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Artificial Intelligence vs. Users' Well-Being and the Role of Personal Factors: A Study on Arab and British Samples

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Abstract

As we navigate an era defined by rapid technological advancement, the pervasive integration of artificial intelligence (AI) into daily life prompts critical inquiries into its impact on individual well-being across different cultural contexts. This study investigates the relationship between AI and well-being across British and Arab populations, focusing on how AI competency—defined as knowledge, skills, and familiarity with AI technology—personality traits, and locus of control influence perceptions of AI's contribution to well-being. A total of 562 participants (281 from each group) completed an online survey, which measured their perceptions of AI's impact on well-being, AI competency, personality traits, and locus of control. Results reveal significant cultural differences, with Arab participants perceiving AI's contribution to well-being more positively than their British counterparts. Higher AI competency, i.e., self-rated proficiency in using AI and adjusting its settings, was associated with a greater perceived positive AI impact on well-being in both groups. The personality trait of neuroticism predicted negative perceptions of AI in both samples, while extraversion and conscientiousness were significant positive predictors in the Arab sample and agreeableness in the British sample. Internal locus of control consistently predicted positive perceptions of AI's contribution to well-being across both cultures. These findings underscore the need for culturally sensitive AI implementations and highlight the importance of fostering AI competency and a sense of control among users to enhance well-being. Future research should explore these dynamics in more diverse cultural settings and consider longitudinal designs to examine the long-term implications of AI use on well-being. Additionally, interventions promoting informed and responsible AI engagement could further improve well-being outcomes.

Keywords Artificial intelligence · Well-being · Digital Well-being · Personality · Culture

Introduction

As we stand on the brink of a new era characterized by unprecedented technological advancement, the pervasive influence of artificial intelligence (AI) continues to infiltrate every aspect of our daily lives. AI algorithms provide personalized recommendations (e.g., while browsing the internet), analyze vast amounts of data (e.g., financial data), and optimize accuracy and planning (e.g., healthcare delivery), as well as support decision-making processes (e.g., optimal routes in navigation). This pervasive integration prompts inquiries into the role of AI in shaping individual well-being and to what extent and whether such impact applies across different cultural frameworks. While AI can enhance well-being by helping to reduce stress and anxiety, e.g., through AI-powered conversational agents for mental health (Danieli et al., 2022), it can also be a source of stress and anxiety

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when people feel left in the dark about how it makes decisions and its level of confidence and reliability (Johnson & Verdicchio, 2017). Previous studies have predominantly focused on the positive contributions of AI in domains such as healthcare, education, and social interactions (Aung et al., 2021; Bittencourt et al., 2023), yet there is limited knowledge on how personal factors, such as personality traits and locus of control, influence these perceptions of AI contribution to well-being. Furthermore, much of the research has centered on WEIRD (Western, educated, industrialized, rich, and democratic) populations, leaving non-Western cultural perspectives underexplored. Recently, AI has experienced a significant boost, transitioning from a tool primarily used in enterprise settings to one used for personal purposes, much like other utility software such as editing, browsing, and searching tools. This new popularity, combined with mixed media reports about AI safety, makes it essential to study who perceives AI as contributing to well-being and in what ways. This study addresses these gaps by investigating AI's impact on well-being across two culturally distinct populations, Arab and British, and exploring the role of individual personal factors. According to Hofstede Insights (https://www.theculturefactor.com/country-comparison-tool), the two cultures are distinct. The differences in uncertainty avoidance and individualism are particularly important, as AI for personal use is still on the rise, with social norms yet to form, and where a certain degree of openness to risk might be expected.

Well-being is a complex concept, encompassing both hedonic (short-term happiness and satisfaction) and eudaimonic (personal growth, meaning, and self-actualization) aspects (Diener, 1984; Diener & Suh, 1997; Ryan & Deci, 2001). Scholars acknowledge the necessity of integrating both perspectives to achieve a more comprehensive understanding. For example, Seligman's PERMA model highlights dimensions such as positive emotions, engagement, and meaning (Seligman, 2011). Studies have shown that AI-powered tools can enhance various aspects of well-being by increasing automation, improving access to services like healthcare and education, as well as providing personalized support (Li et al., 2023; Scoglio et al., 2019). However, AI also presents risks to well-being, such as fear of job replacement and anxiety from skill gaps (Cramarenco et al., 2023; Oosthuizen, 2019).

