainty were negatively correlated with user engagement ($t = -2.167$ and $t = -3.119$, respectively). The Singapore study showed that techno-overload, techno-complexity, and techno-invasion were negatively related to user engagement ($t = -2.185$, $t = -2.765$; $t = -5.062$, respectively), while techno-insecurity and techno-uncertainty surprisingly showed nonlinear correlations with user engagement. In both studies, user engagement is positively related to user experience ($t = 2.009$ for the U.S. study and $t = 2.887$ for the Singapore study).*

***Originality/value.** First, this paper provides agri-techs with a modern framework to better predict the behavioral responses of their employees when managing AI. Second, this paper expands the equation of change in the discipline of change management by introducing the dimension of readiness.*

Keywords extended user engagement theory, technostressors, agri-tech, artificial intelligence, user experience

INTRODUCTION

Recently, the use of robots and artificial intelligence (AI) has grown tremendously and has penetrated several key business sectors and industries (e.g., healthcare, retail, etc.), proving to be rewarding for companies and investors (Aredal & Cianciotta, 2019). The agriculture sector, the focus of this paper, is no exception. As a result, the agri-tech (agriculture and technology) sector has emerged as an inevitable and transformative extension of the agriculture industry (Bloomberg, 2021).

However, to maintain sustainability and continuity, a balanced interaction between robots and humans is essential (Szollosy, 2015). In the context of agri-techs, some recent studies have focused on examining the direct impact of artificial intelligence (AI) on organizational outcomes (e.g., Issa et al., 2022); however, research examining user (employee) responses and levels of engagement in managing AI is sparse and limited. A lack of understanding of the human perspective leads to an imbalanced relationship between robots and humans, resulting in high worker/employee resistance to change (Chandrasekaran et al., 2022).

An imbalanced relationship between robots and humans, associated with unsuccessful coping, leads to the manifestation of stress-related reactions (or technostress in the context of AI) (Atanasoff & Venable, 2017). Technostress, a negative psychological stress state associated with technology use (ineffective coping) (Fischer & Riedl, 2017), is manifested by five main technostressors whose effects on user engagement are examined in this paper (i.e., techno-overload [TO], techno-

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invasion [TINV], techno-complexity [TC], techno-security [TINS], and techno-uncertainty [TUN]) (Tarafdar et al., 2007; Ragu-Nathan et al., 2008). Therefore, the research question is as follows:

RQ. What is the impact of each technostressor related to advanced service robots in agriculture on user engagement? And how does user engagement affect the user experience?

By applying the extended theoretical model of user engagement (Hart et al., 2012), this paper explores six hypothetical relationships that relate directly to the research question. Data were collected from several innovative agricultural sub-organizations (specializing in livestock, fisheries, crops, and/or forestry) in the United States and Asia (particularly in Singapore). Each sample consisted of 232 participants.

Three important gaps are addressed in this paper. First, the field of agriculture is underdeveloped in the AI literature (Nishant et al., 2020). Second, what is missing from Information Systems (IS) research is data on the impact that service robots might have on users (Collins et al., 2021), and therefore user involvement (customer or employee perspective) is not yet fully exploited (Borges et al., 2021). Third, to the authors' knowledge, there is not yet an empirical study in the agri-tech field that has conducted a cross-regional comparison between Western and Eastern markets. Therefore, the new findings may be of great value to local and international stakeholders. By addressing the above gaps, this paper provides agri-techs with a modern framework to better anticipate the behavioral responses of their employees in managing AI and expands the change equation in the change management discipline by introducing the dimension of readiness.

The remainder of this paper is organized as follows: In the next section, the terms AI, agri-tech, and technostress are explained in more detail. Then, the research model and hypothesis development are presented. This is followed by the research methods, where each study is examined separately. We then reflect on the findings and conclude with a joint discussion.

BACKGROUND

Artificial intelligence

Innovation has always been the main driving force for the development of all sectors of the economy. However, the development of innovations can be particularly disruptive as they replace traditional technologies. Cloud computing, the Internet of Things (IoT), big data, AI, and blockchain are some examples of emerging disruptive technologies that can bring both success and disappointment to businesses (Soni et al., 2020). These technologies have been recently introduced in numerous industries (finance, healthcare, automotive, agriculture, etc.), thus establishing the fourth industrial revolution, Industry 4.0.

AI is at the center of outstanding innovation performance and the key mechanism for Industry 4.0. Originally, AI provides opportunities for businesses, such as rapid detection of big data patterns, instant visualization and analysis, improved product design, and the provision of comprehensive insights (Park, 2017). AI helps companies explore real-time data and respond quickly to queries and commands (Wirth, 2018). Recently, AI has emerged as a tool for competitiveness, product/service modernization, and new business models (Campbell et al., 2020).

Numerous descriptions of AI have emerged in various research streams (Longoni et al., 2019; Berente et al., 2019; Duan et al., 2019); however, given the complexity of AI, there is still no widely accepted definition of AI to date, which has led to uncertainty among academics, researchers, experts, and policymakers (Monett & Lewis, 2018). In this paper, AI is defined as the ability of a system to accurately analyze external data, learn from that data, and use the knowledge gained to accomplish goals and tasks through adaptation (Kaplan & Haenlein, 2019).

