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Organizational Readiness Concept for AI: A Quantitative Analysis of a Multi-stage Adoption Process from the Perspective of Data Scientists

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ORGANIZATIONAL READINESS CONCEPT FOR AI: A QUANTITATIVE ANALYSIS OF A MULTI-STAGE ADOPTION PROCESS FROM THE PERSPECTIVE OF DATA SCIENTISTS

Research Paper

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Abstract

Artificial intelligence (AI) is reshaping the business world in ways that enable organizations to create business value and reinvent their business models. Despite the great potential, organizations have difficulties in moving beyond the pilot stage and fully adopting AI applications. To better understand how organizations can implement AI into their core practices, we examine the impact of organizational readiness factors along the adoption process of AI through a quantitative research design. By integrating the organizational readiness factors into the multi-stage adoption process of AI, we unpack the interdependencies between these two literature streams. Due to the multi-faceted nature of organizations, we investigate the differentiating and opposing effects of the organizational readiness factors on the initiation, adoption, and routinization stages of AI.

Keywords: Artificial Intelligence, Organizational Readiness, Adoption Process.

1 Introduction

The race to adopt AI in organizations is in its full swing as it provides organizations the opportunity to generate new business value and disrupt their business models (Brynjolfsson and Mcafee, 2017). In particular, by implementing AI, organizations are able to turn their data into value (Davenport and Ronanki, 2018), develop new products and services (Davenport, 2018; Ransbotham et al., 2019), and improve operational efficiency through data-driven decision-making (Brynjolfsson et al., 2011). Due to its disruptive potential, AI has been deployed in various industries and sectors, including finance (e.g., Fu et al., 2021), healthcare (e.g., Hofmann et al., 2019), and human resources (Black and van Esch, 2020). Given the business impact, AI is considered one of the most promising innovations to remain competitive in the digital age (Seddon et al., 2017; Dremel et al., 2020; May et al., 2020). However, while 50% of the 2,395 participants in a global survey on the state of AI in 2020 stated that their organizations have adopted AI applications in business processes or products, only 16% have implemented AI beyond the pilot stage (Balakrishnan et al., 2020). These findings imply that organizations are still struggling to pass the pilot stage in which AI applications are implemented only in ad hoc pilots rather than being rolled out into enterprise-wide programs. Therefore, the adoption rate of AI does not necessarily reflect that AI applications are fully embedded in core practices. The tendency of not moving beyond the pilot stage indicates that AI poses new challenges to organizations compared to other technologies. Based on the concept of intelligent agents (Russell and Norvig, 2021), AI applications are able to self-learn and make autonomous decisions (Berente et al., 2021). As these given capabilities increase the degree of inscrutability (Berente et al., 2021), associated changes at the task level ultimately affect the human decision-making process. While decisions are no longer made exclusively by humans but are augmented by AI, human-machine collaboration becomes increasingly important for organizations. In order to fulfil new requirements posed by innovations, literature particularly emphasizes to promote organizational readiness (Weiner, 2009; Lokuge et al., 2018; Nguyen et al., 2019). Weiner (2009) argues that organizational readiness is an essential precursor for successful implementations of complex changes as an organization’s change commitment and change efficacy directly influence adoption rates. Despite its great importance, organizational readiness has not yet been extensively empirically studied in research (Weiner, 2009; Lokuge et al., 2018) and, particularly in relation to AI, very little is known about the organizational readiness factors that influence the adoption process of AI. Since only qualitative studies provided theoretical groundwork on the organizational readiness factors for AI (e.g., Kruse et al., 2019; Pumplun et al., 2019; Eitle and Buxmann, 2020), we aim to respond to the research call by Jöhnk et al. (2021) to validate the organizational readiness concept for AI. Furthermore, the indication that adoption rates do not necessarily reflect the full implementation of AI applications demonstrates that the decision-making process for AI adoption is far from trivial. Recent studies tend to treat the adoption of AI applications as a single stage of adoption or non-adoption (Kruse et al., 2019; Pumplun et al., 2019; Eitle and Buxmann, 2020), rather than viewing it as a multi-stage adoption process (Cooper and Zmud, 1990). This binary approach is too short-sighted from a theoretical point of view as the limitation to an one-time adoption decision does not reflect whether an innovation is fully incorporated into the organization and its work routines (Fichman, 2000; Zhu et al., 2006). The extensions to a multi-stage approach can provide profound insights into the influencing factors along the entire adoption process. Since most organizations fail in moving beyond the pilot stage, there is an urgent need for research to investigate the differentiating and opposing effects of the organizational readiness factors on the initiation, adoption, and routinization stages of AI (Cooper and Zmud, 1990). While the initiation stage involves initial assessments, the adoption stage refers to activities for implementing AI applications. The routinization stage deals with the incorporation of AI applications into work routines (e.g., Zhu et al., 2006; Martins et al., 2016). To provide guidance to research and practice, our study seeks to take the entire adoption process into account and provide empirical evidence on the influence of the organizational readiness factors on the adoption stages of AI. Hence, we answer the following research question:

RQ: What organizational readiness factors affect the adoption process of AI and how do they differ across the initiation, adoption, and routinization stages?

In total, 250 respondents participated in our online survey that examines the impact of organizational readiness factors on the adoption process of AI. To the best of our knowledge, we are among the first researchers who address the research call by Jöhnk et al. (2021) to validate the organizational readiness concept for AI using a quantitative research design. As a practical guidance for managers, we recommend, for example, that functional teams should be directly involved in the initiation stage of AI.