Previous studies highlight the substantial impact of personality traits and demographic variables (e.g., age and gender), on individuals' attitudes towards AI and their adoption of AI-powered applications (Kaya et al., 2024; Park & Woo, 2022; Sindermann et al., 2022). Among personality theories, the Big-Five Personality Theory (Costa & McCrae, 1992) stands as the most widely recognized, outlining five principal traits: openness, agreeableness, extraversion, conscientiousness, and neuroticism. In examining human emotional responses to AI applications, previous findings identified associations of extraversion, agreeableness, conscientiousness, and neuroticism with negative emotions. For positive emotions, relations have been solely identified for agreeableness (Park & Woo, 2022). Regarding general attitude towards artificial intelligence, Kaya et al. (2024) reported that none of the personality traits predicted positive attitudes in a sample of Turkish people, whereas negative attitudes were significantly predicted by agreeableness. A similar has been shown in a Chinese sample where fear of AI technology was significantly predicted by agreeableness. In the same study, the German sample showed a significantly positive prediction by neuroticism (Sindermann et al., 2022). However, technology acceptance in the German sample was significantly predicted solely by gender, whereas in the Chinese sample age, openness and agreeableness have been identified as significant predictors. The partly controversial findings from the related attitudes towards AI and acceptance of it across diverse cultural contexts underscore the necessity of exploring whether the impact of personality traits and demographic factors on well-being exists and varies across cultural contexts.

Additionally, locus of control, which represents their belief in controlling their own life circumstances, may shape individuals' perceived impact of AI on their overall well-being. This is especially true considering that one main reason for the so-called "AI Anxiety" is people's perceived AI as a mysterious and uncontrollable machinery (Johnson & Verdicchio, 2017). In considering both the influence of personality traits and locus of control on trust in artificial intelligence, Sharan and Romano (2020) revealed that locus of control emerged as a noteworthy predictor of AI trust, surpassing the influence of the BFI dimensions. In terms of BFI dimensions, they found that neuroticism, as a single personality trait, was negatively associated with trust in AI. The findings are reinforced by a recent study conducted by Singh et al. (2024), which highlights the pivotal role of locus of control in influencing trust dynamics in AI, going beyond conventional personality dimensions. Furthermore, Novozhilova et al. (2024) identified that individuals with a weaker internal locus of control tend to exhibit greater comfort with integrating AI applications into their daily routines. So far, studies on locus of control in the context of AI focused on trust, comfort, or performance-based measures; however, there is a lack of studies examining the relationship between locus of control and well-being in the context of AI.

Researchers already described the relevance of cultural aspects in shaping attitudes towards AI in the context of personality traits (c.f., Sindermann et al., 2022). Moreover, the IMPACT model underscores the relevance of cultural considerations in comprehending attitudes towards AI (Montag et al., 2024a; Montag et al., 2024c). For example, the varying degrees of spirituality within different cultural groups demonstrably influence attitudes towards AI (Montag et al., 2024b). Within the present study, we explore the predictors of AI contribution to well-being (hereafter AI-WB) in both Arab and British samples. According to Hofstede (2001), Arabs (taking Saudi Arabia as an example) typically lean towards greater levels of collectivism, emphasizing group cohesion, interpersonal bonds, and fulfilling social obligations and higher uncertainty avoidance while the British often demonstrate higher levels of individualism, placing greater emphasis on personal freedom and autonomy and lower uncertainty avoidance. Previous research highlights the crucial importance of acknowledging cultural nuances in grasping the connection between AI and well-being, alongside associated factors like personality traits (Montag et al., 2024c). In this study, our focus lies on examining the influence of cultural disparities on AI-WB and the impact of individual factors on AI-WB. We study the cultural differences in AI-WB between the Arab and British samples. Furthermore, we aim to investigate the extent to which personal factors influence AI-WB within both samples. Based on these considerations, the study addresses the following research questions:

- How do cultural differences between Arab and British populations influence perceptions of AI's contribution to well-being?
- To what extent do personality traits (e.g., extraversion, agreeableness, neuroticism) predict perceptions of AI's contribution to well-being in both cultural contexts?
- How does locus of control impact individuals' perceptions of AI's influence on well-being across the two cultures?
- Does AI competency influence how individuals in both cultural groups perceive the role of AI in their well-being?
- How do gender and age impact individuals' perceptions of AI's influence on well-being in the Arab as well as the British sample?