AI is found and discussed in a variety of fields, disciplines, and domains (Dennehy, 2020). It has been shown that AI can lead to transformation in various markets and economies (Chi et al., 2020; Ali et al., 2018). AI also offers the opportunity to innovate work, improve execution, and enhance human capabilities (Dwivedi et al., 2021). Several breakthroughs have driven the recent rise of AI, such as the development of open-source neural networks and sophisticated algorithms, the reduction of hardware manufacturing and management costs, the growth of cloud-based services and automation, the accessibility of big data sources, and maintaining connection and business through the recent COVID-19 pandemic (Coombs, 2020).

In general, AI is divided into weak and strong AI. The first type involves rule-based decision making, while the second type focuses on rule-based decision making (Wolfe, 1991). AI is also divided into different functions such as expert systems, machine learning, robotics, natural language processing, machine vision, and speech recognition (Dejoux & Leon, 2018). This paper focuses on AI-centric robots that are widely used by agri-techs.

Agricultural technology

Disruptive technologies (e.g., AI, machine learning, IoT, big data, drones, blockchain, 5G) have recently caught the attention of numerous industries. The agriculture sector is no different. The technological revolution has reshaped the agricultural technology framework with a strong focus on AI (Spanaki et al., 2022). The transformation of this field into a modern and data-driven sector stemmed from the need to ensure food security for large populations and environmental sustainability (Yahya, 2018).

The original industrial model of conventional agriculture was found to be unsustainable and flawed (Miranda et al., 2019). However, the introduction of artificial intelligence increased the expansion of the agri-tech field, leading to an increase in business investment and academic interest from various disciplines (Lezoche et al., 2020). Nevertheless, there is still no clear definition of agri-tech in the literature, but it is closely related to AI and the move towards smart agriculture (Miranda et al., 2019).

Smart farming is characterized by precision agriculture that includes the use of sensors, satellite imagery, weather tracking, resource monitoring, soil scanning, irrigation systems, harvesting, fertilizers, and navigation applications/tools (Miranda et al., 2019). The purpose of smart agriculture is to improve efficiency and production with minimal use of resources (financial or human).

This paper is about AI-controlled, advanced service robots/machines specifically used in agriculture. These advanced machines are trained to navigate through the fields and harvest the produce with high precision while detecting the crops that have gone bad.

Technostress

Technostress is a psychological and physiological manifestation of stress related to the use of technology (Turel & Gaudioso, 2018). The technostress phenomenon stems from the concept of stress, which includes strains, stressors, and new experiences (Brod, 1984). It is a relatively modern form of work stress that negatively impacts employees (Tarafdar et al., 2014; 2015) and leads to decreased well-being, high levels of fatigue, and devalued work performance (Tarafdar et al., 2007).

Technostress manifests in five main dimensions described as technostressors (i.e., techno-invasion: the feeling of being inundated by technology that blurs the boundaries between personal and professional work; techno-overload: the feeling of being overwhelmed by technological work demands; techno-complexity: the feeling of being constantly challenged by updating technological adaptive capabilities; techno-insecurity: the feeling of insecurity at work associated with advances in technology use and skills; and techno-uncertainty: the feeling of incompetence and inability to keep up with recurring technological changes) (Ragu-Nathan et al., 2008; Tarafdar et al., 2011).

In the IS and technostress literature, there are four main effects of technostress (i.e., physiological, psychosocial, organizational, and societal) (Martínez-Córcoles et al., 2017). The first leads to health deterioration. The second leads to psychological exhaustion. The third leads to social and financial corrosion. In the last episode, technology is seen as a threat and leads to negative emotional reactions, restlessness, and anxiety (Bondanini et al., 2020). This paper focuses on the latter aspect as the overarching concept in which technostress manifests.

RESEARCH MODEL

In the IS research direction, technology acceptance models and frameworks such as TAM feature heavily in the literature and are widely adopted; however, they lack the user experience element (Zardari et al., 2021). User experience is one of the core factors in the acceptance of any technology (Zardari et al., 2021), but no uniformly accepted model directly theorizes user experience as an outcome (Hornbaek & Hertzum, 2017).

Therefore, the user engagement model is used as the main theoretical basis in this paper. Nevertheless, the user engagement model has been extended and redesigned several times to better reflect technological and behavioral developments in business and academic studies.

The foundations of user experience emerge from an examination of the conventional perspective of usability, which does not consider the emotional experience of engaging with a service or product (Norman, 2004). As a result, several frameworks have emerged as extensions that explain the emotive responses and experiences with interactive technologies (e.g., McCarthy & Wright, 2004).

Nevertheless, such frameworks are not able to explain how users make decisions (based on engagement) regarding their experiences, and they do not explicitly account for the interactive nature of user experience. Therefore, this paper uses the extended theory of user engagement from Hart et al. (2012), which explains the emotional influences on user decision-making

during interaction (see Figure 1). In other words, the model focuses on the cognitive aspects (affects, stressors) of user experience as a decision-making process towards interactive technologies.

Studies have been encouraged to test the model in the context of advanced technologies (e.g., AI) (Hart et al., 2012). Nevertheless, to the authors' knowledge, no study has initially attempted to implement the advanced theory of user engagement for the study of AI-centric technologies. The present work is the first to do so. Second, the study of AI's impact on workers and firms has not yet been empirically examined in research (Dragano & Lunau, 2020). This paper examines advanced service robots in agriculture as a type of AI. Third, when explicitly addressing AI-centric technologies (or technologies of any kind), the concept of stress (stressors) is taken out of context. Therefore, this paper theorizes technostress (technostressors) rather than stress (stressors) as a central affect construct (i.e., as an antecedent of user engagement and user experience) (see Figure 1).

