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Culturally-Aware Artificial Intelligence: Personal Values and Technology Acceptance among AI Researchers in China and Germany

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Abstract

INTRODUCTION: AI development is driven by innovation and cultural contexts of collaboration. As AI and IoT systems shape global interaction, understanding cultural influences on technology perception is key for adaptive design and governance. This study compares personal values and AI acceptance among researchers in China and Germany – two leading yet culturally distinct ecosystems.
OBJECTIVES: To identify value patterns supporting trustworthy AI and effective cross-cultural collaboration in research and IoT contexts.
METHODS: A cross-national survey (n = 200) using the Portraits Value Questionnaire (PVQ) and the Digital Technology Acceptance Scale (DTAS) examined factors shaping AI perception.
RESULTS: Chinese participants show higher AI acceptance and stress self-enhancement and conservation; Germans emphasize self-transcendence and greater caution.
CONCLUSION: Findings inform culture-aware AI design, value-aligned governance, and intercultural collaboration.

Keywords: Artificial Intelligence (AI), Cross-Cultural Collaboration, Human-AI Collaboration, Responsible AI, Personal Values, Technology Acceptance

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1. Introduction

AI is shaped not only by technical advances and algorithms but also by the cultural and social contexts in which these systems are developed and deployed. In the context of Global Software Development (GSD), the interplay between human factors and technology has long been acknowledged. As Hofstede et al. [1], Kersten et al. [2], and MacGregor et al. [3] have noted decades ago, many challenges in software development arise not from technical barriers, but from intercultural collaboration. With the increasing globalization of software development, the need to integrate social and cultural considerations into collaborative computing and requirements engineering has become even more pressing [4].

This dynamic is further amplified by the dual-use nature of modern AI systems, which increasingly interact with humans and simulate human behaviour – ranging from recommender systems and chatbots to generative models and autonomous agents [5]. As AI becomes embedded in

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collaborative infrastructures and decision-making processes, the cultural values and acceptance of its developers and users gain new relevance. Recent studies have begun to address how national and organizational cultures influence AI design and deployment [6–11].

Among global AI leaders, the United States, China, and the European Union (including the UK) dominate in scientific output and innovation metrics [12]. Yet, China and the EU differ markedly in their regulatory approaches: China pursues agile, scenario-based regulation, while the EU emphasizes a horizontal, risk-based legal framework [13–16]. Notably, both China and the EU have emerged as frontrunners in AI regulation, actively shaping global standards, while the United States has taken a comparatively hands-off, market-driven approach. These differences reflect broader visions of a "Good AI Society" and shape how AI technologies are governed and perceived.

Although personal values and technology acceptance have been widely studied in isolation, their culturally specific interrelation remains underexplored. Culture, understood as a system of shared values, norms, and behaviours, influences both how people develop and how they interact with technology [17, 18]. In the context of collaborative computing, such cultural underpinnings are critical – especially when transnational teams co-create AI systems or when those systems mediate interaction across cultural boundaries. Academic and industrial researchers play a pivotal role in this ecosystem, influencing not only technological design but also governance practices and user expectations [19].

In this study, the term "AI researcher" refers to academic and industrial professionals who are directly involved in AI-related research or development activities. This includes engagement in tasks such as designing, developing, evaluating, or empirically studying AI systems, as well as regular interaction with AI technologies in a research or innovation context. To ensure conceptual clarity and cross-context comparability, this role definition is operationalized through explicit inclusion criteria, which are detailed in the methodology section.

This study addresses the following research question: *How do personal values and AI-related technology acceptance among academic and industrial AI researchers differ between China and Germany?* To answer this question, we conducted a cross-national survey using two established instruments: the Portraits Value Questionnaire (PVQ) by Schwartz [20] and the Digital Technology Acceptance Scale (DTAS) by Schorr [21]. By identifying culturally shaped patterns of perception and acceptance, this work contributes to the development of more adaptive and value-sensitive AI systems. In particular, our findings support efforts to design collaborative computing infrastructures that are culturally aware, ethically grounded, and better suited for multinational environments. Given the emerging and cross-disciplinary nature of this topic, the study adopts an exploratory design aimed at identifying initial cultural patterns rather than testing predefined hypotheses.

This study makes three key contributions. First, it provides a cross-cultural comparison of personal values and AI-related technology acceptance among academic and industrial AI researchers, a professional group that has received comparatively little empirical attention in prior work. Second, by combining Schwartz's value theory with established technology acceptance models, the study offers an integrated perspective on how cultural values and regulatory contexts jointly shape AI perception. Third, the findings extend existing research on culturally-aware and responsible AI by providing empirically grounded insights relevant for collaborative computing, transnational research, and value-sensitive system design.

2. Background

This chapter begins with a brief comparison of the AI strategies in China and the EU, providing context for the later discussion of results and their differing approaches. The second section introduces the theoretical frameworks for analyzing personal values and technology acceptance. Finally, in the last section, we identify a key research gap that leads us to the research question of this study.

2.1. The AI Strategies of China and the EU

The EU describes its AI Act [22], which came into force on 1 August, 2024, as the first comprehensive legal framework for AI [23]. In contrast, China adopted a more agile, sector-specific approach, introducing interim regulations on generative AI services in mid-2023, which became effective within two months [24]. While the EU is widely regarded as the global leader in complex legislation, China leads in enacting targeted, scenario-based AI regulations [13, 25].