2 Theoretical Background

2.1 Artificial Intelligence

Previous research has not reached a consensus on a uniform definition of AI. In our study, the notion of AI is associated with the concept of an intelligent agent “that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators” (Russell and Norvig, 2021, p. 54). By this definition, AI is not a single application, but rather an agent function that has the ability to learn and act autonomously in a dedicated context. Thus, an AI application performs cognitive functions that can be associated with human thinking, such as self-learning and decision-making (Rai et al., 2019; Berente et al., 2021). Given these unique capabilities, AI comprises machine learning, robotic process automation, and rule-based expert systems (Benbya et al., 2021; Collins et al., 2021). Since the spectrum of application scenarios at the organizational level and across industries is relatively broad, AI is regarded as a general-purpose technology (GPT) that requires purpose-specific considerations (Brynjolfsson et al., 2017; Jöhnk et al., 2021). Due to the unique AI capabilities of self-learning and autonomous decision-making, the sole human responsibility for certain tasks shifts to a human-machine collaboration (Sturm et al., 2021). This change in responsibility leads to an increased level of inscrutability (Berente et al., 2021) which requires context-specific considerations (Jöhnk et al., 2021).

2.2 Organizational Readiness for Change

To emphasize the distinction between our study and previous research on organizational readiness, adoption process, and AI adoption, we conducted a literature review as shown in Table 1.

			Alsheibani et al., (2018)	Alsheibani et al., (2019)	Anton et al., (2020)	Eitle & Buxmann, (2020)	Fukas et al., (2021)	Hamm & Klesel (2021)	Holmström, (2021)	Jöhnk et al., (2021)	Kruse et al., (2019)	Laut et al., (2021)	Pumplun et al., (2019)	Pumplun et al., (2021)	Radhakrishnan & Gupta (2021)	Stecher et al., (2020)
Framework or theory		TOE framework	x			x					x	x	x	x		
		Readiness								x						
		Scorecard							x							
		Maturity models		x			x									
		Resource-based														x
Methodology	**Qualitative**	Literature review						x							x	
		Interviews				x				x	x		x	x		
		Design science		x			x									
		Case study													x	
		Comparative										x				
		Mix-method			x											
	SEM															x

Table 1. Literature review.

As outlined in the literature review, a variety of different frameworks can be used to study AI adoption, indicating that there is no one-size-fits-all theory. However, since the well-established TOE framework by Tornatzky and Fleischer (1990) only considers generic factors, Jöhnk et al. (2021) argue that the organizational readiness concept is particularly suited to address the purpose and context-specific factors of AI. In light of this consideration, we use the organizational readiness concept for our subject of study. To be more precise on the theoretical foundation, the organizational readiness concept has been applied in Information System (IS) literature primarily to examine the degree to which organizations are prepared to adopt new technologies (Lokuge et al., 2018; Nguyen et al., 2019; Jöhnk et al., 2021). Drawing from organizational change literature, organizational readiness reflects a state in which an organization is structurally and psychologically prepared for the upcoming change (Weiner et al., 2008; Weiner, 2009; Lokuge et al., 2018). Rather than focusing solely on structural readiness in terms of human, financial, and material resources, Weiner (2009) suggests that the psychological state (e.g., willing and able) should be considered primarily. According to his research, the concept of organizational readiness is determined by the shared commitment of organizational members to implement change as well as by change efficacy which refers to the shared belief in existing capabilities (Weiner et al., 2008; Weiner, 2009; Lokuge et al., 2018). To be more precise, organizational commitment is reflected in change variance which specifies how organizational members collectively value the change, while change efficacy refers to the assessment of available human, financial, and material resources. The study by Nguyen et al. (2019) suggests considering both structural and psychological perspectives when examining organizational readiness factors by assessing digital assets, digital capabilities, and digital commitment. The combination of both readiness states is proposed primarily because the multi-faceted nature of organizational assets is too complex to measure their assessment solely as part of change efficacy. Since previous studies on organizational readiness (Weiner et al., 2008; Weiner, 2009; Nguyen et al., 2019) provide inconsistent organizational readiness factors, there is a strong need for empirical research to discuss the influencing factors from a theoretical perspective and validate the organizational readiness concept. Particularly in the context of AI, organizations need to be structurally and psychologically prepared for the major changes imposed by the unique AI capabilities of self-learning and autonomous decision-making (Berente et al., 2021). These significant changes can create uncertainties for organizations that can prevent them from moving beyond the initiation stage. Consequently, the organizational readiness concept is particularly appropriate for assessing the organizational state of preparation to leverage the potential of AI.