Methods

This study employed a cross-sectional survey design conducted between October and December 2023, facilitated by the multi-country online research company TGM online research platform (TGMResearch®).

Participants and Procedure

To participate in the current research, individuals needed to fall between the ages of 18 and 60 years, possess familiarity with the concept of AI, be born and currently living in either the UK or an Arab country, and culturally identify as either British or Arab. These inclusion criteria were assessed via a preliminary survey, and only those meeting these requirements were invited to take part in the study. To qualify for inclusion in the Arab sample, individuals were required to reside in a Gulf Cooperation Council (GCC) country. This criterion was established due to the shared values, political stability, social norms, and significant advancements in digital transformation among GCC countries.

After excluding outliers, invalid and incomplete responses, 562 people participated in the present study, 281 from each population. From the UK, 155 females and 126 males aged 18–60 years (M = 34.92 years, SD = 12.50) took part. From Arab 141 females and 140 males aged 18–59 years (M = 32.11 years, SD = 8.47) took part. The study adhered to ethical standards outlined in the Declaration of Helsinki and was approved by the Institutional Review Board (IRB) of Hamad Bin Khalifa University (ID: HBKU-IRB-2024-59). Prior to participating, all individuals provided written informed consent and were assured they could withdraw from the study at any time without consequence. Participants who successfully completed the survey, passed attention checks, and did not receive disqualification due to excessively rapid responses were compensated for their participation. A response was considered rapid if it was completed within 50% or less of the median duration of all participants, excluding outliers who took twice or more of the expected time, primarily due to completing the survey across multiple sessions. Furthermore, mathematical outliers were identified using a two-step process. First, boxplots were used to visually inspect the data for extreme values. Second, outliers were defined as values falling more than 1.5 times the interquartile range below the first quartile or above the third quartile.

Measures

The online survey was administered through the SurveyMonkey platform (Surveymonkey®). To ensure answer quality, attention checks were integrated into the survey. The questionnaires underwent translation from English to Arabic, employing the back-translation method (Brislin, 1970) to ensure consistency and precision. Data collection was conducted within the framework of a broader study (further details available at the Open Science Framework link https://osf.io/jng5m). Participants were required to complete a pre-selection survey, as previously explained, to be eligible for inclusion in the study. To maintain focus, this paper will specifically present sections of the questionnaire that directly pertain to the research questions posed. Initially, participants provided demographic information, including age, gender, education level, employment status, and country of residence. They also rated their competency in the use and management of AI on a 6-point Likert scale, ranging from

1 (not competent at all) to 6 (very competent). Following this, participants proceeded with the questionnaires regarding their perception of how AI contributes to well-being, personality traits, and locus of control.

PERMA Profiler

To gauge participant perceptions of how AI influences well-being (AI-WB) we employed the PERMA Profiler (Butler & Kern, 201&). For the present context, we adapted and customized the questionnaire to the specific case of AI's impact on well-being. The only alteration made in the contextualized version was to the introductory statement. Participants were directed to respond to the PERMA Profiler items using the prompt: "Thinking of Artificial Intelligence, your use of it and its presence in society, how often do you feel..."

Health-related items were omitted from the scale as they were deemed irrelevant to the focus on AI's influence. The original PERMA Profiler comprises 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. Respondents rated each item using an 11-point Likert scale (ranging from 0 = low to 10 = very high). Overall well-being scores were computed by summing the overall happiness item with the five PERMA dimensions, with higher scores indicating better overall well-being. The PERMA Profiler demonstrates a high level of internal consistency, with reported Cronbach's alphas ranging from 0.60 to 0.90 for all PERMA factors (de Carvalho et al., 2023; Pezirkianidis et al., 2021). Specifically, reported Cronbach's alphas for the subscale scores were 0.84 and 0.76 for positive emotion, 0.69 and 0.59 for engagement, 0.86 and 0.74 for relationship, 0.89 and 0.87 for meaning, and 0.84 and 0.76 for accomplishment, for the UK and Arab samples, respectively.

