Uncovering Cultural Differences in Organizational Readiness for Artificial Intelligence: A Comparison between Germany and the United States

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Abstract

Artificial Intelligence (AI) transforms the business world by enabling organizations to leverage new business opportunities through its unique capabilities of self-learning and autonomous decision-making. To unlock the disruptive potential of AI, organizations seek to implement AI applications throughout their business landscape. However, from a cross-cultural perspective, national culture can influence the way organizations implement AI applications. To better understand cross-cultural differences on AI adoption, our study combines Hofstede's national cultural framework with the organizational readiness concept for AI. We examined the moderating role of Hofstede's national cultural dimensions on the organizational readiness factors of AI-process fit, financial resources, upskilling, collaborative work, and data quality. By conducting a multi-group analysis, we aim to identify national cultural differences between Germany and the US in AI adoption.

Keywords: Cultural differences, cross–cultural study, artificial intelligence, machine learning, adoption

1. Introduction

The introduction of technology is profoundly influenced by diverse cultures, leading to different patterns of technological diffusion across societies. Diverse cultures shape the implementation of technologies with their unique attributes and influence the ways these technologies are integrated and used. Cross-cultural research helps organizations identify commonalities and differences in technologies need across societies, leading to more effective global technology strategies (Bharadwaj et al., 2013). This phenomenon is prominently observable in the field of Artificial Intelligence (AI), where the approaches of different countries exemplify the fusion of technology with cultural nuances. As an illustrative example, the interplay between education, workforce development, and AI deployment highlights the impact of cultural disparities: Germany (GER) is strongly committed to vocational training and skills enhancement. The country's AI education is designed to seamlessly incorporate AI applications into traditional industries. A profound effort is made to equip the workforce with AI-related proficiencies essential for sectors like manufacturing and engineering (Eitle & Buxmann 2020). The United States (US), known for its adaptable and entrepreneurial educational framework, tailors AI education towards technology and software development. The focus lies in cultivating skills that transcend various industries, including the dynamic realms of startups and technology-driven enterprises. These national cultural[1] influences are equally evident in the sphere of manufacturing and the integration of AI. GER, renowned for its robust manufacturing sector, has embraced the principles of Industry 4.0, emphasizing the fusion of AI and automation into production processes. AI applications such as predictive maintenance and process optimization are prioritized, augmenting production efficiency. In contrast, the US' diverse industrial landscape extends beyond manufacturing. AI is, for instance, employed to optimize transportation and supply chain management (IPSOS, 2022). Moreover, the US places a premium on AI-powered innovation within software and technology services (Acemoglu et al. 2022).

In academia these cultural differences become evident through an illustrative study that emphasizes different ethical preferences. Awad et al. (2018) introduced a web-based experimental platform called Moral Machine. They conducted a study that revealed variations in ethical preferences across cultures. To identify these cultural differences and nuances, conducting cultural studies becomes crucial. If AI algorithms are developed without considering cultural nuances specific to a particular country, it can result in biased or inappropriate decision-making, causing harm or misunderstanding. Thus, we aim to answer the

[1] We refer to national culture as "culture".

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research question: *How do national cultural differences between Germany and the United States impact AI adoption?*

2. Theoretical Background

2.1. Definition of Artificial Intelligence

According to Russel and Norvig (2021), the notion of AI is based on the concept of an intelligent agent which receives percepts from the environment and acts accordingly. Due to the goal of maximizing performance, intelligent agents seek to perform their actions in a way that yield the best results. To achieve this behavior, intelligent agents must be able to learn from their experiences and adapt their knowledge to new environments. Thus, the capabilities of an intelligent agent enable AI applications to perform cognitive tasks such as self-learning and autonomous decision-making. The resulting shift in tasks may lead to a greater inscrutability in the decision-making process as it is no longer the sole responsibility of humans but is complemented by AI (Berente et al., 2021). Since AI comprises technologies such as expert systems, machine learning, robotics, natural language processing, and machine vision (Collins et al., 2021), the range of application scenarios within organizations and across industries is wide. Due to this broad spectrum, technical advancements, and the development of complementary innovations, AI is considered a general-purpose technology (GPT) (Brynjolfsson et al., 2017).

