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Designing AI to foster acceptance: do freedom to choose and social proof impact AI attitudes among British and Arab populations?

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ABSTRACT
This study examines the impact of two key AI modalities – freedom of choice (FoC) and social proof (SP) – on public attitudes toward AI, focusing on cultural differences between UK and Arab participants. FoC refers to the option of selecting a non-AI, possibly human, alternative, while SP means knowing that others have used AI without issues. Four scenarios were designed, combining the presence or absence of these modalities. The context was a customer service chatbot for a telecommunications company, familiar to all participants. A total of 639 participants (316 British and 323 Arab) were introduced to the modalities and then the scenarios in randomised order, then asked about their reactions. Factor analysis grouped their responses into two categories: personal and social good, and risks and ethical concerns. Results indicate that both modalities positively influence perceptions of personal and social benefits of AI while reducing perceived risks and ethical concerns. When one modality was present, FoC had a stronger effect on improving positive perceptions and reducing concerns than SP. Cultural differences were minor but present, suggesting both groups generally respond similarly. Findings highlight the importance of providing a human alternative and avoiding reliance solely on SP or similar strategies to build trust in AI.

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Artificial Intelligence; attitude; ethical concerns; positive change; freedom of choice; social proof

1. Introduction

The advancement of Artificial Intelligence (AI) marks a transformative shift in various sectors – ranging from healthcare, transportation, and customer service to education (Salau et al. 2022). This transformation is not merely about task automation, it is about the introduction of technologies that are capable of learning, adapting, and making decisions, a realm once thought to be exclusive to human intelligence (Rai, Constantinides, and Sarker 2019). In today's world, AI technologies are capable of understanding natural language, recognising patterns, solving complex problems, and generating new content. Among these capabilities, generative text-based AI is particularly notable for its ability to interact with humans in sophisticated ways, mimicking human-like communication which enables new forms of interaction between humans and machines. However, the integration of AI into various life domains is not without its challenges. The growing integration of AI into daily life raises questions about how individuals perceive and respond to these technologies, particularly as their roles and capabilities continue to expand, and they become the only available option (Ranieri, Di Bernardo, and Mele 2024). These concerns are heightened when AI systems fail to resolve issues efficiently or lack empathy (Tan, Jiang, and Zhu 2024).

Public attitudes toward AI have garnered significant academic attention, driven by a complex interplay of factors that significantly influence its acceptance and adoption across societal domains (Ashfaq et al. 2020; Rahman et al. 2023). These attitudes are shaped by multiple factors, including trust, perceived usefulness, well-being, emotions, and ethical concerns, all of which consistently emerge as critical determinants in shaping users' views toward AI technologies (Choung, David, and Ross 2023; Seo and Lee 2021). Trust is one of the key factors in determining whether individuals are willing to engage with AI. Users are more likely to adopt AI

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systems when they trust the technology's accuracy, reliability, and transparency. For example, Choung, David, and Ross (2023) found that trust, particularly related to AI's functionality and reliability, significantly influenced users' perceived usefulness and willingness to use AI systems in marketing. Similarly, a quantitative study on banking AI-related services confirmed that trust leads to greater confidence in AI's capabilities, which directly correlates with increased adoption of AI technologies (Rahman et al. 2023).

AI technologies have been linked to improving life quality such as by taking over repetitive tasks and enhancing efficiency, which contributes to wellbeing and further reinforces positive attitude toward AI and increases its adoption in various sectors (Naiseh and Shukla 2023). In education, for example, AI-driven tools that offer personalised learning experiences have led to enhanced user engagement, satisfaction, and perceived benefits (Al-Emran and Teo 2020; Jo 2024). In healthcare, AI-powered diagnostic tools improve patient outcomes and promote wellbeing, further reinforcing positive attitudes toward AI (Chew and Achananuparp 2022). AI-based communication tools, such as personalised messaging and automated responses, enhance social engagement and contribute to social connection and well-being (Hohenstein et al. 2023; Liang et al. 2024).

While AI has shown significant potential in enhancing life, public attitudes are not uniformly positive. Ethical concerns are at the heart of discussions about responsible AI design, as they fundamentally shape how these technologies are perceived, developed, and implemented. These concerns stem from several factors, including bias, privacy, transparency, and accountability in decision-making (Felzmann et al. 2019; Konidena et al. 2024). For instance, AI systems used in healthcare may make critical decisions regarding treatment options yet provide little explanation for how those conclusions are reached. This lack of transparency could threaten human autonomy, as individuals may feel powerless to challenge or understand AI-driven decisions that significantly affect their lives (Lysaght et al. 2019). Concerns about AI's role in job displacement and its potential to exacerbate social inequalities are also factors driving negative perceptions (Xia 2023). For instance, the fear that AI will replace human labour across industries can lead to economic insecurity and social anxiety, dampening user acceptance. The dual nature of AI's impact – fostering innovation while simultaneously raising societal concerns – highlights the need for a deeper understanding of public attitudes and the factors shaping them. Such insights are crucial, as these attitudes directly influence the acceptance and successful integration of AI technologies (Cao et al. 2021).

Existing literature mostly explored attitudes toward AI in general terms, often overlooking the importance of context-specific factors that can significantly affect these perceptions. A critical aspect of this context is the role of AI modalities – such as freedom of choice and social proof – in shaping how people perceive and engage with AI technologies. A recently proposed IMPACT framework – emphasising the Interplay of Modality, Person, Area, Country/Culture, and Transparency variables – highlights the importance of considering context-specific factors when examining perceptions of AI (Montag, Nakov, and Ali 2024). In this context, Bandura's (1977) social learning theory becomes particularly relevant, as it suggests that individuals adopt behaviours by observing others, with social norms serving as informal guidelines that influence what is deemed acceptable within a group. In marketing, social proof leverages these norms – through reviews or endorsements – to influence consumer decisions. However, with the advent of AI, these traditional models require re-evaluation. AI systems, especially those designed to be socially interactive, possess a degree of autonomy, continuously engage with users, shaping social norms through dynamic interactions (Graf-Vlachy, Buhtz, and König 2018). Unlike AI tools, which are designed to perform predefined tasks such as data analysis or automation without independent decision-making, AI agents exhibit autonomy, goal-directed behaviour, and adaptability. These agents often utilise models such as the Belief-Desire-Intention (BDI) framework (Georgeff et al. 1999), which conceptualises agents as entities capable of acting based on knowledge, goals, and strategies. AI agents continuously learn from interactions, and personalise experiences based on user preferences and context. For example, intelligent virtual assistants that help users acquire new skills can adapt to users' performance (Le and Wartschinski 2018), demonstrating AI's transition from a passive tool to an interactive intelligent agent. The blurring of lines between AI as a tool and AI as an agent means that AI not only influences users' decisions but also actively participates in shaping consumer behaviour, attitudes, and choices, necessitating a re-evaluation at how social learning and influence unfold in this new landscape. This gap in the literature presents an opportunity to explore how specific modalities impact public attitudes toward AI in more nuanced ways.