2.3 Adoption Process

Research on AI adoption belongs to the diffusion of innovation literature stream (Meyer and Goes, 1988; Cooper and Zmud, 1990; Rogers, 1995) which assumes that the adoption of an innovation occurs over time rather than in an immediate act. Instead of following a multi-stage adoption process approach, a relatively large number of empirical studies on innovation adoption (Zhu et al., 2003; Tung and Rieck, 2005; Venkatesh and Bala, 2012; Borgman et al., 2013; Gutierrez et al., 2015) consider the adoption decision as a single stage of either adoption or non-adoption. Limiting the adoption decision to only one stage makes it nearly impossible to empirically assess differentiating and opposing effects along the entire adoption process (Damanpour and Schneider, 2006; Zhu et al., 2006). Since the implementation of innovation can be dynamic und volatile throughout the adoption process, influencing factors might affect only certain adoption process stages or even exhibit opposing effects (Fichman, 2000). For this purpose, Cooper and Zmud (1990) proposed initially a six-stage adoption process model that comprises the initiation, adoption, adaption, acceptance, routinization, and infusion stages. To be more precise, while the initiation stage formulates the problem statement, the adoption stage refers to decisions regarding resource allocation. The adaption stage includes the development and implementation of the innovation, followed by the acceptance stage in which the actual usage is in focus. While the routinization stage involves incorporating the innovation into work routines, the resulting efficiency gains are reflected in the infusion stage (Cooper and Zmud, 1990). In IS literature, however, the three-stage adoption process model consisting of the initiation, adoption, and routinization stages has gained acceptance in place of the detailed six adoption process stages (e.g., Zhu et al., 2006; Wu and Chuang, 2010; Martins et al., 2016). To follow the widely recognized multi-stage adoption process, we applied the three adoption process stages to the context of AI primarily because the changes regarding the dynamic and volatile environment and the responsibilities imposed by AI applications affect the overall AI adoption process. Organizations need to prepare for these changes to move beyond the pilot stage and successfully implement AI. Particularly the AI capabilities of self-learning and autonomous decision-making determine the influencing factors for AI which, however, may have differentiating or opposing effects on each adoption process stage. To be more precise, we define the adoption process stages of AI as follows: (1) the *initiation* stage addresses the identification of AI use cases and the technical assessment of AI applications, (2) the *adoption* stage involves the decision-making on the allocation of technological, human, and financial resources as well as on the execution of implementation activities, (3) the *routinization* stage refers to the incorporation of AI applications into the work routines of end users (Cooper and Zmud, 1990; Zhu et al., 2006; Wu and Chuang, 2010; Chong and Chan, 2012; Martins et al., 2016). Since most organizations fail in passing the pilot stage of AI implementations, our study seeks to examine the differentiating and opposing effects of the organizational readiness factors on the initiation, adoption, and routinization stage of AI.

3 Hypotheses

The holistic organizational readiness concept for AI with the corresponding hypotheses as well as the assignment of the influencing factors to the five categories of Jöhnk (2021) are shown in Figure 1.

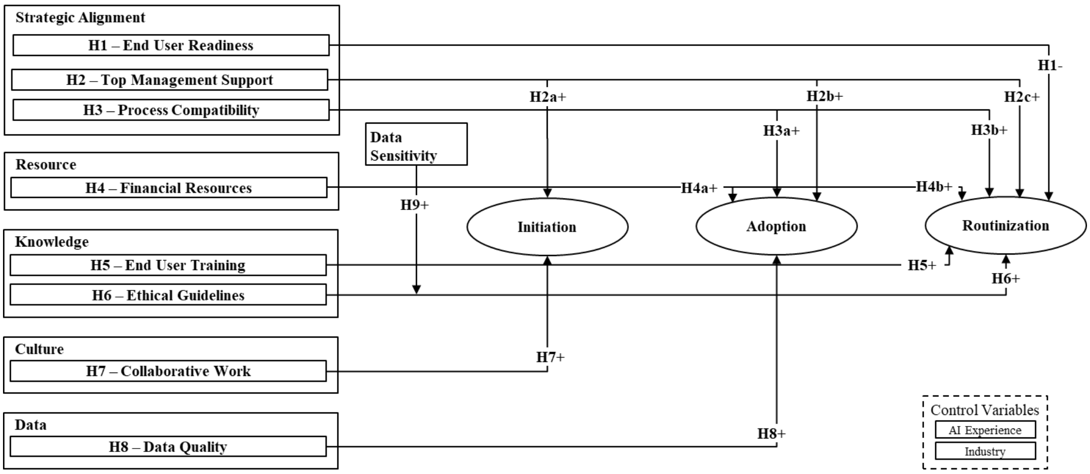

Figure 1. Research model.

Strategic Alignment: *End user readiness (EUR)* describes the willingness and acceptance of end users to use AI applications (Pumplun et al., 2019). If end users perceive AI as an advancement, they might show a higher level of commitment to incorporate AI applications into their work routines. According to the literature on change management, end user readiness is a crucial organizational readiness factor as the more end users value change, the more likely they are to embrace it (Weiner, 2009; Nguyen et al., 2019). In the context of AI, end user readiness is particularly important as AI applications are capable of self-learning and autonomous decision-making (Berente et al., 2021). Since the shift in responsibility changes the decision-making process of humans, end users ultimately become more dependent from AI applications in the routinization stage. Therefore, end users must be able to understand and interpret the outcomes of AI applications to properly incorporate them into their decision-making process (Berente et al., 2021). In case that end users are not able to comply with these requirements in the routinization stage of AI, the human-machine collaboration is at risk. Thus, we propose the following hypothesis:
Hypothesis 1: *Lack of end user readiness is negatively related to the routinization stage of AI.*

Since the executive leadership is in the position to promote mechanisms to address new challenges and requirements posed by AI, *top management support (TMS)* is particularly important (Lokuge et al., 2018; Nguyen et al., 2019; Jöhnk et al., 2021). The study by Martins et al. (2016) revealed that top management support positively influences the initiation stage. According to innovation adoption literature, clearly-communicated messages from top management serve as a starting point for driving innovations by providing guidance and building trust among teams in the initiation stage (Gallivan, 2001; Rai et al., 2009; Berente et al., 2021). Particularly in the case of AI, articulating long-term visions and establishing strategic plans can establish an environment in which AI use cases and technical requirements can be properly evaluated (Lokuge et al., 2018; Nguyen et al., 2019; Jöhnk et al., 2021). According to the adoption stage, previous studies have also indicated that a high degree of top management positively supports the decision-making process for allocating financial, technological, and human resources (Chong and Chan, 2012; Martins et al., 2016; Pumplun et al., 2021). Empowering the legitimacy for technology use among end users and setting performance control mechanisms (Liang et al., 2007; Rai et al., 2009) can strengthen the routinization stage. In the context of AI, the legitimacy of top management is important as tasks previously performed by humans may now be augmented by AI (Berente et al., 2021). Since the change in responsibility affects work routines, control mechanisms may increase the acceptance of end users. Thus, we pose the following hypotheses:
Hypothesis 2a: *Top management support is positively related to the initiation stage of AI.*
Hypothesis 2b: *Top management support is positively related to the adoption stage of AI.*

