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Attitudes Towards AI: The Interplay of Self-Efficacy, Well-Being, and Competency

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Abstract
Artificial intelligence (AI) is revolutionizing society, yet its widespread adoption is accompanied by significant ethical and societal concerns. Through a large survey, this study explores the complex interplay between self-efficacy, AI competency, cultural factors, and attitudes towards AI among UK and Arab participants. We investigate how these factors influence individual's attitudes toward AI and its impact on well-being. Our findings reveal that self-efficacy plays a crucial role in shaping attitudes towards AI, with higher levels of self-efficacy associated with more positive attitudes and enhanced well-being. Moreover, our results show that AI competency serves as a mediator, with increased competence fostering greater confidence and positivity towards AI. Our results also show gender disparities in AI attitudes within the UK sample, with males exhibiting higher positive attitudes and lower negative attitudes compared to females. Cultural differences were evident, with the Arab sample showing higher AI competency, positive attitudes, and overall well-being compared to the UK sample. Our results emphasize the need for culturally sensitive design and implementation of AI to ensure responsible development and implementation of AI for diverse populations.

Keywords Artificial intelligence (AI) · AI attitude · AI well-being · Cultural factors

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Introduction

Artificial intelligence (AI) is increasingly shaping the modern world (Collins et al., 2021). It refers to the development of intelligent machines that can perform tasks requiring human intelligence, such as visual perception, speech recognition, decision-making, and language translation. AI has emerged as a transformative force, influencing various facets of our lives (Wang & Siau, 2019). From automated personal assistants to autonomous vehicles, AI has penetrated diverse sectors, shaping the way we work, communicate, and even perceive the world (Smith & Eckroth, 2017). While the advent of AI has sparked widespread optimism, it concurrently evokes significant concerns in society (Rhee & Rhee, 2019). The multifaceted nature of these concerns is demonstrated in the extensive discussion in the media surrounding the potential ethical, sociopolitical, and economic risks associated with AI (Neudert et al., 2020). Moreover, according to Naiseh (2024), the repercussions of job losses resulting from the integration of AI could exacerbate global inequality by concentrating profits within a smaller cohort of individuals. In addition, notable instances of AI deployment have come under scrutiny for violating human rights; displaying biases; and engaging in discriminatory practices, manipulation, and even illegal activities (Gillespie et al., 2021). The potential social and ethical ramifications of AI have also been underscored, with suggestions that AI may induce societal anxieties and ethical dilemmas (OECD, 2019). These challenges and skepticism around AI highlight a responsible approach to AI development given the significant impact that AI is having and the current hype around potential safety and ethical issues (see also the "containment problem"; Suleyman, 2023). This would require an understanding of people's attitudes towards such technology and relevant factors that contribute to such attitudes. In this study, we examine the relationships between self-efficacy, competency, cultural factors, attitudes towards AI, and well-being among UK and Arab participants. In the following sections, we discuss each of these factors and their relation to AI attitudes.

Attitudes Towards AI and People's Perception of AI Contribution to Well-Being

Understanding people's attitudes towards AI technology and the factors influencing and shaping these attitudes become an important factor that contributes to responsible AI (Zhang & Dafoe, 2019, Lysen and Wyatt). Firstly, public attitudes toward AI can play a pivotal role in shaping the acceptance and adoption of such technology (Horowitz & Kahn, 2021). A positive attitude likely fosters trust (Sindermann et al., 2021b), encouraging individuals to embrace AI systems and amplify their benefits. Conversely, negative perceptions can lead to skepticism and concerns, hindering the implementation of AI technology. Kalra and Groves (2017) highlight that one main reason for the delay in deploying autonomous vehicles stems from the negative public attitude toward them.

Consumer research has increasingly delved into the intricate relationship between individuals and technology, revealing that people's attitudes toward technology are intricately connected to its contribution to well-being, happiness, and positive emotions (Dhiman & Kumar, 2023). It has been shown that people's decision to adopt new technology is highly correlated to its contribution to well-being (Naiseh & Shukla, 2023). A similar notion has been put forward recently to shed light on the so-called AI well-being complex (Montag et al., 2024c). The convenience of communication via digital platforms, coupled with easy access to information and the convenience of online services, has contributed to heightened life satisfaction and perceived well-being (Kross et al., 2021). This, in turn, has led to an overall increase in the adoption of these technological tools (Bhattacharya et al., 2023). It has been discussed that AI technology can enhance individual well-being by shifting responsibilities from humans to machines, thus fostering positive attitudes (Naiseh and Shukla, 2023). These findings suggest that people's attitudes toward AI and their perception of its contribution to well-being may intricately shape the future adoption and deployment of AI in society, making it imperative to prioritize the holistic well-being aspects in the development and integration of AI systems.

The Role of Self-Efficacy and Competency

Various factors shape an individual's attitudes towards AI and their contribution to well-being. In a comprehensive study conducted by Park and Woo (2022), personality traits; psychological elements such as inner motivation, voluntariness, and performance expectations; and technological factors like perceived practicality, ease of use, technology complexity, and relative advantage were identified as predictors of individual attitudes towards AI technology. For further personality associations, see Kaya et al. (2022) and Sindermann et al. (2022). The authors emphasized the intricate connection between AI attitudes and an individual's confidence (self-efficacy) in navigating and mastering these innovations. Technology self-efficacy, rooted in Bandura's (1969) social cognitive theory, emerges as a pivotal determinant of how individuals approach and interact with technology. This psychological construct reflects an individual's belief in their competence to effectively use technology. Studies indicate that individuals with high self-efficacy approach AI interactions with confidence, perceiving technology as an opportunity for growth rather than a source of anxiety (Montag et al., 2023). The impact of self-efficacy on attitudes toward AI is particularly evident in its influence on openness to learning (Balakrishnan et al., 2022). Those with strong self-efficacy are more inclined to acquire new skills related to AI, fostering a positive attitude rooted in a continuous learning mindset. This receptiveness not only facilitates AI technology adoption but also contributes to a sense of accomplishment and well-being as users master new skills (Latikka et al., 2021). Despite theoretical support for the importance of self-efficacy in human-AI interaction, empirical studies addressing this specific nexus are limited, creating a notable gap in understanding the psychological factors influencing people's attitudes toward artificial intelligence. Consequently, this study aims to investigate the nuanced relationship between self-efficacy, individual attitudes, and their contribution to well-being concerning AI.