Big Five Inventory (BFI-10)

The study employed the BFI-10 to evaluate personality traits (Rammstedt & John, 2007). This abbreviated version of the Big Five Inventory encompasses openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (with two items per trait). Respondents rated their agreement with each statement on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The statement "I have a few artistic interests," representing openness, was revised to "I have limited or no artistic interest" for clarity and improved translatability, as the original wording proved confusing in both Arabic and English during pilot testing. Previous studies have demonstrated acceptable internal consistency in the BFI-10 (Costa Mastrascusa et al., 2023; Lovik et al., 2017).

Locus of Control

We utilized the four-item short scale developed by Nießen et al. (2022) to assess the locus of control. The scale comprises two subscales: internal locus of control and external locus of control (with two items per subscale). Responses were made on a 5-point Likert scale from 1 (does not apply at all) to 5 (applies completely). This scale comprises two subscales: internal locus of control and external locus of control, each containing two items. Participants rated their responses on a 5-point Likert scale ranging from 1 (does not apply at all) to 5 (applies completely). To ensure cultural sensitivity, the item "fate often gets in the way of my plans" was modified to "circumstances often get in the way of my plans," considering that in Arab culture, fate is not typically perceived as an obstruction and should not carry a negative connotation. The scale demonstrated sufficient reliability and validity as measures of locus of control (Nießen et al., 2022).

Data Analysis

Descriptive statistics were computed for both samples. Before conducting further statistical analyses, the distribution of all variables was assessed for normality and skewness. Skewness was evaluated by computing skewness values and inspecting histograms for each variable. Variables were considered to exhibit significant skewness if their skewness values fell outside the range of $\pm$ 2 (Curran et al., 1996). When skewness was problematic, we applied appropriate transformation techniques to normalize the data (square root transformation for moderately skewed variables, log transformation for highly skewed variables, a reflection followed by a square root or log transformation for negative skewness). After transformations, the normality of the variables was reassessed to ensure the data met the assumptions of the planned statistical tests. To examine the differences in perceptions of AI impact on well-being between Arab and British samples, an independent *t*-test was employed. Welch's *t*-test was employed when the assumption of homogeneity of variances was violated, as assessed by Levene's test for equality of variances. Welch's *t*-test is preferred in such cases because it adjusts the degrees of freedom to provide a more reliable estimate of the significance of the difference between means, reducing the risk of Type I error (Delacre et al., 2017). Multiple linear regression analysis was conducted to investigate how personal factors influence the perceived contribution of AI to well-being across Arab and British participants. To investigate the predictors of perceived AI-WB, we conducted multiple linear regression analyses separately for the Arab and British samples. The enter method was used for the regression models. In this method, all predictor variables (personality traits, locus of control, AI competency, age, and gender) were entered into the model simultaneously. This approach allows for assessing the unique contribution of each predictor to the dependent variable (AI-WB) while controlling for the effects of other variables in the model. The decision to use the enter method was based on theoretical considerations, ensuring that all variables of interest were included without a stepwise or hierarchical selection process. The data were analyzed using SPSS version 28.

Results

Participant Demographics

Participants provided details encompassing their age, gender, educational background, employment status, and country of residence. A summary of the demographic attributes of both Arab and UK cohorts is outlined in Table 1.

AI-WB Across Arab and British Samples

We compared eight dimensions of well-being between the Arab and British samples using Welch's *t*-test. Compared to an independent samples *t*-test, Welch's test provides better control of type I error rates when two groups have different variances across comparisons (Delacre et al., 2017). To further control for type I error, the alpha level for these tests was adjusted accordingly (0.05/8 = 0.00625). The results of these comparisons are summarized in Table 2.

In Table 2, a notable contrast emerges in how AI contributes to well-being is perceived between the Arab and British contexts. The Arab group reported higher scores for their perceived effects of AI on well-being (M = 7.42, SD = 1.72) compared to the UK group (M = 5.95, SD = 1.79) across all dimensions, except for negative emotions and loneliness, where UK participants reported higher scores than Arab participants.

Personal Factors as Predictors for AI-WB

A multiple linear regression analysis was conducted to determine whether personality traits, locus of control, proficiency in using AI, and sociodemographic characteristics such as age and gender could predict the perceived impact of AI on well-being. Separate models were tested for the Arab and UK samples. The results of the regression analyses are summarized in Table 3.

