Exploring Factors Affecting User Trust Across Different Human-Robot Interaction Settings and Cultures

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ABSTRACT

Trust is one of the necessary factors for building a successful human-robot interaction (HRI). This paper investigated how human trust in robots differs across HRI scenarios in two cultures. We conducted two studies in two countries: Saudi Arabia (study 1) and the United Kingdom (study 2). Each study presented three HRI scenarios: a dog robot guiding people with sight impairments, a teleoperated robot in healthcare, and a manufacturing robot. Study 1 shows that participants' trust perception score (TPS) was significantly different across the three scenarios. However, Study 2 results show a slightly significant variation in TPS across the scenarios. We also found that the relevance of trust for a given task is an indicator of a participant's trust. Furthermore, the findings showed that trust scores or factors affecting users' trust vary across cultures. The findings identified novel factors that might affect human trust, such as controllability, usability and risk. The findings direct the HRI community to consider a dynamic and evolving design for modelling human-robot trust because factors affecting humans' trust are evolving and will vary across different settings and cultures.

CCS CONCEPTS

• **Human-centered computing** → *User studies*; • **Computer systems organization** → *Robotics*.

KEYWORDS

Trust, culture, human-robot trust, factors affecting trust, human-robot interaction

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1 INTRODUCTION

In recent years, robots have been programmed to support and assist humans in various environments as nursing assistants in healthcare [25], guiding blind people indoors and outdoors [29], manufacturing operations, and military operations [9]. Human factors such as trustworthiness and reliance on robots are crucial to ensure the successful integration of robots in these settings. The absence or over-reliance on robots can override such systems, and humans may lose the opportunity to benefit from them. Therefore, understanding the concept of trust and investigating the factors influencing trust is needed for a successful HRI.

Hancock et al. [17, 18] analysed the broad range of factors that affect human's trust in robots during human-robot interaction (HRI) and contributed a model for human-robot trust based on their analysis. Recent empirical findings have shown that factors affecting human trust in robots may vary across settings due to different degree of risk and vulnerability [1, 35, 42], elements that were not found in Hancock's analysis [17]. Similarly, we see limited studies attempting to understand how one factor affecting trust in robots in a given setting presenting a certain degree of risk may not be relevant for another. Considering this, we understand it is not probable to generalize "factors" affecting trust as they may differ due to the dynamic nature of humans' trust in robots across settings.

In addition to different HRI settings, an individual's cultural background also influences their trust in robots [13, 17, 37]. Hancock et al. [17] highlighted that cultural factors influence human trust in robots. However, the studies discussed comprised individuals from the Asian, United States and European cultures [13, 27]. There is a lack of studies considering the Arab culture in the context of factors affecting trust in robots. In addition, many attributes of culture such as communication, skills (psychomotor and cognitive), attitudes, values, beliefs, expectations, cognition, conventional actions, material artefacts and technological know-how have not to our knowledge been explicitly considered [10].

The work described in this paper attempts to reflect on these two identified gaps and investigates the following research questions. RQ1) Does individuals' trust perception of a robot vary across HRI settings? RQ2) Do people from different cultural backgrounds show differences in factors affecting trust and do their perception of trust vary across diverse settings? RQ3) What are the "new" or unidentified factors affecting user trust in robots across diverse settings? In particular, all RQs consider settings that present varying degrees of risk and vulnerability. To investigate these RQs, we conducted two studies that explored the factors affecting trust and variance of trust across three scenarios: guiding blind people, teleoperated diagnoses in healthcare, and a manufacturing/assembly scenario. We conducted studies in Saudi Arabia (KSA) and the United Kingdom (UK). All of the three scenarios were different in the nature of task, interaction type, and degree of risk. We selected these two

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countries because limited studies can be found where Arab culture is compared to European/Western culture in the context of studying trust in robots [17]. Furthermore, the use of robotics is among the top government strategies in different domains such as manufacturing, defence, and nuclear for the near future of the UK [28] and KSA [21]. The novel contributions of this paper are:

- We show that not all factors affecting trust listed in the Hancock et al. [17] model are relevant or essential across various scenarios and cultures.
- We show that factors affecting trust (such as controllability, familiarity, usability and others (see Table 3 & Figure 2)) vary across scenarios in both studies and also varied across two different cultures (KSA and the UK).
- We show that the trust perception and trust relevance scores varied significantly across the two different cultures. However, trust perception did not vary across scenarios in the study conducted in the UK.
- We identified new factors (controllability, familiarity, and risk) in addition to ones identified by [17] in both studies.

2 RELATED WORK

2.1 Trust and factors affecting trust in robots

Trust is a multidimensional concept, and it has been widely researched in several disciplines, such as sociology, psychology, cognitive science, and human-computer interaction [3]. The definition of trust may vary based on the robot's application and domain [23]. However, Abbass et al. provided a comprehensive definition of trust that is used widely in HRI studies as a "multidimensional psychological attitude involving beliefs and expectations about the trustee's trustworthiness derived from experience and interactions with the trustee in situations involving uncertainty and risk." [1]. Because a trustee's trustworthiness and the environment may differ in each HRI scenario, this definition of trust can be applied to our study. This definition shows that psychological attitudes (e.g., expectations, beliefs and experiences) which are different in cultures, and the nature of the environment, including the degree of risk, significantly affect trust in HRI.