Another concept closely linked to understanding the relationship between self-efficacy and individual attitudes towards AI is the level of competency individuals possess with AI (Naiseh & Shukla, 2023; Wang et al., 2023). AI competency serves as a mechanism for mitigating anxiety and fear associated with technology (Li & Huang, 2020). Competency and skills to interaction with interact with technology (Drude & Mabeu, 2024) in general and AI in particular (Naiseh et al., 2022) have been discussed widely in the literature. For instance, Cavanagh et al. (2023) identified specific skills and knowledge needed to utilize digital tools for patient assessment and monitoring and emphasized the importance of ethical considerations and data privacy. Similarly, Chiu et al. (2024) proposed a competency framework of cognitive, social, and technical dimensions to interact with AI technology. Evidence from this recent literature shows that individuals with higher levels of competency are more likely to have positive attitudes towards AI due to their increased understanding of the technology. Hence, we posit that the level of competency could play a significant role in interpreting the relationship between self-efficacy and public attitudes.

Cultural and Gender Differences

Finally, it is crucial to acknowledge that cultural differences can significantly shape the intricate interplay between self-efficacy, AI competency, and attitudes towards AI. Cultural values, norms, and perceptions about technology play an effective role in influencing individual's confidence in their ability to engage with AI (Park et al., 2021). For example, in cultures emphasizing collectivism, where group harmony and conformity hold high value, individuals may approach AI with a communal mindset, influencing their self-efficacy and AI competency differently compared to those in individualistic cultures prioritizing personal autonomy (Chi et al., 2023). In acknowledging these cultural nuances, our study recognizes that variations in culture may influence the strength and nature of the mediating relationship between self-efficacy and public attitude towards AI. Hence, we study this relationship across two distinct cultural contexts of Arab and UK individuals to address the diverse perspectives on attitudes towards technology adoption within these populations. Additionally, considering gender-related differences within each sample of Arab and UK individuals adds a nuanced layer to our investigation, providing a more comprehensive understanding of how cultural factors intersect with gender in shaping attitudes towards AI. The here-presented literature could be also embedded in the recently proposed IMPACT framework. Montag et al. (2024) and Montag et al. (2024) proposed that an interplay between the modality, person, area, country/culture and transparency variables likely shapes attitudes towards AI (and as a consequence also well-being when interacting with AI systems). The investigated factors of self-efficacy and competence fall within the realm of the *P*-variable of the IMPACT model, whereas investigating Arab and British individuals falls within the context of the *C*-variable. Therefore, the present work can be also seen as a test of parts of the proposed IMPACT framework.

Research Questions

In sum, this research investigates the nuanced interplay between technology self-efficacy, competency, and cultural and gender influences, particularly examining cross-cultural perspectives between Arab and British individuals. We form the following research questions:

- RQ1: Does self-efficacy impact individuals' attitudes towards AI?
- RQ2: Does self-efficacy impact individuals' perceptions of AI's contribution to well-being?
- RQ3: Does AI competency mediate the relationship between self-efficacy and both attitudes towards AI and perceived AI contribution to well-being?

This study contributes to the field of responsible innovation by exploring how individual characteristics and cultural backgrounds influence attitudes towards AI and its perceived impact on well-being. Understanding these factors is crucial for designing and deploying AI in a way that fosters positive societal outcomes and minimizes potential risks.

Materials and Methods

Participants and Procedure

Participants were recruited for both UK and Arab participants by utilizing the TGM research online platform (https://tgmresearch.com/), which specialized in obtaining respondents for research studies, including surveys. TGM, with its large subscriber base in the Middle East and UK, allowed us to recruit a diverse sample quickly and ensured demographic representation through quota sampling. This was essential for capturing variations across gender, age, and location in our comparative study. TGM's ability to filter participants by specific criteria and gather responses within a short, consistent time frame added to the validity of our findings, especially on emerging topics like AI and attitudes. However, the sample may have biases, as only platform subscribers participated, and motivations were often tied to monetary incentives. To mitigate this, we requested a diverse audience in terms of profession and income, resulting in a wide range of participant backgrounds. We also used culturally sensitive translations and context-specific examples to ensure accurate responses and minimize misunderstandings that could skew the data.

The UK population included participants from England, Wales, Scotland, and Northern Ireland. The Arab countries considered in our sample were recruited with a focus on the Gulf Cooperation Council (GCC). We limited our Arabic sample to the GCC area due to their special relations, geographic proximity, similar political systems based on Islamic beliefs, and common objectives (Christie, 1986). As inclusion criteria, we only included participants who identified themselves as either Arab or British. Participants were asked a yes/no question in the following way: “I identify as British/Arab in terms of norms and culture.”

Before distributing the survey, an iterative process was followed by the research team to ensure the clarity of the study questions. The study was initially formulated in the English language. The questionnaire was then translated from English to Arabic and the back-translation method (Brislin, 1970) was used to ensure consistency and accuracy. We then ran a pilot test with a small group of participants to ensure the clarity of the survey and eliminate any ambiguity or unclear words and expressions. After gaining ethics approval from the Institutional Review Board (IRB) of the last author’s institution, participants provided informed e-consent with the option to withdraw from the study at any time. Attention checks were included in the survey to ensure data quality. Eligible participants received compensation for their participation, and the study was conducted from the end of October to the middle of December 2023.