Table 1 Participant characteristics

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%)
Competency in AI		
M (SD)	4.08 (1.02)	4.35 (1.05)
Range	1–6	1–6

Table 2 Perceived AI contribution to overall well-being, well-being dimensions, negative emotion, and loneliness

	UK		Arab		Differences between the two samples		
	Mean	SD	Mean	SD	*t*-test	*p*	Cohen's *d* (effect size)
Overall well-being	5.95	1,79.	7.42	1.72	$t(560) = 9.94$	<.001	0.84
Positive emotion	5.81	2.01	7.58	1.97	$t(560) = 10.52$	<.001	0.89
Engagement	6.10	1.84	7.34	1.86	$t(560) = 7.91$	<.001	0.67
Relationship	5.96	2.16	7.27	1.92	$t(560) = 7.62$	<.001	0.64
Meaning	5.79	2.10	7.37	2.03	$t(560) = 9.07$	<.001	0.77
Accomplishment	5.86	1.84	7.45	1.80	$t(560) = 10.35$	<.001	0.87
Negative emotion	4.23	2.10	3.62	2.25	$t(560) = -3.35$	<.001	−0.28
Loneliness	4.35	2.79	3.82	3.06	$t(555.47) = -2.12$*	.035	−0.18

*Welch's *t*-test

Table 3 Multiple regression for predicting perceived AI contribution to well-being (AI-WB)

AI-WB	UK			Arab		
	R^2	Adjusted R^2	*F*	R^2	Adjusted R^2	*F*
	0.34	0.31	13.72	0.49	0.47	26.25
Predictors	*β*	*t*	*p*	*β*	*t*	*p*
Extraversion	0.06	1.05	.294	0.14	3.04	0.003
Agreeableness	0.23	4.34	< .001	0.04	0.89	.377
Conscientiousness	0.06	1.01	.314	0.17	3.12	0.002
Neuroticism	−0.27	−4.10	< .001	−0.23	−4.75	< .001
Openness	0.04	0.87	.386	−0.02	−0.37	.709
Internal locus of control	0.11	2.01	.045	0.28	5.66	< .001
External locus of control	−0.02	−0.48	.630	0.01	0.18	.855
Competency in AI usage	0.22	4.06	< .001	0.24	5.06	< .001
Age	−0.04	−0.64	.521	0.03	0.73	.468
Gender (Male–female)	0.09	1.59	.112	0.04	0.87	.387

For the UK sample, the overall regression model was significant ($F = 13.72$, $p < 0.001$) with acceptable independence of errors. Overall, the tested model explained 31% of the perceived impact of AI on well-being. Within this model, personality traits agreeableness, neuroticism, internal locus of control, and competency using AI-predicted AI-WB, that is, participants who scored higher in personality traits agreeableness, internal locus of control, and competency using AI perceived AI as having a higher contribution to well-being. Moreover, participants who scored lower in the neuroticism personality trait had a higher contribution to well-being.

For the Arab sample, the overall regression model was significant ($F = 26.25$, $p < 0.001$) with acceptable independence of errors. Overall, the tested model explained 47% of the perceived impact of AI on well-being. Within this model, personality traits extraversion, conscientiousness, neuroticism, internal locus of control, and competency using AI predicted the perceived contribution of AI to well-being, that is, participants who exhibited higher levels of extraversion, conscientiousness, internal locus of control, and competency in using AI tended to view AI as having a more significant positive impact on well-being. Conversely, those with lower scores in neuroticism also perceived AI as contributing more positively to well-being.

Within both samples of the UK and Arab, there was no age or gender effect on AI contribution to well-being.

Discussion

In this study, we investigated users' perceptions of *AI's impact* on their well-being by conducting an online survey across two *distinct samples*. The results indicated that participants from Arab viewed AI's contribution to overall well-being and its various dimensions—such as positive emotion, engagement, relationships, meaning, accomplishment, and negative emotion—more favorably than those from the UK sample. Moreover, the Arab sample's perceptions of AI's impact on well-being were significantly higher compared to the British sample. The findings align with the IMPACT model, underscoring the importance of cultural considerations in shaping perceptions of AI (Montag et al., 2024c).