Hancock et al. [17] provided a comprehensive review of the factors affecting trust in HRI and classified them into three classes related to human, robot, and environment. Human-related factors can be separated into ability-based (e.g., competency, engagement, expertise, and awareness) and characteristics-based such as culture, expectancy, comfort, and satisfaction. Robot-related factors can be divided into attribute-based and performance-based. Both attribute-based (e.g., proximity, robot personality, and anthropomorphism) and performance-based (e.g., behavior, reliability of robot, and level of automation) significantly affect trust. Environment-related factors included team collaboration and tasking. For successful HRI in each environment, human and robotic teammates must act positively by sharing the goal, communicating effectively, knowing and performing roles, and putting the needs of teamwork over those of individuals [16]. In addition, the team-related trust factors include role interdependence, team composition, shared mental models, and societal impact [38].

Although Hancock et al. [17] identified the factors that influence trust, they did not highlight risk and vulnerability presented by a task or a setting. The HRI can be varied across settings due to the level of risk [35]. Besides, Abbass et al. [1] has urged the HRI community to reflect on the characteristics presented by different settings. In particular, they have highlighted the importance of the degree of risk, uncertainty, and potential gain to or for the trustor. In addition, the characteristic may vary depending on the culture that could influence trust. Therefore, this paper investigates how trust varies across settings and cultures.

2.2 Trust transfer across settings

Different factors may influence humans' trust in robots across environments [24]. The intensity of a particular factor may be more in one as compared to the other. This is because of the variation of nature of the task, such as rationality and revocability of the tasks [35], risk and human safety [36], and workload [11] in each setting. For instance: risk may be perceived as higher for an interaction where a robot is in close proximity to a human [26]. Very few studies have been conducted on trust transfer in HRI, such as [35, 41, 47].

Robinette et al. suggested that trust factors may vary across different domains and environments due to the level of risk. They conducted an experiment in HRI in a non-emergency task to observe human behaviour and then decide whether or not to follow the robot's instructions in an emergency evacuation scenario. Their results showed that the trust varied between emergency and non-emergency scenarios [35]. However, this work focused only on the risk level and did not compare tasks with the same level of risk.

Soh et al. [41] investigated how humans' trust in robots differ across different tasks. They conducted an experiment using different task household and driving tasks. They found that human trust changed across these tasks. In the same context, Xie et al. [47] also presented a study to explore the impact of robot capability and intention on trust across three different tasks (searching, mapping and firefighting) using an unmanned vehicle. They found that humans trusted robots differently in these tasks based on the robot capability change. However, these studies focused only on the robot's capabilities as a factor influencing the transfer of trust across different settings. From these existing studies, we understand that some factors may become more prevalent in one setting compared to the other. The research described in this paper goes beyond the existing work and focuses on investigating the range of factors influencing trust in different settings and how they vary across different settings.

2.3 Culture and trust

Several studies have investigated the impact of cultural background on HRI trust (e.g., [27, 31, 34, 44]). These studies concluded that people belonging to different cultures are likely to trust robots differently. However, most cross-cultural HRI studies have concentrated on Western vs. East Asian cultures; in contrast, very little research has involved Arab culture [17]. The Arab world is a region of 22 countries with a population of 620 million and straddles the continents of Asia and Africa [39]. We believe that the Arabic region and culture should be involved more fully in HRI research.

Rau et al. [34] investigated the effects of culture, robot appearance and task during HRI on participants from China, Korea and Germany. The results showed that participants differed significantly on the four scales they proposed: likeability, engagement, trust and satisfaction. In addition, Nomura et al. [31] conducted a survey using the *Frankenstein Syndrome Questionnaire* [43] to examine the differences in social acceptance of humanoid robots between Japan and the UK. They found that social acceptance of humanoid robots differed across the two countries. However, that study focused on humanoid robots. In this work, we diversified types of robots in the three scenarios to have a general insight into the transfer of trust across cultures when robot types are different.

Andrist et al. [6] compared the relative effectiveness of knowledge and rhetoric on the credibility of robots between Arabic-speaking robots in Lebanon and English speaking robots in the United States in a collaboration task. The study found that Arabic users were more critical while rating robots' perceived credibility than American users. More recently Lim et al. [27] reviewed cultural influences and factors such as knowledge, expectations, perception, attitude, and behaviour towards robots worldwide. The findings show that cultural backgrounds influence these factors toward robots.

In summary, the previous work in this area has several limitations, including the lack of investigation of the impact of cultures on human trust in different HRI scenarios and the shortage of examining all the aspects of Arab culture, not only language. Through this work, we attempt to see how these factors vary across cultures for three different settings.