Hypothesis 2c: *Top management support is positively related to the routinization stage of AI.*

According to innovation adoption literature, compatibility is considered an essential prerequisite which reflects the extent to which an innovation is consistent with prior experiences and practices of the organization (Rogers, 1995; Xu et al., 2017). Rather than looking at compatibility in general, we follow the recommendation by Jöhnk et al. (2021) and Lokuge et al. (2018) to focus on *process compatibility (PC)* as an organizational readiness factor primarily because AI implementations can lead to substantial changes in business processes. Due to the fact that organizations have often deeply rooted processes in place that have proven successful in the past (Xu et al., 2017), changing these rigid processes is a challenge for organizations in the adoption stage (Venkatesh and Bala, 2012). Since the given AI capabilities of self-learning and autonomous decision-making can alter existing business processes (Berente et al., 2021), decision-makers may regard these changes as an obstacle in the adoption stage. However, instead of insisting on rigid structures, reinventing compatible business processes can be seen as an opportunity to increase organizational efficiency and productivity (Brynjolfsson and Mitchell, 2017). To leverage this potential, Kruse et al. (2019) emphasized the need to acquire AI-related process competences. Considering the end user perspective in the routinization stage, the study by Venkatesh and Bala (2012) showed that the likelihood of rejection increases when new processes are not fully integrated into work routines. Thus, business processes should be designed to be compatible to ensure a smooth integration of AI into end users' work routines. Considering these findings, we believe that compatible business processes positively influences the adoption and routinization stages:
Hypothesis 3a: *Process compatibility is positively related to the adoption stage of AI.*
Hypothesis 3b: *Process compatibility is positively related to the routinization stage of AI.*

Financial Resources: Drawing from innovation adoption literature, the commitment of *financial resources (FR)* is regarded as a major prerequisite for a successful implementation of technologies (Zhu and Kraemer, 2005; Xu et al., 2017). Adopting a new innovation requires large financial investments in resources for hiring employees, providing adequate infrastructure, and ensuring business process integration (Xu et al., 2017). In the case of AI, decision-makers must consider potential uncertainties related to the development, training, and performance of AI models when providing financial resources (Zhang et al., 2020). Especially in the adoption stage, the allocation of sufficient financial resources represents a crucial organizational readiness factor since data scientists need to be hired, hardware and software need to be deployed, and relevant business processes need to be re-designed (Pumplun et al., 2019; Jöhnk et al., 2021). With respect to the routinization stage, the study by Zhu and Kraemer (2005) revealed that financial resources increase the use of innovations by end users. To fulfil the requirement that end users are able to interpret the outcomes of AI applications and incorporate them into their work routines, organizations need to invest in end user training. Thus, we propose the following hypotheses:
Hypothesis 4a: *Financial resources are positively related to the adoption stage of AI.*
Hypothesis 4b: *Financial resources are positively related to the routinization stage of AI.*

Knowledge: Since end user skills and knowledge are essential to realize digital change, *end user training (EUT)* is important for the organizational readiness concept (Nguyen et al., 2019). According to the study by Gutierrez et al. (2015), offering end user training enables organizations to incorporate innovations into the work routines. Providing end users with adequate training on how to use and interact with an innovation can both reduce their anxiety and ambiguity (Schillewaert et al., 2005) and increase their efficiency in using the innovation (Gutierrez et al., 2015; Xu et al., 2017). In the context of AI, the offering of end user training is considered an important organizational readiness factor in the routinization stage primarily due to the new capabilities of self-learning and autonomous decision-making. The associated higher level of inscrutability makes it difficult for end users to understand and interpret the results correctly (Berente et al., 2021). While end users do not only need to incorporate the outcomes of AI applications into their decision-making process, they also need to understand the difference in how to interact with autonomous and self-learning AI applications (Jöhnk et al., 2021). By enabling end users to evaluate non-intuitive algorithmic recommendations and properly interact with AI applications, providing AI-specific end user trainings could increase their acceptance level in the routinization stage. Thus, we pose the following hypothesis:

Hypothesis 5: *End user training is positively related to the routinization stage of AI.*

The influence of *ethical guidelines (EG)* when incorporating innovations into end users' work routines has been overlooked in organizational readiness literature. So far organizations have mainly deterministic IS in place that do not contain self-learning capabilities. However, when AI is deployed, end users may face ambiguous outcomes of AI in their decision-making. As AI applications might pose a risk for biased learning and unethical outcomes (Awad et al., 2018), ethical guidelines should be considered an essential organizational readiness factor in the context of AI. The qualitative studies on AI adoption by Eitle and Buxmann (2020), Jöhnk et al. (2021), Kruse et al. (2019), and Pumplun et al. (2019) emphasized that establishing ethical guidelines may increase the trust of end users in AI applications by decreasing the risk of moral dilemmas and unethical outcomes (Awad et al., 2018). Thus, end users may be more encouraged to incorporate AI applications into their work routines if they are aware that ethical guidelines monitor the behaviour of AI. Hence, we pose the following hypothesis:
Hypothesis 6: *Ethical guidelines are positively related to the routinization stage of AI.*