China's "vertical" or "scenario-based" strategy focuses on sector-specific rules under an "innovation-first" policy [5, 26, 27], maintaining regulatory flexibility while prioritizing industry-driven development. Strategic investments, as outlined in the "New Generation Artificial Intelligence Development Plan" (AIDP), aim to position China as the global AI leader by 2030 [29]. The plan sees AI as a core driver of industrial transformation and technological upgrading. At the same time, Chinese authorities emphasize the need for governance frameworks. The "Beijing AI Principles" and the "New Generation Artificial Intelligence Governance Principles" provide ethical guidance and reflect China's emphasis on promoting responsible AI development across diverse sectors [14, 30–32].

In contrast, the EU follows a "horizontal" regulatory strategy [5], exemplified by the AI Act's four-tier risk classification: minimal, limited, high, and unacceptable risk [22, 23]. This legislation prioritizes societal and individual harm prevention and reflects Europe's strong emphasis on ethics and civil rights [13, 14]. However, the EU acknowledges its comparatively low investment in AI innovation [33], leading to critical voices such as Guntram Wolff's remark: "Europe may be the world's AI referee, but referees don't win" [34]. To address this, "regulatory sandboxes" have been introduced, enabling companies and researchers to test AI systems in real-world settings under reduced compliance burdens, aiming to reconcile innovation with oversight [35].

In summary, China emphasizes economic growth and technological leadership, while the EU prioritizes ethical safeguards and civil liberties. Despite differing approaches, both aim to balance innovation with responsible governance. As Xia argues, these strategies are not mutually exclusive but can complement and inspire global AI policy development [36].

2.2. Connecting Personal Values and Technology Acceptance

Personal values are fundamental guiding principles that shape attitudes, behaviors, and societal norms [37–39]. They help explain individual and collective patterns of behavior and are thus central to understanding human-technology interaction [40].

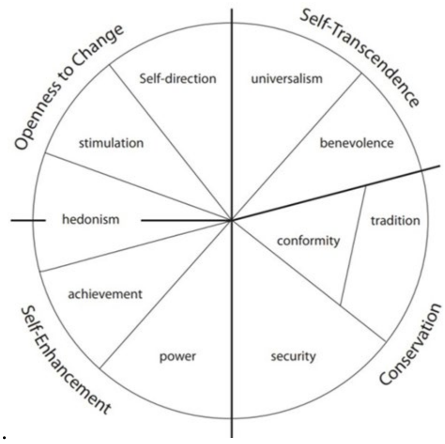

Figure 1. Schwartz's model of the structure of relations among the ten values [42].

A widely recognized framework for studying values is Schwartz's "Theory of Basic Human Values", validated across diverse cultures [41]. It identifies ten universal values grouped along two bipolar dimensions: *Openness to Change* vs. *Conservation* and *Self-Transcendence* vs. *Self-Enhancement* (see Fig. 1) [42]. This circular model shows how closely related or opposing values align and vary depending on context and culture.

In software and requirements engineering, several approaches aim to integrate ethical values into IT development. For example, Thew et al. [43] explore the role of emotions and motivations in requirements gathering, while Ferrario et al. [44] highlight value-based decision-making. A notable approach is Value Sensitive Design (VSD) [45], which incorporates stakeholders' values and helps resolve value conflicts during development. VSD views value integration as an ongoing process, especially relevant for AI, where societal expectations evolve rapidly.

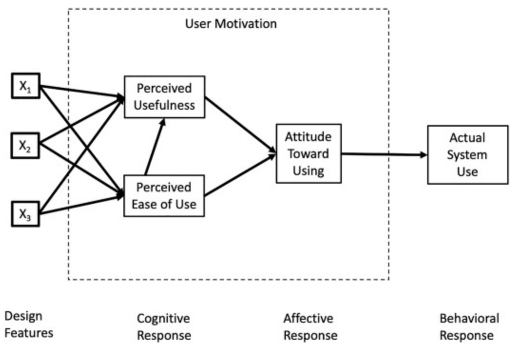

Figure 2. Technology Acceptance Model by Davis et al. [46, 49].

Technology Acceptance involves the perceived usefulness, ease of use, and willingness to adopt a technology [46]. Davis introduced the Technology Acceptance Model (TAM) in the 1980s to address high failure rates in IT adoption [47, 48]. Despite the evolution of many models since, TAM remains a widely used framework [49]. Its four core constructs – *Perceived Usefulness*, *Ease of Use*, *Attitude Toward Usage*, and *Behavioral Intention to Use* – continue to inform acceptance research (see Fig. 2) [46, 49].

Studies increasingly confirm a strong link between personal values and technology acceptance. Seibert et al. [52] identify traits such as openness, conscientiousness, and risk tolerance as key predictors. Sun et al. [53] incorporate cultural values into technology readiness, while Belanche et al. [54] highlight the role of trust and values in the adoption of e-government services. These findings suggest that values are not only relevant for understanding behaviour but also crucial for designing responsible and accepted technologies.

2.3. Research Gap and Research Question

While prior research has explored both personal values and technology acceptance toward AI, as well as their interrelation, comparatively little attention has been paid to how these factors differ across cultural contexts. In particular, there is a lack of comparative studies examining personal values and AI-related technology acceptance in China and the EU.