3 STUDY DESIGN

We conducted two online studies. Study one was conducted in KSA and study two was conducted in the UK. The two studies were used to test the following hypotheses:

H1: The number of factors affecting participants' trust will differ across human, robot, environment related factors in the three HRI settings.

H2: Participants' trust perception score (TPS) (**H2a**) and trust relevance score (TRS) (**H2b**) in the robots will vary significantly across the three HRI settings.

H3: Participants' trust perception score (TPS) and trust relevance score (TRS) will vary significantly across cultures.

To ensure ethical integrity, two applications were submitted to the university ethics board. The applications were approved following a review process.

3.1 Task

The task followed twelve different steps as illustrated in Figure 1 and the task presentation that we used.[1] The task involved watching three videos of human robot interaction in three different scenarios.

(1) Guiding: a dog guide robot led a blind person through narrow and clustered spaces to his destination [46].
(2) Healthcare: a teleoperated robot that assists medical practitioners in diagnosing patients remotely with a nurse's assistance [48].
(3) Manufacturing: a manufacturing robot collaborates with workers on an assembly line to construct a product [12].

[1] https://docs.google.com/presentation/d/1UIB3QNgHHkggqCGz1s_K7Dm3q3yLTD0m/preview

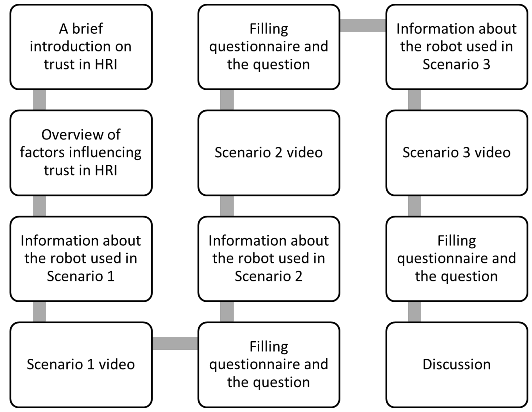

Figure 1: The steps taken in the workshop (upper left to lower right).

3.2 Participants

In study one, we recruited 18 participants (Mean age: 35.16 years, SD = 6.88, 44% female) from KSA. Participants were classified as experienced with robots into high, medium, low and no experience. Participants were categorized as high experienced if they reported having controlled and/or built a robot, medium experienced if they reported using robots several times, and low experienced if they reported interacting with robots a few times. 3 participants had high experience interacting with robots. 4 participants had medium experience interacting with robots. 8 participants had low experience interacting with robots. 6 participants had no experience interacting with robots. In study two, we recruited 18 participants (Mean age: 27.77 years, SD = 7.21, 56% female) from the UK. 4 participants had high experience interacting with robots. 5 participants had medium experience interacting with robots. 4 participants had low experience interacting with robots. 5 participants had no experience interacting with robots. It is worth noting that the experience with robots was similar among participants in both studies. All the participants were postgraduate students and academics in the computer science department at their respective universities. Participants were invited via email and flyers. In each study, we conducted the workshops with a group consisting of three participants at a time. The registration for the study was managed using online application for registration (*Calendly* [2]). The workshop was conducted online via zoom with all the participants.

3.3 Procedure

The study was conducted in two parts: 1) evaluating in the three HRI scenarios; and, 2) a focus group activity. Participants initially received a participant information sheet, consent form, and Zoom link before each meeting. In the evaluating HRI scenarios, participants completed the following steps:

(1) Participants completed the demographics questionnaire.
(2) Participants watched the HRI video.
(3) Participants completed the questionnaire to rate the robot using TPS and TRS respectively.

[2] https://calendly.com

Table 1: Frequency of factors affecting trust across the three scenarios in study 1 and study 2. 'R' refers to Robot, 'H' refers to Human and 'E' refers to Environment.

Scenario	Study 1			Study 2		
	H	R	E	H	R	E
1	3	22	4	4	33	5
2	5	15	1	7	28	9
3	2	14	2	5	25	7

(4) Participants wrote the factors affecting their trust in robots in the demonstrated interaction.
(5) Participants repeated steps 2, 3, and 4 for the other two scenarios.

Focus group activity: At the end of the workshop, we used the mini-group discussion method. The three participants with sufficient knowledge of the topic were asked to discuss the factors affecting trust in the three different scenarios after watching each video in the light of Hancock's model of trust. The groups discussed the following themes in each scenario: 1) Human-related factors, 2) Robot-related factors, and 3) Environment-related factors. The participants had an opportunity in each scenario to discuss their thoughts, and we recorded the discussion to analyse the data. The average duration of each group discussion was 20 minutes.

