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How Many Robots Do You Want? A Cross-Cultural Exploration on User Preference and Perception of an Assistive Multi-Robot System

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***Abstract*—There has been increased development of assistive robots for the home, along with empirical studies assessing cultural differences on user perception. However, little attention has been paid to cultural differences with respect to non-humanoid, multi-robot interactions in homes or otherwise. In this exploratory paper, we investigate how cultural differences may impact users' preferences and perceived usefulness of a multi-robot system by creating an interactive online survey and considering variables often absent in HRI studies. We introduce our multi-robot design and survey construction, and report results evaluated across 191 young adult participants from China, India, and the USA. We find significant effects of culture on both participants' preferences and perceived usefulness of the system between India and China or the USA, but not between China and the USA. We also find effects of culture on perceived usefulness to be partially mediated by participant preferences. Our findings reinforce the importance of considering cultural differences in designing domestic multi-robotic assistants.**

I. Introduction

Assistive technology for the home has long been a focus for Human Robot Interaction (HRI) researchers, who are developing both humanoid (e.g., [1]) and non-humanoid robots (e.g., a robotic walker [2]). Studies have also investigated reactions of users, such as elderly people with mild cognitive impairment [3], toward robotic assistants. While there have been efforts in developing multi-robot system (MRS) across various scales, such as [4] and [5], there is a lack of studies investigating user perceptions when assisted by a MRS. Such exploration needs to consider novel parameters not commonly included in single robot interaction studies, such as robot group shape and size. In addition, user's cultural background is also an important factor to consider when studying HRI in domestic settings. There have been many investigations on the relationship between cultural differences and user behaviors and preferences (e.g., [6]). However, it is not known how cultural differences may play a role in influencing user preferences and perceptions when interacting with a MRS.

The aim of this paper is to explore the relationship between cultural differences and user preferences and perceived usefulness of SORT ("Self-Organizing Robot Team"), a multi-robot, domestic "organizer" system we are developing (reported in [7]). Each robot (Fig. 1) is composed of two cylindrical units connected by a rotation arm with containers

Figure 1. **Left**: One SORT robot prototype. **Right**: One SORT robot delivering an item to a user.

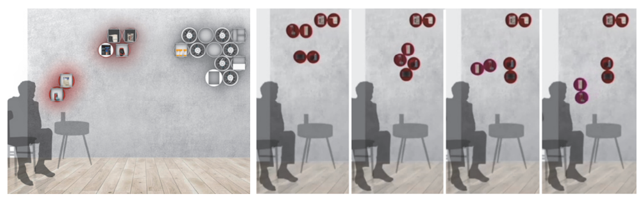

Figure 2. **Left**: Concept rendering showing a group of SORT robots. **Right**: Screen captures of animation showing SORT delivering items.

and display disks snapped on via magnets. The robots adhere to smooth wall surfaces by vacuum suction and achieve locomotion by having each unit swing the other one around. The robots can form a larger group to organize, retrieve and deliver items to a user at scheduled times or as wanted (Fig.2). In this paper, we have investigated participants' perceptual differences and preferences of, specifically, SORT's task completion modes, group shapes, speed, group size, usage of storage compartment and perceived usefulness.

Previously, there have been numerous studies exploring the impact of cultural differences on HRI. Almost all of these studies are based on interactions with one or two humanoid robots. One such study explored different cultures' acceptance of and attitudes towards various humanoid robots [8]. Other researchers evaluated domestic assistive robots across cultures for various age groups, such as older adults [9], and for different spaces, such as in a smart home environment [10], to understand agency, attitude, trust, usability, and likeability. Another study has also focused on robot anthropomorphism and likeability among Japanese and American users, where a strong interaction effect was observed between cultural backgrounds and robot types [11]. In a recent review paper [12] in which 50 cross-culture HRI studies were surveyed, only one [13] investigated participants' reactions when interacting with a small group of robots in a public cafeteria,

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including variables such as robot number and group effects. However, researchers in [13] only used up to three robots; it was also not evident that if participants were given the option to determine robot group size, how many robots they would choose, and how the choice may be affected by cultural differences. In addition, none of the surveyed papers, except [6], considered variables' mediating effects.