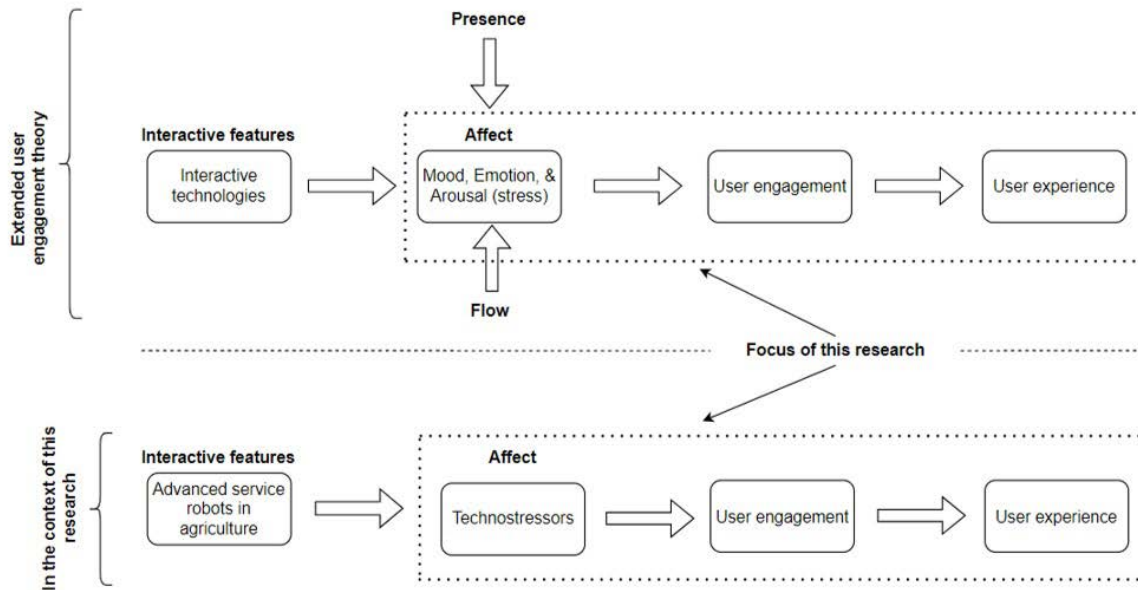


Figure 1. Theoretical framework

Source: Hart et al., 2012*

*Note: Other user experience models (few integrated with TAMs) have been proposed (e.g., Sagnier et al., 2020; Hornbaek & Hertzum, 2017); nevertheless, they either lack the emotions or the user engagement perspectives, which are crucial antecedents to user experience.

Technostressors – User engagement relationship

In the literature, employee (user) engagement was originally defined as employees' alignment with their job tasks and roles (Kahn, 1990). This definition focuses on employees' sense of engagement and involvement and the ways in which they engage and communicate physically, cognitively, and emotionally (Tims et al., 2013). Nonengaged employees, on the other hand, are emotionally disengaged and less involved in work (Truss et al., 2013).

In management research, employee (user) engagement is divided into two main types (i.e., professional and organizational) (Saks, 2006). In this paper, however, the behavioral perspective of engagement is taken (Van Doorn et al., 2010).

The stress literature identifies a negative relationship between work-related stress and employee engagement (Velnampy & Aravinthan, 2013). In technostress research, disengagement is considered to result from depletion of physical or emotional resources (Kahn, 1990). In such cases, disengaged employees physically isolate themselves from work and withdraw emotionally and cognitively, resulting in poor performance and unsafe behavior (Ongori & Agolla, 2008). Thus, there is strong evidence that technostress is theoretically related to employee engagement (Okolo et al., 2013).

In addition, numerous research studies have examined the negative effects of technostress in organizations, such as job dissatisfaction, lack of engagement, poor performance, uncertainty of job requirements, decreased well-being, increased stress, exhaustion, burnout, decreased innovativeness, and noncompliance with technological requirements (Spiros, 2019). Similarly, several studies showed a direct negative relationship between technostress (technostressors) and work engagement (e.g., Vayre & Vonthron, 2019). Building on the arguments above, we therefore hypothesize the following:

H1 – H5. Technostressors relate negatively to user engagement.

User engagement – User experience relationship

In the human-computer interaction literature, the term user experience refers to the holistic experience of using a product, service, or system (technology). User experience is shaped by the content, system functionality, user, and aesthetics of interactive systems (Ahsanullah et al., 2006). Like engagement, it also encompasses affective, behavioral, and cognitive responses and includes emotional, hedonistic, pragmatic, and aesthetic elements (Law et al., 2009). In recent studies, the constructs of engagement and experience have been shown to be positively correlated (e.g., Shoukat & Ramkissoon, 2022; Rather & Hollebeek, 2021). Therefore, we hypothesize that, as is evident in several streams of research:

H6. User engagement relates positively to user experience.