3.4 Measurements

To measure trust and examine changes in trust between different situations, we used the TPS developed by Schaefer [38]. We asked participants to complete the TPS questionnaire to rate their trust in the robot in each scenario. The scale has 40 items and a subscale of 14 items (function successfully, act consistently, reliable, predictable, dependable, follow directions, meet the needs of the mission, perform exactly as instructed, have errors, provide appropriate information, malfunction, communicate with people, provide feedback, and unresponsive) to rate the robot as a percentage. This study used the 14 items subscale because it had the most relevant factors according to the scenarios depicted in the video. Following the instruction given in [38], we computed the trust score by first reverse coding the 'have errors,' 'unresponsive,' and 'malfunction' items, then summing the 14 item scores and dividing by 14.

To measure the relevance of trust, we asked participants to rate the relevance of trust in each scenario on a 5-point Likert-like scale. The scale ranged from *not at all relevant* to *very relevant.*. We coded the frequency of the factors affecting trust across the three settings. We grouped the frequencies for the three themes (human, robot, & environment). This measurement was regarded as "factors" affecting user's trust. We used NVivo 12 software to code the qualitative data to explore the factors influencing human trust in robots.

4 RESULTS

4.1 Quantitative findings

4.1.1 Study 1 (Saudi Arabia). To test **H1**, we conducted a Chi-Square Goodness of Fit Test to determine whether the frequency of human, robot and environment related factors was equal between the three scenarios. The frequency data can be seen in Table 1. We did not find a significant difference among the frequencies of human-related factors, robot-related and environment-related factors across the three scenarios: χ^2 (2, 18) = 1.40, p = 0.49. χ^2 (2, 18) = 2.23, p = 0.33, χ^2 (2, 18) = 2.0, p = 0.37.

To test **H2**, we conducted a one-way analysis of variance (ANOVA) to compare the TPS and TRS across the three scenarios. We found a statistically significant effect of scenarios on the TPS across the three conditions F(2,51) = 3.9, $p < 0.05$. We also conducted a post-hoc test to understand the difference between scenarios. The test indicated that the TPS for scenario 2 was significantly lower than scenario 1 and scenario 3. However, the TPS in scenario 1 did not differ significantly from scenario 3.

We found a statistically significant effect of scenarios for TRS across the three conditions F(2,51) = 11.11, $p < 0.05$. A post-hoc analysis indicated that the trust relevance for scenario 3 was significantly higher than scenario 1 and scenario 2. However, the trust relevance in scenario 1 did not differ significantly from scenario 3. The mean (M) and standard deviation (SD) can be found in Table 2.

4.1.2 Study 2 (United Kingdom). To test **H1**, we conducted a Chi-Square Goodness of Fit Test to determine whether the frequency of human, robot, environment related factors was equal between the three scenarios. The frequency data can be seen in Table 1. We did not find significant differences among the frequencies of human-related factors, robot-related and environment-related factors across the three scenarios, χ^2 (2, 18) = 0.8, p = 0.64. χ^2 (2, 18) = 1.14, p = 0.56, χ^2 (2, 18) = 1.14, p = 0.57.

To test **H2**, we conducted a one-way analysis of variance (ANOVA) to compare the TPS and trust relevance score across the three scenarios. We found an non-significant effect of scenarios on the TPS across the three conditions F(2,51) = 2.670, p = .079. We found a statistically significant effect of scenarios for trust relevance across the three conditions F(2,51) = 3.74, $p < 0.05$. A post-hoc analysis indicated that the trust relevance score for scenario 1 was significantly higher than scenario 3. The M and SD can be found in Table 2.

4.1.3 Results – comparing Studies 1 and 2. To test **H3**, an independent samples t-test was conducted to compare the TPS and trust relevance score across the two studies. The findings show there was a significant difference in the TPS for scenario 1 (t(34) = -2.0, p = 0.05.), scenario 2 t (34)=-2.23, p = 0.03.), and scenario 3 (t (34)=-2.08, p = 0.04.) in study 1 and study 2, respectively. There was a significant difference in the TRS for scenario 1 (t(34) = -1.9, p = 0.05), scenario 2 t(34)=-1.87, p = 0.05.), and scenario 3 (t (34)=4.13, p < 0.001.) in study 1 and study 2, respectively. Overall, both TPS and TRS varies across cultures. The mean and standard deviation for both scores in both studies can be seen in Table 2.

4.2 Qualitative findings

The analysis process was as follows: 1) We transcribed the audio of the group discussion and uploaded transcription files to NVivo. 2) We created the themes that were derived from the Hancock model: human-related, robot-related, and environment-related factors. 3) Author 1 coded the transcripts. 4) Author 3 reviewed the codes to ensure they were relevant to the trust factors and assigned them to the appropriate themes. Here we discuss both studies' results for

Table 2: Mean (M) and standard deviation (SD) of TPS score and relevance score across the three scenarios in Studies 1 and 2.

Scenario	N	TPS score M		TPS score SD		TRS score M		TRS score SD	
		Study 1	Study 2	Study 1	Study 2	Study 1	Study 2	Study 1	Study 2
1	18	0.76	0.78	0.15	0.11	4.11	4.67	0.96	0.69
2	18	0.66	0.77	0.16	0.13	3.50	4.11	1.04	1.28
3	18	0.78	0.82	0.12	0.17	4.83	3.72	0.38	1.07

each theme and later compare with each other. The participants for both studies were coded as Participant (P), P1, P2, P3, ..., P18, respectively. To ensure transparency and open science framework we have made the data analysis sheet available.[3] In Table 3, based on the qualitative analysis, we list participants' identified factors influencing human trust in robots.

