# An Artificial Intelligence (AI)-readiness and adoption framework for AgriTech firms

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## ABSTRACT

With the recent technological advancements, empowered by the self-learning capabilities of algorithms, and the increasing power of machines computation, Artificial Intelligence (AI)-driven technologies have become more pervasive and performant, less costly, and more effective at addressing and solving prevailing business problems. In this respect, firms operating in the AgriTech sector make no exception and are indeed being significantly impacted by AI-driven technologies and systems. We argue in this paper that given the unique characteristics of AI technologies and emerging challenges and aspirations of the AgriTech sector, there is a need for re-examining traditional theorizations of technology adoption and readiness within AgriTech firms. Specifically, we develop a comprehensive AI readiness and adoption empirical framework that delineates the determinants of AI readiness and uncovers a set of key strategic components that can help AgriTech firms better manage their readiness process for AI adoption. We employ a mixed-methods approach and collect through 236 e-surveys and 25 interviews from one of the most influential conferences in the AgriTech field. Our findings have implications for research and practice.

**Key words:** Artificial intelligence; agricultural technology; readiness and adoption; mixed-methods.

## INTRODUCTION

Information systems (IS) scholars have developed throughout the last decades several empirical models and frameworks, unravelling and theorizing the phenomenon of technology adoption and implementation within organizations (e.g., Venkatesh et al, 2003; Davis, Bagozzi, & Warshaw, 1992; Thompson, Higgins, & Howell, 1991). In this regard, the diffusion of innovation theory (Taherdoost, 2018) has emerged as a key theorization in explaining the effects of technological characteristics on technology adoption. This initial theorization led to the development of the perceived characteristics innovating (PCI) theory, which explains user adoption of technological innovation, using conventional technological characteristics such as compatibility, trainability, and voluntariness as predictors (Rogers, 1995, 2003; Moore & Benbasat, 1991). While the PCI framework has greatly enhanced our understanding of the phenomenon of technology adoption within various types of organizations and for different technologies, there is a need for rethinking and further elaborating the model to better fit the emergence of cutting-edge technologies such as Artificial Intelligence (AI) (Jordan, 2017; Keding, 2020), and the unique specificities and challenges faced by evolving sectors such as the AgriTech sector (Bowen & Morris, 2019).

Disruptive technologies have played a key role in revolutionizing the agricultural sector, introducing novel solutions, and optimizing operations and processes (Spanaki, Sivarajah, Fakhimi, Despoudi, & Irani, 2021). In this respect, agricultural technology (AgriTech), the focus of this research, has recently gained important scholarly attention (Lezoche et al, 2020), considering its potential for unlocking some the most prevailing global societal and economic problems (Bowen & Morris, 2019). Also referred to as e-agriculture, digital farming, or smart farming (CEMA, 2019), the AgriTech field is an emerging area of research that attracts significant interest from a multitude of institutional actors including practitioners, governmental actors, and societal constituencies. In this respect, extant research within the AgriTech sector suggests that technology adoption and implementation is faced with a number of prevailing challenges including: the need for sustainable, organic, environmentally-friendly products; emission-cutting production mechanisms; natural resource optimizing systems; and the strive for exploiting the potential of disruptive technologies, enabling new possibilities for firms in the sector.

With the recent technological advancements, empowered by the self-learning capabilities of algorithms (Faraj et al, 2018), availability of big data (George et al, 2014), and the increasing power of machines computation (Ferràs-Hernández, 2018), AI-driven technologies have become more pervasive and performant (Brynjolfsson and McAfee, 2016), less costly (Agrawal et al, 2017), and more effective at addressing and solving prevailing business and societal problems (Gunasekaran et al, 2017; Lee, 2018; Phan et al, 2017).

In this respect, firms operating in the AgriTech sector make no exception and are indeed being significantly impacted by AI-driven technologies and systems. Considering the potential of AI at revolutionizing firms' internal processes and operations (Agrawal et al, 2017; Jordan, 2017; Keding, 2020), and given the multitude of challenges facing the AgriTech sector for creating more sustainable, green products, and deploying resource-optimizing and nature-preserving systems (Bowen & Morris, 2019), there is a need for re-examining traditional theorizations of technology adoption and implementation within AgriTech firms (Spanaki et al, 2021).

This research inquiry is motivated by the recent advancements of AI and its power at transforming firms' operations (Brynjolfsson & McAfee, 2016; Faraj et al, 2018; George et al, 2014; Keding, 2020). We thus endeavor in this paper to re-think and re-imagine the traditional mechanisms and processes that shape technology adoption within the AgriTech sector. Specifically, we aim at exploring two research questions: *1) "What are the determining perceived characteristics of AI adoption within AgriTech firms? "; and 2) "How AgriTech* *firms can maximize their readiness to facilitate the process of AI adoption?"*, to gain a better understanding of the adoption process of AI-driven technologies. In doing so, we focus on developing an AI-based PCI framework that can better fit the specifies of, and better cope with the unique challenges faced by AgriTech firms.

While traditional technological innovations are characterized by obsolete technological characteristics such as (e.g., relative advantage, compatibility, ease of use), AI-driven technologies are shaped by four main elements: mobility, interactivity, communication, and autonomy (COMEST, 2017). This significant difference urges for rethinking and eventually re-configuring the traditional PCI framework to better capture the specific elements characterizing the contemporary AI-driven technologies and systems.

This paper aims at addressing a number of important gaps in the AgriTech and AI literature. First, AgriTech research has been mainly dominated by conceptual studies (Lowenberg-DeBoer et al, 2020; Spanaki et al, 2021), and lacks empirical investigations for validating the initial theorizations in the field (Spanaki, Sivarajah, Fakhimi, Despoudi, & Irani, 2021). Second, while the adoption and implementation effects of several emerging technologies on AgriTech firms have been explored (e.g., Wolfert, Ge, Verdouw, & Bogaardt, 2017; Nukala et al, 2016), the impacts of AI-driven technologies and systems is yet to be explored. Specifically, the perceived role of AI-driven systems in newly developed agricultural operations and processes has received little scholarly attention (Spanaki, Sivarajah, Fakhimi, Despoudi, & Irani, 2021). Further, extant research on the adoption and implementation of AI in business has overlooked the emerging sector of AgriTech (Keding, 2020). Finally, existing theorizations on technology adoption, and implementation do not fully capture the unique specificities and challenges of the AgriTech sector, and are not fully adapted to the revolutionary self-learning capabilities of machine learning (ML) algorithms (Faraj et al, 2018). In light of these research aspirations, we aim at addressing these gaps, and endeavor to develop an AI-based readiness and adoption framework that can better fit the emerging needs of AgriTech firms and ongoing evolutions of AI-driven technologies and systems.

We accomplish our research inquiry through two empirical investigations. First, we run an e-survey questionnaire to collect insights from a highly diversified pool of respondents, taking part in one of the most prominent conferences in the AgriTech field: "2021 4th Global Summit on Agriculture, Food Science, and Technology". Second, we complemented this initial quantitative study with an in-depth qualitative investigation with a diversified pool of interviewees, exploring the narrative judgments of global scholars, managers, experts, and entrepreneurs from the field of AI and AgriTech.