Although our broader interest lies in the comparison between China and the EU, this study empirically focuses on Germany as a key member state. This choice enables consistent and feasible data collection while still offering valuable insights, given Germany's prominent economic, political, and regulatory role within the EU. Nevertheless, we acknowledge that cultural and regulatory diversity exists across EU member states. Thus, Germany is not assumed to represent the EU as a whole, but rather to provide an initial reference point for further comparative studies. Future research could expand this scope to additional countries for broader generalizability.

Academic and industrial researchers play a crucial role in shaping both AI technologies and the surrounding regulatory frameworks. Their values and acceptance of AI affect not only development processes but also public trust and societal integration. By examining this professional group, we aim to identify patterns that are relevant for both technical design and policy development.

Our guiding research question is: How do personal values and AI-related technology acceptance differ between academic and industrial AI researchers in China and Germany?

Beyond theoretical contributions, this study aims to support intercultural collaboration in global AI projects. For example, our findings could inform methods for addressing value conflicts in transnational development teams or support decision-makers in designing culturally sensitive AI regulations.

3. Research Design

First, we outline the *Objectives and Content of the Survey*, including the two embedded questionnaires, along with their theoretical foundations and measurement instruments. The second section, *Data Collection*, details the sampling strategy, participant recruitment, and survey implementation. Finally, the third section, *Data Analysis*, describes the statistical methods used to evaluate the collected data.

3.1. Objectives and Content of the Survey

Schwartz first developed the Schwartz Value Survey (SVS) as a comprehensive tool for measuring personal values across cultures [37, 55]. While widely used in cross-cultural research, the SVS requires respondents to engage in abstract self-reflection and numerical judgment, which can be cognitively demanding, particularly for individuals unfamiliar with such rating scales. In response to these challenges, Schwartz and colleagues later developed the Portraits Value Questionnaire (PVQ) as an alternative approach to measuring values, aiming to improve accessibility and ease of response [20].

The PVQ differs from the SVS in three key aspects. First, the PVQ assesses values indirectly by presenting respondents with short verbal descriptions of fictional individuals who embody specific values (e.g., “Thinking up new ideas and being creative is important to him”). Respondents then indicate how similar each described person is to themselves, making the judgment process more intuitive and contextually grounded than the abstract self-assessments required by the SVS. Second, while the SVS employs a nine-point numerical scale, including negative values, the PVQ uses a simpler six-category response format that does not require numerical transformations. This reduces cognitive complexity and makes the PVQ especially suitable for respondents unfamiliar with numerical scales. Third, the administration time of the PVQ is significantly shorter than that of the SVS which counts 57 items, making it a more practical tool in large-scale surveys and diverse cultural settings. The PVQ is available in three versions: PVQ-21 with 21 items, PVQ-40 with 40 items, and PVQ-R with 56 items. These advantages have contributed to the PVQ’s widespread adoption in psychological and social science research [20].

The PVQ-R also expands the original ten basic values into 19 more specific value facets, offering greater granularity in value measurement. This refinement comes at the cost of increased questionnaire length and complexity, as respondents must evaluate a larger number of value-representative statements. While the PVQ-R allows for a more nuanced analysis, the original PVQ-21 and PVQ-40 remain widely used due to its shorter administration time and lower cognitive demand, making it particularly suitable for large-scale surveys and cross-cultural studies where efficiency and comparability are crucial. In our study, we opted for the PVQ-40 to balance methodological rigor with practical feasibility [55].

Last but not least, one of the most important arguments in favour of the PVQ is its applicability in Confucian cultures, such as China. Jia et al. [56] conducted a comprehensive study testing the PVQ with a diverse sample of 2,569 individuals from different regions of China. The researchers concluded that “the value structure of Chinese people fit well with the theoretical pattern of Schwartz’s theory.” Similarly, Li [57] conducted a study with 235 Chinese participants. Through Confirmatory Multidimensional Scaling (MDS) and Confirmatory Factor Analysis (CFA), he demonstrated that Schwartz value theory is applicable to the Chinese context – though some deviations from the theoretical model were observed.

To assess digital technology acceptance in the context of AI, we employed Schorr’s Digital Technology Acceptance Scale (DTAS) which has been established as both reliable and valid from a psychometric perspective [21]. Schorr initially developed a questionnaire comprising 24 items, drawing on previous studies [e.g., 51, 58, 59]. Through factor analyses with Varimax rotation, she refined the scale by reducing it to the four core concepts of technology acceptance, ultimately retaining only 13 items (e.g., “[Artificial Intelligence] improves my work”). This reduction not only preserved the scale’s conceptual integrity but also enhanced its practical efficiency [18]. This questionnaire makes use of the (classical) 5-point Likert scale.

Regarding language administration, the survey instruments were implemented in a manner consistent with participants’ professional working contexts. Participants in Germany completed the original English versions of the PVQ and DTAS, as English is the predominant working language in international academic and industrial AI research environments. For participants in China, the survey was translated into Chinese to ensure accessibility and to minimize potential comprehension barriers. The Chinese version of the questionnaire was produced using a standardized translation and back-translation procedure. Initial translations were conducted by bilingual researchers familiar with both the subject matter and the cultural context. Independent back-translations into English were then used to verify semantic equivalence. Discrepancies were discussed and resolved collaboratively to ensure conceptual consistency across language versions. This process aimed to establish semantic comparability between the English and Chinese instruments rather than strict linguistic symmetry.