4.2.1 Study 1 (KSA). **Human-related factors.** Participants identified **controllability** as a novel ability-based factor in all three scenarios. In scenario 2, two out of 18 participants highlighted the importance of the amount of control humans have in the robots. P1 commented "the reason for trusting the robot in this scenario is that the healthcare practitioner is involved in the process and can intervene to stop the robot if needed". In scenario 1, two participants pointed out the importance of controllability to maintain safe operations. P9 commented "if there is an issue in the robot, the user should take control to stop the robot". One participant in scenario 3 considered familiarity an essential factor. P13 reported "wider use of robots in manufacturing can increase user's trust".

In addition, in line with Hancock et al. [17], two participants mentioned that prior experience with robots will influence human trust in scenarios 1 and 2. In scenario 1, P9 mentioned "the user should have some experience and knowledge about the robot". In scenario 2, P2 said "the doctor seems to have no experience using the robot, and that could cause trouble". In Figure 2, we can clearly see that factors did vary across different scenarios. For instance: situational awareness was only considered important for scenario 2 by two participants. P14 stated "the community's awareness could affect the use of robots, especially in healthcare". P17 mentioned "people understanding robots and how they work in healthcare is important to trust the robot".

Robot-related factors. Participants identified new performance-based and attribute-based robot-related factors that were not found in Hancock model of trust [17]. Performance-based factors included noise and th robot's energy source. Brand value was identified as an attribute-based factor. One participant in scenario 1 considered noise as an important factor. P6 mentioned "noise is one of the factors to be considered because in this case, the robot is very noisy". Six participants in scenario 1 and 2 considered the robot's energy source as a significant factor affecting user trust. Participants believed that the robot's battery must be qualified to operate the robot to assist people, particularly in outdoor environments. For instance, P16 stated "battery life is the critical element while designing such a system: what if the dog ran out of battery, how does the blind person get home?". P18 also reported the brand value in scenario 1: "the company that makes the robot in the guiding scenario will influence my trust. If Facebook or Google makes the robotic guide robot, my trust will be low because these two companies have a terrible reputation with privacy." Furthermore, performance-based factors including mode of communication and failure rate were commonly presented in all scenarios. Three participants mentioned the mode of communication in all scenarios. For example, P8 stated "in terms of giving feedback, robot dog should communicate verbally to the blind user". Six participants also presented the behaviour factor in scenarios 1 and 2. Participants described the robots' behaviour as speed, smoothness of the movements, precision and following of direction. In scenario 1, P2 stated "robot should respond quickly". P9 mentioned "the robot should choose the correct path". In scenario 2, P15 reported "the robot's movement should not be slow" and another mentioned:"the robot's movement should be fast and precise". In Figure 2, we can clearly see that factors did vary across different scenarios. For example, noise and brand value were only considered in scenario 1.

Environment-related factors. Risk was the only task-based factor that differed from Hancock's model of trust [17]. In scenario 1, P6 commented the robot's malfunction could lead to serious damage for human and environment. In addition, the participants' responses aligned with the factors identified in [17] regarding team performance, physical environment, and task type. P9 mentioned "the physical environment is essential for trust, and that includes path, object, and the type of connection between humans, and all these elements should be working well". To compare the three scenarios, Figure 2 shows that the factors related to the environment varied across scenarios. For instance, the task type was reported important in scenario 1. P12 said "the type of task could affect trust even if the robot is the same". In scenario 3, one participant considered team performance as a team-collaboration factor influencing trust. P17 mentioned "the team performance is fantastic, and this will increase the confidence to use and work with robots".

4.2.2 Study 2 (United Kingdom). **Human-related factors.** Participants identified controllability, accountability, the user's condition and familiarity as factors affecting trust in robots. Interestingly, there was no one common human-related factor across the three scenarios. However, in scenarios 2 and 3, five participants considered controllability as extremely important. For instance, P4 said "a human being present with the patient influences the degree of trust that the patient gives to the robot". In scenario 2, one participant felt that the user's condition was important: P5 reported "the patient's health condition can affect the interaction". One participant highlighted accountability as a significant factor: P8 mentioned "in scenario 2, the leader will be responsible for the interaction". In scenarios 1 and 3, four participants highlighted familiarity as an important factor: P11 stated "the everyday use of robotics in a manufacturing setting can lead to a high degree of trust."

[3]https://drive.google.com/drive/folders/1G4v5jDZSxCrEkcQ3MjZKFgNTL-FT4Zkc

Table 3: Frequency of factors affecting human trust in robots across the three scenarios for Study 1 and Study 2.