To determine the appropriateness of the sample size for the statistical analysis performed, we used Green’s formula (Green, 1991). It suggests that a minimum sample size of $50 + 8\ k$ times the number of independent variables (k) is needed for a linear regression analysis. This indicates that a minimum sample size of 82 participants in each culture is adequate to examine the impact of our four independent variables. Consequently, we aimed for a sample size of at least 250 participants in each group, supported by previous findings demonstrating correlation stability (Schönbrodt & Perugini, 2013). The final UK dataset consisted of 281 participants (44.8% male, aged between 18 and 60 and mean 38.57) and (55.16% female, aged between 18 and 59 and mean 31.94), As for the Arab dataset, 281 participants were recruited (49.8% male, aged 18–59 and mean 34.11 and 50.2% female, aged 18–53 and mean 30.12).

Measures

Demographic Measures

The participants provided information on age, gender, profession, nationality, level of education, religion, and country of residence.

Single-Item General Self-Efficacy Scale (GSE-SI)

Self-efficacy was measured by employing the original English version (Di et al., 2023). The Single-Item General Self-Efficacy Scale (GSE-SI) is a one-item measure of general self-efficacy. The GSE-SI is a 5-point Likert scale that asks respondents to rate their agreement with the following statement: “How confident are you that you can deal effectively with most of the challenges of everyday life?” Respondents can rate their agreement on a scale from 1 (Not at all confident) to 5 (Extremely confident). Di et al. (2023) have shown that GSE-SI has good psychometric properties. It was reliable, with a Cronbach’s alpha of 0.726. It was also valid, with correlations with other measures of general self-efficacy of 0.795 (Di et al.2023).

AI Well-Being

The PERMA Profiler (Butler & Kern, 2016), a widely utilized measure for evaluating overall well-being, was adopted in our study. The original version comprised 23 items, organized into five dimensions with three items each (P, positive emotion; E, engagement; R, relationship; M, meaning; A, accomplishment), along with eight filler items addressing health, negative emotion, loneliness, and overall happiness. Participants provided answers on an 11-point Likert scale (ranging from 0 = “Very Low” to 10 = “Very High”). The total well-being score was computed by summing the overall happiness items with the five PERMA dimensions, with higher scores indicating better overall well-being. The PERMA Profiler demonstrated high internal consistency and a reliable test–retest reliability rate, with Cronbach’s alpha values for its dimensions ranging from 0.90 to 0.76 (de Carvalho et al., 2023). In our modified version, participants were instructed to respond to PERMA Profiler items with a focus on AI, considering their usage and presence in society. AI was defined in our study “AI Technology includes algorithms producing recommended videos on YouTube, Self-Driving Cars, Social Robots such as cleaning robots, ChatGPT, and voice assistant such as Alexa.” Health-related items were eliminated from the scale as they were deemed irrelevant to the social media impact context. Our modified version of PERMA Profiler as a whole demonstrated high internal consistency and a reliable test–retest reliability rate in both the UK and Arabic samples (UK: $\alpha = 0.872$, Arab: $\alpha = 0.921$).

Single Items to Measure Attitudes Towards AI

In addition to the established multi-item measures, the present study also employed a single-item measure to assess attitudes toward AI (Montag & Ali, 2023). The single item consists of two components: positive attitude “I have a positive attitude toward artificial intelligence" and negative attitude "I have a negative attitude toward artificial intelligence." This measure provides a concise and efficient way to gauge an individual's overall stance on AI. Despite its simplicity, this single-item measure demonstrated strong correlations with the two established multi-item measures the Attitudes towards Artificial Intelligence (ATAI) and the General Attitudes toward Artificial Intelligence (GAAI) frameworks, suggesting that it offers a valid and reliable assessment of attitudes toward AI (Montag et al., 2023). This finding supports the utility of single-item measures as a practical and convenient tool for evaluating attitudes toward AI.

Individual Assessment of Their Competency

To gauge an individual's self-perceived expertise in artificial intelligence (AI), we included pre-selection criteria where we explained the meaning of AI and asked participants to confirm their level of familiarity or usage. A single-item measure was used, developed by the research team, asking participants to rate their AI competency on a 6-point Likert scale with the prompt: "Please rate your competency concerning the use and management of AI." The scale ranged from "Not Competent at all" to "Very Competent." This straightforward approach provided us with a quick and general assessment of AI competency, which is particularly helpful when running large-scale studies or when time constraints are a concern (Sarstedt & Wilczynski, 2009). While single-item measures may not fully capture the nuances of actual AI knowledge, they can offer valuable preliminary insights for further investigation and can be used to identify individuals who may require additional training or support in developing their AI skills (Castro et al., 2023). This single-item measure can be easily incorporated into surveys or questionnaires, allowing for a convenient and efficient assessment of AI competency among a wide range of participants (Jovanović & Lazić, 2020). We, however, recognize the importance of measuring competency in a more nuanced way, whether in the use, adjustment, or control over AI and its various facets. This approach would be especially necessary if we also study attitudes towards specific design aspects or modalities of AI operations (Montag et al., 2024).

Data Cleaning and Analysis

In total, 681 participants were recruited for this study. The first Arab sample comprised $N = 281$ participants. This sample consisted of 140 males and 141 females, with a mean age of 32.11 years (SD = 8.46) and an age range of 18–59 years. The UK sample totaled 337 participants. However, 56 participants were excluded from this sample due to reporting an age older than 60. This exclusion decision was based on the absence of such participants in the Arabic sample, aiming to ensure consistency in age demographics between the two groups for a more valid comparison. Consequently, the final UK sample comprised 281 participants, including 126 males and 155 females, with a mean age of 34.922 years (SD = 12.49) and an age range of 18–60.