2.2. Organizational Readiness Concept for AI

To effectively navigate the extensive organizational changes that come with adopting innovation, organizations must strive to attain a state of readiness at the organizational level. This condition reflects whether an organization is structurally and psychologically prepared for the upcoming organizational change (Weiner, 2009). Rather than considering these two states separately, Nguyen et al. (2019) suggest combining both perspectives when assessing organizational readiness for innovation adoption. Since AI is considered a GPT, we decided to use the organizational readiness concept according to Jöhnk et al. (2021) as the basis for examining cultural differences in AI adoption. To provide a holistic view of the state of organizational readiness for AI, we rely on the *five categories* that comprise the organizational readiness concept (Jöhnk et al., 2021): *strategic alignment, resources, knowledge, culture, and data.*

The category *strategic alignment* consists of five factors: AI-business potentials, customer AI readiness, top management support, AI-process fit, and data-driven decision-making. In this study, we focus on the AI-process fit since the AI experts of our study possess specialized knowledge about the intricacies of AI technologies and their integration into organizational processes. By concentrating on AI-process fit, we tap into their domain-specific insights to understand how these experts perceive the alignment between AI technologies and existing organizational workflows.

The category *resources* consist of three factors: Financial budget, personnel, and IT infrastructure. We focus on financial budget because it is a critical aspect of AI adoption. We seek to understand how different cultures allocate and manage finances, revealing their priorities. Focusing on financial budgeting allows for cross-cultural comparisons regarding financial resource allocation strategies. Since different cultures may make different investment decisions in AI adoption, understanding these variations can help to develop targeted strategies for maximizing AI readiness in diverse cultural environments.

The category *knowledge* consists of three factors: AI awareness, upskilling, and AI ethics. We concentrate on the factor upskilling since AI experts are intimately familiar with the specific skills and competencies required to effectively integrate AI technologies. By focusing on upskilling from their perspective, the study can provide tailored insights into the areas of knowledge enhancement that are crucial for successful AI adoption.

The category *culture* consists of three factors: Innovativeness, collaborative work, and change management. Collaborative work is a fundamental element of organizational readiness, especially in the context of AI adoption. It involves the effective coordination of diverse skill sets and perspectives, making it essential to understand how cultural dimensions impact collaborative efforts in embracing AI technologies. It examines how AI experts perceive the collaborative dynamics within their organizations.

The category *data* consists of four factors: Data availability, data quality, data accessibility, and data flow. In an initial step influenced by the research discourse, we direct our attention toward data quality. Data quality is foundational to the reliability and effectiveness of AI applications. To gain meaningful insights from AI technologies, it is important to ensure that data is accurate and consistent. Focusing on data quality delves into the core of AI's functionality.

2.3. Hofstede’s National Cultural Framework

In a cultural context, there is no one-size-fits-all strategy for adopting innovation as the diffusion of technologies is not bound by national borders and can, therefore, be influenced by cultural effects. In IS literature, the most predominate definition refers to Hofstede (2001) who defines culture as “the collective programming of the mind that distinguishes the members of one group or category of people from another” (Hofstede, 2001, p. 9).

We aim to investigate the diversity of culture at the organizational level and examine cultural differences between GER and the US in the context of AI adoption. These two countries were selected primarily because they lead the ranking in AI adoption due to the high number of productive AI applications and use cases (Loucks et al., 2019). In addition, these two countries have distinct innovation ecosystems. The US, with Silicon Valley as a global technology hub, is known for its entrepreneurial spirit and tech startups. GER has a strong industrial base and is recognized for its engineering and manufacturing capabilities. We use Hofstede’s (2001) main cultural dimensions of individualism, uncertainty avoidance, and long-term orientation to examine our RQ. This selection is based on the fact that these dimensions exhibit the most pronounced variations in the scores. **Individualism** is defined as the extent to which individuals prefer independence over inclusion in a group. In an organizational context, members of an individualist society tend to be self-reliant and show a high degree of initiative (Hofstede, 2001). GER has a relatively high score: 67. In contrast, the US has a high score: 97. **Uncertainty avoidance** is defined as the willingness of dealing with an ambiguous and unknown situation. From an organizational perspective, the risk of unpredictable circumstances can be minimized through regulations (Hofstede, 2001). GER has a relatively high score: 65. In contrast, the US has a relatively low score: 46. **Long-term orientation** is defined as the tendency to prioritize the future by relying on pragmatic approaches. In an organizational context, these societies promote long-term success and visions, while short-term oriented societies focus on achievements in the near future (Hofstede, 2001). GER has a high score: 83. In contrast, the US has a low score: 26.