Culture: According to the study of Cao et al. (2010), *collaborative work (CW)* is considered a source of competitive advantage as a close collaboration among stakeholders in terms of frequency and direction can influence the success of innovations. Particularly in the initiation stage of a project, a joint knowledge creation between stakeholders contributes to a better understanding of the problem statement and the requirements. Instead of working in traditional structures and silos, AI implementations rely on integrating different perspectives to evaluate AI use cases and to assess specific technical and functional requirements (Jöhnk et al., 2021). According to the qualitative studies by Kruse et al. (2019), Pumplun et al. (2019), and Eitle and Buxmann (2020), establishing an innovative collaborative work model in which data science and functional teams work together can help initiating AI projects. A strong interaction and communication between these teams can accelerate innovation cycles by fostering ideas and prototyping. Since the evaluation of AI use cases requires both the problem statement by functional teams and the technical assessment of the AI models by data science teams, we pose the following hypothesis:
Hypothesis 7: *Collaborative work between data science and functional teams is positively related to the initiation stage of AI.*

Data: According to the study of Weill and Vitale (1999), *data quality (DQ)* represents a technical quality that has a substantial impact on the performance of IS. Previous research on innovation adoption indicated that data quality positively influences the adoption rate of technologies (e.g., Cruz-Jesus et al., 2019). Especially with respect to the self-learning capabilities of AI applications, the organizational readiness factor of data quality is considered a crucial requirement to train AI models on large data sets. Particularly in the adoption stage, this premise implies that higher quality of training data in terms of accuracy, reliability, and consistency will lead to higher prediction accuracy (Pumplun et al., 2019; Jöhnk et al., 2021). However, since training data is prone to data quality issues due to decentralized data sources (Eitle and Buxmann, 2020), obtaining high-quality data is challenging for organizations (Davenport, 2018; Pumplun et al., 2019). Considering these findings, we assume that improving data quality can increase the organizational readiness for AI:
Hypothesis 8: *Data quality is positively related to the adoption stage of AI.*

To address a sub-aspect of the complex ethical debate on AI (Awad et al., 2018), we address *data sensitivity (DS)* in relation to ethical issues. In IS literature, it is widely discussed that data sensitivity is perceived as risky when processing personal information (e.g., Kehr et al., 2015). Since the risk of loss increases as the information becomes more sensitive, organizations must ensure sufficient protection when incorporating AI applications into work routines. In the field of human resources (HR), for example, numerous personal data are processed and evaluated as part of the application process (Black and van Esch, 2020). As this data contains sensitive information such as gender, age, and personal preferences, a misuse and disclosure of this data in AI applications can lead to severe consequences for organizations. The case of Amazon can be used as prime example for gender discrimination in the application process as their AI-based HR software favoured men over women (Dastin, 2018). This example illustrates that the misuse of sensitive data in AI applications can lead to ethical dilemmas in

the routinization stage. By assuming that a higher level of data sensitivity will encourage organizations to establish more ethical guidelines for AI, we propose a moderator effect:
Hypothesis 9: *The more sensitive the data, the more ethical guidelines will be established in the routinization stage of AI.*

4 Methodology

As presented in Table 1, we conducted a literature review to distinguish our study from previous research on organizational readiness, adoption process, and AI adoption. Following the recommendations by Webster and Watson (2002), we used the search string "Artificial Intelligence" AND "organizational readiness" OR "adoption" OR "readiness" in the AIS electronic library database to identify relevant literature. For data collection, the survey-based approach in the form of a questionnaire was used to obtain a large sample set for the data analysis and to reduce the common method bias (CMB) by reaching many participants from different organizations. Considering the data analysis, a quantitative research design was applied to validate the impact of the influencing factors on the adoption process of AI.

4.1 Conceptual Research Design

Regarding the conceptual research design, we followed the established guidelines for instrument development (i.e., item creation, scale identification, and instrument validation) proposed by Moore and Benbasat (1991) and MacKenzie et al. (2011). As shown in Figure 2, the conceptual research design comprises item creation and scale development (referred to as part 1) as well as instrument validation (referred to as part 2). In part 1, we defined the conceptualization and the nature of constructs. By reviewing prior research and related constructs, we identified the constructs and items through a deductive approach. Based on this selection, we developed an a-priori model (e.g., Burton-Jones and Straub, 2006) for organizational readiness for AI which consists of eight reflective constructs and one moderator variable. The items were selected from literature and will be presented in the next section.

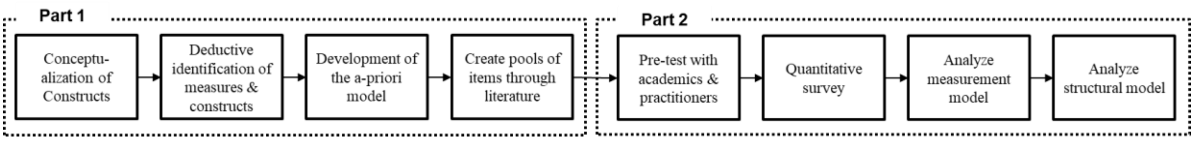

Figure 2. Conceptual research design.

4.2 Measurements

The development of the applied constructs and items was derived from research on organizational readiness, adoption process, and AI adoption. Modifications in wordings were made to adapt to the AI context. To ensure the validity and reliability of the constructs, we used multi-item measurements based on a seven-point Likert scale ranging from "1 strongly disagree" to "7 strongly agree". With respect to part 2, we conducted a pre-test with 12 academics and practitioners who worked in the field of AI to validate and adjust the items. Based on their feedback, we improved the terminology of AI by refining expressions and words. The dependent variables of our study reflect the adoption process stages of initiation, adoption, and routinization in the context of AI. The participants assigned themselves to one of the following adoption process stages: (0) no intention to implement AI, (1) intention to implement AI, (2) adoption of AI, and (3) incorporation of AI. Table 7 provides an overview of the selected items of the dependent, independent, and the moderator variables. To rule out unexpected effects, we controlled for the industry and the number of years of AI experience.