2. Background Study

2.1. Freedom of Choice and AI

The modality of freedom of choice, indicating the availability of alternatives not requiring interaction with AI systems (e.g. interacting with humans or manual supervision) could play a role in user trust and satisfaction. Self-determination theory (Ryan and Deci 2017) implies that user motivation to use a system relates to the perception of having control over its use, relatedness to the purpose of that use, and the ability to make independent decisions about whether or not to interact with it and adopt its outcome (Dupuy et al. 2016; Kim and Gupta 2014). This concept aligns with the notion that when users have the freedom to decide whether to interact with AI or non-AI alternatives, it reinforces their sense of autonomy and satisfaction. Studies in customer service have shown that limiting interactions to AI, such as offering interaction with chatbots solely, can lead to negative impacts and possibly reactance. For instance, Luo et al. (2019) found that when customers were informed that they are interacting with an AI chatbot, purchase rates significantly declined. Users perceived chatbots as less empathetic and knowledgeable compared to human workers. In the healthcare sector, a study by Juravle et al. (2020) found that participants trusted AI doctors less than human doctors for diagnoses. However, trust in AI was significantly increased when patients were given the option to choose between AI and human doctors, with a gentle nudge toward the AI option, underscoring the importance of freedom of choice in shaping patient's attitudes toward AI. Similarly, studies in the realm of IT consumerization demonstrated that when users have the freedom to select from multiple technological options, they experience a heightened sense of autonomy and satisfaction, which can improve their overall engagement with the technology (Fasolo, Misuraca, and Reutskaja 2024). As users feel in control over AI systems, their trust and satisfaction increase (Balakrishnan and Dwivedi 2021). As suggested by Technology-to-Performance Chain (TPC) framework, free will to use technology or not, along with social norms, influences users' attitudes and system usage (Staples and Seddon 2004). Therefore, it is important to explore how freedom of choice – whether to interact with AI or opt for human alternatives – can influence users' attitudes toward AI, which could foster acceptance and utilisation of AI benefits.

2.2. Social Proof and AI

Social proof, as defined by Cialdini (2007) , refers to the phenomenon where individuals conform to and rely on the actions and behaviours of others, particularly in uncertain situations, to guide their own decisions. This principle is based on social learning theory (Bandura 1977), which emphasises observational learning, and conformity theory (Asch 1951), which highlights the tendency to align behaviour with group norms. These theories underscore the significance of social influence in behavioural adaptation.

In the context of technology acceptance, research shows that people's attitudes and decisions to adopt new technologies are often shaped by observing the behaviours of others (Wang, Meister, and Gray 2013). Social influence has been identified as a key factor in various domains, including the adoption of social networking sites (Ku, Chen, and Zhang 2013), fostering trust in fitness technologies (Beldad and Hegner 2018), and the acceptance of mobile banking apps (Sitorus et al. 2019). Recent studies have further highlighted the role of social influence in promoting the adoption of AI-based tourism services (Chi, Gursoy, and Chi 2022), shaping perceptions of benefits and emotions in AI service delivery (Gursoy et al. 2019), and encouraging trust and behaviour through chatbot interactions using information disclosure nudges (Carmichael et al. 2022). However, while Carmichael et al. (2022) employed Amazon Mechanical Turk (MTurk), a crowdsourcing platform for data collection, their methodology did not account for individual cultural differences. Moreover, another study demonstrated that observing others use an algorithm significantly increased trust in its recommendations, often more than the algorithm's accuracy alone (Alexander, Blinder, and Zak 2018). Additionally, research has shown that social influence fosters trust in diverse contexts, such as websites (Seckler et al. 2015), AI integration within teams (Rojas and Li 2024), and digital service solutions through nudging (Schneider et al. 2020). However, while these studies emphasise the importance of social proof in shaping technology adoption and user behaviour, they often overlook the potential impact of cultural factors on the effectiveness of social proof.

The role of social influence in technology adoption is explained through theoretical frameworks such as the Technology Acceptance Model (TAM2) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003; Venkatesh and Davis 2000). TAM2 incorporates subjective norms from the Theory of Planned Behaviour (TPB) to highlight how social influence shapes decisions to adopt technology. Similarly, UTAUT identifies social influence as a critical determinant of user acceptance. Additionally, UTAUT shows that voluntariness (freedom of technology choice) moderates the impact of social influence, with weaker effects in voluntary contexts and stronger effects in mandatory ones. In the AI context, exploring the impact of these modalities and their interplay in shaping users' attitudes toward AI – while considering the influence of cultural factors

– can provide critical insights into promoting AI acceptance and fostering positive user attitudes.

2.3. Cultural Context in AI Studies

Cultural differences play an essential role when examining attitudes toward AI, as such attitudes are shaped by cultural contexts, personal experiences, and societal norms (Belanche, Casaló, and Flavián 2019, 2020) For instance, concerns about AI's role in data collection are highlighted in discussions of ethics, with Western nations typically emphasising data privacy, while more collectivist cultures may justify reduced privacy in favour of collective benefits, particularly when AI is seen as serving the greater good (Wong 2020). Recent research has shown that attitudes towards AI vary across cultures (Sindermann et al. 2022). For instance, a study aligning with Hofstede's cultural dimensions, found that cultural factors like uncertainty avoidance significantly affect trust in automation across different countries (Chien et al. 2016). Specifically, cultures with high uncertainty avoidance, such as in Saudi Arabia and Turkey, exhibit more cautious attitudes toward automation, while cultures with lower uncertainty avoidance, like the U.S., tend to place higher trust in such technologies. Hofstede's cultural dimensions framework, developed through extensive research into global cultural differences, highlighted key cultural distinctions such as collectivism and uncertainty avoidance (Hofstede 1984). According to the Hofstede Insights (The Culture Factor Group 2025), countries in the Arab Gulf Cooperation Council (GCC), such as Saudi Arabia, score higher on both uncertainty avoidance and collectivism compared to more individualistic countries like the UK. In this context, Arab GCC cultures could be more influenced by social norms in AI adoption than individualistic cultures such as the UK, where autonomy and personal freedom are more emphasised. These cultural distinctions underscore the need to explore how factors like social norms and freedom of choice affect attitudes toward AI across different cultural groups.

3. The Present Study

Given the introduced literature and in alignment with the recently proposed IMPACT model (Montag, Nakov, and Ali 2024), in the current study, we aim to investigate the importance of modalities of freedom of choice and social proof (fall within the realm of the M-variable of the IMPACT model), and culture (fall within the realm of the C-variable) in shaping people's attitude toward AI, contributing to a deeper understanding of the factors that drive both positive and negative perceptions of AI across different Arab and UK cultures. Our findings seek to inform the development and adoption of AI technologies that aligned with users' needs and expectations.

The research addresses the following questions:

Do Social Proof and Freedom of Choice matter in shaping attitude towards AI?

Do Social Proof and Freedom of Choice compensate for or outweigh each other in shaping attitudes toward AI?

4. Methods

4.1. Participants

A total of 639 participants were recruited online from the UK (316) and Arab Gulf Cooperation Council (GCC) countries (323). For the UK sample, females comprised 69.62%, and in the GCC sample, 54.49% were female. The choice to include Arab GCC countries was deliberate, reflecting their common values, social norms, political stability, economic status, and continuous progress in digital advancement (INCIT 2022). Arab societies are characterised by collectivism and a emphasis on social norms, which differ significantly from Western societies that prioritise individualism and autonomy (Hofstede n.d.). These contrasting cultural attributes provide a relevant context for exploring how the modalities of Freedom of Choice and Social Proof influence attitudes toward AI across different cultures. To participate in the study, participants had to be at least 18 years old, be born and live in the UK or Arab GCC, identify as either British or Arab GCC in terms of culture and norms, and be a user of or familiar with AI. Ensuring that participants were users of or familiar with AI provided a baseline understanding of the technology, enabling them to engage meaningfully with the scenarios presented in the study. Attitude toward AI has been shown to play a role in the continued use of AI (Kang, Choi, and Kim 2024), which suggests that familiarity with or usage of AI is an important factor to explore. However, evaluating familiarity or usage as a variable in this study would have broadened the scope beyond its primary focus of investigating how Freedom of Choice and Social Proof shape attitudes toward AI. Attitudes toward AI are critical for its acceptance and adoption, as the Technology Acceptance Model (TAM2) (Venkatesh and Davis 2000) highlights that users' perceptions of technology drive its acceptance and use. This framework has also been reframed for AI, supporting the relevance of understanding attitudes toward AI (Montag and Ali 2025, 1–7). By focusing on attitudes, this study aims to provide insights into the cognitive and affective factors that influence users' willingness to engage with AI. This approach is particularly important for understanding how factors such as Freedom of Choice or Social Proof can shape perceptions and build trust, which are essential to maintaining usage with satisfaction.