Scholarly studies using Hofstede's cultural dimensions have faced criticism from various angles (e.g., Beugelsdijk, 2019). The concept of culture operates at a macro-level (Srite & Karahanna, 2006), emphasizing a recurring critique of Hofstede's framework, specifically the argument of cultural homogeneity. This argument challenges the assumption that domestic populations are uniform entities, while nations actually comprise diverse ethnic groups (Nasif et al., 1991). Conversely, countries do embody shared historical experiences that shape their national identity and prevailing cultural values (Beugelsdijk, 2019). Therefore, when analyzing cultures as the focus of our study, Hofstede's scores can be viewed as representing averages derived from samples of their populations. Consequently, these scores have been considered a widely accepted and frequently used approach.

2.4. Culture and AI Adoption

While numerous studies have explored the influence of culture on innovation adoption at the individual-level (Srite & Karahanna, 2006), there is a discernible gap in research that extends this examination to the organizational context. Building on this foundation, a subset of studies has delved into the domain of organizational innovation adoption. Notably, these studies narrow their focus to specific contexts, including enterprise resource planning systems (Waarts & van Everdingen, 2005), IT infrastructure (Png et al., 2001), introduction of novel products, ideas, or behaviors (Yeniyurt & Townsend 2003), and software production (Walsham, 2002). In addition, prior research concentrated on frameworks at the individual level such as the common Technology Acceptance Model (TAM) that investigates the acceptance of emerging technologies (McCoy et al., 2015). Preceding studies explored the impact of culture on mobile learning adoption (Wang & Zander, 2018).

There's a big gap in understanding how culture influences the link between organizational readiness and AI adoption in the field of culture and adoption research. Reevaluating AI adoption is crucial because AI's unique attributes distinguish it from earlier technologies such as rule-based systems. Notably, AI applications are often inscrutable due to their data-driven learning approach (Rudin, 2019). Unlike their predecessors, these systems do not always yield predictable outcomes and may even propose erroneous strategies (Domingos, 2012), making their integration into organizational landscapes distinct from other systems. Consequently, the adoption of AI applications requires substantial organizational transformation. Acknowledging this, Kane et al. (2021) emphasized the significance of exploring how organizations can proactively prepare for an AI-driven future. Due to the limited existing research, our study undertakes the task of elucidating the impact of culture on the factors of organizational readiness for AI adoption.

3. Hypotheses

Our research model in Figure 1 shows the impact of culture on the organizational readiness factors for AI. To define the hypotheses for cultural differences in AI adoption, we combine Hofstede’s (2001) cultural framework with the organizational readiness concept for AI (Jöhnk et al., 2021).

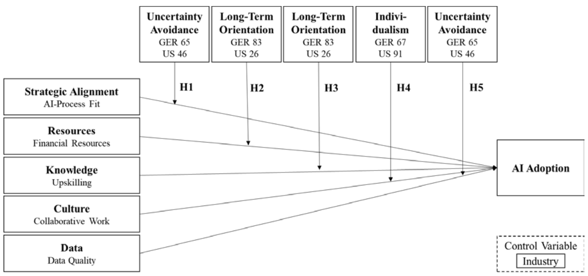

Figure 1. Research model.