## LITERATURE REVIEW

### The Traditional PCI Theoretical Model

During the last decades, numerous behavioral theories and models (e.g., theory of reasoned action, social cognitive theory, motivational model, uses and gratification theory, technology-organization-environment, etc.) emerged in the IS literature that explain the perceived effects of different factors (cognitive, behavior, personality, motivation, environment, social, psychological) on technology (or new technology) acceptance, intention, or adoption (Venkatesh et al, 2003; Davis, Bagozzi, & Warshaw, 1992). Such models have been used for both individual and organizational perspectives. Nevertheless, this research focuses on the PCI theoretical model. The PCI, which is an extension of the DOI, explicitly explains the direct effects of different technological characteristics (relative advantage, compatibility, ease of use, result demonstrability, image, visibility, trialability, and voluntariness) on technology adoption.

Throughout the years, most of the models mentioned above (and their extensions (e.g., unified theory of acceptance and use of technology, technology acceptance model) have been developed to fit certain contexts and situations; nevertheless, the PCI theoretical model remains underdeveloped. In the IS literature, scholars have missed the urgent need to innovate the theoretical model (rather than only extending) to match the rapid diffusion of innovations (e.g., AI). The authors believe that the current traditional technological characteristics (i.e., relative advantage, compatibility, ease of use, result demonstrability, image, visibility, trialability, and voluntariness), which are antecedents in the PCI framework, can be replaced with other characteristics that properly analyze the effects of advanced AI technologies.

Instead, this research focused on advanced types of innovation characteristics (mobility, interactivity, communication, and autonomy) that are more adequate to cutting-edge technologies (e.g., AI-driven robots) (see Figure 1).

**AI-driven robots in agriculture**

Only recently managerial and organizational research on AI and robotics began to develop in the literature (Raj & Seamans, 2019). Previous literature mainly focused on the technical perspective of AI and robotics.

The concept of AI has witnessed multiple reforms since its introduction in 1955 by McCarthy (McCarthy et al, 1955; Trunk, Birkel, & Hartmann, 2020). Different academic fields (e.g., psychology, computer science, cognitive psychology, philosophy, etc.) have different conceptualizations of AI (e.g., Stephan & Klima, 2020; Goel & Davies, 2020). Nevertheless, in IS and management disciplines, recent definitions relate to AI as a technology that imitates human intelligence or a machine (mainly robotics) that performs tasks typically carried out by humans (Patel, Rai, Das, & Singh, 2021; Bolander, 2019).

AI can be of two general types (i.e., general AI and narrow AI). The first refers to advanced software capable of independent thinking and decision-making. The second refers to software dependent on advanced algorithm coding and methods. The latter learns from the input data to create predictions, discover patterns, and develop its efficiency; hence, also known as machine learning (Broussard, 2018). Machine learning, among many others such as image recognition, speech recognition, problem-solving, and natural language processing, is considered one of the main functions of AI (Kietzmann, Paschen, & Treen, 2018).

Three main approaches through which AI is used in businesses: assisted, augmented, and autonomous intelligence (Garbuio & Lin, 2019). The first aims at improving and enhancing the accuracy of the ongoing tasks. The second alters the nature of the task and business model (through natural language processing and data analysis). It is used for customization, accuracy, and prevention. The third refers to AI as independent and automated.

Regardless of the approaches, in practice, AI has been integrated into many fields, operations, processes, industries, and businesses to achieve optimal performance (e.g., e-commerce, fraud detection, marketing, finance, healthcare, information analysis) (Lee, Dabirian, McCarthy, & Kietzmann, 2020; Garbuio & Lin, 2019; Xing, Cambria, & Welsch, 2018). The agriculture sector is no different.

The agriculture sector is the most crucial source of food security and sustainability for the world (Ben Ayed & Hanana, 2021). Nevertheless, certain challenges (e.g., scarcity of natural resources, quality control, climate change) exist that may hinder the sector's development. Thus, to achieve sustainability, growth, and effective decision-making, the use of advanced technologies (i.e., AI) is a need (Ben Ayed & Hanana, 2021).

In modern times, agriculture involves complex tasks that require automation for efficiency. Thus, AI-related innovations have been rapidly integrating into the agricultural sector (Ben Ayed & Hanana, 2021) to forecast weather, analyze crop infections, improve yield, and enhance farming tasks. One significant illustration of such innovations is robots (Albiero, 2019).

From a general perspective, a robot is defined as any machine that automatically performs complex labor work or tasks regardless of its level of automation (semi or fully automated) (Raj & Seamans, 2019). From a technical approach, a robot is a system that draws on an interplay among multidisciplinary operations and processes (sensing, codes, theories, etc.) related to AI logic (Albiero, 2019). Three general types of robots have been identified: industrial (manufacturing), professional (services), and collaborative (direct technology-human interaction) (Murashov, Hearl, & Howard, 2015).

Robots have been successfully used in several industrial applications before their successful implementation in agriculture (Vamshidhar Reddy, Vishnu Vardhan Reddy, Pranavadithya, & Kumar, 2016). Because of such success, the global market of agricultural robots is estimated to reach 20 billion by 2025 (M&M, 2020). Agricultural robots have been shown to increase agricultural efficiency and productivity (Zhao, Yang, Zheng, & Dong, 2020; Albiero, 2019). Agricultural robots are of multiple types (e.g., field, aerial, swarm) and used for various tasks (e.g., mainly inspection, cutting, harvesting, cultivation, milking, pruning, and spraying) (Shamshiri et al, 2018). This research did not focus on any specific task or type.

## RESEARCH MODEL & HYPOTHESES DEVELOPMENT

Advanced AI characteristics (mobility, interactivity, communication, and autonomy), which are antecedents in this research, are considered with high impact on the AgriTech sector (Pesce et al, 2019).

Mobility empowers a robot (semi or fully automated robot) to function and process tasks like humans (walking, swimming, flying) in any setting. Interactivity is the characteristic that distinguishes an advanced technology from a conventional one (computers, software, programs). It involves the use of sensors and micromotors that scan the environment for information and thus characterizing the robot with humanistic traits (senses of sight, touch, hear, etc.). Communication characteristic refers to the use of natural language processing by robots to communicate with humans. Such a characteristic functions through gestures, voice, or speech recognition algorithms. Lastly, autonomy refers to the capacity for a machine or robot to fully function without (or with very minimal) human intervention, command, or control (Bekey, 2012).

Nevertheless, to date, there is no unifying theory of innovation adoption (Jöhnk, Weißert, & Wyrtki, 2021). The PCI theory focuses more on system features rather than the prediction of outcomes (Taherdoost, 2018). Therefore, this research further extends the theoretical framework with organizational readiness for change (ORC) theory. The ORC theory suggests that achieving a high level of innovation adoption is dependent on the level of readiness (Snyder-Halpern, 2001) (see Figure 1). Readiness may be either organizational or individual (employees) readiness (Parasuraman, 2000).