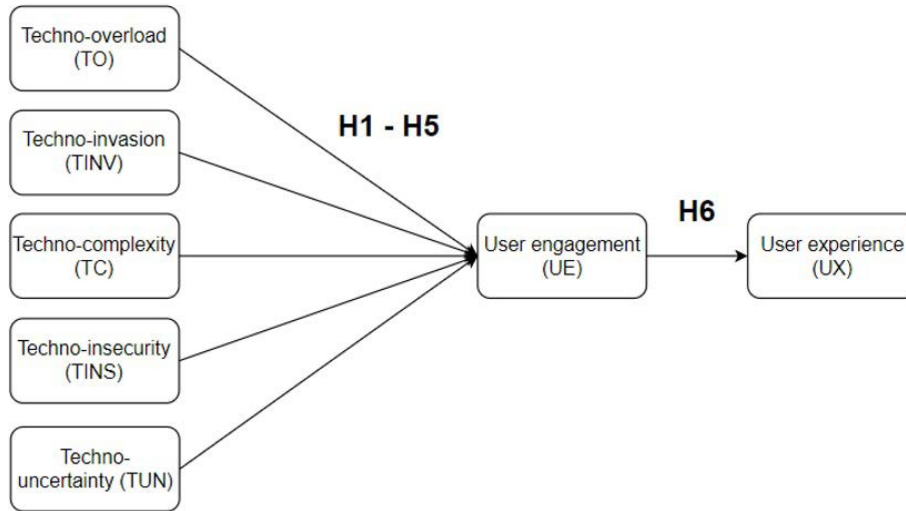


Figure 2. Hypothesized research model
Source: Authors' own model.

METHOD

The U.S. study

To investigate the six hypotheses with 25 construct items (see Table 1 in the Appendix), an e-survey approach was used for both studies. This study focused on the U.S. agri-tech sector. The sample consisted of employees and workers from several farms ("smart" farms) in different U.S. states. Farms that did not use advanced AI systems in their daily operations were excluded. Thirty-two smart farms were originally contacted. However, only eleven agreed to participate (34% acceptance rate). Prior to data collection, the authors conducted a thorough background check on all companies and ensured full anonymity. Within eight weeks, 294 responses were collected. After reviewing the data for incomplete or missing records, 232 final responses were identified.

Regarding the sample description, four main demographic characteristics (i.e., age, gender, experience with AI service robots in agriculture, and type of position) were included in the electronic survey. The 36- to 44-year-old age group achieved the highest frequency of 64 (27.58%), while the 18- to 26-year-old age group achieved the lowest frequency (frequency = 23; 10%). Males were the predominant gender (frequency = 207; 90% of participants). Regarding experience with AI in agriculture, frequency and percentage was highest at 4 to 6 years (126; 54%), while experience was lowest at 6 to 8 years (32; 14%). Finally, machine workers (blue collar) and engineers (white collar) were the positions with the highest participation (159 combined; 68.5%). Scientists had the lowest frequency (8; 3.5%).

The Singapore study

This study focused on the agri-tech sector in Singapore. Singapore plays an important role in the agri-tech sector. The Asian country is home to more than 70 million small farms, a leader in vertical farming, the largest supplier of agricultural products, a capital of technology development, and an innovation hub for the agri-tech sector (The Business Times, 2019).

Thirty-nine smart farms were originally contacted. However, only eight agreed to participate (20% acceptance rate). Over twelve weeks, 251 responses were collected. After cleaning the data for incomplete or missing information, 198 responses were eventually obtained. Nevertheless, another round of data collection was conducted to achieve the same sample size as the U.S. study, with three more farms participating in the survey.

Among demographic characteristics, the 45- to 53-year-old age group had the highest frequency of 77 (33.19%), while the 18- to 26-year-old age group had the lowest frequency (frequency = 14; 6%). Males were the predominant gender (frequency = 196; 84.5% of participants). Regarding experience with AI in agriculture, the frequency and percentage was highest with 6 to 8 years (103; 44%), while experience with less than 2 years was the lowest (17; 7%). Finally, machine workers (blue collar) and engineers (white collar) were the positions with the highest participation (combined 138; 59.5%). Consultants had the lowest scores (11; 4.7%).

RESULTS

For the U.S. study, the Harman's one factor test provided insights as follows: 7 components (equal to the number of variables found in the hypothesized model), initial eigenvalues > 1 , percent of variance = 4.229, and cumulative percent = 71.066. Thus, common method bias is not an issue. Second, convergent and discriminant validities showed satisfactory estimates (all Cronbach alphas (CRs) > 0.70 ; AVEs > 0.50 ; MSVs $<$ AVEs) (Fornell & Larcker, 1981). Third, the appropriateness of the model (model fit) provided an adequate overall measurement (CMIN/DF = 2.150 [< 3]; CFI = .911 [$> .900$]; RMSEA = .066 [$< .080$]) (Hair et al., 2010; Hooper et al., 2008). For the goodness-of-fit (model accuracy), the scores were $R = .478$; $R^2 = .228$; Adjusted $R^2 = .214$. Furthermore, the VIF scored 1.33 (< 5); thus, multicollinearity is not an issue (Gruber et al., 2010). Finally, factor loadings showed significant correlations (> 0.30 ; Yusoff et al., 2013) (see Table 2 in the Appendix).