The scales assessing AI competency, AI positive and negative attitudes, AI well-being, and general self-efficacy exhibited skewness and kurtosis between ± 2 (Rampersad & Althiyabi, 2020; Curran et al., 1996). Therefore, the normality assumption was not violated. Gender-related differences within each sample were examined using an independent *t*-test (employing Welch's *t*-test when necessary). Pearson and Spearman's correlations were calculated to explore associations among the relevant variables. Both correlations were computed to enable comparisons, and no meaningful differences could be observed. Multiple linear regression analyses were conducted to evaluate whether self-efficacy, age, and gender could predict attitudes toward AI (both positive and negative) and AI well-being. Subsequently, mediation analysis, involving 1000 bootstrapping resamples, was conducted to examine the mediating effect of AI competency on the relationship between self-efficacy, and attitudes towards artificial intelligence, as well as between self-efficacy and AI well-being. All analyses were performed using JASP software (JASP team, 2022). The data associated with this work can be found at https://osf.io/rc7zh/?view_only=94c4c1c4b80347b2bc76987129786915.

Study Limitation

One limitation of this study is the scope of the sociodemographic stratification used. While we included key factors such as age, gender, and education level, we recognize that additional dimensions, such as occupation, socioeconomic status, and geographic variables (e.g., urban vs. rural), could provide a more nuanced understanding of the sample. Future studies could expand upon these variables to offer a more comprehensive view of sociodemographic influences on attitudes towards AI.

Second, several variables, such as AI competency, self-efficacy, and attitudes toward AI, were assessed using single-item measures. While these measures offer convenience and simplicity, they may not capture the full complexity or the multidimensional nature of these constructs. Although single-item measures have demonstrated acceptable reliability in prior studies, they inherently lack the nuance and depth provided by multi-item scales, which could lead to an oversimplification of participants' views or competencies.

Another limitation concerns our approach to defining culture. In this study, we primarily focused on national and ethnic identity (Arab GCC vs. British) as the basis for cultural comparison. However, culture encompasses a wide array of dimensions, including race, ethnicity, spirituality, religion, sexual orientation, gender identity, geography, socioeconomic status, education, language, and more (National Academy of Science, 2020). We acknowledge that not all of these factors were accounted for in our study, which may limit the generalizability of our findings regarding cultural attitudes towards AI. Still, we believe that our choice of two clearly distinct frameworks extends to cover not only ethnicity and nationality but also various dimensions, including those proposed by Hofstede (The Culture Factor, n.d.) such as Individualism and Uncertainty Avoidance.

Furthermore, our study utilized a single-item measure to assess attitudes towards AI, which may not fully capture the complexity of participants' perspectives. However, the choice of single item can be also seen as a methodological strength as we wanted not to impose any constructs to measure that attitude and rely on the overall attitude and the way each individual forms it. Particular measures for attitude such as ATAI (Sindermann et al., 2021a) assume a specific conceptualisation for what forms an attitude, e.g., whether AI will destroy humanity or lead to job losses.

Finally, despite employing a rigorous translation process with the back-translation method and conducting pilot tests, subtle cultural and linguistic differences may have affected participants' interpretations of the survey items. For instance, the translation of the term "artificial intelligence" into Arabic is not unique and each way may evoke different associations and connotations in the GCC context. Additionally, the differences observed may not be due to ethnicity and nationality but rather to contextual factors such as the portrayal of AI in the media and government policies.

Results

Descriptive Statistics

Table 1 provides an overview of the demographic characteristics of the study participants, comprising a total of 562 individuals, evenly distributed between the UK and Arab countries, with 281 participants in each region. As one can see, the samples do not differ regarding gender ratio, age, or employment.

Table 2 presents the descriptive statistics for AI fear, AI acceptance, AI positive attitude, AI negative attitude, AI competency, and self-efficacy across the UK and Arab samples, segmented by gender. Additionally, gender differences for each sample are examined using *t*-tests. Results revealed a significant disparity in AI positive attitude within the UK sample, where males exhibited a higher positive attitude towards AI ($M=3.35$, $SD=1.02$) compared to females ($M=3.02$, $SD=0.99$), $t\,(279)=-2.74$, $p=0.01$, and $d=-0.33$. Conversely, males in the UK demonstrated a significantly lower negative attitude towards AI ($M=2.65$,

Table 1 Participants demographics

Variables	UK ($N=281$)	Arab ($N=281$)
Gender (%)		
Male	126 (44.84%)	140 (49.82%)
Female	155 (55.16%)	141 (50.18%)
Age		
M (SD)	34.92 (12.50)	32.11 (8.47)
Range	18–60	18–59
Education (%)		
No formal education	3 (1.07%)	-
Primary education (elementary)	1 (0.36%)	-
Secondary education (high school)	69 (24.55%)	38 (13.52%)
Pursuing or completed vocational or technical education	56 (19.93%)	12 (4.27%)
Pursuing or completed undergraduate degree (bachelor's)	112 (39.86%)	202 (71.89%)
Pursuing or completed postgraduate degree (master's, Ph.D., etc.)	40 (14.23%)	29 (10.32%)
Employment (%)		
Full-time employment	155 (55.16%)	158 (56.23%)
Part-time employment	58 (20.64%)	36 (12.81%)
Run my own business	7 (2.49%)	17 (6.05%)
Unemployed	23 (8.19%)	21 (7.47%)
Student	16 (5.69%)	23 (8.18%)
Retired	6 (2.14%)	3 (1.07%)
Homemaker	11 (3.91%)	22 (7.83%)
Other	5 (1.78%)	1 (0.36%)