3.2. Data Collection

The study targeted AI researchers in academic and industrial settings in China and Germany. Academic researchers were defined as those employed at universities or research institutions, while industrial researchers were those engaged in research and development roles within companies engaged in research-related tasks.

To operationalize the term “AI researcher,” participation in the survey was limited to individuals who reported direct involvement in AI-related research or development activities. This included tasks such as designing, developing, evaluating, or empirically studying AI systems, as well as the regular professional use of AI-based technologies in a research or innovation context. Both academic and industrial participants were required to self-identify their role as research-oriented and to confirm active engagement with AI in their professional activities. Given the exploratory nature of the study, no minimum publication or patent threshold was imposed. However, respondents’ years of experience and disciplinary background were collected to allow for contextual interpretation and potential subgroup analyses.

An online survey was developed encompassing the following demographic items on the first page: gender, age, field of work, years of experience, and the more specific origin of the research institution within China and Germany. This was followed by the PVQ and the DTAS.

Participants were recruited through a multi-faceted approach to maximize reach within the academic and industrial research communities. The survey was distributed via several online professional networks, targeting relevant groups and communities. Additionally, personalized email invitations were sent to a selection of academic and industrial research institutions, requesting them to forward the questionnaire link to their research staff. The data collection period spanned approximately seven months, from December 16, 2024, to June 16, 2025.

3.3. Data Analysis

Our data analysis followed the three-step approach outlined by Pfleeger and Kitchenham [60], encompassing *Data Validation*, *Response Partitioning*, and *Data Coding*. This structured approach ensured the rigor and transparency of our analysis process.

Data validation: Prior to analysis, data validation was conducted to ensure accuracy and integrity. Responses were screened for completeness, with missing data handled through exclusion. Data distributions were visualized to identify inconsistencies. Internal consistency was assessed using Cronbach’s alpha, yielding 0.90 for PVQ and 0.92 for DTAS. Descriptive statistics were calculated, and independent t-tests were performed to compare mean values between samples. The significance level (α) was set at 0.05. Since this was an exploratory analysis, no corrections were applied for multiple testing. Accordingly, the results should be interpreted as indicative of emerging cultural patterns rather than conclusive statistical differences. All statistical analyses were performed in R version 4.4.2. Formal consent was not required, as participation was voluntary and anonymous, and the study adhered to all relevant regulations.

Response Partitioning: Given that both groups in our study consisted of researchers (even though in different settings), we opted for a holistic approach to the analysis, considering the entire sample as a unified group. While academic and industrial researchers operate in distinct environments, both possess advanced education and are deeply involved in research activities. We posited that this shared background and professional focus would likely outweigh any potential variations in personal values or AI acceptance due to their specific work context. Furthermore, analyzing the data holistically allows for a broader understanding of the relationship between the cultural aspects of personal values and technology acceptance towards AI, rather than focusing on the nuances between specific subgroups. This decision allowed us to maximize the statistical power of our analyses and draw more generalizable conclusions between China and Germany.

Data coding: The surveys employed two different types of scales. The PVQ utilized a six-level scale, requiring respondents to rank 40 values from 1 to 6. These rankings were directly assigned numerical values from 1 (“Not at all like me”) to 6 (“Very much like me”) for each value. The 13 DTAS values used a 5-point Likert scale, ranging from 1 (“Strongly disagree”) to 5 (“Strongly agree”). These responses were likewise assigned numerical values from 1 to 5.

4. Results

The first section, *Sample Demographics*, provides an overview of the respondents’ characteristics. The second section, *Personal Values of the Respondents*, and the third section, *AI Acceptance of the Respondents*, present the results obtained from our survey by comparing the responses from China and Germany side by side. The last section, *Differences by Gender and Age*, examines how variations in personal values and AI acceptance are influenced by respondents' gender and age.

4.1. Sample Demographics

A total of 200 responses were collected, with 100 from China and 100 from Germany.

Table 1. Age distribution of survey participants.

Age	China	Germany
18-24	0	3
25-34	18	28
35-44	49	29
45-54	10	21
55-64	19	17
65 or older	1	2
Prefer not to say	3	0

Table 2. Work experience distribution of survey participants.

Work experience	China	Germany
Less than 1 year	16	3
1-3 years	33	13
4-6 years	14	10
7-10 years	5	20
More than 10 years	32	54

Table 3. Distribution of survey participants by discipline.

Discipline	China	Germany
Arts and Humanities	14	8
Business and Economics	15	7
Computer Science and Information Technology	2	2
Education	6	7
Engineering and Technology	0	0
Environmental and Earth Sciences	2	4
Health and Medicine	2	1
Law and Legal Studies	2	1
Life sciences	3	8
Mathematics and Statistics	9	5
Physical Sciences (e.g., Physics, Chemistry)	14	8
Social Sciences	15	7
Other	16	29

The gender distribution in China was relatively balanced, with 50 respondents being male and 44 female. A small proportion of six chose not to specify their gender. In Germany, the distribution was more skewed, with 56 respondents being male and 39 female. Four respondents were diverse and one respondent chose not to disclose his or her gender.