**Innovation characteristics and AI readiness relationships**

Organizational readiness has multiple definitions and measures (Miake-Lye et al, 2020). At an individual level, it is referred to as the degree to which individuals/employees are mentally and behaviorally set for organizational change (Weiner, 2009). At an organizational level, it is defined as a comprehensive attitude for change (Holt, Feild, & Harris, 2007). From an information systems (IS) approach, readiness (e-readiness or technology readiness) refers to organizational (or individual) ability/capability to adopt and benefit from technological innovation (Richey, Daugherty, & Roath, 2007; Parasuraman, 2000) and thus gaining competitive advantage in the market (Wiesbock & Hes, 2020).

In this research, AI-driven robots are the disruptive innovation in focus. Specifically, this research identifies AI as a set of underlying techniques that allow an entity to react or behave intelligently (Russell, Norvig, Davis, & Edwards, 2016), and AI readiness as a degree of preparedness for any change involving AI (AlSheibani, Cheung, & Messom, 2018).

From a general perspective, first, in IS research, innovation has been recognized as one of the primary sources of competitive advantage and sustainability (Bullinger, Auernhammer, & Gomeringer, 2004). Furthermore, other studies showed that AI technology characteristics (e.g., relative advantage and compatibility) positively relate to AI readiness (AlSheibani, Cheung, & Messom, 2018). Second, in sustainability research, digital capabilities have shown to positively relate to organizational readiness and organizational readiness positively relates to digital innovation (Zhen, Yousaf, Radulescu, & Yasir, 2021).

From a specific stance, mobility can be directly related to dynamism or dynamic capability. This multidimensional characteristic refers to the likelihood to systematically resolve problems and take decisions through resource configuration. Such a construct is characterized by sensing, learning, coordinating, and integrating (Pavlou & El Sawy, 2011). These same traits, which are organization-oriented, are found in AI-driven robots. The dynamic capability has been directly related to competitive advantage (Barreto, 2010), innovation (Ellonen, Wikstrom, & Jantunen, 2009), and disruptive innovation (Pandit, Joshi, Gupta, & Sahay, 2017).

Interactivity is considered one of the most significant characteristics in technology-mediated environments (Javornik, 2016). Interactivity has been characterized into user–machine, user–user, or user–message interaction (Cho & Leckenby, 1997). Nevertheless, different understandings of interactivity are found in multiple research streams (see Table 1).

*Table 1 : Conceptualizations of interactivity*

| Conceptualization | Research | Source |
|---|---|---|
| Continuous technology-mediated communication | Marketing strategy | Day (1998) |
| Predominant explanatory construct for the undertaken tasks | Marketing strategy | Deighton & Kornfeld (2009) |
| Feature-based driver - interface functionality that allows synchronisation of communication | Consumer behaviour | Sundar (2004); Mollen & Wilson (2010) |
| Complex concept consisting of machine interactivity and person interactivity | E-Business | Suntornpithug & Todorovic (2010) |
| User perception - perception towards the features of technology during interaction | Consumer behaviour / | Song & Zinkhan (2008); Mollen & |

| | | |
|---|---|---|
| | Marketing / Media | Wilson (2010); Voorveld, Neijens, & Smit (2011) |
| Modality/medium type - functional view that is related to technological features and functions that permit users for taking actions and initiate interactions | Digital technologies | Sundar, Jia, Waddell, & Huang (2015) |
| Message type - tool that provides message exchanges between different parties | Digital technologies | Sundar, Jia, Waddell, & Huang (2015) |
| Source type - degree the technology establishes the user as the source of communication and the one in control, either through selection of content<br>or its creation and customisation | Digital technologies | Sundar, Jia, Waddell, & Huang (2015) |

Regardless of the diverse conceptualizations and research streams of interactivity, throughout the last two decades, interactivity has been identified as the most prominent characteristic that positively relates to digital (Deighton & Kornfeld, 2009; Sundar, Jia, Waddell, & Huang, 2015) and advanced technologies (augmented and virtual realities) (Lakkis & Issa, 2021).

In the marketing and media domains, communication is interrelated within the concept of interactivity. Interactivity refers to the extent to which two or more entities communicate with synchronized degrees of influence (Liu & Shrum, 2002). Nevertheless, in the AI field, communication is more closely related to the system's information processing capacity. Information could be linguistic, textual, or any other type. Information processing capacity, which is derived from information technology (IT) resources/capabilities, relates to the ability to gather, analyze, merge, and diffuse the input data to cope with uncertainty (Huang, Pan, & Ouyang, 2014). Such types of IT capabilities are efficient in removing communication restrictions (Brown & Duguid, 2001). Information processing capacity is also closely related to the conceptualization of learning (i.e., machine/deep learning in the case of AI). It consists of codifying, integrating, storing, and assessing big data/information in the form of input and output (Amalina, Suhaimi, & Abas, 2020); thus, directly associated with information management. Furthermore, merged with machine learning, natural language processing, an AI-driven method, can design systems that learn to perform tasks independently and understand human language.

Autonomy first emerged as an individual/personality trait (psychology), then advanced to work-related tasks (design), and recently integrated into innovation (characteristic and capabilities) (e.g., autonomous vehicles, robots, or machines). In early literature, autonomy has been identified as the degree of freedom to complete work-related tasks (Hackman & Oldham, 1976) and directly linked to independence (self-determination) in decision-making (Morgeson & Humphrey, 2006). In the IS literature, autonomy is identified as a system's non-functional feature that outlines other functions while constantly adjusting its actions and behavior to changes in the environment (Janiesch, Fischer, Winkelmann, & Nentwich, 2019). From a technical perspective, autonomy requires pre-configured automation to perform independent decisions (Janiesch et al., 2019). Autonomy has shown to be a significant antecedent to work satisfaction, high performance, motivation, and user service innovation (Ye & Kankanhalli, 2018), in which its absence leads to reduced readiness to adapt to new environments, tasks, or tools (Sonnentag, Volmer, & Spychala, 2008).

Therefore, in alignment with these arguments, the authors raise the following hypotheses:

**Hypothesis 1:** Mobility positively relates to AI readiness.

**Hypothesis 2:** Interactivity positively relates to AI readiness.

**Hypothesis 3:** Communication positively relates to AI readiness.

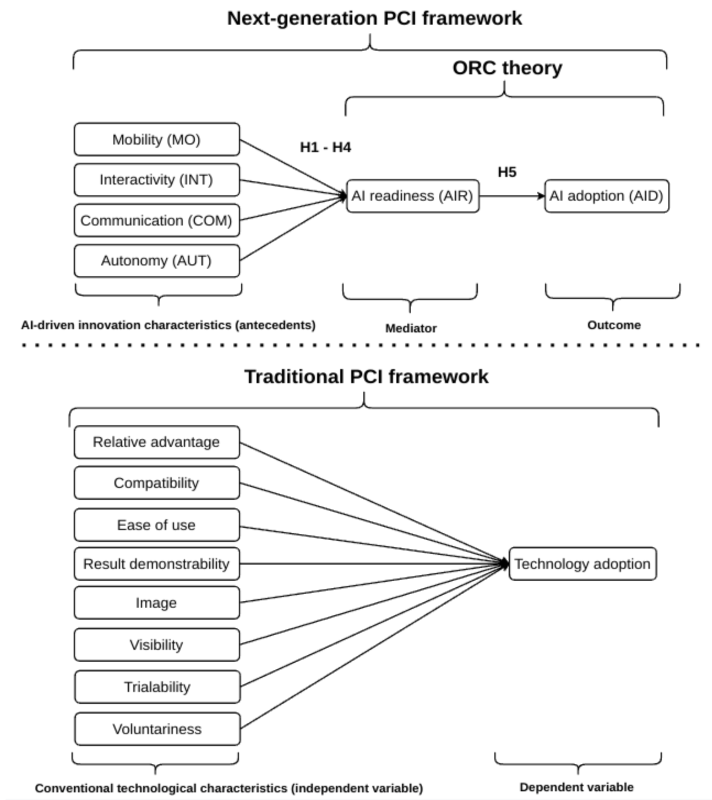
**Hypothesis 4:** Autonomy positively relates to AI readiness.