AI-Process Fit (PF): According to the innovation adoption literature, compatibility is a prerequisite for innovation adoption in organizations (Xu et al., 2017). Since standardization, reengineering, and implementation of new business processes facilitate AI adoption (Kruse et al., 2019), we follow the recommendation of Jöhnk et al. (2021) to consider AI-process fit as an organizational readiness factor. Generally, organizations rely on long-established business processes that have proven themselves in the past and provide them control over their innovation adoption (Xu et al., 2017). However, when these business processes need to be adjusted, organizations face major challenges (Venkatesh & Bala, 2012). Even though these alterations are very likely in the field of AI (Brynjolfsson et al. 2017), the necessary adjustments related to business processes are subject to uncertainties. Even though the given AI capabilities of self-learning and autonomous decision-making increase human-machine collaboration (Berente et al., 2021), it is relatively unclear to what extent AI applications will augment decision-making processes. In this context, pertinent insights can be drawn from organizational literature, which posits that control strategies offer a strategic avenue for mitigating uncertainties (Thompson, 1967). This line of thought is notably mirrored in the domain of cultural studies, exemplified by Hwang's work (2005), where processes fostering control are consistent with the concept of uncertainty avoidance, as they demonstrate an ability to limit unforeseeable variables. The cultural dimension of uncertainty avoidance revolves around an individual's inclination toward structured as opposed to unstructured situations. Recognizing the pivotal role that uncertainty assumes as an environmental precursor to control mechanisms, we heed Hwang's advice (2005) and investigate the alignment between AI processes and the cultural aspect of uncertainty avoidance. This dimension refers to the extent to which organizations in cultures with high uncertainty avoidance scores establish rules and predefined processes to eliminate unforeseen events and to increase control in AI adoption (Javidan et al., 2006). In contrast, cultures with low uncertainty avoidance scores are more willing to take risks and do not need that much control mechanisms (Hofstede, 2001). Since the uncertainty avoidance score is higher in GER (65) than in the US (46), we expect a cultural difference in the sense that the US is better at coping with uncertainties related to AI. Organizations from GER are more likely to establish standards and structured business processes when adopting AI. Considering these findings, we define the following hypothesis: **H1:** The positive effect of AI-process fit on AI adoption is stronger in GER than in the US.

Financial Resources (FR): The allocation of financial resources is considered a crucial organizational readiness factor when implementing innovation. Organizations need to allocate sufficient financial budget, for example, to establish the required infrastructure, ensure business process integration, and attract new candidates (Xu et al., 2017). Previous research commonly examined the moderating influence of long-term orientation and financial background. For instance, Khlif et al. (2015) investigated the moderating role of long-term orientation in the relationship between financial profitability and social and environmental disclosure. Additionally, Bahadir (2020) discovered that the level of long-term orientation moderates the impact of financial development on total advertising spending, a higher long-term orientation results in a more pronounced positive effect. Thus, with respect to Hofstede’s (2001) cultural framework, we associated financial resources with the cultural dimension of long-term orientation (Waarts & van Everdingen, 2005). Countries with a short-term orientation often seek rapid returns on financial investments. In the context of AI adoption, they may prioritize projects offering immediate efficiency gains or cost savings over longer-term endeavors requiring substantial initial investments. Instead of committing financial resources to a single AI initiative, short-term cultures tend to favor incremental investments. They allocate smaller funds to multiple projects promising quick returns, spreading risk in line with their preference for immediate outcomes. Thus, the relatively low score of US (26) indicates that organizations tend to focus more on immediate results, regarding AI applications

and are, therefore, more willing to make the necessary investments.
Countries with a high long-term score tend to see AI adoption as a gateway to sustainable growth. Countries with a high long-term orientation score, such as GER (83), are often inclined to allocate significant financial resources to building a robust AI infrastructure. They see AI as a strategic investment. At the same time, they take a cautious approach to resource allocation. They conduct careful assessments of potential AI projects to ensure alignment with the organization's long-term goals. Based on these ideas, we assume that countries with lower long-term orientation scores such as the US may regard AI adoption as an opportunity for more immediate returns and efficiencies rather than prioritizing long-term growth and strategic investments in AI infrastructure such as countries like GER. Based on the discrepancy in long-term orientation between GER (83) and the US (26), we anticipate a cultural difference in AI adoption. Thus, we propose the following hypothesis: **H2:** The positive effect of financial resources on AI adoption is stronger in the US than in the GER.