For the Singapore study, the Harman's single factor test provided insights as follows: 7 components, initial eigenvalues > 1 , % of variance = 5.180, and cumulative % = 66.851. Thus, common method bias is not an issue. Second, convergent and discriminant validities showed satisfactory estimates (all Cronbach alphas [CRs] > 0.70 ; AVEs > 0.50 ; MSVs $<$ AVEs) (Fornell & Larcker, 1981). Third, the appropriateness of the model (model fit) provided an adequate overall measurement (CMIN/DF = 2.366 [< 3]; CFI = .905 [$> .900$]; RMSEA = .077 [$< .080$]) (Hair et al., 2010; Hooper et al., 2008). For goodness-of-fit (model accuracy), the scores were $R = .407$; $R^2 = .165$; Adjusted $R^2 = .147$. Furthermore, the VIF scored 1.19 (< 5); thus, multicollinearity is not an issue (Gruber et al., 2010). Finally, factor loadings showed significant correlations > 0.30 (see Table 3 in the Appendix; Yusoff et al., 2013).

Hypotheses analysis

For the U.S. study, H1 (TO-UE) was not supported ($t = 2.609$, $\beta = .161$, $p < .05$); H2 (TINV-UE) was supported ($t = -2.167$, $\beta = -.135$; $p < .05$); H3 (TC-UE) was not supported ($t = 6.998$, $\beta = .409$, $p < .01$); H4 (TINS-UE) was supported ($t = -3.119$, $\beta = -.186$; $p < .01$); H5 (TUN-UE) was not supported ($t = 6.013$, $\beta = .369$, $p < .01$); and H6 (UE-UX) was supported ($t = 2.009$; $\beta = .131$; $p < .05$) (see Figure 3).

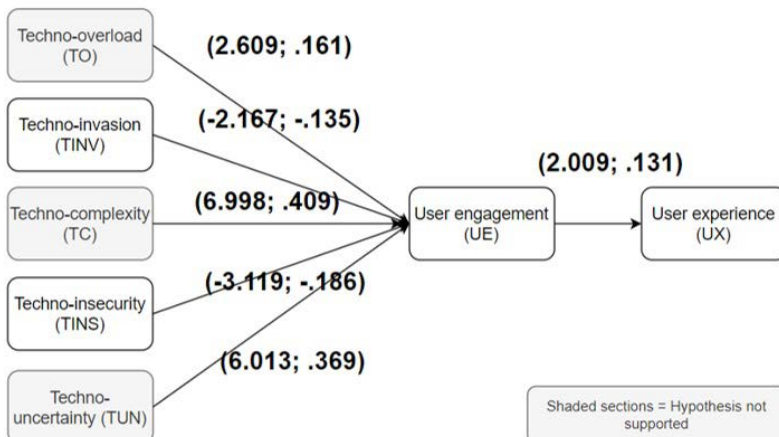


Figure 3. Empirical research model (t values; beta values)
Source: Authors' own model.

For the Singapore study, H1 (TO-UE) was supported ($t = -2.185$, $\beta = -.133$, $p < .05$); H2 (TINV-UE) was supported ($t = -5.062$, $\beta = -.314$, $p < .01$); H3 (TC-UE) was supported ($t = -2.765$, $\beta = -.172$, $p < .01$); H4 (TINS-UE) was not supported ($t = -.885$; $\beta = -.056$; $p > .05$); H5 (TUN-UE) was not supported ($t = .155$; $\beta = .010$; $p > .05$); and H6 (UE-UX) was supported ($t = 2.887$, $\beta = .187$, $p < .01$) (see Figure 4).

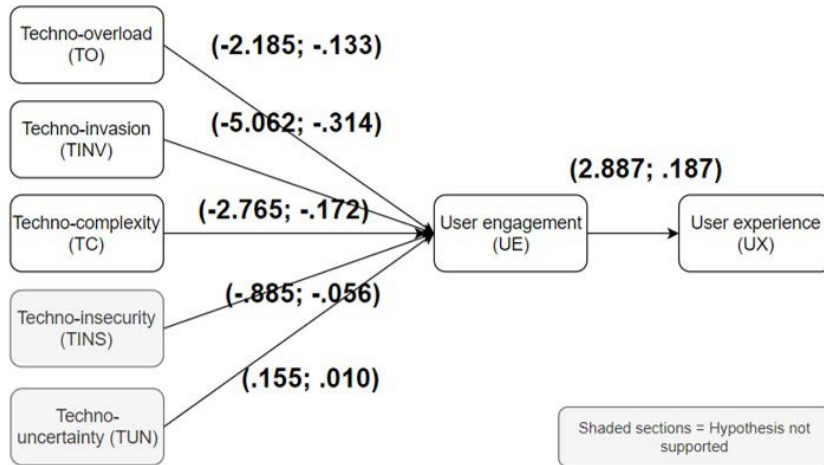


Figure 4. Empirical research model (t values; Beta values)
Source: Author's own model.

To interpret the empirical results, this paper highlights the different effects of the studied technostressors in two different contexts. In the technostress literature, most studies have treated technostressors as a single construct. Despite their significant contributions to the literature, this has led to limited insights and misconceptions. The present work shows that each dimension hides a unique interpretation of user responses within human–technology interaction.

Specifically, TO and TC have a double effect. For example, the TO dimension has a positive and a negative relationship with user engagement. In this sense, TO can be either a motivator or a burden. Similarly, TC has been shown to have both positive and negative effects. In such cases, TC can play the role of a challenge or a struggle.

TINV showed similar negative relationships in both contexts. In this sense, the digital invasion is changing users' interactions with their environment and blurring the boundaries between private life and work life.