**AI readiness and AI adoption relationship**

AI readiness and adoption research is embryonic and underdeveloped (Jöhnk, Weißert, & Wyrtki, 2021). Yet, multiple recent studies (empirical and conceptual) have shown that AI readiness is positively related to AI adoption (Jöhnk, Weißert, & Wyrtki, 2021; Pumplun, Tauchert, & Heidt, 2019; Alsheibani et al., 2018). Therefore, based on the literature, it is plausible to hypothesize the following:

**Hypothesis 5:** AI readiness positively relates to AI adoption.

*Figure 1: Research model and proposed hypotheses*




## EMPIRICAL STUDIES

### Study 1: Quantitative Investigation

For the quantitative study, data was analyzed using SPSS 23.0, AMOS 23.0, and smartPLS3. STATA 14.2 was further implemented to double-check and verify the findings. Several software tools were implemented because each software delivers diverse aspects of validity and no general acknowledgment exists yet on types of tests that reflect adequate validity standards (Lombard et al., 2015).

An E-survey questionnaire was implemented to examine the proposed hypotheses. The questionnaire was developed to be compact and short in length to encourage a high response rate. The survey consisted of 19 constructs' items (see Table 2) and seven demographics (gender, age, nationality, level of education, type of profession, technology/innovation experience, agriculture experience). All the items followed a seven-point Likert scale (strongly disagree, disagree, somewhat disagree, neither agree nor disagree, somewhat agree, agree, and strongly agree).

*Table 2. Questionnaire items*

| | |
|---|---|
| ***Mobility*** *(adopted from dynamic capability of innovation; Pandit, Joshi, Gupta, & Sahay, 2017; Pavlou & El Sawy, 2011)* | |
| MO 1 | The advanced machines are effectively able to spot, understand, and pursue opportunities or tackle threats at the workplace (sensing capability) |
| MO 2 | The advanced machines are able to restructure existing functional competencies with new knowledge (learning capability) |
| MO 3 | The advanced machines are able to integrate individual knowledge and inculcate it into the operational capabilities via collective sense-making (integrating capability) |
| MO 4 | The advanced machines are able to facilitate reconfiguration by assigning and organising tasks and resources in the new operational capability set up (coordinating capability) |
| ***Interactivity*** *(adapted from media characteristics; Yuping, 2003)* | |
| INT 1 | The advanced machines facilitate multi-communication channels among the users |
| INT 2 | The needed information is received without any delay |
| INT 3 | When using the advanced machines, receiving instantaneous information is guaranteed |
| ***Communication*** *(adapted from information management ; Devece-Caranana, Peris-Ortiz, & Rueda-Armengot, 2015)* | |

| | |
|---|---|
| COM 1 | The advanced machines are efficient in capturing relevant and up-to-date information from the environment (collecting information) |
| COM 2 | The advanced machines have procedures to systematically codify and store information (assessing information) |
| COM 3 | The advanced machines can transmit and developing knowledge through communication, dialogue, and debate (identifying and distributing information) |
| ***Autonomy*** *(adapted from design autonomy; decision-making autonomy; Morgeson & Humphrey, 2006)* | |
| AUT 1 | The advanced machines are effectively able to choose their own method to develop applications and finish tasks |
| AUT 2 | The advanced machines have full control over which type of applications to design or tasks to complete |
| AUT 3 | The advanced machines are fully capable to decide on their own what/which applications should be designed or tasks to finish first |
| ***AI Readiness*** *(adapted from technology readiness; Berndt, Saunders, & Petzer, 2010)* | |
| AIR 1 | I prefer the use of the most advanced technology available. |
| AIR 2 | I enjoy the challenges of figuring out how high-tech gadgets work. |
| AIR 3 | I feel confident that machines will do what you tell them to do. |
| ***AI Adoption*** *(adapted from intention to adopt; Brown & Venkatesh, 2005; Venkatesh et al., 2003)* | |
| AID 1 | I can imagine using advanced technologies (AI-driven) regularly in my workplace. |
| AID 2 | I plan to use advanced technologies (AI-driven) in the future. |
| AID 3 | I intend to use advanced technologies (AI-driven) in everyday work. |

***Common method bias***

Before the regression analysis, common method bias was not found to be a major issue (see Table 3). Furthermore, several technical remedies and statistical control tests were implemented (i.e., separation of the criterion and predictor measures; CLF method within the CFA model) (Podsakoff, Mackenzie, Lee, & Podsakoff, 2003) to rule out the possibility of common method bias.

*Table 3. Harman's One Factor Test*

| Total Variance Explained | | | | | | |
|---|---|---|---|---|---|---|
| Component | Initial Eigenvalues | | | Rotation Sums of Squared Loadings | | |
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 3.903 | 20.541 | 20.541 | 2.879 | 15.152 | 15.152 |
| 2 | 3.303 | 17.382 | 37.923 | 2.674 | 14.075 | 29.227 |
| 3 | 2.405 | 12.660 | 50.583 | 2.556 | 13.454 | 42.681 |
| 4 | 1.998 | 10.516 | 61.100 | 2.218 | 11.675 | 54.356 |
| 5 | 1.727 | 9.091 | 70.191 | 2.111 | 11.110 | 65.466 |
| ***6**** | ***1.189*** | ***6.260*** | ***76.450*** | ***2.087*** | ***10.985*** | ***76.450*** |
| 7 | .701 | 3.688 | 80.139 | | | |

** Eigenvalues > 1.0; cumulative 76.450%; No single or general factor emerged for most of the variance*

Factor loadings showed significant correlations (see Table 4). Convergent and discriminant validity showed satisfactory estimates (see Table 5). Finally, the appropriateness of the model was assessed providing an adequate overall measurement model fit (see Table 6).