4.3 Data Collection and Data Analysis

Regarding the data collection process, we contacted 2,153 data scientists via LinkedIn along with a brief explanation of the research scope and invited them to participate in our study. Out of this total number, 1,351 contacts clicked on our survey and 257 participants completed the questionnaire, yielding a completion quote of 19 %. This total count does not include the respondents who assigned themselves to (0) no intention. After sorting out 7 participants who failed the attention check, our sample size is n=250. It distributes among the adoption process stages as follows: initiation n=51, adoption n=98, routinization n=101. The distribution regarding the control variables of industry and AI experience is shown in Table 2. Our results indicate that no CMB is found in the data (Podsakoff et al., 2003).

Industries (IND)	Automotive	Consulting	E-Commerce	Energy	Finance	IT	Logistics	Manu-facturing	Marketing	Healthcare	Other	**AI experience (EXP)**	
												<1 y	4.4 %
												1-2 y	25.2%
												3-5 y	30.4%
in %	7.2	3.6	11.6	5.2	10.8	25.2	3.6	7.6	4.0	8.8	12.4	**>5 y**	40%

Table 2. Description of sample set.

With respect to the data analysis, we used the partial least squares (PLS) method for analyzing the measurement and the structural model using SmartPLSv3 (Fornell and Larcker, 1981). While this statistical method is widely used in IS research (Chin, 1998), the method is particularly well-suited for our study as it is recommended for complex structural models and allows us to simultaneously test relationships between various independent and multiple dependent variables (Gefen et al., 2000; Hair et al., 2006; Lowry and Gaskin, 2014).

5 Results

Literature proposes the Standardized Root Mean Square Residual (SRMR) as a model fit index that calculates the difference between observed correlations and the model's implied correlations matrix (Hu and Bentler, 1999; Hair Jr et al., 2016). We tested the model fit and obtained the value of .048 which is below the threshold of .08 proposed by Hu and Bentler (1999). To provide first insights into the descriptive statistics of the variables, we present the means and standard deviations in Table 3.

Constructs	**EUR**	**TMS**	**PC**	**FR**	**EUT**	**EG**	**CW**	**DQ**	**DS**	**INI**	**ADO**	**ROUT**
Mean	4.078	4.560	5.530	5.770	4.151	5.367	5.657	4.588	6.787	5.427	5.960	5.218
SD	1.592	1.554	1.251	1.319	1.649	1.572	1.073	1.286	1.347	1.144	1.054	1.400

Table 3. Means and standard deviations.

5.1 Measurement Model

In order to validate the measurement model, we investigated the convergent and discriminant validity according to Hair et al. (2006). To ensure convergent validity, we assessed the criteria of item loadings, the composite reliability (CR), Cronbach's Alpha (α), and the average variance extracted (AVE). To ensure that the item loadings exceed the threshold of .7, we analyzed and removed the items below the threshold recursively until all items had a reliability of at least .7 (Hair et al., 2006). After removing the two items EUR3 and PC1, all item loadings were higher than the threshold of .7 (Nunnally, 1967; Chin, 1998) except of TMS4. Based on the recommendation of Hair et al. (2016), we decided to keep this item since the corresponding construct already exceeds the AVE threshold of .7. Our study fulfils the criteria of the CR and Cronbach's α exceeding the threshold of .7 (Hair Jr et al., 2016) as well as AVE exceeding the threshold of .5 (Fornell and Larcker, 1981) as presented in Table 4. Discriminant validity shows the extent to which the measurements of the constructs differ and is examined using the Fornell–Larcker criterion (Fornell and Larcker, 1981). As shown in Table 5, the square root of AVE for each construct was greater than the correlation values of the construct with other constructs. In summary, the data analysis of the measurement model demonstrates that our study fulfils the criteria for convergent and discriminant validity.

	EUR	TMS	PC	FR	EUT	EG	CW	DQ	DS
Factor loadings	.858-.958	.687-.951	.908-.911	.941-.955	.913-.941	.920-950	.751-.889	.753-.921	.752-.923
CR	.905	.917	.906	.947	.950	.954	.921	.908	.941
Cronbach'α	.806	.886	.792	.888	.924	.929	.893	.868	.933
AVE	.827	.738	.827	.899	.865	.872	.699	.712	.729

Table 4. Assessment of convergent validity.

	EUR	TMS	PC	FR	EUT	EG	CW	DQ	DS
EUR	**.909**								
TMS	-.099	**.859**							
PC	-.120	.354	**.909**						
FR	-.178	.177	.285	**.948**					
EUT	-.158	.590	.336	.239	**.930**				
EG	-.021	.205	.185	.320	.211	**.934**			
CW	-.160	.343	.185	.353	.312	.160	**.836**		
DQ	.027	.204	.210	.092	.173	.180	.117	**.844**	
DS	-.002	-.183	-.040	.057	-.088	.062	.125	-.035	**.854**

Table 5. Assessment of discriminant validity based on the Fornell-Larcker criterion.

5.2 Structural Model

In the following Table 6, we present the results of the structural model analysis, including the estimated path coefficients with asterisks indicating significant paths. The R^2 value describes how much variance of the dependent variables is explained by the independent variables of our research model. The data analysis revealed that the R^2 value of the three dependent variables (initiation, adoption, and routinization) were 4.8%, 9.4%, and 18.3% which are considered acceptable results. To measure the effect size (Cohen, 1992), we examined the f^2 values which reflect the influence of the independent variables on the dependent variables. Our results revealed low and medium effect sizes on the initiation (f^2 =.05), adoption (f^2 =.10), and routinization (f^2 =.22) stages of AI (Cohen, 1992, p. 157).