As shown in [14], using online surveys with robot images and videos can be an effective way to measure users' initial reactions. In addition to allowing the recruitment of large numbers of participants, online surveys are particularly beneficial to human – multi-robot interaction studies where researchers may not have a fully functional MRS and where the Wizard of Oz method is difficult to implement at a group scale. For these reasons, our paper reports on the development and results of a novel interactive, online survey instrument (especially apt during the pandemic period) and fills a gap in cultural difference investigations with non-humanoid and multi-robot systems.

II. METHODS

A. Dependent Measures

We examined the following variables, some of which had not been studied extensively before and are novel to human – multi-robot interactions. Variables (a) through (g) measure user preferences, and variable (h) measures perceived usefulness.

(a) Delivery task mode – sequential: robots deliver items one by one.

(b) Delivery task mode – concurrent: robots deliver all items at the same time.

(c) Group shape – Circle over *Group shape – Random*: previously, much attention had been given to the design of individual robots. However, robots in group can also form various shapes to convey meaning and users may have preferences on different group formations.

(d) Robot speed.

(e) Robot number – Stationary: users may have different preferences for the number of robots in a group.

(f) Robot number – Moving: in addition, users may have different preferences and tolerances for the number of robots that are moving. Participants who select large robot groups may in fact prefer only one or two robots moving at a time.

(g) Storage compartment: as implied from our previous study [7], for items that cannot fit in a SORT container, an additional system of larger storage compartments on a track was provided.

(h) Perceived usefulness: for dependent variables measuring perceived usefulness, we used a validated subscale from [15] with a Cronbach's Alpha of 0.865.

B. Survey Construction

We constructed an interactive online survey in English on Qualtrics (question items are summarized in Fig. 3) which takes 10-15 minutes to complete. We first asked participants for background information including age, self-identified gender, nationality, and if they had lived in their home countries for most of their lives (>90%). We then introduced our multi-robot system, "Self-Organizing Robot Team" (SORT), designed for organizing household belongings, fetching and delivering items to users as scheduled or needed (the robots' design, envisioned use cases and early evaluations are reported in [7]). Three images and one animation video were shown to the participants (Fig. 1 and 2). After the introduction, we asked participants to self-rate their understanding of the robot on a 5-point scale (1 for "I do not understand SORT at all"; 5 for "I understand SORT completely").

To measure variables (a) and (b), participants were asked to view two animations. The first animation showed SORT delivering items one by one in a sequential manner; the second showed SORT delivering all items at once. The participants were then asked to rate how much they liked each option on a