Themes	Sub-themes	Study 1 - Initial codes (Frequency)	Study 2 - Initial codes (Frequency)
Human-related factors	Ability-Based	Controllability (5)	Controllability (5)
		Prior experiences (2)	Prior experience (1)
		Situation awareness (2)	Situation awareness (2)
		Familiarity (1)	Familiarity (4)
			Accountability (1)
			User's condition (1)
	Characteristics-Based	Culture (2)	Culture (2)
Robot-related factors	Performance-Based	Behavior (6)	Behavior (20)
		Reliability (6)	Reliability (20)
		Predictability (2)	Predictability (1)
		Mode of communication (2)	Mode of communication (8)
		Failure rate (19)	Failure rate (18)
		Noise (1)	Noise (1)
		Robot's energy source (6)	Robot's energy source (2)
		Level of automation (1)	Dependability (3)
			Consistency (7)
			Usability (4)
	Attribute-Based	Adaptability (4)	Adaptability (1)
		Robot type (1)	
		Brand value (1)	
Environment-related factors	Team Collaboration	Team performance (2)	Team performance (2)
	Tasking	Task type (1)	Task type (3)
		Risk (1)	Risk (8)
		Physical environment (2)	Physical environment (5)
		Multi-tasking requirements (1)	Choice of use (2)
			Clarity of task (1)

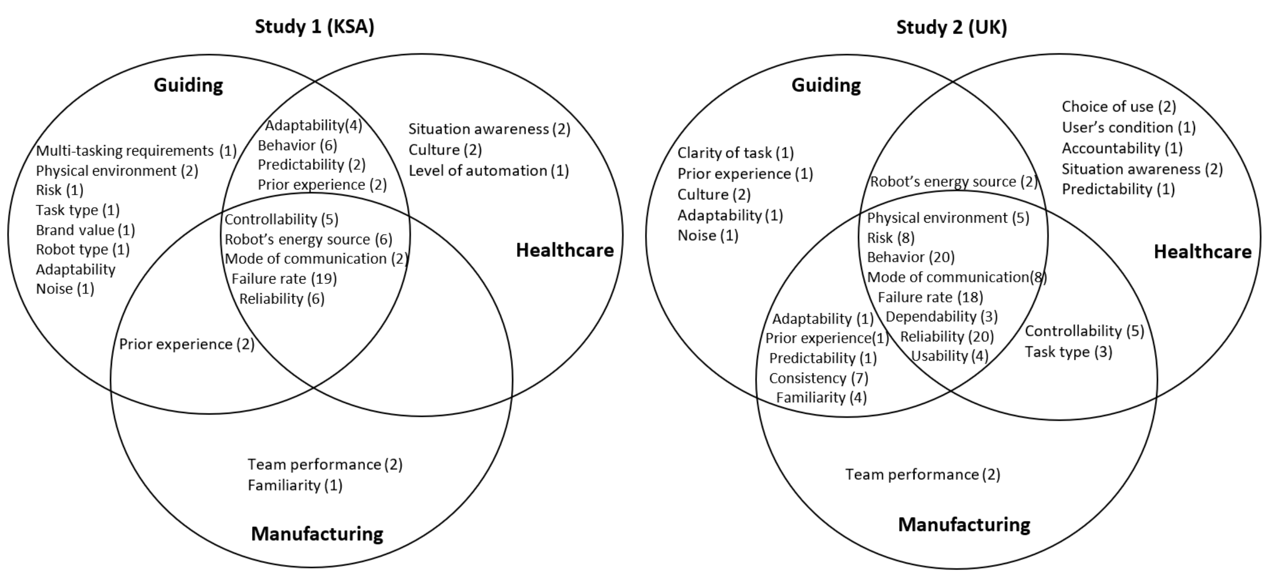

Figure 2: Commonalities and differences among factors affecting human trust in robots across three scenarios in Studies 1 & 2.

Robot-related factors. The findings represent five common factors in all scenarios in line with Hancock's model of trust [17]: behaviour, mode of communication, dependability, failure rate, and reliability. In addition, the analysis identified new performance-based factors, including consistency, usability, noise, and the robot's energy source. Seven participants considered consistency as a critical factor influencing user trust in scenarios 1 and 3. For instance, P11 stated "in scenario 1, I see the consistency is important, does the dog keep moving forwards towards the goal, or does it keep shuffling back?". Four participants reported usability as an important factors. P4 mentioned "has the robot been demonstrated that it's more efficient than human?". Two participants considered the robot's energy source as significant in scenarios 1 and 2. P3 mentioned "the robot's battery should be considered while designing the robot". P6 reported noise in scenario 1 "the dog robot is noisy; that could affect the use and trust". In general as shown in Figure 2, we can clearly see that factors did vary across different scenarios. For example, noise was only considered in scenario 1.