Upskilling (UPS): An essential organizational readiness factor for increasing the adoption rate of innovation refers to upskilling. In other words, employees require proper training on a technology to better understand and use it more effectively (Jöhnk et al., 2021; Xu et al., 2017). Since users feel more confident in using an innovation through the acquired skills and competencies, the level of anxiety and ambiguity may decrease (Schillewaert et al., 2005). Particularly in the case of AI, an appropriate skill set is required to be able to interact with the unique AI capabilities of self-learning and autonomous decision-making. Since the level of inscrutability might increase due to the distribution of decision power between humans and AI applications (Berente et al., 2021), users need to learn how to correctly interpret the outcomes of AI applications and incorporate them into the decision-making process (Jöhnk et al., 2021). With respect to Hofstede's (2001) cultural framework, the associated persistence is mainly reflected by the cultural dimension of long-term orientation (Waarts & van Everdingen, 2005). According to the findings of Özbilen (2017), long-term oriented countries consider learning a work value which increases the motivation to acquire new knowledge and skills. By encouraging learning through upskilling, cultures with high long-term orientation scores are more likely to successfully implement innovation due to the acquired expertise (Özbilen, 2017). Considering these insights, we assume that GER (83) is more inclined to promote AI specific user training than the US (26). Thus, we pose the hypothesis: **H3:** The positive effect of upskilling on AI adoption is stronger in GER than in the US.

Collaborative Work (CW): Creating and assimilating knowledge through close collaboration among stakeholders enables organizations to better understand the requirements of innovation (Cao et al., 2010). With respect to AI adoption, a close collaboration between functional and data science teams is particularly important to assess functional problems and the technical feasibility of use cases and corresponding AI applications (Eitle & Buxmann, 2020; Kruse et al., 2019). Rather than maintaining traditional siloed structures, collaborative work between these teams can accelerate innovation cycles as frequent interactions and short lines of communications drive ideation and prototyping (Pumplun et al., 2019). Drawing on Hofstede's (2001) cultural framework, the degree of collaboration is mainly determined through the cultural dimension of individualism. Since collective societies that score is low on individualism are more concerned with the needs of the group, they prefer group decisions over individualistic actions. The study by Magnusson and Peterson (2014) showed that collective cultures tend to strengthen collaboration as group goals can primarily be achieved through interpersonal ties and shared visions. By ensuring a constant information flow, cross-functional teams in collective societies are more likely to contribute to organizational-wide collaboration (Engelen et al., 2012). Since a close collaboration between functional and data science teams facilitates the implementation of AI, we anticipate a cultural difference between GER and the US in AI adoption. The lower score in GER (67) compared to the high score in the US (91) indicates that GER encourages closer collaboration between these teams than the US. Thus, we pose the hypothesis: **H4:** The positive effect of collaborative work on AI adoption is stronger in GER than in the US.

Data Quality (DQ): Data quality management is a major concern in organizations which becomes even more relevant as the amount and variety of data increases, analysis capabilities enhance, and business process integration matures (e.g., Glowalla & Sunyaev, 2013). In the context of AI, the quality of training data is particularly important since the outcomes of AI applications are based on historical data (Sturm & Peters, 2020). If data quality is not reliable, the results of AI applications might be biased or prone to ethical issues (Awad et al., 2018). In general, data quality issues are mainly caused by incomplete data in the form of missing values or incorrect data (Sturm & Peters, 2020). According to Welzer and Hölbl (2000), the different handling of data quality issues may be related to the differences in values and beliefs that arise from culture. Since reliable outcomes through the correctness and accuracy of data help to provide reliable outcomes and consequently create certainty in organizations, data quality can therefore be related to the cultural dimension of uncertainty avoidance (Hofstede, 2001; Welzer & Hölbl, 2000). High uncertainty avoidance cultures, such as GER, tend to favor structured and well-defined decision-making processes. They are more inclined to seek clear information before making decisions, as uncertainty is often perceived as a source of risk. In contrast, low uncertainty avoidance cultures, such as the US, may be more comfortable with ambiguity and may be willing to accept a certain degree of uncertainty in their decision-making. Overall, countries in high uncertainty avoidance cultures, such as GER (65) may be less willing to adopt AI applications if data quality is perceived as a potential source of increased uncertainty compared to countries with low uncertainty such as the US (46). Thus, we hypothesis: **H5:** The positive effect of data quality on AI adoption is stronger in GER than in the US.