*Table 4. Factor loadings*

| | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| INT1 | .094 | .015 | -.021 | .110 | -.114 | **.863** |
| INT2 | .343 | .174 | -.013 | -.091 | .096 | **.711** |
| INT3 | .015 | .060 | -.022 | .089 | -.017 | **.816** |
| MO1 | **.760** | .167 | -.160 | .022 | -.015 | .262 |
| MO2 | **.802** | -.090 | .070 | -.002 | -.087 | .000 |
| MO3 | **.855** | .079 | -.033 | .026 | -.062 | .179 |
| MO4 | **.868** | -.029 | .021 | .217 | -.090 | -.006 |
| COM1 | -.105 | -.149 | .091 | .185 | **.787** | -.099 |
| COM2 | -.045 | .005 | .143 | -.088 | **.800** | -.055 |
| COM3 | -.081 | -.144 | .083 | .036 | **.813** | .084 |
| AUT1 | .100 | .131 | .124 | **.673** | .227 | .159 |
| AUT2 | .087 | .056 | -.073 | **.912** | .039 | -.039 |

| | | | | | | |
|---|---|---|---|---|---|---|
| AUT3 | .031 | .060 | .021 | **.889** | -.109 | .046 |
| AID1 | .024 | .144 | **.879** | .021 | .061 | -.023 |
| AID2 | -.037 | .083 | **.905** | .051 | .153 | -.017 |
| AID3 | -.051 | .179 | **.902** | -.015 | .127 | -.022 |
| AIR1 | .014 | **.917** | .103 | .086 | -.119 | .107 |
| AIR2 | .025 | **.911** | .171 | .094 | -.022 | .088 |
| AIR3 | .048 | **.894** | .150 | .070 | -.159 | .038 |

*Table 5. Descriptive statistics, Convergent & Discriminant validity*

| | Mean | St.Dv | CR* | AVE * | MSV** | AID | MO | INT | COM | AUT | AIR |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AID | 2.423 | 1.392 | .904 | .758 | .088 | **.871** | | | | | |
| MO | 5.600 | 1.126 | .861 | .611 | .127 | -.071 | **.781** | | | | |
| INT | 5.114 | 1.034 | .764 | .521 | .127 | -.050 | .357 | **.722** | | | |
| COM | 2.735 | 1.314 | .764 | .522 | .072 | .268 | -.206 | -.121 | **.723** | | |
| AUT | 4.209 | 1.066 | .816 | .607 | .031 | -.009 | .177 | .095 | .114 | **.779** | |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AIR | 4.559 | 1.373 | .928 | .811 | .088 | .297 | .106 | .212 | -.233 | .155 | **.900** |

**CR > 0.70 & AVE > 0.50 (Fornell & Larcker, 1981); Convergent validity is satisfactory*
***MSV < AVE (Fornell & Larcker, 1981; Discriminant validity is satisfactory)*

***Endogeneity***

Durbin–Wu–Hausman (DWH) test (augmented regression test) for endogeneity concerns and Durbin–Watson (DW) test for autocorrelation issues were implemented. No endogeneity was found since the Durbin (score) chi2(1) > 0.05 and Wu-Hausman > 0.05. Hence, since both p values are greater than 0.05, we accept the null hypothesis that states there is "no correlation between the variables". In addition, autocorrelation was not found to exist among the constructs (Durbin-Watson (d) estimate provided 2.0).

***Hypothesis testing***

In terms of hypothesis testing, the empirical analysis provided several interesting insights. H1 (MO-AIR) was not supported (t= -.433; β= -.029; p> .05); H2 (INT-AIR) was supported (t= 2.523; β= .167; p< .05); H3 (COM-AIR) was not supported (t= -3.121; β= -.199; p< .05); H4 (AUT-AIR) was supported (t = 2.861; β = .183; p< .05); H5 (AIR-AID) was supported (t= 4.365; β= .274; p< .05) (see Table 6 & Figure 2).

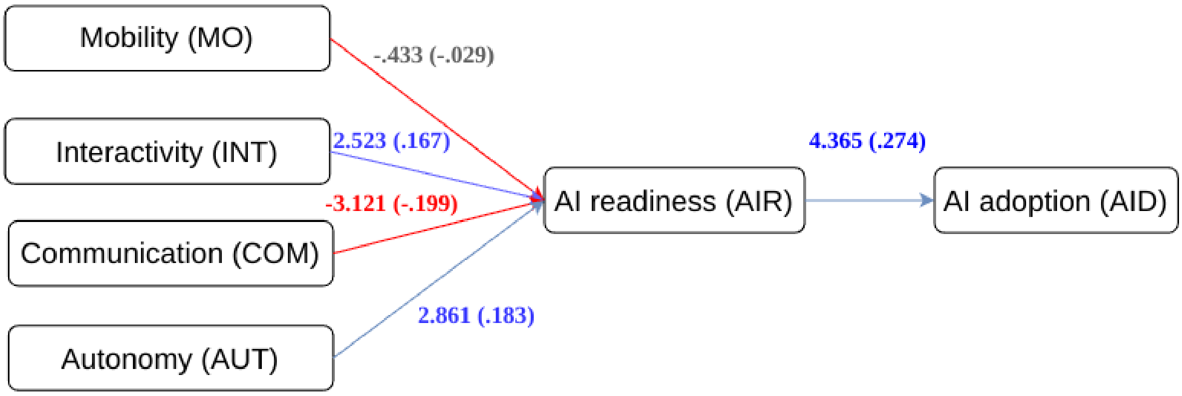
*Table 6: Regression analysis*

| **Variables** | **AI Readiness (AIR)** | | | |
|---|---|---|---|---|
| | t | Stnd ß | Unst. ß | Hypotheses |
| | | | | |
| Mobility (MO) | -.433 | -.029 | -.036 | *H1 Not supported* |

| | | | | |
|---|---|---|---|---|
| Interactivity (INT) | 2.523* | .167* | .221* | H2 Supported |
| Communication (COM) | -3.121* | -.199* | -.208* | *H3 Not supported* |
| Autonomy (AUT) | 2.861* | .183* | .235* | H4 Supported |
| | | **AI Adoption (AID)** | | |
| AI Readiness (AIR) | 4.365* | .274* | .278* | H5 Supported |
| R | .317 | R | .274 | |
| $R^2$ | .100 | $R^2$ | .075 | |
| Adjusted $R^2$ | .085 | Adjusted $R^2$ | .071 | |
| VIF** | 1.12 | VIF** | 1.08 | |
| | | **Model fit** | | |
| CMIN/DF | | 2.603 | (< 3) | (Hair et al., 2010) |
| CFI | | .908 | (> .900) | (Hair et al., 2010) |
| RMSEA | | *.080* | (< .080) | (Hooper et al., 2008) |

**<.05; **VIF estimates 1/(1−R2) < 5 (Gruber, Heinemann, Brettel, & Hungeling, 2010); thus, multicollinearity is not a concern*

*Figure 2: Empirically tested research model (t values, Beta values)*




Therefore, H1 and H4 showed to be positively significant whereas H3 showed to be negatively significant. Nevertheless, H1 showed to be insignificant. Such a finding led the authors to further investigate the effect of mobility on AI readiness. Thus, the authors examined the possibility of a curvilinear relationship between mobility and AI readiness. The results showed that mobility nonlinearly affects AI readiness (see Table 7). In other terms, a cubic (s-shaped) relationship exists in which AI readiness changes (increases and decreases) depending on the constant increase in perceived mobility (see Figure 3).