The largest age group in China was 35–44 years, representing nearly half of the respondents (see Tab. 1). In Germany, the age distribution was more evenly distributed, with the 35–44 age group as the largest group as well (n=29). In China, the largest group in terms of years of experience in their field (see Tab. 2) had 1–3 years (n=33), followed by those with more than 10 years of experience (n=32). In Germany, more than half of the respondents (n=54) reported having over 10 years of experience in their respective fields. Tab. 3 presents the research fields of the respondents.

4.2. Personal Values of the Respondents

The results of the PVQ (see Fig. 3 and 4) reveal moderate differences between respondents from China and Germany, with several statistically significant contrasts. However, despite these differences, the overall variation remains moderate, as none of the value differences exceed 0.8 on average.

When mapped onto the Values (see Fig. 3), the most pronounced difference is observed in Tradition, which is 0.8 points higher in the Chinese group (mean score: 3.5) compared to the German group (2.7). In both groups, however, this is the lowest of the values (together with Power in the German group), which again represents a commonality.

A similar trend is seen in Power, where the Chinese respondents score 0.6 points higher (mean: 3.4 in China vs. 2.6 in Germany, ($p < 0.001$). Together with Achievement, this value contributes to the higher-order category of *Self-Enhancement* (see Fig. 4), which exhibits a statistically significant 0.6-point difference ($p < 0.001$) between the respondents from China (3.8) and Germany (3.2).

The Chinese group also scores notably higher in the higher-order value *Conservation* (comprising the values Conformity, Tradition, and Security), with an average score of 4.0, compared to 3.5 in the German group, marking a 0.5-point difference ($p < 0.001$).

In contrast, the difference in *Openness to Change* (including Hedonism, Self-Direction, and Stimulation) is less pronounced, with the Chinese group scoring 4.3 and the German group 4.1. Self-direction is the most important value for both groups, which is 0.4 higher in Germany (5) than in China (4.6), which is statistically not significant ($p = 0.110$).

Finally, for *Self-Transcendence* (encompassing Universalism and Benevolence), the pattern is reversed, with the German group scoring slightly higher (4.6) than the Chinese group (4.3), although this difference is not statistically significant as well (p = 0.065).

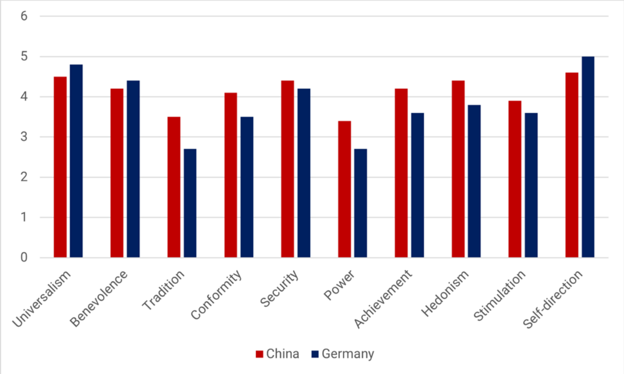

Figure 3. Attribution of the PVQ results to the ten basic human values.

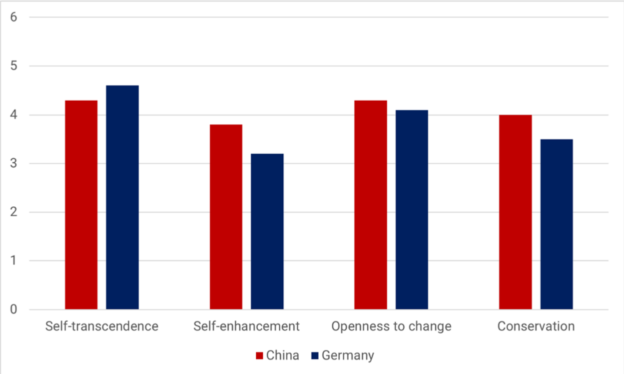

Figure 4. Higher order values derived from the ten basic human values.

4.3. AI Acceptance of the Respondents

Technology acceptance regarding AI is consistently higher among respondents from China compared to those from Germany across all items of the DTAS (see Fig. 5 and 6). However, despite these differences being statistically significant, none exceed a full-point difference on the scale.

The most pronounced disparity is observed in Item 10 (“I use Artificial Intelligence without any worries”), which received the lowest level of agreement in both groups. The mean score for this item was 3.2 in the Chinese group and 2.3 in the German group, marking a 0.9-point difference, indicating a notably higher level of confidence in AI among Chinese respondents.

A difference of 0.6 points is observed in the core concept *Attitudes Towards Usage*, which comprises Item 11 (Fun), Item 12 (Anticipation), and Item 13 (Enjoyment). Here, the Chinese group achieved an average score of 3.6, whereas the German group scored 3.0 (see Fig. 6) ($p < 0.05$).

In the core concept of *Perceived Usefulness*, which is made up of items 1 (Improvement), 2 (Effectiveness), 3 (Productivity), and 4 (Usefulness), the Chinese group scored 4.3, therefore 0.5 higher than the German group with 3.8 ($p < 0.001$).

Within the core concept *Behavioural Intention to Use*, which is made up of items 5 (Frequency in the future) and 6 (Extension in the future), the Chinese group is 0.4 above the German group. In this category, the Chinese group has a mean value of 4.0, while the German group has a mean value of 3.6 ($p < 0.01$).