Table 2 Descriptive statistics for AI positive attitude, AI negative attitude, AI competency, and self-efficacy across the UK and Arab samples, categorized by gender

	UK				Arab				Cultural differences
	Total sample ($N=281$)	Male (126)	Female (155)	Gender differences	Total sample ($N=281$)	Male (140)	Female (141)	Gender differences	Total samples ($N=562$)
AI competency	4.08 (1.02)	4.15 (0.99)	4.02 (1.05)	t (279) = − 1.07, p = 0.284, d = − 0.13	4.35 (1.05)	4.34 (1.10)	4.36 (1.01)	t (279) = 0.09, p = 0.0.93, d = 0.01	t (560.00) = 3.09, p = 0.002, d = 0.26
Self-efficacy	4.35 (0.78)	3.67 (0.87)	3.45 (1.10)	t (78.76) = − 1.89, p = 0.06, d = − 0.22*	4.00 (1.03)	4.41 (0.72)	4.29 (0.84)	t (279) = − 1.32, p = 0.19, d = − 0.16	t (528.34) = 10.61, p < 0.001, d = 0.90*
AI positive attitude	3.17 (1.02)	3.35 (1.02)	3.02 (0.99)	t (279) = − 2.74, p = 0.01, d = − 0.33	3.88 (0.90)	3.91 (0.92)	3.84 (0.88)	t (279) = − 0.72, p = 0.47, d = − 0.09	t (551.90) = 8.75, p < 0.001, d = 0.74*
AI negative attitude	2.80 (1.10)	2.65 (1.13)	2.92 (1.07)	t (279) = 2.07, p = 0.04, d = 0.25	2.24 (1.12)	2.25 (1.21)	2.23 (1.04)	t (272.47) = − 0.12, p = 0.91, d = − 0.01*	t (560.00) = − 5.95, p < 0.001, d = − 0.50
AI well-being	5.95 (1.79)	5.99 (1.82)	5.91 (1.78)	t (279) = −043, p = 0.67, d = − 0.05	7.42 (1.72)	7.62 91.550	7.23 (1.87)	t (270.65) = − 1.87, p = 0.06, d = − 0.22*	t (560.00) = 9.94, p < 0.001, d = 0.84

*Welch's t-test

SD = 1.13) in comparison to females, t (279) = 2.07, p = 0.04, and d = 0.25. However, no such gender-based patterns were observed in the Arab sample. Notably, all other variables did not exhibit statistically significant differences between gender groups in both the UK and Arab samples.

Cultural differences were evident across all examined variables. AI competency exhibited a significantly higher level in the Arab sample (M = 4.35, SD = 1.05) compared to the UK sample (M = 4.08, SD = 1.02), t (560.00) = 3.09, p = 0.002, and d = 0.26. Conversely, self-efficacy was significantly higher in the UK sample (M = 4.35, SD = 0.78) in contrast to the Arab sample (M = 4.00, SD = 1.03), t (528.34) = 10.61, p < 0.001, d = 0.90. Furthermore, AI positive attitude demonstrated a significant increase in the Arab sample (M = 3.88, SD = 0.90) compared to the UK sample (M = 3.17, SD = 1.02), t (551.90) = 8.75, p < 0.001, and d = 0.74*. Conversely, Arab participants exhibited significantly lower AI negative attitude (M = 2.24, SD = 1.12) compared to the UK sample (M = 2.80, SD = 1.10), t (560.00) = − 5.95, p < 0.001, d = − 0.50. Finally, AI well-being was significantly higher in the Arab sample (M = 7.42, SD = 1.72) than in the UK sample (M = 5.95, SD = 1.79), t (560.00) = 9.94, p < 0.001, d = 0.84.

Correlation Analysis

Pearson's and Spearman's correlations, as displayed in Tables 3 and 4, unveiled noteworthy connections among all the studied variables within both the UK and Arab samples. Across both groups, significant associations were observed among the variables under investigation (AI competency, self-efficacy, AI positive attitude, AI negative attitude, and AI well-being). Additionally, negative correlations (r = − 0.24, p < 0.001) emerged between age, as a confounding variable, and AI competency in the UK sample, suggesting a decline in AI competency with increasing age among UK participants. A similar pattern was observed in the Arab sample, where a significant negative correlation (r = − 0.12*, p < 0.05) was found between AI competency and age. In contrast, the other variables exhibited no significant associations in the Arab sample. However, no significant associations were identified between age and self-efficacy, AI positive attitude, AI negative attitude, or AI well-being in either sample.

Linear Regression Analysis

In examining the relationship between the dependent variables AI positive attitude, AI negative attitude, and AI well-being with the independent variable self-efficacy, a linear regression analysis was conducted, including covariates age and gender. The results, as summarized in Table 4, indicate that self-efficacy remains a significant

Table 3 Pearson (r) and Spearman (rho) correlations for AI well-being, AI positive attitude, AI negative attitude, AI competency, and self-efficacy in the UK sample

Variables	UK	1	2	3	4	5	6
1. AI competency	Pearson's r	—					
	Spearman's rho	—					
2. Self-efficacy	Pearson's r	0.27***	—				
	Spearman's rho	0.25***	—				
3. AI positive attitude	Pearson's r	0.38***	0.21***	—			
	Spearman's rho	0.38***	0.22***	—			
4. AI negative attitude	Pearson's r	−0.34***	−0.21***	−0.87***	—		
	Spearman's rho	−0.33***	−0.21***	−0.87***	—		
5. AI well-being	Pearson's r	0.33***	0.44***	0.40***	−0.39***	—	
	Spearman's rho	0.30***	0.45***	0.39***	−0.39***	—	
6. Age	Pearson's r	−0.24***	−0.02	−0.03	0.04	−0.10	—
	Spearman's rho	−0.24***	−0.03	−0.01	0.03	−0.11	—