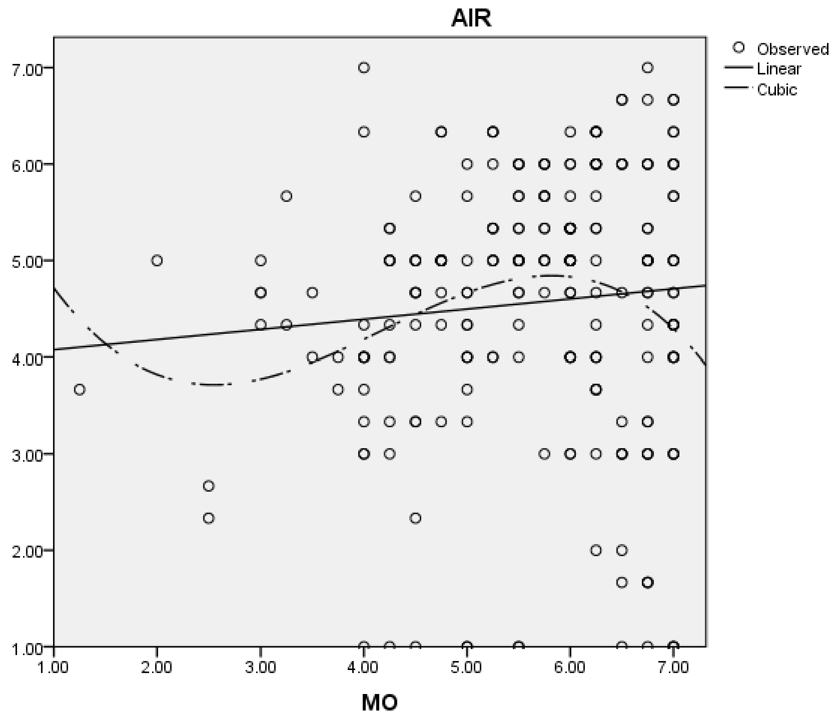
*Table 7 : Nonlinear regression analysis (curve estimation)*

| **Variables** | **AI Readiness (AIR)** | | | |
|---|---|---|---|---|
| | t | Stnd ß | Unst. ß | |
| | | | | |
| Mobility | -1.436 | -2.356 | -2.872 | Not significant |
| Mobility squared *2 | 1.831 | 6.879 | .810 | Not significant |
| Mobility cubed *3 | -2.066* | -4.507* | -.065* | *Significant* |
| R | | .199 | | |
| $R^2$ | | .040 | | |

| Adjusted $R^2$ | .027 | |
|---|---|---|

*<.05

*Figure 3: Mobility - AI readiness s-shaped (cubic) relationship*




### *Mediation analysis*

Mediation effects were also examined. Submodel 1 showed partial mediation effects. Thus, MO has both direct and indirect relationships with AID (the path from MO to AID is reduced in absolute size but is still different from zero when AIR is introduced). Whereas, submodels 2, 3, & 4 showed full mediation effects. In other words, the characteristics only have indirect effects on AID (i.e., the characteristics no longer affect AID after AIR is controlled) (see Table 8).

*Table 8 : Mediation analysis*

| Submodel | Lower CI | Upper CI | Point | P value | Result |
|---|---|---|---|---|---|
| (1) MO-AIR-AID | -.0118 | .0922 | .0300 | >.05 | Partial mediation |
| (2) INT-AIR-AID | .0170 | .1517 | .0754 | <.05 | Full mediation |
| (3) COM-AIR-AID | -.1407 | -.0160 | -.0661 | <.05 | Full mediation |

| | | | | | |
|---|---|---|---|---|---|
| (4) AUT-AIR-AID | .0105 | .1483 | .0642 | <.05 | Full mediation |

** 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)*

## Study 2: Qualitative Investigation

### *Approach taken*

We complement our primary quantitative investigation with an in-depth qualitative analysis (Cameron, 2008; Clark et al., 2019; Vergne, 2012) organizations maximize their readiness for AI adoption. We aim at unravelling some of the key areas and elements on which firms have to focus as part of their preparation process for adopting AI-based technologies. In doing so, we employ a set of grounded theory procedures that draw from both the 'Straussian' and 'Glaserian' schools of thought. Specifically, we adopt Strauss and Corbin's (1990b) interpretation of grounded theory, which allows for the emergence of important themes and patterns in the data while assuming some prior knowledge through broad questions identified in the literature. We use this complementary methodological approach to fill some of the voids and address some of the shortcomings of our primary quantitative analysis (Cameron, 2008; Clark et al., 2019; Vergne, 2012). The main aim is to seek in-depth qualitative insights from a diversified pool of subject matter experts on the field under investigation.

### *Research Setting and Sources of Evidence*

We investigate our research question within the AgriTech sector, which provides, given its unique characteristics, newly emerging needs and challenges (Shepherd, et al., 2018), a unique opportunity for exploring the ways in which AI-driven organizations can manage their adoption of this revolutionary technology.

To explore our research question, we collected interview data from one of the most influential conferences within the field of AgriTech: "2021 4th Global Summit on Agriculture, Food Science, and Technology". We rely on an in-depth analysis of 25 interviews with a highly diversified sample of interviewees comprising managers, entrepreneurs, scholars, and experts from the field of AI and AgriTech. The speakers were solicited and interviewed to share their insights on how firms within the AgriTech sector can maximize their readiness for the adoption of state-of-the-art AgriTech AI-powered systems and technologies.

**Sampling method**

We use the purposeful sampling strategy, which aims at including information-rich cases that have knowledge and expertise relevant to the phenomenon being explored (Breckenridge & Jones, 2009; Coyne, 1997; Glaser & Strauss, 1967; Suri, 2011). Our sampling strategy consisted of selecting participants by virtue of their capacity to provide richly-textured insights about the subject under investigation. As such, we focused on AI and AgriTech managers, entrepreneurs, scholars, along with experts to uncover the AI readiness key components that can facilitate the process of AI adoption.

***Data Analysis and Coding Methodology***

We pursued a grounded theory approach to data analysis (Strauss and Corbin, 1990). The analysis process involved three main stages: i) Identifying relevant segments of text through 'micro-analysis'; ii) creating a large set of codes through 'open coding'; and iii) Identifying the key themes for AI readiness through 'axial coding'.

*Phase 1: Identifying relevant segments of text through 'micro-analysis'*

Following Strauss and Corbin (1990), the first phase started by a microanalysis, which consisted of screening the sources of evidence that have been collected to identify segments of texts that were relevant to the mechanisms and strategic action that were involved in the readiness process for AI adoption. This micro-analysis was performed by two co-authors independently. The authors agreed to maintain only the accounts that were consensually judged relevant to the investigated research question.

*Phase 2: Creating a large set of codes through 'open coding'*

The second phase started by 'open coding' (Strauss and Corbin, 1990), which consisted of creating a large set of codes that classify the identified AI readiness accounts from phase 1. Specific codes were used to label and summarize the identified accounts for the construction of AI readiness key components. This process was performed by two co-authors in isolation to minimize the subjective interpretation of the data and better capture all the AI readiness accounts embedded in the interview data. A comparison of the two coding schemes was accomplished, resolving eventual inconsistencies between the two coders.

*Phase 3: Inductive analysis of the AI readiness key components.*

In phase 3, open coding was followed by what Strauss and Corbin (1990) refer to as axial coding, which involved grouping the large set of codes under broader theoretical categories, that we label as: AI readiness key components. They constitute the main categories in our empirical framework of AI readiness.