Environment-related factors. The findings identified new ability-based factors including risk, the clarity of task and the choice of use. The risk factor was common in all scenarios, and eight participants mentioned this. Participants believe autonomous robots can represent more risk to people, mainly when close to them. For example, P1 reported "in scenario 1, if the robot stops working in a bustling road that is a hazard". In scenario 1, P9 stated the clarity of the task "the task should be straightforward and align with the object". P16 also mentioned the choice of use in scenario 2 "choice of use is one of the factors that might influence trust because using robots is not always an option". Participants' responses aligned with Hancock's model [17] regarding team performance, the physical environment and task type. The physical environment was shared in all scenarios. The physical environment includes path, object, and the type of connection between human and robot based on participants' explanations. The task type was a common factor in scenarios 2 and 3. As we can see in Figure 2, environment-related factors varied across the three scenarios. For example, clarity of task was only considered in scenario 1, whereas the choice of use was only in scenario 2.

4.2.3 Results – comparing studies 1 and 2. When comparing the two studies, we find new factors that were not included in [17]. Participants mentioned controllability (59% of times) followed by familiarity (29% of times) in both studies as significant human factors affecting their trust in the robot. Interestingly, controllability was considered important in all three scenarios in study 1, but in study 2 it was considered important only in scenarios 2 and 3. Likewise, familiarity was raised once in scenario 3 in study 1, but was cited more frequency in scenario 1 and 2 in study 2 (see Figure 2). For robot-related factors, participants mentioned the robot's energy source (36% of times), consistency (32% of times) and usability (18% of times). Similar to the human-related factors, participants did not consider these factors in all scenarios. In study 1, energy source was highlighted in all scenarios. On the contrary, energy source was cited only in scenario 1 and 2 in study 2 (see Figure 2). Lastly, for environment-related factors, risk (75% of times) turned out to be the most frequently stated factor affecting a participant's trust in the robots. Intriguingly, risk was considered important in scenario 1 in study 1 while in study 2, participants deemed it important in all the scenarios (see Figure 2). Table 3 further highlights the common factors among the two studies. In summary, the qualitative analysis indicated cultural differences in the two studies when highlighting the importance of factors affecting trust across different scenarios. In addition, the analysis identified the significance of a factor based on how frequently it was stated by participants; however, we remain conscious that more empirical evidence is needed to establish the significance of a given factor affecting trust. The percentage of the frequency of a new factor was computed by dividing the number of times a new factor was highlighted by the total number of new factors highlighted for a certain type of factor (human, robot, or environment) in both studies.

5 DISCUSSION

5.0.1 Quantitative findings. **H1** indicated that the frequency of factors affecting trust would vary across the three HRI settings. We show that the number of factors (human-, robot-, environment-related) in the two studies did not differ significantly across the scenarios. Hence, H1 was rejected in the light of frequency analysis. Regardless, we see several significant trends and discuss them through the lens of both quantitative and qualitative findings. First, interestingly, robot-related factors were found to be most frequently highlighted in both studies. This finding is comparable with Lewis et al. [26], which has shown that robot-related factors are the most influencing factors affecting trust in robots. Second, although the number of factors did not differ across scenarios, the qualitative insights provide evidence that factors affecting users' trust vary across different HRI scenarios. We can clearly see from the analysis that several factors were considered important in one scenario but not in another (see Figure 2). For instance, Noise was considered important in scenario 1 in both studies but not in scenario 2 and 3. Lastly, and intriguingly, the number of robot-related and environment-related factors was significantly higher in study 2 when compared to study 1. This suggests that participants in the UK stated more and new factors (consistency, usability, and clarity of task) compared to the participants in KSA. All of these finding highlight the multi-facetedity of trust as a construct and reflect on the challenge of measuring it in different HRI settings [1].

H2 predicted that trust in the robots would differ across the three HRI settings. We did see a significant variation of TPS in study 1 but a non-significant variation of TPS in Study 2. Hence, H2a is partially accepted. This finding builds on the existing work that highlights how users' trust ratings vary across different tasks [35, 40, 47]. We see that participants' TPS only differed significantly between scenario 2, scenario 1 and scenario 3 in both studies. It is worth highlighting that scenario 2 dealt with a healthcare context. We speculate that participants were more cautious when trusting robots in healthcare settings. Past work shows that the adoption of robots in healthcare raises performance expectancy, trust, privacy and ethical concerns [4, 30]. It was also intriguing to see that TPS was highest in scenario 3 (manufacturing), followed by scenario 1 (guiding) in both studies. This finding builds on existing literature that has reported how participants assign stereotypes towards robots based on their body shape [8] or their context of use or prior experience [2]. Hence, in this case, participants may have held positive notions about robots in manufacturing or guiding blind users, and this may have resulted in a higher trust score.

The TRS varied significantly across scenarios in both studies. Hence **H2b** was accepted in both cases. Intriguingly, trust was considered least relevant in scenario 2 in study 1 and scenario 3 in study 2. We speculate that due to the teleoperated nature of the robot in scenario 2, overall, participants may have found it to be less relevant as a human had control of the robot. This was also reflected in their comments described in the qualitative findings. In contrast, we speculate due to participants' backgrounds (living in the UK) and their prior experience, scenario 3 (manufacturing) was regarded least relevant in study 2. We understand that people in Europe are more familiar with industrial robots than those in the Arab regions. Comparability, we see a higher level of progression in terms of the use of robots in manufacturing in the UK [14].