Item 7 (Simplicity), item 8 (Thoughtlessness), item 9 (Carefreeness), and item 10 (No worries) contribute to the core concepts *Perceived Ease of Use*. In this category, the German group recorded its closest average score of 3.6 with the Chinese group scored 0.3 points higher at 3.9 ($p < 0.01$).

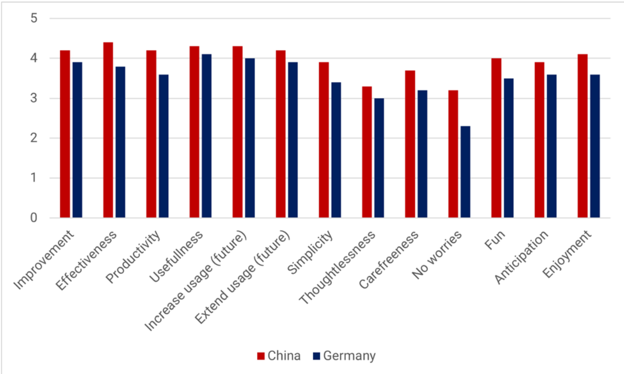

Figure 5. Results of the 13 items of the DTAS.

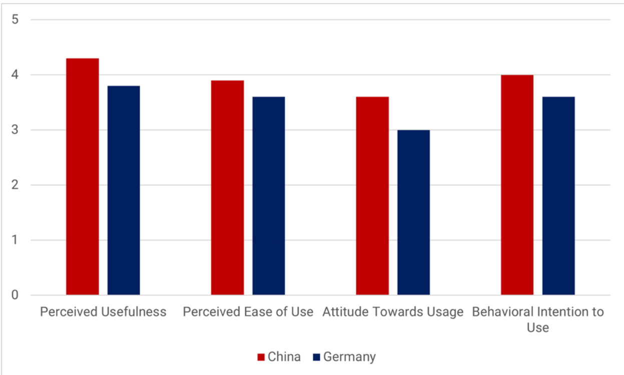

Figure 6. The four core concepts of Technology Acceptance derived from the 13 items of the DTAS.

4.4. Differences between Gender and Age

In the German group, no significant differences were found between men and women in the distribution of values. In contrast, the Chinese group showed significant gender differences. Males scored significantly higher than females on the following subscales: Benevolence (4.4 vs. 3.9, ($p < 0.001$), Tradition (3.7 vs. 3.3, p = 0.04), Conformity (4.3

vs. 3.8, $p < 0.01$), Security (4.7 vs. 4.2, $p < 0.001$), Power (3.6 vs. 3.0, $p < 0.01$), and Achievement (4.5 vs. 3.9, $p < 0.001$).

Chinese participants under 35 scored higher on self-direction compared to those 35 and older (4.8 vs. 4.3, $p = 0.01$). No other PVQ or DTAS subscales showed significant differences between age groups. Similarly, German participants under 35 scored higher on hedonism than those 35 and older (4.0 vs. 3.6, $p = 0.01$), with no other PVQ or DTAS subscales showing significant age-related differences.

5. Discussion

Previous studies on AI acceptance and cultural values have primarily focused on general user populations, organizational settings, or single-country contexts. While existing research highlights the importance of cultural factors and ethical considerations in AI systems, direct cross-national comparisons of AI researchers as key socio-technical actors remain scarce. By focusing on Sino-German research contexts and explicitly linking value orientations to AI acceptance, this study extends prior work and offers a more differentiated understanding of how cultural and regulatory environments shape professional engagement with AI.

In this chapter, we analyze and interpret the results in relation to our research question and the regulations within China and Germany. The first section compares personal values, while the second examines technology acceptance. The third section introduces implications especially for researchers. Finally, in the fourth section, we critically assess the study's validity by listing its threats for validity in a limitations section.

5.1. Comparison of the Personal Values

The results of the PVQ reveal statistically significant, albeit moderate, variations in personal values between Chinese and German respondents. Of course, it would hardly be possible to derive a comprehensive cultural-historical interpretation from the results of the PVQ. This is only possible to a limited extent and would require further interdisciplinary studies. Nevertheless, numerous studies show a connection between cultural values and regulation [61, 62, 63]. In this respect, this context will form the focus of the following discussion.

A prominent divergence is observed in the value Power, though notably, it remains the lowest-ranked value in both cohorts, indicating a shared perspective on its relative importance. The higher-order value Self-Enhancement (Power, Achievement) exhibits a higher rating in the Chinese group, reflecting the emphasis on competitiveness and success within Chinese professional and educational spheres, aligning with prior research that highlights the Chinese societal emphasis on success and status as drivers of social mobility and national advancement. A survey on the competitive mindset of Chinese youth shows that nearly 60 percent of young people aged 31-35 said they 'often' (57.92 percent) felt competitive pressure, the highest value among all ages. Their perception of the pressure of 'promotion' (50.00 percent) was even more pronounced [60]. There is a phenomenon that illustrates this point: 鸡娃（Tiger Parenting）, i.e. parents trying to make their children more competitive in education [65]. High expectations regarding academic and professional success are reflected in ambitious work cultures, such as extended working hours in some technology sectors. These practices are often associated with a strong dedication to innovation and excellence. These work norms reflect the societal expectation that professional success is achieved through relentless dedication, leading to an intensely competitive landscape [66].