Empirical evidence from a previous study on cultural differences in the acceptance and fear of AI provides further support, by indicating that Arabs demonstrate higher acceptance and less fear of AI compared to their British counterparts (Liebherr et al., under review). In general, we argue that the collectivist versus individualist cultural orientation contributes to differences between the samples. Arab cultures tend to be more collectivist, emphasizing community and social cohesion (Hofstede, 2001). Consequently, AI applications that enhance communal well-being might be seen as more beneficial in these contexts compared to the more individualistic culture of the UK. Furthermore, in the UK, there might be more skepticism and caution regarding AI due to concerns about privacy, job displacement, and ethical implications, which can influence perceptions negatively (Bhatnagar and Devyani, 2024) Although the difference was not statistically significant, the UK sample reported a higher average score for AI's contribution to loneliness compared to the Arab sample.

The study further aimed to identify factors that influence perceptions of AI's contribution to well-being across different samples. Regarding the impact of *AI competency*, the results indicated that higher levels of competency predict a greater perceived positive contribution of AI to well-being in both samples. So far, technological competence, which enables individuals to effectively use, manage, and innovate with technology, has been frequently highlighted as a key determinant of success in the modern world (Hargittai & Hinnant, 2008; Van Deursen & Van Dijk, 2011). Our findings extend this understanding by revealing that technological competence, particularly in AI, not only drives success but also enhances well-being. Individuals with higher AI competency are more likely to perceive AI as a beneficial factor in their lives, suggesting that the ability to navigate and leverage AI technologies can improve their quality of life. Corroborating evidence for our discoveries is evident in related domains, highlighting that heightened proficiency in technology correlates with increased acceptance of a specific application (Antonietti et al., 2022; Baturay et al., 2017). Based on our current results and previous findings, we emphasize the importance of expertise in AI applications and technology in general. By fostering AI competency and promoting informed and responsible AI use, we can cultivate more positive attitudes towards AI and harness its potential to enhance overall well-being across diverse populations.

Personality traits significantly predicted individuals' AI-WB, though their relevance varied between the samples. However, when it comes to *neuroticism*, the results remained consistent across both the Arab and UK samples, suggesting that individuals with lower levels of neuroticism tended to perceive AI as making a more positive contribution to well-being. As for most, the introduction of new technology, whether it is AI-based or not comes along with an increased level of threatening and stressful consequences (Costa & McCrae, 1992). As we know that people with a higher level of neuroticism have more problems coping with stressful situations without much emotion (Lakhal & Khechine, 2017), it is understandable that they may perceive AI technologies as more threatening or worrisome. The uncertainty and potential risks associated with AI may trigger greater levels of anxiety and apprehension among individuals high in neuroticism, leading them to view AI as less conducive to their overall well-being. In line with Hamburger et al. (2022), who suggested that customizing technology based on personality traits can enhance user trust and confidence in the context of autonomous driving, we recommend a similar approach for AI applications. Extraversion and conscientiousness emerged as key predictors within the Arab but not the UK sample. In encompassing aspects such as sociability, assertiveness, and enthusiasm, *extraversion* was identified to positively relate to AI-WB. Within the present study, we did not specify the AI context to which participants should refer their responses. This represents a significant limitation, which we will return to later. Consequently, we lack insight into which AI applications or areas of application participants were considering when providing their answers. We can only assume that they were referring to the most commonly used AI applications. According to the latest statistics, AI-powered communication tools are among the most popular ones (Haan and Rob, 2023). These platforms enable individuals to easily share experiences, engage with others, and maintain social relationships, all of which contribute to their sense of well-being. As more outgoing and sociable individuals, extraverts likely experience increased benefits from AI applications, perceiving these technologies as facilitating social connections and interactions (John et al., 2008). This argumentation also provides an explanation for the different findings between the samples, as the Arabs are more collectivist, emphasizing community and social cohesion, as already mentioned (Hofstede, 2001). Interestingly, in considering the impact of extraversion on acceptance and fear of AI, previous studies also failed to identify a significant prediction within German and Chinese samples (Sindermann et al., 2022). The role of *conscientiousness* in interacting with AI technologies has been a subject of controversy in previous studies. While some studies reported significant findings (Huo et al., 2022; Park & Woo, 2022), others have failed to find a significant relationship (Kaya et al., 2024), or have reported mixed results across different samples (Sindermann et al., 2022). Those studies that identified a significant impact highlighted the role of conscientiousness in shaping acceptance of technology (Huo et al., 2022), reducing negative emotions associated with technology (Park & Woo, 2022), and promoting positive behaviors (Hawi & Samaha, 2019; Rivers, 2021). Despite the sometimes-contradictory results, we can summarize those aspects such as thoughtfulness, good impulse control, and goal-directed behaviors that fall under conscientiousness contribute to more mindful and effective use of technologies in general and AI applications in particular. This conscientious approach to technology use can enhance well-being by fostering a sense of control, reducing stress, and promoting positive outcomes. In the present study, we identified a positive relationship between *agreeableness* and AI-WB in the UK sample, but not in the Arab sample. Supporting findings for the impact of agreeableness come from studies on attitudes towards AI, showing that people with a higher level of agreeableness have a more positive attitude towards AI (Park & Woo, 2022; Stein et al., 2024). Interestingly, individuals with higher levels of agreeableness tend to be more tolerant of the negative aspects of AI (Kaya et al., 2024; Schepman & Rodway, 2023). We suggest that this increased level of tolerance—likely due to core components of agreeableness such as trust, altruism, kindness, and affection (Gosling et al., 2003; McCarthy et al., 2017)—facilitates better adjustment to technological innovations, leading to an increased level of well-being. While it is argued that *openness* is related to innovativeness (Park & Woo, 2022) and the tendency to adopt innovations (Agarwal & Prasad, 1998; Ahn et al., 2016), we did not identify any relationship between openness and AI-WB in either sample. This is consistent with previous studies on AI, which have commonly found that openness does not predict how individuals perceive AI (Charness et al., 2018; Devaraj et al., 2008; Kaya et al., 2024; Park & Woo, 2022; Schepman & Rodway, 2023; Stein et al., 2024).