***Findings***

Our analysis has led to the identification of a set of three AI readiness components that delineate how firms operating within the AgriTech field manage their readiness process for AI adoption. We label these key readiness components as: *1) Established human-machine collaboration mindset; 2) Pre-identified AI strategic impacts; and 3) Robust technological infrastructures and data management capabilities.* We analyse our data in light of the findings from study 1 in relevance to the role of the AI readiness construct in shaping the relationship between AI adoption and technology perceived characteristics, and aim at uncovering deeper qualitative insights to construct a comprehensive framework for AI readiness within the AgriTech sector.

*AI readiness first component: Established human-machine collaboration mindset*

AgriTech firms strive for finding practical tools that optimize their internal practices and operational systems. In this vein, the integration of human and algorithmic intelligence seems to be an important block in constructing future AgriTech AI-driven business models. However, in light of the evident differences in the nature of human's and machine's capabilities, a number of adoption and implementation challenges surface.

Our findings reveal that AI scholars and AgriTech experts predict human-machine collaboration to be a fundamental prerequisite for successful AI adoptions within the AgriTech sector. While machines are better at scanning complex environments and processing large amounts of unstructured data, humans are better at performing tasks that requires high levels of creativity and novelty. As such, AgriTech firms are faced with a real strategic opportunity for driving performance thanks to the synergies that can be potentially obtained from using the best of what machines can do and coupling that with the best of what humans can do in the field.

> "The aim is not a total replacement of our human capital. As opposed to what some experts may claim, many of the tasks that workers perform in the field can be hardly substituted by technology."
> *(AgriTech expert 1)*

> "It is important to promote the spirit of collaboration between workers and robots. This kind of mindset is a key element that can facilitate the process of technology acquisition. For that to happen, most agricultural workers need to go through a process of training to acquire the relevant skills."
> *(AgriTech manager 3)*

While some sectors may opt for a full machine delegation and decision-making automation, AgriTech firms would privilege employing "human-confirmation modes", namely when it comes to important and risky decisions in the field. Human confirmation of

AI decisions can help build the trust between the human and the AI and prepares the ground for an effective collaboration between the two.

> "From our experience, people have often a hard time trusting the AI for taking the final decision. To address this problem, new features have been integrated to the system to build the trust. It is called the "human-confirmation mode". The app says -- a threat was detected and here is what the AI wants to do about it, do you confirm? -- The trust is built through time as the person sees that the AI is taking the right decision every time."
> *(AI scholar 2)*

There is another important dimension to human-machine collaboration. Most firms are faced with significant opposition and scrutiny after launching their strategies for AI adoptions. There is a dominant belief that artificially intelligent robots will still away people's jobs. As such, human-AI collaboration emerges as an "ethical", "socially acceptable" adoption strategy for AgriTech companies that aim at enhancing the capabilities of their employees and managers, as supposed to the radical alternative of an integral replacement of their human collaborators. Thus, promoting the human-machine mind-set can assure employees and maximize AI readiness. Human-machine collaboration seems to prevail as a wiser strategic option for "socially-responsible" AgriTech firms that aim at simultaneously yielding the benefits of AI's unique capabilities on the one hand, and preserving their valuable human capital and corporate legitimacy on the other.

*AI readiness second component: Pre-identified strategic impacts*

Many contemporary organizations adopt external practices as a response for institutional pressures (Bromley and Powell, 2012). Such firms would implement cutting edge technological practices, which have an ambiguous links to the firms' core goals (Jabbouri et al., 2019; Wijen, 2014).

In this respect, it is highly important for organizations that seek to yield the maximum benefits of AI capabilities, to undergo a thorough strategic analysis. This preliminary process aims at diagnosing the firms' most prevailing business problems, that can be potentially addressed through AI implementation. Organizations should not fall in the trap of adopting AI as a "symbolic action" (Bromley and Powell, 2012), to cope with increasing pressures for being "technology-driven" (Jabbouri et al., 2019).

Adoption of cutting edge technologies requires mobilizing significant resources. As such, it is important to link these strategic choices to the most prominent strategic needs of the firm. This way the firm can avoid decoupling the adopted technology from the daily practices and internal processes. Our qualitative accounts portray some of these arguments:

> "For many agricultural firms, AI has become a must, not an option. But, saying this you still want to do it right. You need to ask the right questions: how am I going to do it; who is going to be involved with the AI; which department, which business unit; which people?"
> "It's part of the process to specify all these elements before you dive into it."
> *(AI expert 4)*

Our findings suggest that AI adoption needs to be preceded by a set of strategic diagnoses, that can help AgriTech managers clarify the utility, usefulness, and impact of AI adoption on their firms. This constitutes identifying the most imminent strategic needs that can be potentially resolved through AI implementation, as well as the business units, production lines, processes, and collaborators that would be directly or indirectly impacted by AI adoption.

> "The way I see it is that I wouldn't go for it (AI) if I don't see an actual impact. You know these AI systems demand significant investments. You have got to install it (AI system), make it operational, then maintain it over time."
> "My starting point would be the ROI. If it's worth it then, am totally in."
> *(AgriTech entrepreneur 2)*

The high rate of failure of technology adoption and implementation (Jabbouri et al., 2019) compels AgriTech firms to devote more effort into preparing the ground and maximizing their readiness for future adoptions. In this regard, the AI readiness process comprises a set of strategic actions to be performed prior to the AI adoption. This includes assessing the ROI, the estimated impact on performance and operations, and the specific strategic needs that can eventually be addressed through AI.

*AI readiness third component: Robust technological infrastructures and data management capabilities.*

AI is a complex technology of which the implementation requires a robust technological infrastructure. In this respect, the adoption of AI technologies within AgriTech firms necessitates the existence of a number of fundamental technological blocks; robust and effective technological infrastructures that are key to the proper functioning of a AI-driven firm's operational systems, production lines, and internal processes.

> "If you're thinking of adopting a certain AI tool to improve your business, you need to make sure you have the appropriate ground for that. First, are your collaborators familiar with the basic technological functioning? Second, have you already used other technological tools in your managing your operations at all?"
> "The idea here is that your adoption of technology should be done in a progressive manner. You need to build the right culture for that and make sure that your business units are smoothly digesting newly employed technologies."
> *(AgriTech scholar 3)*

Our findings reveal that AI can be considered as one of most advanced levels of digital transformation. For instance, ML algorithms drive their predictive and self-learning capabilities from the availability of big data. As such, a firm's capacity for collecting, filtering, and categorizing colossal amounts of data proves to be a key competence when it comes to preparing the proper ground for AI adoption. Such a unique competence for efficient data management is yet a longstanding challenge for many firms with the AgriTech sector due to the limitations of their internal computing and data processing capabilities.

Given the multiplicity and complexity of tasks performed by AI systems within the AgriTech field ranging from robotic self-operation to hyper-precise weather forecasting, and supply chain hyper-efficient management, AI adoption compels adopting companies to build extremely reliable and performant technological infrastructures. Specifically, we found that the process of extracting raw data and converting it to a usable strategic asset is a key prerequisite to the success of any AI adoption. While many AgriTech firms sit on treasures of unstructured data, yielding the maximum benefits of AI adoptions can be almost unachievable unless the valuable asset of data is properly extracted, filtered, organized, categorized, and translated to workable formats.