Similarly, Conservation (Conformity, Tradition, Security) demonstrates a higher score in the Chinese group. Conversely, the German's lower score reflects its historical emphasis on individual freedoms and social progress, where traditional values hold less central influence [67].

Openness to Change (Hedonism, Self-direction, Stimulation) presents a more balanced distribution, with a minimal difference. Self-direction is paramount in both groups, albeit slightly more so in Germany, suggesting shared valuation of autonomy and innovation, yet with distinct interpretations. In Germany, it aligns with personal independence, while in China, it may be more closely associated with strategic decision-making within social structures. Conversely, Self-Transcendence (Universalism, Benevolence) is rated slightly higher by German respondents, reflecting the EU's risk-based approach within the AI Act.

In summary, these variances mirror broader regulatory and cultural divergences in AI governance: China's focus on innovation and structured oversight aligns with its societal emphasis on self-improvement and preservation, while the EU's focus on ethical considerations and civil rights aligns with its prioritization of Self-Transcendence. Despite these differences, shared value hierarchies suggest a foundational commonality in attitudes toward AI and technological advancements. At this point, it should be emphasised once again that both approaches also include the focus of the other: The EU AI Act contains elements that are intended to strengthen economic competitiveness, while China contains elements that are intended to reduce ethical and social risks.

5.2. Comparison of the AI Acceptance

The results of DTAS reveal consistently higher AI acceptance among the Chinese group compared to the German group, though differences remain within a one-point scale range, indicating a shared recognition of AI's benefits and potential.

A notable divergence emerges in *Perceived Ease of Use*, with the German group scoring significantly lower. This suggests Chinese respondents perceive AI as more intuitive, potentially due to its widespread integration in daily applications, fostering familiarity. In a survey from 2022, 78% of Chinese respondents (the highest proportion of surveyed countries) agreed with the statement that products and services using AI have more benefits than drawbacks [68]. Conversely, EU regulatory discussions and concerns about transparency may contribute to a more cautious usability perception.

Similarly, *Attitude towards Usage*, reflecting enjoyment and anticipation of AI technologies, shows a higher score in the Chinese group. This aligns with China's technological culture, where AI is often viewed as a driver of progress. The EU's emphasis on ethical and regulatory considerations may foster a more sceptical attitude.

5.3. Implications for Requirements Engineering

This study primarily supports early-phase requirements elicitation and stakeholder sensitization, rather than prescriptive system design decisions.

Our findings reveal consistent cultural differences in personal values and AI acceptance between Chinese and German researchers. Chinese participants score higher in Self-Enhancement and Conservation, whereas German participants emphasize Self-Transcendence. Moreover, Chinese respondents report greater ease of use and confidence in AI technologies, while German researchers display a more cautious attitude. These patterns suggest that cultural value orientations and regulatory environments significantly shape how AI is perceived, trusted, and integrated into professional practice. Designers and system developers should therefore recognize that assumptions about usability, transparency, and trustworthiness vary across cultural and institutional contexts. Awareness of these factors helps anticipate differences in user expectations early in the design process.

From a requirements engineering perspective, these differences can be reflected in a small set of recurring design dimensions:

- **Degree of automation:** The extent to which the AI system performs tasks autonomously, such as generating recommendations or executing actions without human intervention.
- **Transparency and explainability:** The degree to which the system provides understandable explanations, rationales, or confidence indicators for its outputs and recommendations.
- **Allocation of control between human and system:** The distribution of decision authority and responsibility, including human-in-the-loop mechanisms, confirmation requirements, and override options.
- **Handling of uncertainty and risk:** How uncertainty, confidence levels, potential errors, and risk-related information are communicated, mitigated, and managed within the system.

These dimensions primarily affect non-functional requirements, interaction design choices, and governance-related constraints, rather than core system functionality.

To illustrate how such value-oriented differences may translate into concrete requirements considerations, consider the design of AI-based decision support systems in healthcare. In contexts characterized by higher Conservation and Self-Enhancement values, as observed among the Chinese respondents, higher baseline acceptance of AI may be associated with a greater tolerance for automation and system-driven recommendations. In such settings, AI systems might prioritize efficiency, streamlined workflows, and stable default behaviors, for example by offering stronger recommendation confidence or reduced interaction overhead for routine clinical decisions.

In contrast, in contexts where Self-Transcendence and risk sensitivity are more pronounced, as observed among German respondents, healthcare AI systems may need to emphasize transparency, explainability, and explicit human oversight. Requirements may therefore include more detailed justifications for AI recommendations, clearer communication of uncertainty, and stronger mechanisms for clinician control and override. Rather than assuming a one-size-fits-all solution, these differences suggest that healthcare AI systems should support configurable interaction modes that allow adaptation to culturally shaped expectations regarding trust, responsibility, and ethical accountability.

Importantly, these implications should be understood as hypothesis-generating design considerations rather than prescriptive rules. Future design-oriented and experimental research is required to empirically validate how value orientations influence concrete usage patterns and safety outcomes in clinical AI systems.