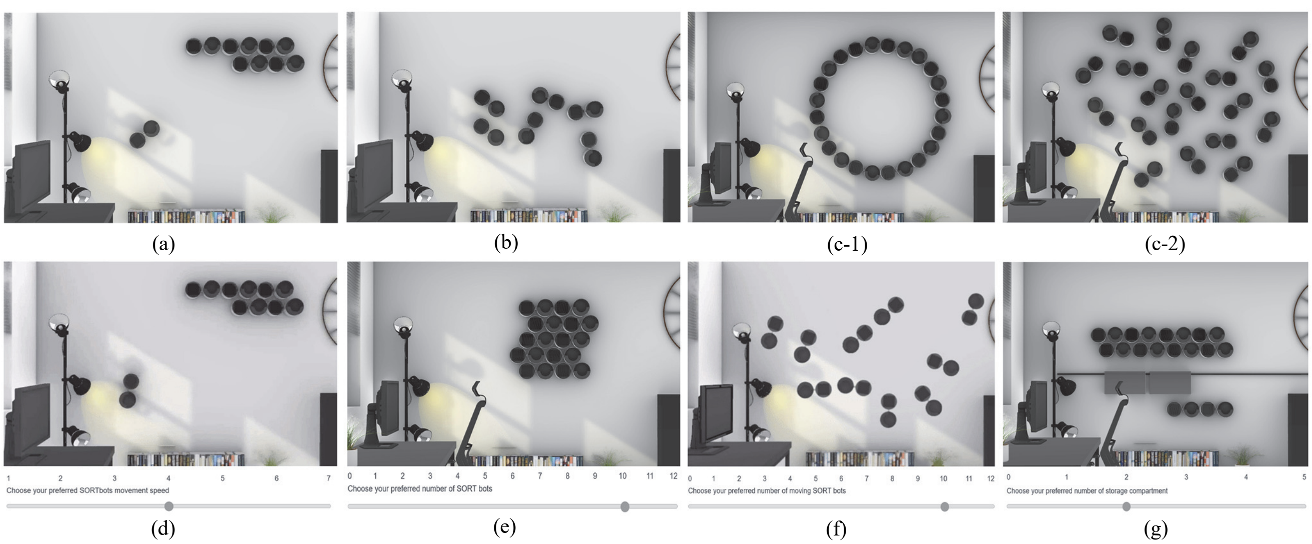

Figure 3. Interactive survey items. **(a)** Delivery task mode – Sequential: animation showing robots deliver items one by one. (**b**) Delivery task mode – Concurrent: robots deliver items all at once. **(c-1)** Group shape – circle. **(c-2)** Group shape – random. **(e)** Speed: animation with slider showing 7 different speed options. **(e)** Robot number – Stationary: image with slider showing group size options (0 to 12). **(f)** Robot number – Moving: animation with slider showing group size options (0 to 12). **(g)** Storage compartment: image with slider showing 0-5 compartments on a track for larger items.

7-point scale (1 for "Dislike a great deal"; 7 for "Like a great deal.") To measure variable (c), participants were asked to view two images, one showing robots forming a geometric circle and the other showing random placements, and then select which one they preferred. For variable (d), seven animated GIFs were created showing various robot speeds, participants were asked to use a slider (1 for slowest; 7 for fastest) to select their favorite speed. For variables (e) and (f), participants were asked to use sliders (ranging from 0 to 12) to select their preferred number of stationary robots from thirteen static images and number of moving robots from thirteen animated GIFs. We selected 12 as the maximum based on our previous interview results [7], however, participants were given the option to enter a response if their preferred robot number exceeded 12. Lastly, for variable (g), participants were asked to use a slider (ranging from 0 to 5) to select their preferred number of compartments on a track. To measure perceived usefulness, three questions adapted from [15] were included on a 7-point Likert scale (1 for "Strongly disagree"; 7 for Strongly agree) including: (1) "I think SORT will be useful to me."; (2) "It would be convenient for me to have SORT."; and (3) "It's good to make use of the SORTbots."

The interactive portion of the survey was developed as a JavaScript addon in Qualtrics. For slider questions, each slider position points to a unique JPEG or GIF file rendered to show various robot properties. This novel presentation feature granted increased freedom and better questionnaire delivery, in lieu of the traditional way of asking participants to imagine various robot effects. A demonstration is included here: https://youtu.be/0ppWPkTUXqQ.

C. *Participants*

We recruited participants via the university's human subjects pool management system (SONA), Amazon Mechanical Turk (with filter criteria >98% and >5000 survey completion) and by campus email. Students responded through the university SONA system received 1 research credit for degree course fulfilment; MTurk workers were paid 2 US dollars per survey (approximately \$0.15 per minute); while individuals contacted by emails were not compensated, they represent a small percentage (3%) in the participant pool. IRB approval was obtained from the university review board. In total, 242 participants from various cultures who are proficient in English answered the survey, 51 were dropped due to incomplete or illogical responses (e.g., age = 1); countries with fewer than 20 responses [16] and participants who self-rated that they did not understand SORT for the most part or they did not understand SORT at all were also excluded. This resulted in 191 responses (137 from university SONA system, 48 from MTurk, 6 from email contacts) being used for analysis. Among them, 117 were females, 74 were males, and the average age was 23.6 (SD=5.4); 164 (85.9%) had lived in their home countries for over 90% of their lives. No participants had seen the robots prior to the study.