In the realm of *locus of control*, we identified the internal locus of control as a key predictor of AI-WB in both samples. Individuals with an internal locus of control feel that they are masters of their lives and capable of influencing their environment (Duttweiler, 1984; Lefcourt, 1991), making them more empowered and capable of managing their interactions with new technologies. In line with our findings, we argue that this sense of control likely reduces anxiety and increases confidence when engaging with AI technologies leading to a higher level of well-being. Further support for our assumption comes from early findings that suggested extending the technology acceptance model by including an internal locus of control (Tseng & Hsia, 2008). More recent findings on trust in AI algorithms also highlight the key role of locus of control (Singh et al., 2024). Based on the present and previous findings on the relevance of internal locus of control, developers should consider this in designing systems. Users should be provided with more control and customization options, thereby fostering a sense of agency.

To our best knowledge, the present study is the first one considering the impact of personal factors on AI-WB. However, despite the valuable insights, there are some limitations that need to be mentioned. One we already mentioned is that we did not specify the AI context to which participants should refer their responses. Therefore, we do not know to which AI applications or areas of application (health, social media, insurance) their answers are related. Furthermore, people may not fully understand how AI impacts their well-being, particularly in terms of hidden influences or long-term consequences. In the present study, our focus was specifically on two cultural contexts: the UK and Arab societies. While this methodological approach enhances the robustness of our findings, conducting additional replication studies is essential to ensure broader relevance across Eastern and Western countries. Furthermore, future studies should also include objective measures of well-being to provide a more comprehensive understanding of the relationship between personal factors and AI-WB.

Conclusion

In conclusion, our study sheds light on the complex interplay between personal factors and individuals' perceptions of AI's impact on well-being across different cultural contexts. We found that cultural differences were significantly associated with these perceptions, with individuals from Arab societies generally holding more favorable views of AI's contribution to well-being compared to those from the UK. Moreover, factors such as technological competence, personality traits, and locus of control emerged as key predictors of AI well-being perceptions. While these findings are insightful, there are limitations to our approach. The cross-sectional nature of the study prevents us from making causal claims, and the reliance on self-reported data may introduce biases. Future research should aim to address these limitations by employing longitudinal designs to explore the long-term effects of AI use on well-being and by incorporating objective measures of well-being. Additionally, future studies should delve deeper into understanding the mechanisms underlying these cultural differences and their implications for AI adoption and well-being. Exploring how interventions aimed at promoting informed and responsible AI use can positively influence perceptions of AI's impact on well-being would also be valuable. Given the rapid advancements in AI technology, it is essential to continuously assess and adapt well-being measures to capture the evolving impact of AI. Furthermore, incorporating diverse cultural perspectives in the design and development of AI systems will ensure their relevance and effectiveness across global contexts.

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Data Availability The dataset associated with this work is uploaded at https://osf.io/jng5m.

Declarations

Conflict of Interest The authors declare no competing interests.

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