These insights have direct implications for international collaboration in AI design and deployment. Cross-cultural requirements engineering and responsible AI development must account for differing value systems and acceptance thresholds. Collaborative systems intended for global use – especially in transnational research, digital health, or autonomous systems – should include flexible, context-sensitive design options reflecting diverse expectations of usability, trust, and ethics. For example, interactive systems may offer configurable transparency levels, culturally adaptive feedback styles, or alternative modes of human-AI interaction aligned with users' preferred balance between control and automation. Designers should test such features with culturally diverse user groups rather than assuming global uniformity in acceptance criteria.

To strengthen cross-cultural collaboration in AI projects, we recommend integrating structured value reflection into early development phases. Transnational teams could adopt participatory design workshops [70] that explicitly surface and negotiate value tensions [45].

Facilitated value-mapping exercises or stakeholder personas can help align differing priorities. Researchers and project leads should institutionalize such practices – for instance, through intercultural checklists in requirements documentation or design sprints involving participants from multiple cultural backgrounds. This fosters shared ownership and mutual understanding in international collaborations.

For the field of collaborative computing, our study highlights the need to align technical system design with socio-cultural realities. Educational programs and research initiatives should therefore integrate intercultural competence alongside technical training. This enables teams from diverse backgrounds to co-create AI systems that are both functionally effective and socially acceptable. Universities and research institutions should provide training that combines ethical reasoning with cultural literacy, preparing developers and policymakers to navigate regulatory and collaborative diversity.

Finally, on the governance level, the divergent approaches of China and the EU – innovation-driven versus risk-based – may offer complementary strengths. A hybrid governance model combining strategic flexibility with normative oversight could inspire globally viable frameworks for collaborative AI. Promoting such convergence requires mutual understanding, sustained dialogue, and sensitivity to regional value systems within the broader ecosystem of human-AI-system collaboration. For policymakers, this implies aligning governance instruments with regional value orientations – for instance, complementing the EU's ethics-focused approach with China's scenario-based innovation model. Regulators should also support bilateral research programs or joint testbeds that evaluate AI systems under both innovation- and risk-oriented frameworks.

By making such context-sensitive design considerations explicit, requirements engineering can move beyond cultural awareness toward actionable, yet flexible, design hypotheses that can be evaluated and refined in subsequent system development cycles.

5.4. Limitations

Our study acknowledges several methodological limitations that may affect the interpretation and generalizability of its findings. Following established evaluation frameworks, these are discussed in terms of construct, internal, and external validity, as well as reliability considerations. Given the exploratory nature of the research, the findings should be viewed as indicative rather than definitive.

Construct Validity: Although the PVQ and DTAS are well-established instruments with documented cross-cultural applicability, certain limitations must be acknowledged. While careful translation and back-translation procedures were applied for the Chinese version and semantic equivalence was systematically reviewed, formal statistical tests of cross-language measurement invariance were not conducted. Additionally, the use of English-language instruments for participants in Germany assumes a high level of professional English proficiency, which is typical in international AI research contexts but may still introduce subtle interpretation differences. As this study follows an exploratory design, future confirmatory research should explicitly test measurement invariance across language versions to further strengthen cross-cultural comparability.

Internal Validity: Regional or subcultural factors within China and Germany were not differentiated. More fine-grained analyses across locations, institutions, or demographics could reveal additional patterns.

External Validity: Despite efforts to recruit a diverse sample, disciplinary and sectoral differences may have influenced responses. Some self-selection bias is possible. Future studies should distinguish more clearly between research domains to improve generalizability.

Reliability: Social desirability bias cannot be fully excluded. However, anonymous participation and collaborative data evaluation helped mitigate this risk and enhance consistency. As this study follows an exploratory design, statistical corrections for multiple testing were not applied; accordingly, the results should be interpreted as indicative trends, and future confirmatory analyses should validate these initial findings with larger samples.

6. Conclusion

This study has provided a comparative analysis of personal values and AI-related technology acceptance among AI researchers in China and the EU member Germany – two key players in global AI development and regulation.

Overall, this work contributes to the growing body of research on culturally-aware AI by empirically demonstrating how personal values and regulatory contexts jointly influence AI acceptance among researchers. These insights complement and extend existing studies in collaborative computing and responsible AI, including prior work published in EAI venues, by providing a focused comparison of two globally influential AI ecosystems.

Our findings reveal moderate yet meaningful cultural distinctions. Chinese respondents scored higher in Self-Enhancement and Conservation values, along with a generally higher level of AI acceptance, particularly in terms of perceived ease of use and positive attitudes toward usage. German participants, by contrast, emphasized Self-Transcendence and demonstrated greater caution toward AI systems, consistent with the EU's risk-sensitive regulatory approach. Notably, both groups shared a recognition of AI's usefulness, indicating a common ground for collaboration.

These insights highlight the significance of cultural and regulatory context in shaping human-AI interaction and system design. For the field of collaborative computing, this underscores the importance of embedding value-sensitive and culturally-aware considerations into requirements engineering, system governance, and transnational development processes. Designing AI systems that align with diverse cultural expectations can support more effective collaboration between human and technical actors across institutional and national boundaries.

Future research should build on these findings by incorporating dimensions such as trust, ethical alignment, and stakeholder diversity. Such efforts will be essential for developing adaptive, trustworthy, and inclusive AI-enabled collaborative systems in increasingly global and heterogeneous environments.

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