Constructs	EUR	TMS	PC	FR	EUT	EG	CW	DQ	EXP	IND
Initiation	-	.004	-	-	-	-	.203**	-	-.072	.056
Adoption	-	.257***	-.090	.079	-	-	-	.105*	-.051	.079
Routinization	-.103**	-.164**	.227***	.102*	.120*	.093*	-	-	.067	-.081

Table 6. Results of the structural model. *p < .10, ** p < .05, *** p < .001

In terms of strategic alignment, our results revealed that the lack of end user readiness is significantly negatively related to routinization. Furthermore, while top management support has a significant positive path coefficient to adoption, the significant negative impact on routinization is contrary to our assumption. The path coefficient from top management support to initiation, however, is not significant. Even though the path coefficient of process compatibility to adoption is not significant, it has a significant positive path coefficient to routinization. Thus, while the hypotheses H1, H2b, and H3b within the strategic alignment category are supported, H2c is partially supported. H2a and H3a are not supported. Furthermore, our results show that financial resources have no significant path coefficient to adoption but a significant positive path coefficient to routinization. Therefore, while H4b is supported, H4a is not supported. Considering the category of knowledge, end user training has a significant positive path coefficient to routinization and ethical guidelines have a significant positive path coefficient to routinization. According to these results, H5 and H6 are supported. As part of the category of culture, collaborative work between data science and functional teams is significantly positively related to the initiation stage, supporting H7. Since data quality has a significant positive path coefficient to adoption, H8 is also supported. Our results revealed a significant positive influence of the moderator variable data sensitivity (.127, $p < .10$). According to Hair et al. (2016), our moderator effect has a medium effect size of .026 on the path coefficient between ethical guidelines and routinization and therefore supports H9.

6 Discussion and Implications

6.1 Interpretation of Results

Strategic Alignment: According to our results, *the lack of end user readiness* has a significant negative impact on the routinization stage of AI (H1). This finding indicates that end users who perceive AI applications as difficult to operate tend to resist incorporating them into their work routines. Since AI applications are able to self-learn and make autonomous decisions (Berente et al., 2021), end users might have difficulties in interpreting the outputs correctly. When the degree of inscrutability and the lack of transparency (Berente et al., 2021) prevents end users from understanding decisions made by AI applications, they are more likely to reject them. Therefore, we suggest increasing the level of understanding among end users to strengthen the human-machine collaboration in the routinization stage. Furthermore, we found a significant positive path coefficient between *top management support* and the adoption stage of AI (H2b). Our results confirm the findings of previous innovation adoption studies (e.g., Martins et al., 2016) that top management support influences the adoption decision by providing sufficient financial, technological, and human resources. Contrary to our assumption, we found a significant negative path coefficient between top management support and the routinization stage of AI (H2c). According to this finding, it seems that there is no explicit need for top management to encourage end users to use AI applications through performance control mechanisms if end users regard them as advancements. With respect to the routinization stage, our results also show a positive significant influence of *process compatibility* (H3b). This finding indicates that process compatibility tends to convince end users to incorporate AI applications into their work routines. An explanation could be that end users who do not experience any interruptions in their work routines, are more likely to use AI applications. Thus, we encourage organizations to design compatible business processes.

Financial Resources: Moreover, our results show that financial resources are significantly positively related to the routinization stage (H4b). This finding suggests that financial investments are primarily needed to provide dedicated AI end user training in the routinization stage of AI.

Knowledge: In line with previous studies (Xu et al., 2017), we found that *end user training* has a significant positive impact on the routinization stage of AI (H5). This finding indicates that organizations should provide dedicated AI end user training which helps end users to operate AI applications more efficiently. A plausible explanation could be that end users should be able to understand the overarching statistical concept since AI applications are based on probability theory. In particular, in the case of ambiguous outcomes, end users must be able to recognize them and act appropriately (Jussupow et al., 2021). Furthermore, as proposed by previous qualitative studies on AI adoption (e.g., Jöhnk et al., 2021) we found a significant positive path coefficient between *ethical guidelines* and the routinization stage of AI (H6). Thus, our results confirm that end users are more likely to incorporate AI applications if ethical guidelines are in place that reduce the risk for biased learning and unethical outcomes. Thus, we encourage organizations to establish ethical guidelines when implementing AI applications.

Culture: Our results confirm the assumption by Eitle and Buxmann (2020), Kruse et al. (2019), and Pumplun et al. (2019) that *collaborative work* between data science and functional teams has a significant positive impact on the initiation stage of AI (H7). This finding indicates that close interaction and communication between these teams facilitates the identification of AI use cases and the technical assessment of AI applications. While functional teams have dedicated knowledge about the problem statement and the requirements, data science teams have the expertise to develop AI models.

Data: Our results show that data quality is significantly positively related to the adoption stage (H8). This finding is in line with previous qualitative studies on AI adoption (Pumplun et al., 2019; Eitle and Buxmann, 2020; Jöhnk et al., 2021) that suggest that higher data quality can lead to more successful AI implementations due to the increased prediction performance. Thus, our study proposes that organizations should pay particular attention to providing high-quality data for AI model development.

Moderator Data Sensitivity: Based on our results, we found a significant moderator effect of data sensitivity on the path coefficient between ethical guidelines and the routinization stage of AI (H9). To mitigate the risk of ethical dilemmas, this finding suggests that the more sensitive the data is, the more ethical guidelines should be established in the routinization stage.