III. Results

The data were analyzed using the R language and JASP, an R-based graphic interface. We used library BayesFactor for Bayesian analysis and library Lavaan for Structural Equation Modeling (SEM). We conducted both classical ANCOVA and Bayesian ANCOVA to examine the effects of culture on dependent measures while controlling for age and gender. We used a logistic regression model for binary variable (c) on group shape, and a path analysis to investigate mediating effects for variable (h) on perceived usefulness. The results are shown as boxplots in Fig. 4 and summarized in Table. I with post-hoc results in Table. III, variable (c) is shown in Table. II.

TABLE I. Compiled Results for User Preference and Perceived Usefulness.

Dependent measures	df	F	p	η^2	ω^2
(a)	2	9.14	<0.001	0.09	0.08
(b)	2	4.82	0.009	0.05	0.04
(d)	2	2.15	0.120	0.02	0.01
(e)	2	3.94	0.021	0.04	0.03
(f)	2	4.34	0.014	0.04	0.03
(g)	2	2.96	0.054	0.03	0.02
(h)	2	14.17	<0.001	0.13	0.12

Results for binary variable (c) group shape-circle over group shape-random are shown in Table II.

Note: (a) Delivery task mode – sequential, (b) Delivery task mode – concurrent, (e) Robot speed, (f) Robot number – stationary, (g) Robot number – moving, (h) Perceived usefulness.

TABLE II. Result for User Preference on (c) Group Shape-Circle Over Group Shape-Random.

Preference by culture (compared to India)	Odds Ratio	z	Wald test - df	Wald test -p
China	0.85	-0.29	1	0.77
USA	0.32	-2.29	1	0.02

TABLE III. Compiled Post Hoc Mean Difference Comparisons

Comparison	(a)	(b)	(e)	(f)	(g)	(h)
China - USA	0.5	-0.1	-0.4	0.4	-0.3	0.3
China - India	-1.1*	-1.4**	0.3	-1.9	-2.3	-4.8***
USA - India	-1.6***	-1.3*	0.7	-2.3*	-2.0	-5.1***

* p(tukey) < 0.05, **p(tukey) <0.01, ***p(tukey) <0.001

Note: Results shown are mean differences averaged over the levels of Gender: Female.

Note: (a) Delivery task mode – sequential, (b) Delivery task mode – concurrent, (e) Robot speed, (f) Robot number – stationary, (g) Robot number – moving, (h) Perceived usefulness.