4. Research Design and Data Analysis

Regarding data collection, we applied a survey-based approach and developed a questionnaire. Drawing from the established literature on organizational readiness, AI adoption, and culture, we derived the measurements for the following constructs: AI-process fit (Xu et al., 2017) (e.g., "AI applications fit well with the main work processes of your organization."), financial resources (Chong & Chan, 2012) (e.g., "Your organization has the financial resources to purchase hardware and software required for AI projects."), upskilling (Schillewaert et al., 2005) (e.g., "The employees receive sufficient training to use the AI applications effectively."), collaborative work (Cao et al., 2010) (e.g., "During AI projects, the data science team and the specialist departments involved have informal communication."), and data quality (Weill & Vitale, 1999) (e.g., "The training data used in AI applications are accurate."). The items of the independent variables are measured based on a seven-point Likert scale ranging from "1 strongly disagree" to "7 strongly agree". To determine to what extent AI applications have been implemented in organizations, our dependent variable of AI adoption encompasses three intensity levels (Chong & Chan, 2012; Maas et al., 2018). While low intensity refers to the evaluation of AI use cases and appropriate AI applications, medium intensity involves the allocation of resources to implement AI applications. High intensity includes the incorporation of AI applications into work routines. With respect to the sample set, we invited 2,153 AI experts from GER and the US to participate in our online survey on LinkedIn, of which 1,351 experts clicked on the survey. After sorting out incomplete surveys and those with a failed attention check, 232 participants completed our survey which results in a completion rate of 17%. After splitting the total sample into two groups based on the categorial variable culture by which the organization is managed, we obtained two subsamples with 155 participants for GER and 77 participants for the US. To ensure their expertise in AI, we also inquired about their years of experience (YoE) in AI. The distribution is shown in Table 1:

YoE	GER (%)	US (%)
<1	4.5	3.9
1-2	25.2	22.0
3-5	33.5	26.0
>5	36.8	48.1

Table 1. Years of experience.

We also present industry distribution in Table 2.

Industries in %	Auto-motive	E-Commer	Energy	Finance	IT & Software	Logistics	Manu-facturing	Marke-ting	Health-care	Other
GER	16	8	6	8	19	9	8	5	9	12
US	3	16	3	17	27	7	5	3	9	12

Table 2. Distribution of industries.

The quantitative data analysis for our research model was conducted in a three-stage approach. First, we used SmartPLSv4 to analyze the measurement model in terms of validity and reliability for both countries separately. Secondly, in preparation for the multi-group analysis (MGA), we assessed the measurement invariance of composite models (MICOM) (Henseler et al., 2016). Thirdly, the MGA was conducted to determine the differences in path coefficients between GER and the US (Henseler et al., 2009). The partial least squares (PLS) method was primarily chosen because of the exploratory nature of our study and the lower sample size as the number of observations (Fornell & Larcker, 1981; Gaskin & Lowry, 2014).

4.1. Measurement Model

To ensure content validity, we followed the recommendations of McKenzie et al. (1999) to adapt the items to the context of AI. To obtain feedback on the terminology, the questionnaire was reviewed and adjusted by a panel of 12 AI researchers and practitioners. With respect to construct validity of the measurement models, we tested convergent validity and discriminant validity for each country separately (Hair et al., 2016). Convergent validity was assessed using the criteria of indicator reliability, composite reliability (CR), Cronbach's Alpha (α), and average variance extracted (AVE). To ensure indicator reliability, constructs should explain at least 50% of the variance of their respective indicators, which corresponds to a threshold of .7 for factor loadings (Hair et al., 2006). Factor loadings were higher than the threshold of .7 (Nunnally, 1978). Our study also reached the threshold of .7 for composite reliability and Cronbach's Alpha (α) which indicates internal consistency of all items (Nunnally, 1978). Regarding AVE, our results exceeded the threshold of .5 (Fornell & Larcker, 1981). Thus, convergent validity was ensured for both measurement models. Regarding discriminant validity, our study fulfilled the heterotrait-monotrait ratio (HTMT) for both measurements. Discriminant validity was established between the constructs as the HTMT values are below .90 (Henseler et al., 2015). In summary, our data analysis shows that convergent and discriminant validity were met for both samples.