> "Artificial intelligence's power stems from the availability of data. Say, I want to train a ML algorithm to solve a specific business problem, then I have to supply it with tremendous amounts of appropriate, meaningful data which can fit the specific characteristic of my algorithm."
> "Most firms sit on giant pools of proprietary data. But, very few would take the time and the energy to mind through it. In order to do that, they need to build the right infrastructures. They need to deploy a team of data experts to filter all the junk they have in their backyard. And, that is consequent in terms of time and money."
> *(AI expert 1)*

In data-driven organizations operating in the AgriTech field, managers can make proper strategic decisions, only if they devote sufficient time to thoroughly examine the numerous data pieces they have access to. In this vein, it is crucial for AgriTech firms, as part of their AI readiness process, to build sustainable data processing channels that can in turn be coupled with the self-learning and self-improvement capabilities of ML algorithms following AI adoption. This way AgriTech firms can derive the most value of their AI adoptions, thus becoming more efficient at solving day-to-day prevailing business problems.

## DISCUSSION

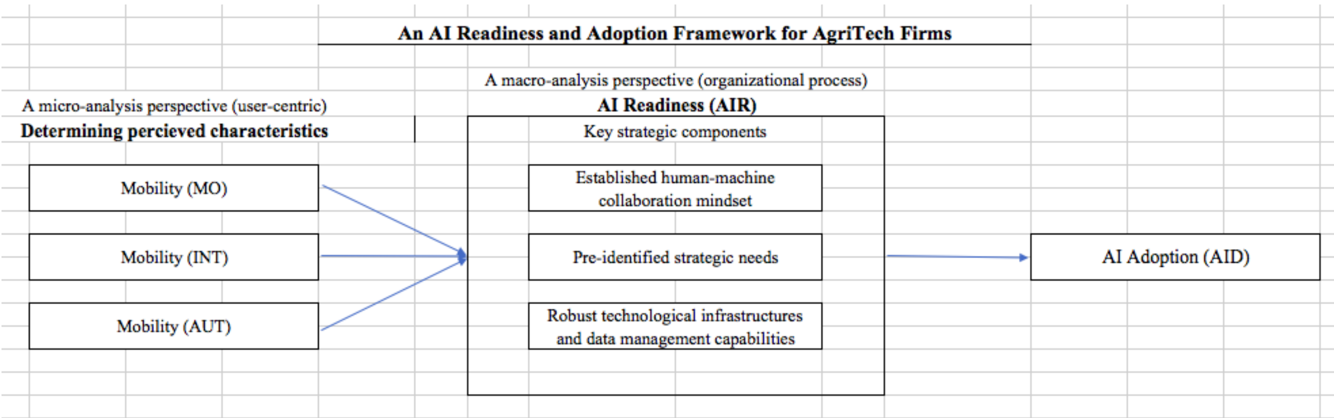
### Implications for Research

While our quantitative study sheds light on the perceived characteristics of AI innovations in relation to the organizational process of AI adoption, and the role of AI readiness in shaping the relationship between the independent and dependent variables, the complementary qualitative analysis explores how AI readiness can be maximized to facilitate and prepare the ground for an optimized AI adoption process. Using a mixed-methods approach increases the robustness and reliability of research (Cameron, 2008; Clark et al., 2019; Vergne, 2012). As such, this mixed-methods approach has led us to constructing a comprehensive empirically grounded framework that plausibly explains the key mechanisms of AI readiness and adoption within AgriTech firms.

Our study has a number of key contributions. First, our empirical model delineates the relationships between a set of AgriTech-specific AI perceived characteristics and AI adoption, as well as the mediating role of the AI readiness construct. This empirical framework can potentially better fit the characteristics of the AI technology (Faraj et al, 2018; (Ferràs-Hernández, 2018; George et al, 2014), and better capture the unique challenges and emerging aspirations of the AgriTech sector (Bowen & Morris, 2019; Shepherd et al., 2018). Further, it complements and enriches the traditional PCI model (Rogers, 2003) and represents a more suitable strategic tool for AI-driven organizations. Second, our qualitative analysis portrays some of the best practices that firms within the AgriTech sector implement through the process of AI readiness and AI adoption. Our framework provides key propositions and practical recommendations for how firms can better prepare the ground for AI adoption within their internal processes and operations, linking the AI transformation to the firms' core strategy (Kane et al., 2015; Schallmo et al., 2017; Warner & Wäger, 2019).

Figure X illustrates our empirical framework for AI readiness and adoption.

*Figure 4: An illustration of AI readiness and adoption framework for AgriTech firms.*




Our quantitative study relies on a micro-analysis perspective as it places the user at the center of its focus. We explored the relationships between AI innovating characteristics and AI adoption from a user-centric perspective. As such, we provide insight to how technology users in AgriTech firms can better cope with disruptive tools and devices that are powered by the automation and self-operation of AI systems. On the other hand, our qualitative analysis focuses on a macro-analysis perspective. It sheds lights on the key organizational process of disruptive technology adoption. As such, it uncovers some of the key components of the AI readiness process. We delineate a set of important elements and strategic actions that AgriTech firms should focus on to maximize their readiness and facilitate the process of AI adoption. Our qualitative analysis has enabled us to enrich our initial empirical framework from study 1, and led to developing a more comprehensive framework for AI readiness within the AgriTech field. This way, we add to the global debate on disruptive technology adoption (Appio et al., 2021; Colbert et al., 2016) within the AgriTech field (Bowen & Morris, 2019; Shepherd et al., 2018).

**Implications for Practice**

Our research delivers two key practical implications. First, from an AI design and development perspective, this study provides a set of propositions and practical recommendations in relevance to creating the ideal conditions for successful AI adoptions within the Agritech field. Focusing on a user-centric perspective, our quantitative findings shed light on the key must-have characteristics that AI tools, devices, and systems should incorporate to maximize user acceptance and adoption within an AgriTech firm. As such, AI developers can focus on incorporating these key elements in the conception and design process of AI innovations.

Second, our empirically grounded model provides AgriTech managers and decision-makers with a set of key components that shape the readiness process for AI adoption within the field. Our framework constitutes a strategic tool that can help AgriTech entrepreneurs better manage the AI readiness process, linking eventual AI adoption to their firms' key strategic needs and goals.

## Limitations and Future Research

Our research has a few limitations that can be addressed by future research. First, our data is collected from one of the most influential conferences in the AgriTech sector. While this setting is highly suitable for collecting data from relevant respondents and interviewees, it limits the size of our sample for both the quantitative and qualitative investigations. In this regard, future research in the field can test our hypotheses and qualitative findings within larger samples and within other organizational settings. One path, could be to target international firms, managers, entrepreneurs, experts, and scholars from the field of AI and AgriTech, and aim at assessing the collective perceptions and discourse of such audiences on the topic of AI adoption within AgriTech firms. Within this vein, the process of AI adoption is often seen as the primary phase of a rigorous strategic process of implementation and achievement (Bromley & Powell, 2012; Jabbouri et al., 2019; Wijen, 2014). As such, the post-adoption phase of AI could be explored to unravel some of the implementation challenges and goal achievement barriers.

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