The participants inclusion criteria were assessed using a pre-selection survey, and only those meeting these criteria were considered eligible for the main study survey. To ensure data quality, an extensive cleaning process was undertaken post-survey completion, removing participants who failed multiple attention checks, provided contradictory responses, or completed the survey in a speedy manner. Speedy responses were operationally defined as those completed within 50% or less of the median completion time, calculated after the exclusion of outliers. Outliers were defined as participants whose completion time exceeded twice the expected completion time, often due to completing the survey across multiple sessions.

The data for this study was collected as part of a larger project available at (https://osf.io/7ydwf/?view_only=f275ae745d334fc08c11243efb992140), from the end of October 2023 to the middle of December 2023. The data collection occurred via TGM (tgmresearch.com), a multi-country online data collection platform. The study was approved by the Institutional Review Board (IRB) of the first author's institution, ensuring participants provided informed consent and were aware they could withdraw at any time. Participants were compensated for their involvement.

4.2. Questionnaire design and measures

The questionnaire was designed using SurveyMonkey (surveymonkey.com). The questionnaire was developed in English and subsequently translated into Arabic following the recommended back-translation method (Brislin 1970). A pilot study was conducted on small participant groups from both the UK and Arab GCC to ensure the survey was well understood and to eliminate any ambiguous or unclear expressions.

Our study incorporated a set of scenarios to represent different levels of the modalities under study. While using an interactive chatbot could enhance ecological validity by better aligning the scenario design with real-world interactions, the scenario-based design was sufficient to operationalise freedom of choice and social proof at this exploratory stage. Given this, user perceptions of the modalities may vary depending on the interactive style of chatbots – such as an adaptive, personalised AI chatbot versus a scripted chatbot with predefined responses (Terblanche 2024). Nevertheless, examining how these variables interact with different chatbot interaction styles constitutes a separate research question that lies beyond the scope of this study. Furthermore, this method is used in relevant literature related to attitudes toward AI, especially in exploratory research. For example, one study explored trust in AI across various contexts, employing hypothetical scenarios to explore the role of affective factors in influencing trust in AI systems (Gillath et al. 2021). Similarly, another study also used a scenario-based approach to examine user preferences and trust in medical consultations by comparing analogy, digitalised, and AI-based methods through an online survey (Mayer et al. 2024). We conducted a thorough validation of the scenarios to ensure clear representativeness, undergoing multiple iterations to refine every aspect, including the selection of chatbot agents. Chatbots have gained a ubiquitous presence across numerous interactive platforms, and people are generally familiar with these AI-driven interfaces, particularly in telecommunications, where they are frequently used for services like customer support. Importantly, the choice of chatbots also aimed at minimising the perceived criticality of AI in participants' responses. Initially, we considered using a car scenario, exploring whether participants would accept AI more readily in fully autonomous or semi-autonomous vehicles. However, during the face validation phase, we realised that participants' fears related to autonomous cars might overshadow their reactions to freedom of choice and social proof. This led us to select chatbot agents, a more familiar and less critical AI application, to ensure that participants' responses were primarily influenced by the factors of freedom of choice and social proof, rather than by concerns over the criticality and high risks associated with other AI systems. For example, perceived high risks in interactions with AI can significantly impact a user's trust in the AI (Stuck, Tomlinson, and Walker 2022) whether or not there is a freedom of choice or social proof. Each scenario was presented with a coloured image that was designed to clearly and exclusively represent its specific context, and these images underwent several amendments. We face-validated the scenarios with three participants from Arab countries and three from the UK to ensure clarity and accuracy in mapping responses to the specific context of each modality ('Yes' indicating availability, and 'No' indicating absence) for both freedom of choice and social proof. Additionally, we asked participants to identify any unusual or distracting elements in the scenarios or images that could introduce noise or act as potential confounding variables. For example, when initially stating that the human agent was available, participants found it too plain, questioning the need for AI. We revised this to specify that the human agent 'may require some waiting time', providing better contextual clarity. This validation process was critical in minimising bias and ensuring the scenarios were robust and reliable.

The survey began by gathering demographic information including gender, age, education level, and employment status. The participants were then presented with an introduction of AI using the following text:

> Artificial Intelligence (AI) is centred around creating machines that possess the ability to accomplish activities typically necessitating human intelligence, including making recommendations, recognizing images, interpreting natural language, and the process of decision-making. For example, AI is used in self-driving cars, voice assistants like Siri, and recommendation systems like those on streaming platforms such as YouTube and Netflix.

After this introduction, participants were asked whether they use or are familiar with AI technologies as this was part of the inclusion criteria. To enhance the participants' understanding of the modalities explored in this study, they were then presented with text explanations and visual illustrations (Figure 1) about the concepts of Freedom of Choice and Social Proof:

The following section of the survey will introduce social characteristics related to AI, followed by scenarios of using advanced AI agent. In this scenario, you will interact with your internet provider about offers, bills, technical issues, or personal info changes. They offer an advanced AI agent that can interact through text, voice, and video, closely resembling human interaction. The agent is your primary point of conversation.

***Freedom of Choice**: Involves the option to use AI. Lack of choice occurs when AI is the only interaction, like AI customer service without a human alternative.*

***Social Proof:** Reflects AI's successful use by others. For instance, limited adoption by people of driverless cars results in low social proof.*

Subsequently, a set of 4 scenarios accompanied by illustrations were presented to participants, as shown in Figure 2, followed by a consistent set of questions after each scenario. The sequence of scenarios was randomised, yet the order of questions for each scenario remained unchanged. Examples of the presentation of a scenario are provided below:

***[Freedom of Choice: No]** – You can't start with talking to a human agent; you must interact with this AI virtual agent. This AI might transfer you to a human later, but it's not guaranteed.*

***[Social Proof: No]** – You do not know people who used this AI virtual agent.*

The questions following each scenario were designed to evaluate key aspects of accepting and adapting AI technologies, including trust, wellbeing, usefulness, perceived risks, and ethical concerns. Utilising single-item measures offers advantages such as brevity and has been shown to be reliable. For instance, a single-item measure has been used to assess trust in AI across cross-cultural settings (Montag, Becker, and Li 2024). Another study that compared single-item and multi-item trust measures found that single-item trust measures can be reliable and valid (Castro et al. 2023). The Attitudes Toward Artificial Intelligence (ATAI) scale includes a single item to measure trust as a component of a positive attitude (Sindermann et al. 2021), further demonstrating the applicability of single-item measures in assessing trust in AI technologies. Additionally, a single-item measure has been used to assess attitudes toward AI (Montag and Ali 2023), further supporting the use of the single-item measurement approach. The questions asked after each scenario are as follows:

Measure	Question	Likert scale
Trust	'How much do you trust that this AI technology makes good-quality decisions?'	1 ('No trust at all') to 7 ('Extreme trust').
Enhancing Wellbeing	'Overall, how much does this AI technology enhance your wellbeing?'	0 ('Not at all') to 10 ('Completely').
Feeling pleasant	'Please choose the figure that accurately represents how you feel toward this AI technology'	1 ('I am unhappy and angry') to 9 ('I am happy and delighted') – corresponding facial expressions were attached to each number.
Perceived risk	'I am concerned about potential risks associated with this AI technology'.	1 ('Strongly disagree') to 6 ('Strongly agree')
Positive change	'I believe that this AI application can bring about positive changes, both personally and for society',	1 ('Strongly disagree') to 6 ('Strongly agree')
Ethical implications	'To what extent you are concerned with the ethical implications of this AI technology?'	0 ('I am not at all concerned') to 10 ('Completely concerned')
Recommend	'How likely are you to recommend the use of this AI technology in your daily life?'	0 ('Not at all') to 10 ('Entirely sure')

4.3. Data analysis

Descriptive statistics were conducted for both samples. Following this, an Exploratory Factor Analysis (EFA) was performed to determine the factor structure of the items for each scenario. A Linear Mixed Modelling (LMM) was employed to estimate the effects of

Figure 1. Visual illustration of the concepts of freedom of choice and social proof.

modalities on the attitude towards AI. The advantage of using the LMM is that it enabled us to estimate fixed effects while considering the random variance associated with participants (i.e. how much of the overall error variance is accounted for by the differences in overall rating between participants) (Judd, Westfall, and Kenny 2012). In addition, mixed-effect models are robust methods of estimating fixed effects when the distributional assumptions are objectively violated which is a common case when a dependent variable is measured on an ordinal scale (Schielzeth et al. 2020). Further exploratory analyses, including t-tests to compare modalities between UK and Arab groups, and subgroup analyses using LMM by gender, are provided in the supplementary materials for reference.

5. Results

5.1. Demographics

Table 1 presents a summary of the demographic characteristics of both the Arab and UK participant groups.

5.2. Exploratory factor analysis (EFA)

The seven items of the modalities were analyzed using Exploratory Factor Analysis (EFA) on each of the two samples separately to determine their underlying factor structure. To evaluate the adequacy and suitability of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were calculated. The overall KMO measures for all modalities for the European sample, and the Arab sample were above 0.88, and 0.86, respectively. Bartlett's test of sphericity for each sample was statistically significant ($p < .001$). These results indicate that the data are appropriate for the EFA (Bartlett 1954; Kaiser 1974)(Bartlett 1954; Kaiser 1974).

The parallel analysis revealed a consistent pattern across the modalities, yielding two factors that significantly accounted for the variance within each sample

Table 1. Demographic characteristics of participants in the Arab and UK samples.

Variables	UK (N = 316)	Arab (N = 323)
Gender (%)		
Male	96 (30.38)	147 (45.51)
Female	220 (69.62)	176 (54.49)
Age		
M (SD)	40.81 (10.35)	33.07 (9.05)
Range	18–60	18–57
Education (%)		
No formal education	-	-
Primary education (elementary)	0.63	0.62
Secondary education (high school)	24.68	14.86
Pursuing or completed vocational or technical education	22.47	4.03
Pursuing or completed undergraduate degree (bachelor's) [(1)]	32.91	68.42
Pursuing or completed postgraduate degree (master's, Ph.D., etc.)	19.31	12.07
Employment (%)		
Full time employment	53.16	54.80
Part time employment	17.40	11.45
Run my own business	4.75	6.50
Homemaker	6.96	9.91
Student	2.22	7.74
Retired	3.48	2.17
Unemployed	8.23	5.88
Other	3.80	1.55

[(1)]The observed differences between the UK and Arab regions are mainly due to the lower popularity of vocational or technical education in the Arab region.

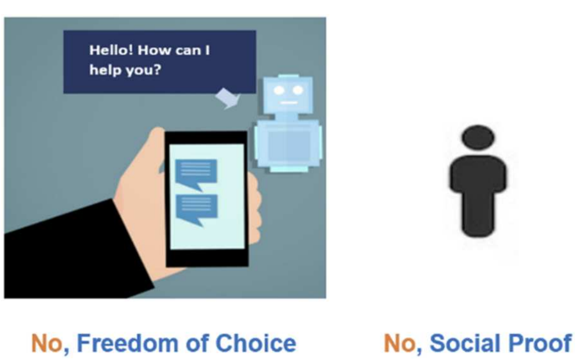

Figure 2. Example of scenarios illustration in the survey.

Table 2. EFA Factor loading of the modalities' questions.

UK Sample								
	NN Modality		NY Modality		YN Modality		YY Modality	
	Factor 1	Factor 2	Factor 1	Factor 2	Factor 1	Factor 2	Factor 1	Factor 2
Enhancing Wellbeing	0.940		0.962		0.977		0.961	
Feeling pleasant	0.869		0.878		0.879		0.897	
Recommend	0.891		0.913		0.889		0.890	
Trust	0.849		0.762		0.807		0.809	
Positive change	0.809		0.833		0.770		0.808	
Ethical implications		0.823		0.827		0.824		0.788
Perceived risk		0.769		0.844		0.799		0.759
Arab Sample								
	NN Modality		NY Modality		YN Modality		YY Modality	
	Factor 1	Factor 2	Factor 1	Factor 2	Factor 1	Factor 2	Factor 1	Factor 2
Enhancing Wellbeing	0.975		0.920		0.966		0.979	
Feeling pleasant	0.968		0.944		0.921		0.942	
Recommend	0.907		0.895		0.820		0.869	
Trust	0.842		0.853		0.879		0.818	
Positive change	0.624		0.567		0.522		0.593	
Ethical implications		0.716		0.741		0.867		0.741
Perceived risk		0.734		0.742		0.599		0.735

NN: **N**o Freedom of choice, **N**o Social proof; NY: **N**o Freedom of choice, **Y**es Social proof; YN: **Y**es Freedom of choice, **N**o Social proof; YY: **Y**es Freedom of choice, **Y**es Social proof.

namely Factor 1: 'perception of contributions to personal and social good' and Factor 2: 'perceptions of ethical concerns, and risks', as shown in Table 2. **For the European sample**, the factors accounted for: NN modality: 54.8% and 73.7%; NY modality: 55.0% and 76.5%; YN modality: 54.2% and 73.8%; YY modality: 55.2% and 73.0% of the variance. Similarly**, for the Arab sample**, the variance accounted for by the two factors was as follows: NN modality: 54.2% and 69.2%; NY modality: 51.3% and 67.1%; YN modality: 49.8% and 65.3%; YY modality: 51.7% and 67.6%. These findings indicate that, regardless of the sample, two factors capture the variance in responses across the different modalities, underscoring the potential to categorise the seven items into two variables.

Descriptive statistics, including means and standard deviations for the EFA factors across modalities, are provided in Table 3.

Table 3. Means and standard deviations for EFA factors across modalities.

Modality M (SD)	UK	Arab
NN_ Personal Social Good Perception	3.123 (1.804)	5.497 (2.107)
NN_ Ethical Concern Risk Perception	5.078 (1.834)	4.511 (1.945)
NY_ Personal Social Good Perception	4.216 (1.826)	6.055 (1.768)
NY_ Ethical Concern Risk Perception	4.296 (1.872)	4.393 (1.971)
YN_ Personal Social Good Perception	4.579 (1.743)	6.454 (1.542)
YN_ Ethical Concern Risk Perception	4.141 (1.803)	3.991 (2.000)
YY_ Personal Social Good Perception	5.237 (1.789)	6.811 (1.520)
YY_ Ethical Concern Risk Perception	3.778 (1.825)	3.859 (2.165)

NN: **N**o Freedom of choice, **N**o Social proof; NY: **N**o Freedom of choice, **Y**es Social proof; YN: **Y**es Freedom of choice, **N**o Social proof; YY: **Y**es Freedom of choice, **Y**es Social proof.
Factor 1: Personal Social Good Perception (Range: 0.6–8.4). Factor 2: Ethical Concern Risk Perception (Range: 0.5–8.0).