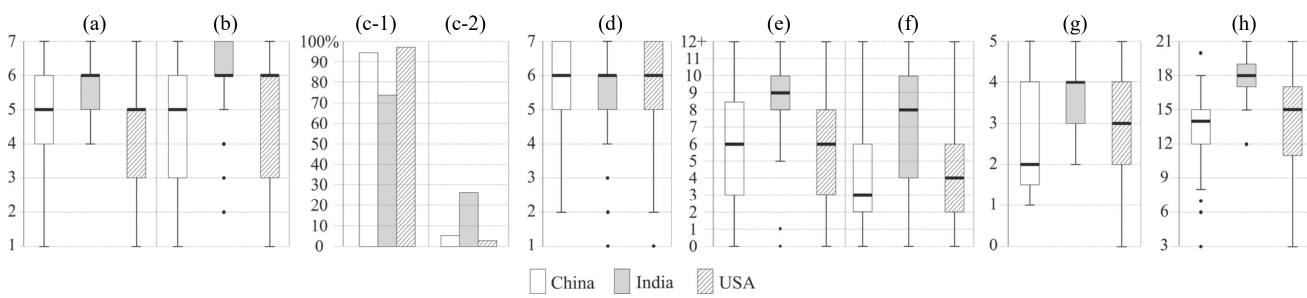

Figure 4. Compiled graph results of: **(a)** Delivery task mode – sequential. **(b)** Delivery task mode – Concurrent. **(c-1)** Group shape – Circle. **(c-2)** Group shape – Random. **(d)** Robot speed. **(e)** Robot number – Stationary. **(f)** Robot number – Moving. **(g)** Storage compartments. **(h)** Perceived usefulness.

A. User Preference

(a) *Delivery task mode – Sequential*. A main effect of culture was found. The difference was significant with medium effect size. Participants showed different preferences: 4.66 (SD = 1.41) for China, 5.73 (SD = 0.67) for India, and 4.29 (SD = 1.61) for the USA. Post-hoc testing using Tukey method revealed significant difference between India and China ($p = 0.01$) or the USA ($p < .001$), but no significant difference between China and the USA ($p = 0.21$).

(b) *Delivery task mode – Concurrent*. A main effect of culture was found. The difference was significant with small effect size. Participants showed different preferences: 4.40 (SD = 1.90) for China, 5.95 (SD = 1.30) for India, and 4.78 (SD = 2.00) for the USA. Post-hoc testing using Tukey method revealed significant difference between India and China ($p = 0.010$) or the USA ($p = 0.02$), but no significant difference between China and the USA ($p = 0.94$).

(c) *Group shape – Circle over Group shape – Random*. A main effect of culture was found. 94.3% Chinese participants, 73.2% Indian participants and 98.3% US participants preferred the circle shape over the random formation. A significant difference between India and USA was observed while coding Random shape as 1. As seen from the odds ratio in Table. II, participants from the USA were only 0.32 ($p < 0.02$) times as likely to choose the circle shape over the random shape compared to participants form India.

(d) *Robot speed*. No main effect was found. The difference was not significant with small effect size. Participants preferred faster speeds on average.

(e) *Robot number – Stationary*. A main effect of culture was found, participants showed different preferences: 6.23 (SD = 3.47) for China, 8.37 (SD = 2.91) for India, and 5.84 (SD = 3.16) for the USA. Post-hoc testing using Tukey method revealed significant difference between India and the USA ($p = 0.019$), but no significant difference between China and the USA ($p = 0.83$) or India ($p = 0.06$).

(f) *Robot number – Moving*. A main effect of culture was found. The difference was significant with small effect size. Participants showed different preferences: 4.20 (SD = 3.37) for China, 7.07 (SD = 3.51) for India, and 4.37 (SD = 2.98) for the USA. Post-hoc testing using Tukey method revealed significant difference between India and China ($p = 0.01$) or the USA ($p = 0.04$), but no significant difference between China and the USA ($p = 0.89$).

(g) *Storage compartments*. A weak main effect of culture was found, the difference was only marginally significant with small effect size. Participants showed different preferences: 2.66 (SD = 1.39) for China, 3.51 (SD = 0.87) for India, and 2.77 (SD = 1.41) for the USA.

(h) *Perceived usefulness***.** A main effect of culture was found. The difference was significant with large effect size. The three Likert scale results were added together with range from 3 to 21. Participants showed different preferences: 13.40 (SD = 3.85) for China, 17.85 (SD = 1.81) for India, and 13.80 (SD = 4.43) for the USA. Post-hoc testing using Tukey method revealed significant difference between India and China ($p < .001$) or the USA ($p < .001$), but no significant difference between China and the USA ($p = 0.941$).