4.2. Measurement Invariance

To analyze the moderating effect of culture on the organizational readiness factors for AI and to examine cultural differences between GER and the US, we conducted an MGA. The PLS-MGA procedure was used to compare the path coefficients between the two countries (Henseler et al., 2009, pp. 308-309). To ensure that the same constructs are measured in both groups, we tested measurement invariance by using the MICOM procedure and followed the three-step approach of (1) configural invariance, (2) compositional invariance, and (3) equality of composite's mean values and variances (Henseler et al., 2016). Based on our results, we were able to ensure configural and compositional invariance. With respect to step 3, we assessed the equality of the composites' mean values and variances between GER and the US. This condition holds for all constructs except for PF, UPS, and DQ which slightly fall out of the range. Thus, the measurement invariance is partially fulfilled and allows us to proceed with the MGA.

4.3. Results of Multi-Group Analysis

According to our results, our dependent variable explained 19% of variance in AI adoption which represents an adequate explanatory power. By examining uncertainty avoidance, we identified a significant difference between the two countries in AI-process fit. The positive effect of AI-process fit on AI adoption is stronger in GER than in the US (H1, $p = .050$). Thus, H1 is supported. With respect to long-term orientation, our results revealed a significant difference on the effect of financial resources on AI adoption. In this vein, the positive effect of financial resources on AI adoption is stronger in the US than in GER (H2, $p = .037$). Thus, H2 is supported. By further analyzing long-term orientation, we found no significant difference between the two countries regarding upskilling (H3, $p = .118$). Thus, we cannot confirm H3. In addition, we discovered that the positive effect of collaborative work on AI adoption is stronger in GER than in the US due to individualism (H4, $p = .037$). Thus, we confirm H4. Finally, we also observed a stronger effect of data quality on AI adoption in GER than in the US (H5, $p = .047$) due to uncertainty avoidance. Thus, H5 is supported.

5. Discussion

AI-Process Fit (PF): According to our results, the positive effect of AI-process fit on AI adoption is stronger in GER than in the US. This finding is in line with the cultural dimension of uncertainty avoidance since the higher score in GER (65) indicates that these organizations are not predestined in dealing with uncertain and unpredictable situations compared to the US (46). This means that in a GER (higher level of uncertainty avoidance), the alignment between AI processes and the organization's needs and practices has a more influence on AI adoption. Given their cultural inclination towards reducing uncertainty, organizations in GER are more likely to adopt AI applications when they fit well with their existing business processes. Conversely, in the US, where there is a lower level of uncertainty avoidance, the influence of AI-process fit on AI adoption is weaker. This finding indicates that organizations in the US may be more willing to adopt AI technologies even if there is not a perfect alignment with their existing processes, reflecting a greater tolerance for uncertainty. **Financial Resources (FR):** Given the significant discrepancy in long-term orientation scores between GER (83) and the US (26), the result suggests a notable cultural difference in AI adoption. It indicates that countries with lower long-term orientation scores, such as the US, tend to view AI adoption as an opportunity for immediate returns and efficiencies rather than prioritizing long-term growth and strategic investments in AI infrastructure, as observed in countries like GER. These results could shape the perception of AI in diverse cultural contexts. The way AI is perceived within organizations can differ significantly across cultures. Cultures characterized by a high long-term orientation may regard AI as a strategic catalyst for long-term growth, whereas cultures with a lower long-term orientation may perceive it primarily as a tool for attaining immediate efficiency improvements. **Upskilling (UPS):** In contrast to our expectation, our results showed no significant difference between GER and the US in the effect of upskilling on AI adoption. A possible explanation could be rooted in the realities of today's globalized world, where the abundance of talent and expertise frequently surpasses national borders. In both GER and the US, organizations enjoy access to a vast global talent pool. Consequently, these organizations tend to adopt comparable approaches to upskilling initiatives as they strive to maintain competitiveness on a worldwide level. **Collaborative Work (CW):** Our results revealed that the positive effect of collaborative work on AI adoption is stronger in GER than in the US which is in line with the cultural dimension of individualism. The lower score of individualism in GER (67) compared to the US (91) implies that such cultures favor close collaboration between functional and data science teams and show a stronger inclination toward collective efforts and teamwork. Collaborative work is highly valued in such cultures, as it aligns with the collective goals and harmonious working environments that are characteristic of collectivist societies. On the contrary, the US has one of the highest scores in individualism (91) and, therefore, tends to have a high degree of independence and autonomy in decision-making. The cultural preference for individual initiatives and achievements might result in a somewhat weaker association between collaborative work and AI adoption in the US. **Data Quality (DQ):** The level of uncertainty avoidance in a culture can influence how organizations perceive and prioritize data quality in the context of AI adoption. High uncertainty avoidance cultures are likely to be more demanding of data quality due to their risk-averse nature, potentially moderating the impact of data quality on AI adoption.