5.3. Perception of AI's contributions to personal and social good, ethical concerns and risks across the modalities

A Linear Mixed model (LMM) was conducted with modality and perceptions toward AI factors as fixed effects. Study subjects were treated as random effects. The dependent variable was the participants' ratings to items measuring their perceptions of AI. **In the UK sample,** The LMM analysis revealed a conditional R^2 of .259, indicating that 25.9% of the variance in the dependent variable is explained by both the fixed and random effects in the model. The marginal R^2, representing the variance explained by the fixed effects alone, was .095, indicating that 9.5% of the variance is accounted for by the fixed effects. The model's fit was statistically significant, $\chi^2(8) = 2030.069$, $p < .001$ for the conditional model, and $\chi^2(7) = 1067.642$, $p < .001$ for the marginal model.

The LMM showed that there was a main effect of modality ($F(3, 8525) = 14.129$, $p < .001$). The effect of perceptions toward AI factors was not significant ($F(1, 8525) = 0.557$, $p = .455$). Furthermore, there was an interaction between modality and perceptions toward AI factors ($F(3, 8525) = 245.359$, $p < .001$), suggesting modality (Freedom of choice and Social proof) affect the perceptions toward AI factors. To disentangle the interaction, Post Hoc comparisons using the Bonferroni corrections were performed between modality and perceptions toward AI factors. As shown in Table 4, all comparisons were significant, except for the comparison between perceptions of ethical concerns, and risks when the modality is NY vs NY. The interaction plot, illustrated in Figure 3, indicates that in the NN modality, perceived personal and social good are significantly reduced while ethical concerns and perceived risks are significantly higher compared to other modalities. This highlights an inconsistency in trends between perceived personal and social good and risks across the different modalities.

In the Arab sample, The LMM analysis revealed a conditional R^2 of .284, indicating that 28.4% of the variance in the dependent variable is explained by both the fixed and random effects in the model. The marginal R^2, representing the variance explained by the fixed effects alone, was .153, indicating that 15.3% of the variance is accounted for by the fixed effects. The model's fit was statistically significant, $\chi^2(8) = 2431.500$, $p < .001$ for the conditional model, and $\chi^2(7) = 1750.891$, $p < .001$ for the marginal model.

The LMM showed that the main effect of modality was significant ($F(3,8714) = 7.47$, $p < .001$). The effect of perceptions toward AI factors was highly significant ($F(1, 8714) = 1574.31$, $p < .001$), indicating substantial variation in perceived personal and social contributions, ethical concerns, and risks associated with AI. Furthermore, there was an interaction between modality and perceptions toward AI factors ($F(3,8714) = 73.07$, $p < .001$), suggesting modality (freedom of choiceand social proof) affect the perceptions toward AI factors.

Further Post Hoc comparison of the interaction between modality and perceptions toward AI factors revealed significant differences among several levels, adjusted for multiple comparisons using the Bonferroni method. As shown in Table 4, all comparisons were found to be statistically significant, except for the following comparison: (1) between perceptions of ethical concerns, and risks when the modality is NN vs NY, and (2) between perceptions of ethical concerns, and risks for YN versus YY. The interaction plot is illustrated in Figure 3.

6. Discussion

While the administration of AI in products and systems offers significant benefits, such as improving efficiency, it also raises concerns that may limit its broader acceptance and prevent it from reaching its full potential. These concerns, including issues around user autonomy and ethical risks, create barriers to widespread adoption (Prunkl 2024). Understanding public attitudes toward AI and the factors that influence its acceptance is therefore crucial. To explore these dynamics, this study applies the IMPACT framework (Montag, Nakov, and Ali 2024), which proposed that the interplay between Modality, Person, Area, Country/Culture, and Transparency shapes public attitudes toward AI. Specifically, this study examines how Freedom of Choice and Social Proof – key components of the Modality variable – affect perceptions of AI. Our findings reveal that the presence of Freedom of Choice and Social Proof plays a crucial role in shaping positive attitudes toward AI. When both modalities are present, participants reported lower levels of perceived ethical concerns and risks, and an increased perception of AI's personal and social benefits. In particular, participants noted enhanced trust, feelings of emotional happiness, wellbeing, and optimism about the role of AI in making positive change. Notably, Freedom of Choice was found to be more important than Social Proof. Conversely, the absence of both modalities led to markedly negative reactions, particularly in the UK, where the perceived benefits of AI were much lower compared to the Arab GCC countries, reflecting a cultural tolerance for reduced personal autonomy in favour of the collective good. This aligns with the collective nature of Arab cultures, emphasising group harmony and social norms (Hofstede 2001).

When Both Modalities Are Present: our findings demonstrated that the presence of both Freedom of Choice and Social Proof leads to more favourable outcomes in user attitudes toward AI. Participants who were exposed to scenarios where they could choose between AI agent and human agent interaction and observed others successfully using AI systems reported the lowest levels of perceived ethical concerns and risks, alongside the highest perception of AI's contributions to personal and social good. Freedom of Choice gives users a sense of autonomy, empowering them to take control of their interactions (Deci and Ryan 2013). When combined with Social Proof, where users observe others benefiting from AI, it further validates the technology's reliability and ethical standing. The findings were consistent across both cultural groups, underscoring emphasising that giving users both choice and validation through social endorsement significantly improves positive attitude and acceptance of AI.

Our findings align with prior research exploring factors of technology adoption, where freedom of choice among technology options has been shown to promote users' satisfaction, wellbeing, and perception of control (Klesel and Oschinsky 2019; Schwartz and Cheek 2017). For instance, in an experimental setting involving tablets, participants who were allowed to select their preferred device to perform certain tasks reported higher levels of perceived usefulness, satisfaction and enjoyment compared to those constrained to a specific device (Klesel and Oschinsky 2019) . These benefits align with our findings, where participants who

Table 4. Post Hoc comparison: of the interaction between modality and perceptions factors.