B. Bayesian ANCOVA

We conducted non-parametric Kruskal-Wallis tests since outcomes for variable (a), (b) and (g) did not pass Levene's test for homoscedasticity ($p < 0.05$), and we found significant differences for all three tests ($p < 0.005$). We also observed similar results from Bayesian ANCOVA results where the models with culture variable as predictors were favored over the models without culture variable. This serves as confirmation for our classical ANCOVA results reported above.

C. Mediation Effect

We conducted Structural Equation Modeling to explore how the effect of culture on perceived usefulness was mediated by preferences for different delivery task modes (a), (b) and storage compartments (g). We coded the culture variable as 1 for India, and 0 for China and the USA since we did not find any significant difference between China and the USA in any of our post-hoc tests. We allowed residual covariance between (a) and (b) due to the similarity between the two questions. Covariance results are shown in Table IV.

TABLE IV. COMPILED COVARIANCE

	Culture	**(a)**	**(b)**	**(g)**	**(h)**
Culture	0.17	-	-	-	-
(a)	0.23	2.33	-	-	-
(b)	0.21	0.62	3.68	-	-
(g)	0.13	0.36	0.17	1.81	-
(h)	0.70	2.89	3.88	2.11	18.06

Note: (a): Delivery task mode – sequential. (b): Delivery task mode – Concurrent. (g): Storage compartments. (h): Perceived usefulness.

Here we proposed and validated a model (Fig. 5) where the effect of culture on perceived usefulness – variable (h) was partially mediated by delivery task modes – variables (a) and (b), and storage compartment – variable (g). As shown in Table. V, the model fits the data well. Robot speed – variable (c), group shape – variable (d), and group size – variables (e) and (f) were non-task related preferences that bear weak mediating effects on usefulness and, hence, were excluded. The model indicates that 64.7% of the effect was mediated: 24.7% by (a) delivery task mode – sequential, 24.4% by (b) delivery task mode – concurrent, and 15.6% by (g) storage compartments. Both direct and indirect effects are significant at 0.01 level. We also compared the proposed model with a competing model where the effect of culture was fully mediated, without the direct path from culture to usefulness. The competing model fits the data only marginally well, $\chi 2$ (3, n=191) = 7.307, $p = 0.063$, and is significantly worse than the proposed model: $\chi_{diff2} = 5.487$, $df_{diff} = 1$, $p = 0.020$.

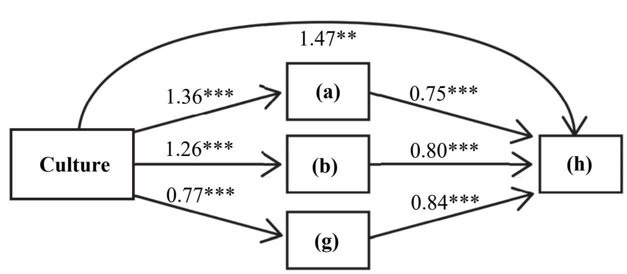

Figure 5. Path diagram of partially mediated model. **(a)** Delivery task mode – sequential. **(b)** Delivery task mode – Concurrent. **(g)** Storage compartments. **(h)** Perceived usefulness. **: $p < 0.01$, ***: $p < 0.001$.

TABLE V. COMPILED SEM RESULTS

	χ2	p	GFI	AGFI	NFI
Fit measures	1.82	0.402	0.995	0.965	0.989
Ideal threshold *		>0.05	>0.95	>0.95	>0.95
	NNFI	**CFI**	**RMSEA****	**SRMR**	
Fit measures	1.006	1.000	0.000	0.024	
Ideal threshold *	>0.95	>0.95	Close to 0	<0.05	

* Ideal thresholds indicate range for a good fit model.

** 90% Confidence Interval from 0.000 to 0.139 with a p value of 0.556

Note: Goodness of Fit (GFI) and Adjusted Goodness of Fit (AGFI) indicate the adjusted proportion of variance as accounted for by the estimated population covariance. Normed-Fit Index (NFI) and Non Normed-Fit Index (NNFI) indicate the improvement of fit by the model of interest relative to the null model. Comparative Fit Index (CFI) is a revised form of NFI that is not very sensitive to sample size. Root Mean Square Error of Approximation (RMSEA) is a parsimony-adjusted index. Standardized Root Mean Square Residual (SRMR) is the standardized square-root of the difference between the residuals of the sample covariance matrix and the proposed model.