The finding further demonstrated compelling trends. In particular TPS was directly proportional to TRS. It suggests an increase in TPS will cause an increase in TRS or vice versa. Surprisingly, participants in study 1 gave a lower TPS and TRS in scenario 2, and this was in contrast with other scenarios. We understand that participants may have found the healthcare scenario less relevant and therefore showed lower trust in the robot. It suggests participants' trust in a robot is dependent on their perception of the relevance (less or more) of the robot in a given setting.

Lastly, **H3** indicated that participants' TPS and TRS would vary significantly across cultures. The analysis confirmed that the TPS and TRS differed significantly across the two different regions. Hence, H3 is accepted. These findings are in line with related work results. (e.g, [6, 27, 44] which also shows that multiple factors associated with an individual's culture affect their perception of trust in robots. Further, the findings show that the TPS scores in all scenarios were higher in study 2 than in study 1. Previous studies have shown that participants from Western countries show more trust in robots compared to participants from Eastern countries [20]. In particular, Andrist et al. [6] has shown that Arab participants were more critical of social robots' credibility compared to US participants. These findings also help clarify this trend.

5.0.2 Qualitative findings. We found new factors related to humans, robots and the environment. The human-related factors included controllability, familiarity, the user's condition and accountability. In both studies, participants considered controllability as an important human-related factor in all scenarios except scenario 3 in study 2. We see work in HRI, particularly on measuring or modelling trust in real-time, and found that the amount of control a human operator has in the interaction or the number of times a human takes control during HRI is an indication of their trust [15, 22]. But, interestingly, it is important to understand how much control is sufficient in order to build trustworthy robots; and, how this varies across different settings [7]. Participants also highlighted accountability as one of the factors. Accountability can be well connected with the amount of control human will have in an autonomous robots. Perhaps, this finding helps us think and reflect on the aspect of responsibility in the case of an incident [32, 33].

The robot-related factors included energy source, consistency, usability, noise and brand value. The environment-related factors included task clarity, choice of use, and risk. Brand value was the only new factor in study 1. We found that individuals belonging to Arab culture care more about brands than Europeans [5] and believe that this explains the given finding. The risk factor was common in both studies. Participants believed that the degree of risk involved in a task can affect their trust. For example, in the guide robot scenario, all participants in both studies reported risk because the blind human was in a vulnerable situation. Other factors identified the vulnerability of such a robot's energy source. For instance, participants were worried about the battery life of the robot in the guide robot scenario. Since we analyse our data in the light of Hancock et al.'s model [17], we consider risk to be a new factor. It is interesting to note that recent work also reflects on the role of risk in human robot trust [19, 42]. We also see common factors in study 1 and 2 that can be seen in Hancock et al.'s model of trust [17] (see Table 3). Reliability and failure rate were presented in all scenarios in both studies. According to Washburn et al. [45], reliability and errors rate factors are related to each other and have a strong relationship with human trust. All participants in both cultures stated the mode of communication factor in all HRI as a significant factor. For example, participants suggested that the robot communicate verbally since the user is blind. We posit that when the user has a proper way to communicate with the robot and receives clear feedback, the level of trust will increase significantly. In summary, the take-away finding from this work is that not all factors are relevant for all HRI scenarios due to the differences in the nature of the setting and the degree of risk and vulnerability presented.

6 CONCLUSIONS, LIMITATIONS AND FUTURE WORK

In this paper, we investigated how participants' trust varies across three different human-robot interaction (HRI) settings (a dog robot-guided blind people, a teleoperated robot in healthcare, and a manufacturing robot). We also studied how this trust varies across two different cultures (Saudi Arabia (KSA) and the United Kingdom (UK)). In addition, we investigated how factors affecting users' trust differ across HRI settings and cultures. We conducted two studies: one in KSA and one in the UK. We found the following: 1) participants' trust perception differed across HRI settings in the KSA study but not in the UK study. 2) Participants identified several "new" factors that affect their trust in robots in both studies across the three settings. These findings are thought-provoking and highlight the importance of the multifacetedness of the metric known as "trust". The findings also highlight that the dynamic nature of a given HRI setting (healthcare, manufacturing or guiding) can challenge the idea of a one-size-fits-all model for human-robot trust. Furthermore, they reflect that the models of human-robot trust should consider a dynamic and evolving design because it presents a great challenge to cover all factors in a single one.

In both studies, the attributes of participants were limited. They were all academics and students in a Computer Science department, and of a similar age group. Future work will consider replicating this work across diverse cultures, and will also involve participants from more diverse backgrounds. Future work will continue to consider HRI contexts presenting varying risks and vulnerabilities. We hope that the outcomes of these studies will help us understand novel factors affecting trust, and will later enable the HRI community to conduct empirical studies to ascertain the value of these factors that could affect users' trust in robots across diverse settings.

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