	Modality | Perception Factor		Modality | Perception Factor	Difference	SE	T	df	$p_{bonferroni}$
UK Sample								
NN	Personal Social Good	NY	Personal Social Good	−1.093	0.069	−15.831	8525	< .001
NN	Personal Social Good	YN	Personal Social Good	−1.4557	0.069	−21.084	8525	< .001
NN	Personal Social Good	YY	Personal Social Good	−2.1139	0.069	−30.617	8525	< .001
NN	Ethical Concern Risk	NY	Ethical Concern Risk	0.7816	0.1092	7.16	8525	< .001
NN	Ethical Concern Risk	YN	Ethical Concern Risk	0.9367	0.1092	8.58	8525	< .001
NN	Ethical Concern Risk	YY	Ethical Concern Risk	1.2991	0.1092	11.9	8525	< .001
NY	Personal Social Good	YN	Personal Social Good	−0.3627	0.069	−5.253	8525	< .001
NY	Personal Social Good	YY	Personal Social Good	−1.0209	0.069	−14.786	8525	< .001
NY	Ethical Concern Risk	YN	Ethical Concern Risk	0.1551	0.1092	1.42	8525	1.000
NY	Ethical Concern Risk	YY	Ethical Concern Risk	0.5174	0.1092	4.74	8525	< .001
YN	Personal Social Good	YY	Personal Social Good	−0.6582	0.069	−9.533	8525	< .001
YN	Ethical Concern Risk	YY	Ethical Concern Risk	0.3623	0.1092	3.319	8525	0.025
Arab Sample								
	Modality | Perception Factor		Modality | Perception Factor	Difference	SE	T	Df	$p_{bonferroni}$
NN	Personal Social Good	NY	Personal Social Good	−0.559	0.0768	−7.271	8714	< .001
NN	Personal Social Good	YN	Personal Social Good	−0.958	0.0768	−12.471	8714	< .001
NN	Personal Social Good	YY	Personal Social Good	−1.315	0.0768	−17.114	8714	< .001
NN	Ethical Concern Risk	NY	Ethical Concern Risk	0.118	0.1214	0.969	8714	1.000
NN	Ethical Concern Risk	YN	Ethical Concern Risk	0.52	0.1214	4.283	8714	< .001
NN	Ethical Concern Risk	YY	Ethical Concern Risk	0.652	0.1214	5.366	8714	< .001
NY	Personal Social Good	YN	Personal Social Good	−0.399	0.0768	−5.199	8714	< .001
NY	Personal Social Good	YY	Personal Social Good	−0.756	0.0768	−9.843	8714	< .001
NY	Ethical Concern Risk	YN	Ethical Concern Risk	0.402	0.1214	3.314	8714	0.026
NY	Ethical Concern Risk	YY	Ethical Concern Risk	0.534	0.1214	4.397	8714	< .001
YN	Personal Social Good	YY	Personal Social Good	−0.357	0.0768	−4.643	8714	< .001
YN	Ethical Concern Risk	YY	Ethical Concern Risk	0.132	0.1214	1.083	8714	1.000

perceived Freedom of Choice reported more positive attitudes toward AI, including greater happiness, satisfaction, and perceived value of the technology.

Autonomy is an essential element of human well-being, involving a person's capacity to make independent choices and decisions that align with their own motivations (Deci and Ryan 2000). In line with Self-Determination Theory, autonomy is experienced when individuals, driven by internal motivations and personal values, make informed decisions after carefully considering available options (Ryan and Deci 2000). Our findings align with this theory, as participants who had the option to choose between AI and human agents reported more positive perceptions of AI. This suggests that the ability to choose whether to engage with AI or rely on human alternatives enhances an individual's sense of control.

In term of social proof, this principle implies that people turn to social cues on how to behave and think, especially in situations of uncertainty (Cialdini 2007). Similarly, Social Cognitive Theory suggests that individuals learn and model attitudes and behaviours

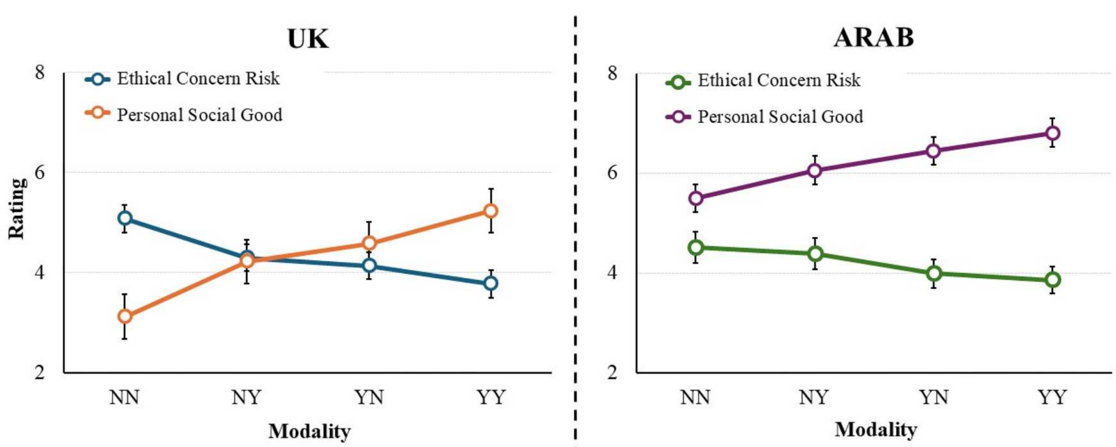

Figure 3. The interaction between modalities and perception factors. Error bars represent the standard error of the mean. In both samples, NN: No, Freedom of choice No, Social Proof; NY: No, Freedom of choice Yes, Social Proof; YN: Yes, Freedom of choice No, Social Proof; YY: Yes, Freedom of choice Yes, Social Proof.

by observing others (Bandura 1986). In line with these theories, the extended model of Technology Acceptance Model (TAM2) indicates that social influence processes, such as social proof, can notably affect perceived usefulness and ease of use (Venkatesh and Davis 2000). In this context, our study showed that when users see others successfully engaging with AI, they develop a positive attitude toward AI, suggesting this observation acts as validation that the technology is acceptable. These findings align with the literature, which highlights the significant role social proof plays in shaping attitudes toward new technologies (Albayati 2024; Gaczek et al. 2023; Saravanos et al. 2024). For example, a study demonstrated that showcasing the number of satisfied customers – a form of social proof – helped reduce enhanced trust in and willingness to accept AI-generated medical recommendations (Gaczek et al. 2023). One potential explanation of this effect could be that people often rely on others' behaviours when they lack direct experience or knowledge. In uncertain situations, they are more likely to adopt the attitudes or behaviours they observe, perceiving these as more credible and trustworthy (Cialdini 2007). Consequently, when users encounter social proof, such as others' positive experiences with AI, it provides a form of validation that reduces uncertainty and promotes favourable attitudes toward the technology. The important role of social proof has been also outlined in the Theory of Planned Behaviour (Ajzen 1991), where it has been put forward that social norms play an important role to predict intention to show a behaviour (here to use the AI system). Social norms would be met, if also your peers are using an AI-system. The here observed finding (combination of freedom of choice and social proof) results in favourable views of the AI-system.

When Both Modalities Are Absent: The absence of both Freedom of Choice and Social Proof led to significantly negative reactions, particularly among UK participants. In these instances, participants reported much lower perceptions of personal and social benefits from AI, coupled with heightened ethical concerns. This outcome suggests that when AI is imposed as the only option without providing evidence of its success through others' experiences, it alienates users. Despite not being directly related to trust, the lack of Freedom of Choice heightened perceptions of risk and ethical concerns, suggesting that risk appraisal and trust evaluation may become more emotive than cognitive. Reactance Theory explains that when individuals perceive threats or restrictions to their autonomy, they are prompted to exhibit motivational and cognitive responses to restore that freedom (Brehm and Brehm 2013; Rosenberg and Siegel 2018; Steindl et al. 2015). In this context, when users feel compelled to engage with AI systems without having an alternative, they perceive a lack of autonomy which can trigger reactance, resulting in negative emotional and cognitive responses such as heightened risk perception and ethical concerns. These findings are corroborated by studies that show restricting choice in AI interactions increases negative perceptions and mistrust (Sankaran et al. 2021). Our results corroborate these findings, as participants exhibited more negative attitudes when deprived of alternative options to interacting with AI systems. Furthermore, research has shown that AI technology can either enhance or undermine users' sense of autonomy, which is directly linked to their overall wellbeing (André et al. 2018). The lack of both autonomy and social validation can intensify negative reactions and make it harder for users to trust and accept the technology. In such cases, user alienation becomes more pronounced, leading to a resistance to AI acceptance.