TINS showed a negative relationship with user engagement in the first study, but an insignificant relationship in the second study. This dimension relates to the concept of self-efficacy. In the U.S. context, technology is seen as the main driver of uncertainty. As technology creates strong competition and stimulates change, this leads to an increased sense of insecurity, so workers may feel threatened that they will be replaced by more highly skilled individuals. In Singapore, employees are constantly exposed to technological training that minimizes the level of uncertainty. Thus, there is neither a positive nor a negative correlation with user engagement.

TUN showed a positive relationship with user engagement in the first study, but an insignificant relationship in the second study. TUN can be closely linked to the concept of perceived usefulness. Thus, this dimension reflects the evolution and change of the technologies used. In the U.S. context, changes in technologies focus on improving features to assist employees in their daily tasks and to reduce time and energy consumption. In the Singapore context, new technologies are developed daily and have become the workplace norm.

Mediation effects

For the US study, subunits 1, 2, 4, and 5 exhibited partial mediation effects. Hence, there is a significant correlation between UE and UX, and there are also some direct effects between the technostressors and UX. Thus, TO, TINV, TINS, and TUN have both direct and indirect effects on UX. Whereas subunit 3 confirmed full mediation effects, UE has a tendency to reduce the significance of the correlation between TC and UX. Consequently, TC might no longer have an impact on UX after UE is controlled. In this vein, TC only has indirect impact on UX.

For the Singapore study, subunits 3, 4, and 5 exhibited partial mediation effects. Hence, there is a significant correlation between UE and UX, and there are also some direct effects between the technostressors and UX. Thus, TC, TINS, and TUN

have both direct and indirect effects on UX. Whereas, subunits 1 and 2 confirmed full mediation effects. UE tends to reduce the significance of the correlation between TO or TINV and UX. Consequently, TO or TINV might no longer have an impact on UX after UE is controlled. In this vein, TO or TINV only have an indirect impact on UX (see Table 4).

Table 4. Mediation analysis

	Subunit	Lower CI	Upper CI	Point	P value	Mediation
U.S. study	(1) TO-UE-UX	-.0562	.0100	-.0171	<.05	Partial
	(2) TINV-UE-UX	-.0022	.0537	.0190	>.05	Partial
	(3) TC-UE-UX	-.1516	-.0409	-.0930	<.05	Full
	(4) TINS-UE-UX	-.0062	.0595	.0223	<.05	Partial
	(5) TUN-UE-UX	-.0800	.0234	-.0241	<.05	Partial
Singapore study	(1) TO-UE-UX	-.0814	-.0013	-.0388	>.05	Full
	(2) TINV-UE-UX	-.3512	-.0099	-.1567	>.05	Full
	(3) TC-UE-UX	-.1964	.0091	-.0863	<.05	Partial
	(4) TINS-UE-UX	-.0554	.0141	-.0179	<.05	Partial
	(5) TUN-UE-UX	-.0311	.0755	.0101	<.05	Partial

* *Medcurve macro analysis (SPSS); If zero is not found within the interval, then there is a significant mediating effect (i.e., full mediation) (Preacher & Hayes, 2004; 2008).*

Source: Authors' own data.

DISCUSSION

In the U.S. study, both TO and TC (as well as TUN) had positive relationships with UE, so the hypotheses were not supported; whereas TO and TC (excluding TUN) in the Singapore study showed negative relationships with UE, thus supporting the hypotheses. Therefore, the results of the U.S. study are consistent with the work of Srivastava et al. (2015), in which technostressors may be positively associated with engagement. Under such conditions, higher levels of technostressors lead to higher levels of engagement and thus promote motivation. TINV, on the other hand, showed a negative association with UE in both studies, supporting the work of Vayre and Vonthron (2019).

For the Singapore study, all hypotheses were supported except H4 and H5, which had insignificant correlations (i.e., TINS-UE and TUN-UE). These results are consistent with the work of Mohammed (2022), who showed that there is no significant relationship between technostress and work engagement.

Nevertheless, the authors investigated the possibility of nonlinear relationships between antecedents (TINS & TUN) and UE in the Singapore study (see Figures 5 and 6). The results show that UE remains neutral and constant as TINS and TUN increase (confirming the insignificance of linear regression analysis), up to certain thresholds at which UE transitions to an incremental pattern (in the case of TINS), while it transitions to a decremental pattern (in the case of TUN). These results are consistent with recent studies in the technostress literature that show similar nonlinear relationships (Chandra et al., 2019; Issa & Bouchaib, 2018). Nevertheless, both cases are complementary. In the case of TINS, the user becomes more familiar with the device over time, minimizing uncertainty. This is partly due to Asian culture and work norms, where excellence and self-improvement are considered the standard. In the case of TUN, the user is overwhelmed with the constant follow-ups to the inexorable advances in technologies, which eventually leads to disengagement. In this case, uncertainty overwhelms the user.

Limitations and future research directions

Given the modest contributions of this work, there are three limitations. First, this work did not measure a specific type of AI service robot/machine used by agri-techs. The authors did not distinguish between their types or functions. Such characteristics would be difficult to control across different markets and geographic locations. Second, this paper failed to further explore s-shaped relationships. Such curvilinear effects offer new opportunities for future studies that build on the findings of this paper. Third, the authors were unable to control for the demographic composition of the sample of either study. The original goal was to study only blue collar employees (workers/technicians) and not blue- and white-collar employees (managers, administrators). Blue collar employees are the direct users of these types of AI-controlled robots. Due to internal conditions/restrictions imposed by the smart farms, however, this type of attribute was unattainable.