*$p < 0.05$

**$p < 0.01$

***$p < 0.001$

Table 4 Pearson and Spearman correlations for AI well-being, AI positive attitude, AI negative attitude, AI competency, and self-efficacy in the Arab sample

Variables	Arab	1	2	3	4	5	6
1. AI competency	Pearson's r	—					
	Spearman's rho	—					
2. Self-efficacy	Pearson's r	0.28***	—				
	Spearman's rho	0.29***	—				
3. AI positive attitude	Pearson's r	0.33***	0.22***	—			
	Spearman's rho	0.35***	0.24***	—			
4. AI negative attitude	Pearson's r	−0.28***	−0.20***	−0.74***	—		
	Spearman's rho	−0.31***	−0.25***	−0.75***	—		
5. AI well-being	Pearson's r	0.42***	0.51***	0.51***	−0.47***	—	
	Spearman's rho	0.44***	0.49***	0.53***	−0.51***	—	
6. Age	Pearson's r	−0.12*	0.01	−0.02	0.01	0.11	—
	Spearman's rho	−0.15*	0.01	−0.03	0.00	0.09	—

*$p < 0.05$

**$p < 0.01$

***$p < 0.001$

predictor of AI positive attitude (UK: F (3, 277) = 6.90, $p < 0.001$, $R^2_{adjusted} = 0.059$; Arab: F (3, 277) = 4.84, $p = 0.003$, $R^2_{adjusted} = 0.040$), AI negative attitude (UK: F (3, 277) = 5.80, $p < 0.001$, $R^2_{adjusted} = 0.049$; Arab: F (3, 277) = 3.84, $p = 0.010$, $R^2_{adjusted} = 0.030$), and AI well-being even when accounting for the influence of age and gender (UK: F (3, 277) = 23.63, $p < 0.001$, $R^2_{adjusted} = 0.195$; Arab: F (3, 277) = 34.06, $p < 0.001$, $R^2_{adjusted} = 0.262$) (Table 5).

Mediating Effect of Competency

Following the significant results from correlation and regression analysis, mediation analysis was conducted to examine the mediating effect of AI competency in the relationship between self-efficacy and the three dependent variables—AI positive attitude, AI negative attitude, and AI well-being. To account for the potential effect of age and gender, these variables were included as covariates in the analysis. For the UK sample, the mediation model results showed significant total effect of self-efficacy on positive attitude towards AI ($\beta = 0.195$, SE = 0.058, $p < 0.001$), negative attitude towards AI ($\beta = -0.196$, SE = 0.058, $p < 0.001$), and AI well-being ($\beta = 0.441$, SE = 0.054, $p < 0.001$). The direct effect was not significant for positive attitude ($\beta = 0.106$, SE = 0.057, $p = 0.060$) indicating full mediation of AI competency in the relationship between self-efficacy and AI positive attitude in the UK sample. However, the direct effect was significant for negative attitude ($\beta = -0.118$, SE = 0.058, $p = 0.040$) and AI well-being ($\beta = 0.386$, SE = 0.054, $p < 0.000$) suggesting partial mediation of AI competency. The indirect

Table 5 Linear regression analysis of AI well-being, AI positive attitude, AI negative attitude, with self-efficacy and covariates age and gender

Outcome	Predictors	UK			Arab		
		β	*t*	*p*	*β*	*t*	*p*
AI positive attitude	Self-efficacy	0.195	3.346	< 0.01	0.217	3.693	< 0.001
	Gender[a]	− 0.158	− 2.612	0.009	− 0.034	− 0.557	0.578
	Age	− 0.068	− 1.122	0.263	− 0.033	− 0.590	0.590
AI negative attitude	Self-efficacy	− 0.196	− 3.334	< 0.01	− 0.200	− 3.390	< 0.001
	Gender[a]	0.120	1.970	0.050	− 0.022	0.359	0.720
	Age	0.071	1.167	0.244	0.005	− 0.077	0.938
AI well-being	Self-efficacy	0.441	8.159	< 0.001	0.501	9.721	< 0.001
	Gender[a]	0.00	− 0.003	0.998	− 0.049	− 0.921	0.358
	Age	− 0.087	− 1.567	0.118	0.097	1.837	0.067

β coefficient representing the estimated change in the dependent variable for a one-unit change in the independent variable. *t*-value test statistic used to assess whether the regression coefficient is significantly different from zero. *p*-value is a probability value indicating the likelihood of observing the test results under the null hypothesis.

[a]Male, 0; female, 1

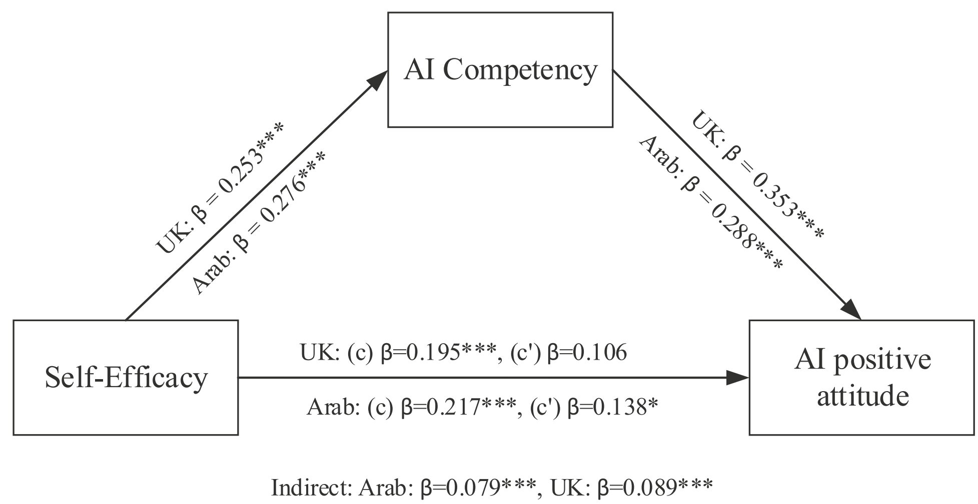

Fig. 1 Mediation model between self-efficacy and AI positive attitude through AI competency: (c) total effect, (c') direct effect. *p < 0.05; ***p* < 0.01; ****p* < 0.001