When Comparing Both Modalities: our findings revealed that Freedom of Choice had a more significant impact on participants' attitudes toward AI. Participants who were provided with the opportunity to choose between interacting with AI or human agents exhibited more positive attitudes and greater trust in AI than those who were shown social proof only. This suggests that user autonomy plays a more critical role in shaping favourable perceptions of AI than social validation alone. In line with these findings, research by Brandimarte, Acquisti, and Loewenstein (2013) showed that when users feel a sense of control over their information and interactions – even when it involves privacy risks – they are more willing to engage with technology. This underscores the critical role that autonomy plays in fostering trust and acceptance of AI systems.

These findings can be interpreted through the lens of existing literature, which emphasises that providing individuals with a sense of control reduces fear and fosters trust (Gunnar 1980). For instance, research has demonstrated that perceived control over using self-service technology increases trust, leading to increased perceived value and intention to use the technology (Collier and Sherrell 2010). Similarly, Degachi, Tielman, and Al Owayyed (2023) found that perceived control positively influences trust dimensions, such as benevolence and competence, in interactions with AI chatbots. Additionally, a study found that when individuals perceived higher levels of subjective control, they reported less fear and anxiety in response to threatening situations (Kaufmann and Neumann 2019). In line with these findings, our study highlights that control reduced fear and increased positive attitude toward AI, including increasing trust, perceived value, wellbeing and emotional happiness. In contrast, while Social Proof can reinforce trust through validation, it is less effective without the foundational element of user autonomy. This conclusion supports existing research emphasising the importance of fostering autonomy in human-machine interactions to rebuild trust and promote AI acceptance (De Visser, Pak, and Shaw 2018). Additionally, regulatory bodies such as the European Union have emphasised the need for respecting autonomy to ensure ethical AI development (Hleg 2019). Our study extends this understanding by showing that allowing users to choose whether to engage with AI enhances their sense of autonomy, leading to improved trust and perception of the technology.

Although the overall trend in findings is similar, the degree of impact differs across cultures. The finding that UK participants exhibited heightened perceptions of risk and ethical concern in response to the absence of autonomy, compared to the absence of social proof, underscores the cultural significance of individual freedom in Western societies. In these cultures, autonomy and independence are central values (Triandis 2001), making the absence of choice a critical factor contributing to increased ethical concerns and perceived risks. Interestingly, when either autonomy or social proof was absent, the perceived risk and ethical concern difference was not significant. This suggests that the lack of freedom or social proof makes individuals less receptive and unable to distinguish between the two modalities in terms of their impact on ethical concerns. These findings align with literature suggesting that social proof is perceived as less autonomy-threatening. For instance, Wachner, Adriaanse, and De Ridder (2020) demonstrated that social norm nudges – an example of social proof – are less likely to elicit negative autonomy perceptions compared to other nudges. Our findings further suggest that the lack of social proof can make AI appear autonomy-threatening and, consequently, less ethical. Additionally, the absence of social proof may increase perceptions of risk and unreliability regarding new technology. (Zimmermann, Somasundaram, and Saha 2024) found that new technologies lacking social proof were associated with heightened uncertainty and decreased technology adoption. Similarly, (Schweitzer 2015) showed that a perceived lack of an installed base (social proof) negatively impacts technology adoption by reducing perceived usefulness and ease of use while also mediating perceived risk.

In the Arab GCC, both autonomy and social proof played important roles in shaping perceptions. While autonomy remains important, social proof also had a notable influence on reducing ethical concerns and enhancing positive perception toward AI. This suggests that both individual autonomy and collective validation contribute to shaping attitudes toward AI adoption. In these collectivist cultures, the presence of social proof place role on societal harmony (Hofstede 2001). Collectivist cultures, such as those in the Arab GCC has high levels of uncertainty avoidance, further amplify the reliance on social proof as a means of mitigating risks associated with AI technologies (Sharma et al. 2024). People are likely to reduce perceived risk when they observe others benefiting from the technology, as it provides reassurance that the AI system is effective, and socially acceptable. Observing others' positive experiences creates a sense of collective validation, indicating that the potential risks are manageable, and the technology aligns with societal acceptance. This psychological reliance on the behaviour of others is particularly strong in collectivist societies, where individuals often prioritise group harmony and shared decision-making over individual experimentation (Hofstede 2001). This highlights the importance of incorporating social validation mechanisms in AI systems to reduce perceived risk and foster trust in such cultural contexts.

Moreover, media portrayals of AI further shape these perceptions. In regions like the Arab GCC, AI is frequently depicted as a tool for societal progress and innovation, often framed within the context of economic growth (Halaweh 2018), potentially influencing public attitudes toward its adoption. These cultural and media differences provide insight into the varying levels of acceptance and concerns surrounding AI technologies across different regions. The cultural findings observed in the present work fit also with the aforementioned IMPACT framework (Montag, Nakov, and Ali 2024), whereas the C-variable states that both cultural and regulatory aspects of different countries/regions play an important role in shaping views on AI-systems. Recent research observed that cultural differences in AI-attitudes are relevant to be studied (Montag, Becker, and Li 2024; Sindermann et al. 2022).

6.1. Practical implications

The results also show the importance of presenting alternatives to AI and underscore that the dependence on demonstrating others' adoption of AI does not diminish the need for these alternatives. The validity of our results across diverse cultural frameworks, specifically within the Arab GCC and the United Kingdom (UK), enhances the robustness of our findings. This contribution is particularly noteworthy in addressing the replication crisis prevalent in psychological research, characterised by a predominant reliance on samples (Western, Educated, Industrialised, Rich, and Democratic) (Henrich, Heine, and Norenzayan 2010).

Our findings contribute to the literature on AI adoption by demonstrating the pivotal role that Freedom of Choice and Social Proof modalities play in shaping user attitudes toward AI, as proposed by the IMPACT model (Montag, Nakov, and Ali 2024). Importantly, our study goes beyond trust, examining the impact of these modalities on the perception of AI in terms of enhancing wellbeing, emotional happiness, and perceived positive change. The study reveals that both Freedom of Choice and Social Proof are two key factors shaping public attitudes toward AI, with Freedom of Choice emerging as the more influential factor. The study underscores the importance of providing users with the freedom to choose between interacting with AI or human agents. AI systems that offer alternative interaction modes – rather than imposing AI as the only option – foster a stronger sense of control, thereby improving user satisfaction and trust. These insights offer actionable recommendations for developers, organisations, and policymakers.

Organisations that integrate AI into their services should ensure that users are given options, as this can lead to higher adoption rates, better user experience, and more positive attitudes toward AI technologies. For example, a study that followed Google and Microsoft's HCI guidelines (Gervazoni and Quaresma 2023), found that users were dissatisfied with chatbots due to a lack of trust and autonomy. Building on our study findings, we recommend that AI-based chatbot developers integrate both Freedom of Choice and Social Proof to foster user acceptance of AI and maximise its benefits. For instance, when a product is new and lacks reviews or word-of-mouth endorsements, developers should emphasise the robustness of the testing process and the inclusivity of the design, such as involving representative user groups in development. Organisations could also highlight their client-cantered business model and demonstrate benevolence to enhance user trust (Mayer and Davis, 1999). Furthermore, chatbot designs could incorporate Social Proof to enhance trust through real-time feedback, success stories, and usage statistics (Gervazoni and Quaresma 2023). Freedom of Choice can also be integrated by offering alternatives for interaction, allowing users to switch between chatbots and human agents. In cases where multiple interaction options are not economically feasible, organisations should implement a structured feedback system that allows users to report concerns and challenges, ensuring systematic and timely responses. Additionally, chatbots should enable freestyle interaction in cases where scripted responses may feel restrictive, mimicking human-like interactions to enhance user satisfaction. However, achieving this requires extensive AI training that involves testing with diverse user groups to ensure inclusivity and adaptability. By incorporating these design features, organisations can better align AI services with user expectations, fostering trust and satisfaction.