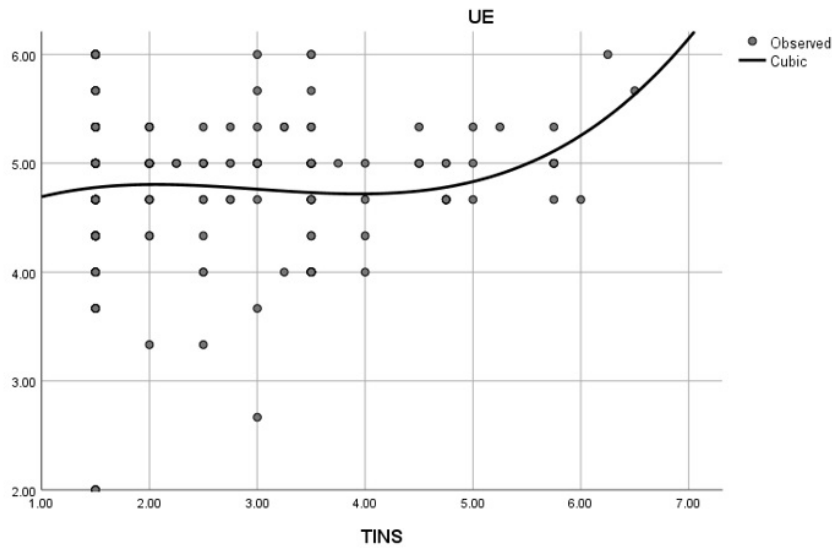


Figure 5. TINS-UE cubic s-shaped relationship
Source: Authors' own results.

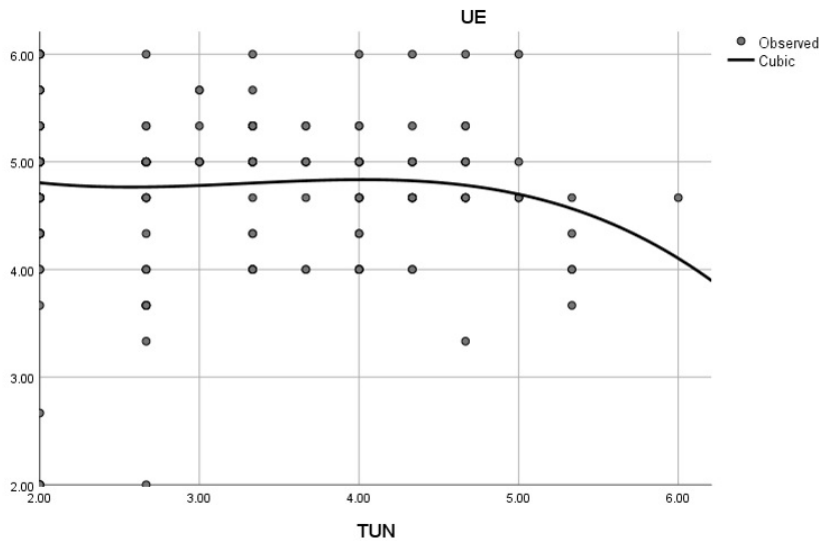


Figure 6. TUN-UE cubic s-shaped relationship
Source: Authors' own results.

IMPLICATIONS AND CONCLUSION

This paper has two implications. The first implication is to provide a modern and updated version of the extended user engagement model. The novelty lies in the introduction of five dimensions of user responses that are more appropriate in the AI context. Despite its relevance to the literature, the current version of the user engagement model is outdated when theorizing contemporary AI-related innovations. agri-techs or other AI-focused sectors should adopt the modern framework to interpret user responses more accurately.

The second implication focuses on the practical perspective. It begins by acknowledging the existence of nonlinear patterns. This paper argues that curvilinear relationships occur when there is an imbalance between individual skills/abilities and technological changes/developments/tasks. Such an imbalance represents the gap created by the introduction of a new

technology (or feature) until employees develop the skills to use it properly. During this gap, the employee must adapt to the new changes. In many cases, however, the employee or worker may refuse to use the technology.

Therefore, agri-techs should begin considering solutions to determine if the employee/worker is “ready” to adopt/accept the new/updated technology. Implementing such transitional solutions can reduce employee resistance and thus minimize the gap. In this way, agri-techs can save time, energy, and costs.

This is of great importance for agri-techs, as they have recently started to hire workers and employees (for operational and production activities) from rural areas. As a result, there is a high level of resistance because workers do not understand how AI tools work. In such cases, high levels of resistance can hinder business growth and performance.

Consequently, this paper proposes a novel measurement for identifying the users’ willingness to engage by incorporating the “readiness” dimension within the “equation of change” in change management. This paper refers to readiness (AI readiness) as the individual’s ability to adopt and benefit from the technological innovation.

Original equation:

Dissatisfaction (D) x Vision (V) x First step (F) < Resistance (R)

Revised equation:

Dissatisfaction (D) x Vision (V) x First step (F) x Readiness (R) > Resistance (R)

The authors of this paper argue that the original “equation of change” must be reframed to remain valid and credible in the face of rapid changes in AI. In addition, the equation ignores the role of employees in the change process. The revised equation best fits into the digital transformation initiatives that agricultural companies are currently undergoing. In this sense, contemporary change management is taking place.