6.2 Theoretical Contributions

Although AI is considered one of the most promising innovations (Brynjolfsson and Mcafee, 2017), the majority of organizations are not able to move beyond the pilot stage (Balakrishnan et al., 2020). This tendency indicates that current research lacks insights into organizational readiness factors and their impact on the adoption process of AI (Jöhnk et al., 2021). By examining what and how organizational readiness factors influence the initiation, adoption, and routinization stages of AI, we answer the research question and contribute to theory as follows: **First**, to investigate what organizational readiness factors affect the adoption process stages of AI, we established a research model that combines the literature streams on organizational readiness and adoption process. While previous studies have typically viewed these literature streams as independent from each other (e.g., Zhu et al., 2006; Lokuge et al., 2018), we sought to unfold these interdependencies in the context of AI. By intertwining these literature streams into a holistic organizational readiness concept for AI, we were able to identify what influencing factors are essential for managing the complex change of implementing AI applications. Our results showed that organizational readiness is not only a precursor limited to the initiation stage but also has a significant impact on the adoption and the routinization stages. Thus, our study provides empirical groundwork for the research on organizational readiness and the adoption process of AI. **Second**, rather than considering adoption as a single stage, we used a multi-stage adoption process approach which explicitly distinguishes between the three adoption process stages initiation, adoption, and routinization (Gallivan, 2001; Damanpour and Schneider, 2006). As emphasized by Fichman (2000), this process-oriented approach allows us to detect differentiating and opposing effects of the organizational readiness factors on the dedicated adoption process stages of AI. Top management support is an excellent example of demonstrating how organizational readiness can vary along the adoption process of AI. While top management support has no significant influence on the initiation stage, it has a significant positive effect on the adoption stage, but a significant negative influence on the routinization stage of AI. **Third**, our study contributes to theory by responding to the research call by Jöhnk et al. (2021) to quantitively validate the findings related to the organizational readiness concept for AI. To the best of our knowledge, we are among the first researchers who evaluate the influence of organizational readiness factors on the adoption process of AI using a quantitative research design.

6.3 Practical Contributions

Our study provides organizations practical guidance on AI adoption and helps managers to identify relevant organizational readiness factors that can influence each adoption process stage of AI. For instance, when *initiating* an AI implementation, managers should promote the collaboration between data science and functional teams. With respect to the *adoption stage* of AI, top management should ensure an adequate allocation of technological, human, and financial resources for the implementation of AI applications. Taking the *routinization stage* of AI into account, our study showed that the degree of process compatibility influences the willingness of end users to incorporate AI applications into their work routines. Since end users appreciate a high level of process compatibility, our findings suggest that managers should focus on integrating the AI application into the existing process landscape.

7 Conclusion, Limitations, and Future Research

By examining the influence of organizational readiness factors on the distinct adoption process stages of AI, our study contributes to research on organizational readiness and adoption process of AI. Despite these contributions, our study is subject to some limitations. By selecting data scientists as the primary target audience, we limited the sample set to a small niche. Even though our sample set contains different industries, our findings cannot be generalized to all organizations. Future studies may seek to increase the sample size to extend the findings of this study. Second, a mix-method research design could provide additional findings compared to a quantitative data analysis. Third, since we observed a moderator effect of data sensitivity, we suggest an in-depth analysis of this moderator and its implications.

Appendix

	Dependent Variables
INI	Your organization intends to use AI applications if possible.; Your organization collects information about AI applications with the possible intention of using it.; Your organization evaluates AI use cases.; Your organization conducts pilot test(s) to evaluate AI applications. (Chong and Chan, 2012; Martins et al., 2016)
ADO	Your organization invests resources to adopt productive AI applications. (Martins et al., 2016)
ROUT	The use of AI applications has been incorporated into the end user's regular work practice.; The end user's use of AI applications is pretty much integrated as part of his/her normal work routine.; The end user's use of AI applications is now a normal part of his/her work.; The end user uses AI applications in a standardized way during his/her daily work tasks. (Maas et al., 2018)
	Independent and Moderator Variables
EUR	EUR1: The use of AI applications is difficult for end users to learn. EUR2: AI applications are difficult for end users to operate compared to traditional systems. EUR3: AI applications are difficult for end users to maintain compared to traditional systems. (Xu et al., 2017)
TMS	TMS1: Top management articulates a vision for the use of AI applications. TMS2: Top management articulates a strategy for the use of AI applications. TMS3: Top management establishes goals for the use of AI applications. TMS4: Top management defines deployment standards for AI applications. (Rai et al., 2009)
PC	PC1: AI applications complement the main traditional systems (e.g., legacy system). PC2: AI applications fit well with the main needs of your organization. PC3: AI applications fit well with the main work processes of your organization. (Venkatesh and Bala, 2012; Xu et al., 2017)
FR	FR1: Your organization has the financial resources to purchase hardware and software required for AI. FR2: Your organization has the financial resources to implement AI. (Chong and Chan, 2012)
EUT	EUT1: Your organization extensively trains end users in using AI applications. EUT2: Your organization provides complete instructions and practices for using AI applications. EUT3: End users receive sufficient training to use the AI applications effectively. (Schillewaert et al., 2005)
EG	Your organization must adhere to ethical guidelines in the process of… EG1: ... designing AI use cases. EG2: … pre-processing the training set. EG3: … developing AI models. (Tractinsky and Jarvenpaa, 1995)
CW	During AI projects, the data science and functional teams involved … CW1: … have frequent contacts on a regular basis. CW2: … have open and two-way communication. CW3: … have informal communication. CW4: … have many different channels to communicate. CW5: … influence each other's decisions through discussion rather than requests. (Cao et al., 2010)
DQ	The training data used in AI applications … DQ1: … are accurate. DQ2: … are reliable. DQ3: … are current. DQ4: … are consistent. (Tractinsky and Jarvenpaa, 1995)
DS	How sensitive do you perceive the information requested by AI? DS1: Demographics (e.g., gender) DS2: Secure identifiers (e.g., medical history) DS3: Contact information DS4: Community interaction (e.g., social network profile) DS5: Personal preference DS6: Financial information of people (Kehr et al., 2015)

Table 7. Items of the dependent, independent and moderator variables.

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