For Policymakers: The study's findings highlight the need for regulatory measures that ensure perceived autonomy in AI interactions, especially within Arab cultures, where AI regulatory frameworks are still evolving. Policymakers in these regions should prioritise creating regulations that safeguard user autonomy by mandating alternative interaction modes, where users can choose between AI and human agents. This is particularly important as a means of fostering acceptance of AI systems in these cultural contexts. The European Union's Ethics Guidelines for Trustworthy AI provide a framework for structuring such regulations, emphasising the key principle of autonomy in AI design and deployment (Hleg 2019). Our study reinforces these principles, further contributing to the conceptualisation of autonomy – specifically the importance of Freedom of Choice – in the context of AI (for more details see (Prunkl 2023)). This is consistent with the concept of 'nudging systems', where Freedom of Choice is recognised as a key component of autonomy (Vugts et al. 2020). Furthermore, our findings extend the importance of autonomy beyond perceived trust to influence perceptions of AI in ways that enhance both personal well-being and broader social benefits and reduce perceived risks and ethical concerns.

We also mention that policymakers should recognise the need to balance autonomy with AI capabilities. While autonomy fosters a sense of control and trust, studies have shown that reliance on perceived autonomy can have unintended consequences. For instance, a previous study demonstrated that when users feel in control, they may be more willing to disclose sensitive information concerning their privacy (Brandimarte, Acquisti, and Loewenstein 2013). Therefore, policymakers should ensure that regulations not only promote user autonomy but also safeguard users and protect users from potential risks associated with AI systems. Similarly, Social Proof must be applied with caution to avoid unintentionally pressuring or manipulating users, thus raising ethical concerns. Drawing parallels from nudging systems, which are designed to guide behaviour without overtly restricting choice, critics have argued that these systems can inadvertently undermine user autonomy and empowerment (Schmidt and Engelen 2020). Social Proof can risk becoming coercive rather than empowering. Studies highlight that such tactics may unintentionally manipulate users and could even be exploited in malicious contexts, such as cybersecurity phishing in social engineering (Taib et al. 2019). To address these risks, AI developers and policymakers should prioritise transparency when implementing Social Proof to uphold user autonomy and ensure responsible AI. Cheong (2024) emphasises that accountability in algorithmic decision-making not only safeguards user well-being but also ensures ethical alignment. This accountability provides a framework for implementing Social Proof in a non-coercive manner and can potentially act as a safeguard against misuse.

6.2. Limitations and future work

This study has several limitations that should be considered for future research. It is cross-sectional in nature, which limits our ability to infer causality from the findings. There is a limitation regarding potential confounding variables within the experimental scenarios. However, in our experiment exploring the modalities of choice and social proof, we ensured the selection of a technology – specifically a customer service agent – and employed face validation to ensure participants rated their responses based on the presented modality. This approach helped mitigate the influence of other factors, such as the perceived criticality of AI in high-stakes sectors (e.g. healthcare or fully automated vehicles), where high criticality may impact perceptions differently. Additionally, familiarity with AI and prior experience may influence how individuals perceive and respond to AI technologies. Research has demonstrated that familiarity with AI can influence user trust (Gillath et al. 2021). However, this study did not include familiarity with AI as a variable, as evaluating this aspect would have broadened the scope beyond its intended focus. Future research could explore how social proof, freedom of choice, and attitudes toward AI influence AI adoption and usage itself. For example, prior studies have highlighted that AI adoption is influenced by factors such as social influence, performance expectancy, effort expectancy, and facilitating conditions (Emon et al. 2024). Their findings also suggested that attitude toward technology mediated the relationship between social influence and AI adoption. Building on these insights, future research could expand our work by examining how the studied modalities (social proof and freedom of choice) impact the actual use of AI, and whether this relationship is mediated by attitudes toward AI. The study focused on two cultural contexts – British and Arab GCC countries – which may limit the generalizability of the findings to other cultural settings. However, selecting these regions highlights distinct cultural dimensions – individualism in the UK and collectivism in the Arab GCC – which enhances the ability to examine social influence and autonomy in decision-making processes. While other collectivist societies, such as Japan, are well-known for their long-standing advancements in technological infrastructure and integration of robotics and AI into daily life (Robertson 2014), the Arab GCC countries are at an earlier stage of AI adoption. The rapid digital transformation in the GCC region, driven by substantial governmental investments and strategic initiatives, such as the establishment of the Saudi Data and Artificial Intelligence Authority (SDAIA) in Saudi Arabia which represents a strategic effort to advance AI governance (SDAIA 2024). Moreover, the Arab GCC countries are consumers of AI technologies, with production still in its early stages (Nick Studer 2024; Sophie Smith 2020). This dynamic may influence perceptions of Freedom of Choice and Social Proof, as AI is viewed more as an imported product rather than one produced locally. In contrast, the UK benefits from a more established AI ecosystem, with ongoing efforts to implement AI regulations and has received media attention regarding AI-related issues (GOV.UK 2023, 2024). These contrasts in technological maturity make Arab GCC countries particularly valuable for examining public attitudes toward AI. Future research could also explore a broader range of cultural contexts to expand the understanding of these factors.

The data were collected using self-report methods, which may be prone to biases, such as recall bias. Participants were provided with clear definitions of the modalities and photos in each scenario to reduce recall bias. A potential limitation of ecological validity was addressed by participants' familiarity with chatbots in everyday life. Additionally, the use of photos throughout the survey further enhanced the realism of the scenarios. We conducted a thorough face validation process to ensure participants fully understood the survey and the scenarios, and they were given the option to exit the survey at any time. While these steps were taken to enhance ecological validity, incorporating an interactive design could better reflect real-world interactions. For example, research has shown that using conversational agents or chatbots can provide a more immersive experience for participants (Richards, Vythilingam, and Formosa 2023). Future research could build on our approach by incorporating more interactive designs and exploring the interaction between our research variables – Freedom of Choice, Social Proof, and chatbot interaction style (e.g. adaptive vs. scripted interaction). For example, a study comparing generative (adaptive) coaching chatbots with scripted coaching chatbots found that users exhibited higher adoption rates when interacting with adaptive chatbots (Terblanche 2024). Future studies could investigate whether users would tolerate a lack of Freedom of Choice or Social Proof if the chatbot employs an adaptive conversational style rather than a scripted, rule-based approach. In addition, we acknowledge the importance of the tone and framing in the AI agent which may moderate the difference between the presence and the absence of each of the modalities studied (e.g. Freedom of Choice and Social Proof). An interactive design could also help mitigate potential perceptions of an unpolished or overly directive tone in the scenarios.

Attention checks were included throughout the survey to maintain data quality and assess participant attentiveness. Responses that were contradictory or that failed these attention checks were removed during data cleaning. Furthermore, data were collected anonymously to protect confidentiality and reduce the likelihood of social desirability bias.

7. Conclusion

The present study highlights the important roles of freedom of choice and social proof in shaping positive attitudes toward AI. Specifically, providing users with a choice between AI and human agents fosters a stronger sense of autonomy, leading to increased satisfaction and trust in AI systems. The presence of social proof also positively influences AI perception, though to a lesser extent than freedom of choice. Hence, providing users with the choice to rely on an AI system or a human agent to interact with is of relevance to create autonomy on the user side. Future research should explore additional modalities and cultural contexts to further understand how different modalities affect AI acceptance.

Disclosure statement

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