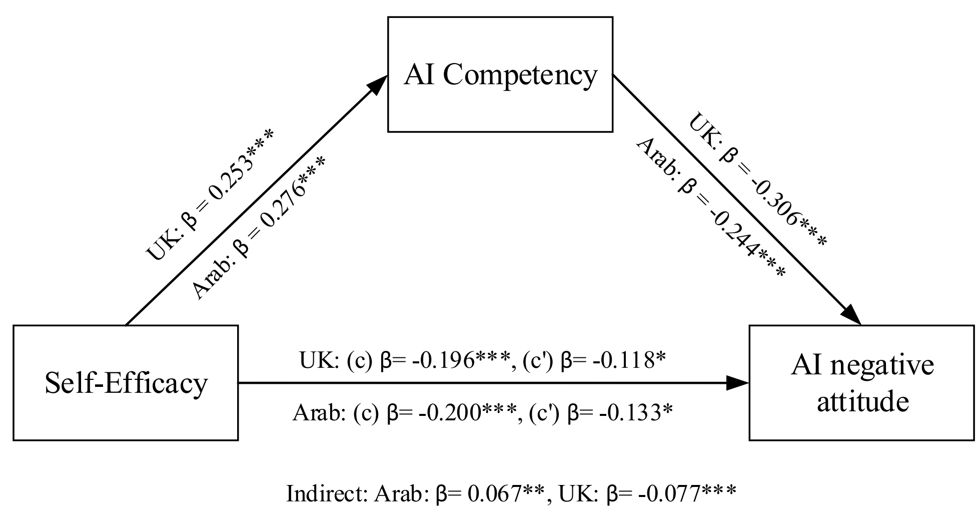

Fig. 2 Mediation model between self-efficacy and AI negative attitude through AI competency: (c) total effect, (c') direct effect.**p* < 0.05; ***p* < 0.01; ****p* < 0.001

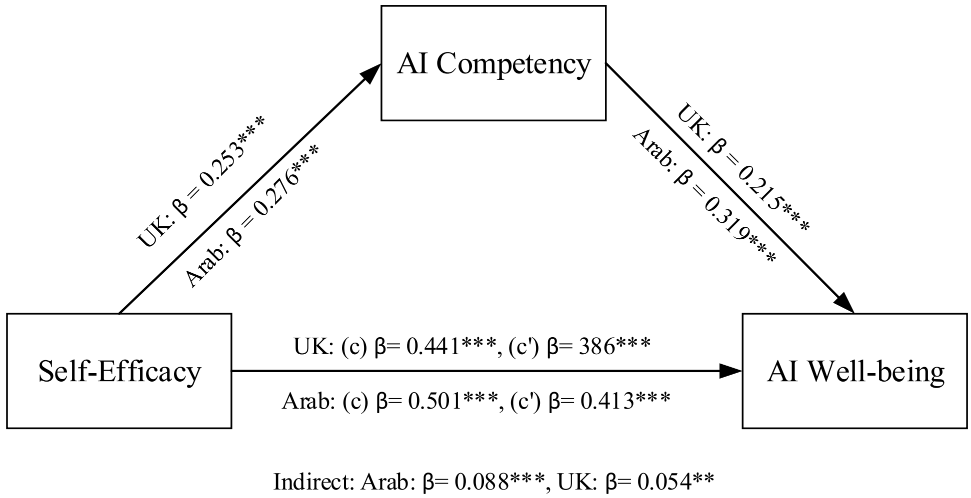

Fig. 3 Mediation model between self-efficacy and AI well-being through AI competency: (c) total effect, (c') direct effect. *$p<0.05$; **$p<0.01$; ***$p<0.001$. β represents the regression coefficients used to quantify the relationships between variables

effect of AI competency was significant for positive attitude ($\beta=0.089$, SE $=0.025$, $p<0.001$), negative attitude ($\beta=-0.077$, SE $=0.023$, $p<0.001$), and AI well-being ($\beta=0.054$, SE $=0.019$, $p=0.003$) (Figs. 1, 2, and 3). In the Arab sample, the mediation model results showed significant total effect of self-efficacy on positive attitude towards AI ($\beta=0.217$ SE $=0.058$, $p<0.001$), negative attitude towards AI ($\beta=-0.200$, SE $=0.059$, $p<0.001$) and AI well-being ($\beta=0.501$, SE $=0.051$, $p<0.001$). The direct effect was significant for positive attitude ($\beta=0.138$, SE $=0.058$, $p=0.018$), negative attitude ($\beta=-0.133$, SE $=0.059$, $p=0.025$), and AI well-being ($\beta=0.413$, SE $=0.050$, $p<0.001$). The indirect effect of AI competency was significant for positive attitude ($\beta=0.079$, SE $=0.023$, $p<0.001$), negative attitude ($\beta=-0.067$ SE $=0.022$, $p=0.002$), and AI well-being ($\beta=0.088$ SE $=0.023$, $p<0.001$) indicating partial mediation of AI competency in the relationship between self-efficacy and each of AI positive attitude, AI negative attitude, and AI well-being in the Arab sample (Figs. 1, 2, and 3).