6. Limitations and Implications

While previous IS research lacks empirical cross-cultural studies on AI adoption, our study seeks to combine Hofstede's (2001) cultural framework with the organizational readiness concept for AI. While examining cross-cultural dynamics on AI adoption by using Hofstede's (2001) cultural dimensions, we found cultural differences between GER and the US. Despite these valuable insights, our study is subject to several **limitations** which, however, present opportunities for future research. First, even though the study was conducted in two Western countries, this selection may have influenced our findings and could have biased the role of culture. To reduce the risk of bias, researchers could select multiple countries and increase cultural diversity by including non-western countries. Second, given the relatively modest disparity in the power distance dimension score between GER and the US, we have not considered its influence in our analysis. It is important to note that while power distance could potentially impact the adoption of innovations, as suggested by researchers such as Yeniyurt & Townsend (2003), other studies, including the work of Png et al. (2001), have not consistently identified a significant influence. Consequently, we propose that future research delve into the effect of power distance on organizational readiness, as this aspect remains a valuable avenue. Third**,** the scope of the organizational readiness concept introduced by Jöhnk et al. (2021) is limited. While we have embarked upon an initial exploration of this framework, it is essential to acknowledge that our analysis did not encompass all 18 factors that constitute the organizational readiness concept. Our study, therefore, represents a preliminary step in this direction. We encourage researchers to undertake more extensive empirical studies to validate the full spectrum of organizational readiness factors.

The **theoretical contribution** of this paper is threefold. First, this study responds to the call for research to provide insights into cross-cultural dynamics on innovation adoption and the interaction of national and organizational cultural values (Leidner & Kayworth, 2006; Srite & Karahanna, 2006). By combining Hofstede's (2001) cultural framework with the organizational readiness concept for AI (Jöhnk et al., 2021), we were able to contribute to the discussion on how culture influences AI adoption. Rather than solely reporting country-specific discrepancies, we focused on relating these differences to Hofstede's (2001) cultural dimensions. Second, recent research on organizational readiness and AI adoption is mainly based on a qualitative research design on an individual level to set the theoretical basis (Jöhnk et al., 2021; Pumplun et al., 2019). There is a lack of quantitative studies on organizational level which evaluates the effect of cultural differences on AI adoption. We applied a quantitative research design to validate the qualitative findings and provide evidence of the moderating role of culture.

The study provides **practical contributions** for organizations. To ensure successful AI adoption, our study helps managers to identify appropriate organizational readiness factors relevant to the culture by which their organizations is managed. In summary, our findings provide guidance on how to manage AI adoption in an intercultural environment and improve organizational efficiency. For instance, in cultures characterized by a high level of uncertainty avoidance, such as GER, organizations should prioritize aligning AI processes with their existing practices. Conversely, in cultures with lower uncertainty avoidance, such as the US, organizations may be more open to AI adoption even if there is not a perfect alignment with their existing processes, reflecting a greater tolerance for uncertainty. The significant difference in long-term orientation scores between GER and the US suggests that countries with lower scores, such as the US, may view AI adoption as an opportunity for immediate returns and efficiencies. In contrast, countries with higher, such as GER, prioritize long-term growth and strategic investments in AI infrastructure. Managers should align their AI strategies with the cultural orientation of their respective countries. Understanding the cultural context can help organizations determine whether to focus on short-term gains or invest in long-term AI capabilities. In cultures with lower individualism scores like GER, promote close collaboration between teams. In contrast, in highly individualistic cultures like the US, prioritize individual initiatives and autonomy in decision-making over collaboration. Collaborative work's effectiveness in driving AI adoption can vary based on cultural individualism or collectivism.

7. References

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