Agri-techs have already set ambitious plans for full-scale AI integration. Yet a lack of understanding of their employees’ behavioral responses when dealing with advanced technologies can lead to unexpected problems in the future. When developing their transformation strategies, agri-techs should consider the individual perspective of human–AI interaction rather than focusing solely on the development of the technology itself.

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Declaration of Interest Statement

There is no financial/personal interest or belief that could affect our objectivity. The authors report there are no competing interests to declare.

Data Availability

Data will be made available on request.

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APPENDIX

Table 1. Questionnaire items

Techno-overload (<i>Ragu-Nathan et al., 2008; Tarafdar et al., 2007</i>)	
TO 1	I am forced by this technology to work much faster
TO 2	I am forced by this technology to do more work than I can handle
TO 3	I am forced by this technology to work with very tight time schedules
Techno-invasion (<i>Ragu-Nathan et al., 2008; Tarafdar et al., 2007</i>)	
TINV 1	I spend less time with my family due to technology
TINV 2	I have to be in touch with my work even during my vacation due to this technology
TINV 3	I have to sacrifice my vacation and weekend time to keep current on new technologies
TINV 4	I feel my personal life is being invaded by this technology
Techno-uncertainty (<i>Ragu-Nathan et al., 2008; Tarafdar et al., 2007</i>)	
TUN 1	There are always new developments in the technologies we use in our work
TUN 2	There are constant changes in the software
TUN 3	There are constant changes in the hardware
Techno-complexity (<i>Ragu-Nathan et al., 2008; Tarafdar et al., 2007</i>)	
TC 1	I do not know enough about this technology to handle my job satisfactorily
TC 2	I need a long time to understand and use new technologies
TC 3	I do not find enough time to study and upgrade my technology skills
Techno-insecurity (<i>Ragu-Nathan et al., 2008; Tarafdar et al., 2007</i>)	
TINS 1	I do not share my knowledge with co-workers for fear of being replaced
TINS 2	I feel constant threat to my job security due to new technologies
TINS 3	I have to constantly upgrade my skills to avoid being replaced
TINS 4	I am threatened by co-workers with newer technology skills
User engagement (<i>Schaufeli & Salanova, 2007</i>)	
UE 1	I am enthusiastic towards this technology
UE 2	I am dedicated towards using this technology
UE 3	I am absorbed with this technology's efficacy
User experience (<i>Finstad, 2010</i>)	
UX 1	This technology's capabilities meet my requirements (in terms of effectiveness)
UX 2	Using this technology is a frustrating experience (in terms of satisfaction)
UX 3	This technology is easy to use (overall experience)
UX 4	I have to spend too much time correcting things with this technology (in terms of efficiency)
UX 5	I think I would need a technological system with more features for my tasks (in terms of effectiveness)

Note: All items followed a seven-point Likert scale from strongly disagree to strongly agree.

Table 2. Factor loadings (U.S. study)

	1	2	3	4	5	6	7
TO1	.834	--	--	--	--	--	--
TO2	.727	--	--	--	--	--	--
TO3	.808	--	--	--	--	--	--
TINV1	--	.755	--	--	--	--	--
TINV2	--	.799	--	--	--	--	--
TINV3	--	.852	--	--	--	--	--
TINV4	--	.843	--	--	--	--	--
TUN1	--	--	.790	--	--	--	--
TUN2	--	--	.777	--	--	--	--
TUN3	--	--	.800	--	--	--	--
TC1	--	--	--	.699	--	--	--
TC2	--	--	--	.894	--	--	--
TC3	--	--	--	.861	--	--	--
TINS1	--	--	--	--	.834	--	--
TINS2	--	--	--	--	.852	--	--
TINS3	--	--	--	--	.913	--	--
TINS4	--	--	--	--	.870	--	--
UE1	--	--	--	--	--	.806	--
UE2	--	--	--	--	--	.747	--
UE3	--	--	--	--	--	.615	--
UX1	--	--	--	--	--	--	.753
UX2	--	--	--	--	--	--	.759
UX3	--	--	--	--	--	--	.727
UX4	--	--	--	--	--	--	.809
UX5	--	--	--	--	--	--	.653

Source : Authors' own.

Table 3. Factor loadings (Singapore study)

	1	2	3	4	5	6	7
TO1	.815	--	--	--	--	--	--
TO2	.768	--	--	--	--	--	--
TO3	.482	--	--	--	--	--	--
TINV1	--	.693	--	--	--	--	--
TINV2	--	.780	--	--	--	--	--
TINV3	--	.808	--	--	--	--	--
TINV4	--	.850	--	--	--	--	--
TUN1	--	--	.768	--	--	--	--
TUN2	--	--	.754	--	--	--	--
TUN3	--	--	.833	--	--	--	--
TC1	--	--	--	.653	--	--	--
TC2	--	--	--	.881	--	--	--
TC3	--	--	--	.852	--	--	--
TINS1	--	--	--	--	.827	--	--
TINS2	--	--	--	--	.873	--	--
TINS3	--	--	--	--	.857	--	--
TINS4	--	--	--	--	.859	--	--
UE1	--	--	--	--	--	.829	--
UE2	--	--	--	--	--	.759	--
UE3	--	--	--	--	--	.792	--
UX1	--	--	--	--	--	--	.681
UX2	--	--	--	--	--	--	.817
UX3	--	--	--	--	--	--	.766
UX4	--	--	--	--	--	--	.718
UX5	--	--	--	--	--	--	.679

Source: Authors' own.