Discussion

Artificial intelligence (AI) systems have the potential to significantly enhance well-being by automating routine tasks and freeing up time for creative activities (Feijóo et al., 2020; Naiseh and Shukla, 2023). These benefits are evident in various sectors such as healthcare, where AI-driven diagnostic tools enhance patient care (Ali et al., 2023), and manufacturing, where automation improves efficiency (Nti et al., 2022). However, societal concerns related to ethics and privacy can temper the positive impact of AI (Ragot et al., 2020). Our study advances this discussion by exploring how self-efficacy and AI competency influence attitudes towards AI and their effects on well-being across UK and Arab populations.

The cultural differences observed in our study align with previous research (Sindermann et al., 2021b). Arab participants reported more positive attitudes and greater well-being related to AI, which may be attributed to higher levels of trust in authority and collectivist values (Ali et al., 2006). In contrast, UK participants, with a longer and more complex history of AI development, expressed more skepticism, reflecting concerns frequently discussed in public media and academia (Blease et al., 2019). These findings are consistent with earlier research highlighting how cultural context shapes attitudes towards technology (Grassini and Ree, 2023; Sindermann et al., 2022). Our study contributes by illustrating how these cultural factors intersect with individual self-efficacy and AI competency, emphasizing the importance of context in shaping AI attitudes.

In line with Bandura's social cognitive theory (Bandura, 1997), our findings support the notion that self-efficacy plays a critical role in shaping positive attitudes towards technology. Similar to earlier studies (Venkatesh et al., 2003), we found that higher self-efficacy was linked to more favorable views on AI, as well as enhanced well-being. Furthermore, AI competency emerged as a key mediator, where individuals with higher competency levels translated their confidence into more positive attitudes and greater well-being (Cho et al., 2010). This reflects broader findings that emphasize the interconnectedness of self-efficacy, competency, and well-being in technology adoption (Montag et al., 2024).

The implications of these findings are significant for both AI education and policy development. Enhancing self-efficacy and AI competency through targeted educational programs could help mitigate anxieties about AI, such as concerns regarding job displacement, privacy, or technological dependency (Liao & Chen, 2024). By empowering individuals with the skills and confidence to engage with AI technologies, societies can foster a more positive outlook on AI's role in daily life. Furthermore, focusing on competency-building could not only improve user interaction with AI systems but also create a positive feedback loop, where higher confidence encourages further engagement with AI, ultimately leading to greater well-being. A design implication of the extension of our findings lies in the domain of explainable AI (XAI). As AI becomes more pervasive in sensitive areas like healthcare, education, and governance, the need for AI systems that are transparent and interpretable is more urgent. Our findings suggest that promoting AI competency and self-efficacy could be further enhanced by making XAI more accessible and inclusive to diverse users. When individuals are equipped not only with the skills to use AI but also with the ability to understand and interpret AI decisions, their trust and positive attitudes towards AI could increase even more. Explainable AI, by making algorithmic decisions clearer and more accessible, could reduce fears related to the "black-box" nature of AI (Naiseh et al., 2023) and empower users to feel more in control, thus improving both attitudes and well-being.

From a cultural perspective, our study highlights the necessity of designing culturally sensitive AI policies. Tailoring interventions that account for the differing levels of trust, attitudes, and concerns regarding AI across cultural groups will be essential to ensuring the equitable integration of AI into diverse societies. For example, in contexts where there is more skepticism towards AI, such as the UK, educational initiatives could focus on enhancing both AI competency and explainability, providing individuals with tools to critically engage with AI systems. In contrast, in regions like the Arab world, where attitudes toward AI are more positive but potentially overconfident, efforts could emphasize fostering realistic understandings of AI capabilities and limitations, particularly through explainability measures that ensure a more balanced view of AI's role in decision-making processes.

Conclusion and Future Research

In this study, we explored the relationship between self-efficacy, attitudes towards artificial intelligence (AI), and well-being, while considering cultural and gender differences. Our findings revealed that higher self-efficacy is associated with more positive attitudes towards AI and enhanced well-being, irrespective of cultural background. Notably, Arab participants showed more positive attitudes and higher AI competency levels compared to UK participants. These results underscore the importance of considering cultural contexts when addressing concerns and promoting acceptance of AI technologies. Tailoring educational programs and interventions to enhance self-efficacy and AI competency could be pivotal in fostering positive attitudes towards AI and improving overall well-being. However, it is crucial to acknowledge the limitations of our study, including its cross-sectional design and reliance on self-report measures. Moving forward, longitudinal studies and more nuanced measurement approaches will be essential to further understand the complex interplay between self-efficacy, attitudes towards AI, and well-being. Additionally, considering the potential influence of factors like spirituality on attitudes towards AI could provide valuable insights. In conclusion, our findings highlight the significance of self-efficacy in shaping attitudes towards AI and well-being, with cultural and gender factors also playing significant roles. By addressing these factors through targeted interventions and inclusive policy-making, we can work towards fostering a more positive and equitable societal stance towards AI integration.

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AB: data collection and preparation, formal analysis, reviewing and editing.

SA: data collection and preparation, formal analysis, reviewing and editing.

DC: reviewing and editing.

DA: reviewing and editing.

CM: reviewing and editing.

RA: study design, data collection and preparation, reviewing and editing, project management.

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Data Availability The dataset is available through the Open Science Framework at the following link: https://osf.io/rc7zh/?view_only=94c4c1c4b80347b2bc76987129786915

Declarations

Conflict of Interest The authors declare no competing interests.

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