IV. DISCUSSION

A. Implication

Participants from India, compared to China and the USA, showed higher favorability toward both delivery task modes, a comparatively higher preference for random group shape over the circle shape, about equally high preference on robot speed, and higher preference on larger group size, storage compartment numbers and higher perceived usefulness of the SORT system. With these findings in mind, we also acknowledge that it is impossible to create a unique robot for each culture. Instead, the results provided here contribute to the robot design process whereby focusing on adapting soft parameters, such as robot group behaviors, to specific user groups, we may be able to create more culturally appropriate and considerate interactions for all stakeholders.

The differences in delivery task modes and robot numbers may be attributed to the person's polychronic (multi-tasking) or monochronic (one thing at a time) orientation. Monochronic countries such as the USA [17], were expected to prefer lower robot numbers and rate robot single-tasking more favorably. However, as our results contradict this stereotype, we acknowledge that it is becoming increasingly difficult, if not impossible, to classify an entire society as polychronic or monochronic. As noted in [17], being aware of cultural differences is an important first step in fostering mutual understanding and productive cross-cultural interaction. Similarly, for robot speed where participants from all three cultures preferred faster options on average, the result contradicts stereotypes about India as a polychronic oriented culture that perceives time as non-linear [18] where a preference for slower robot speed was expected. These results imply that prior theories or assumptions may not be readily applicable in creating hypotheses for human multi-robot interactions across cultures. As previous studies, such as [19], had demonstrated, in the transfer of culture-based knowledge from Human-Human Interaction to HRI, sensitivity to cultural differences is necessary for future studies to avoid biases and stereotypes in designing interactive multi-robot systems.

Our study also uncovered results that are unexpected and require further examination. We learned that 26.8% of participants from India preferred the random group shape over the geometric circle, whereas the percentage for China (5.7%) and the USA (1.7%) were significantly smaller. Also, on average, participants from India want more robots and have higher tolerance for robots moving simultaneously. While the survey question used was depicting a specific scenario and room environment, the participants may be thinking about their own environment and ways of completing the same tasks, which could be very different based on cultural customs.

Previous literature had classified societies as Low context (Western) and High context (Asian) [20], where such concept was used in many cross-culture HRI studies such as [6]. However, we found no difference between participants from China and the USA, and a significant difference for participants from India compared with the other two countries, which suggests that previous comparisons of "East vs. West" maybe an over-simplified model. "Asia" or the "East" carries broad social, political, demographic, historical and religious differences such that it is difficult to provide an all-encompassing definition for what constitutes an Asian culture.

In addition, previous cross-culture HRI studies primarily included participants from developed regions where people may have become more familiar and comfortable with the concept of being assisted by robots. As shown in the review paper that surveyed 50 cross-culture HRI studies [12], very few included participants from developing regions: one study included Kazakhstani and another considered Pakistani, while two included participants from India, which is a populous and quickly developing region with great potential for the growth of domestic assistive technologies. Understanding cultural differences and user needs for these countries, where the deployment of domestic robots must follow local customs, would be an important step forward for human multi-robot interaction designs.

Lastly, variables (a), (b), and (g) were found to be mediating the effects of culture on perceived usefulness. This model demonstrates that including mediators in statistical analysis for cross-culture HRI studies can be beneficial in uncovering relationships and exploring underlying mechanism by which one variable influences another variable.

B. Limitations

There are a few limitations. First, participants recruited may not fully represent their respective cultures. Even though 85.9% of the participants self-rated that they had lived in their home countries for most of their lives (>90%), it was unknown how much influence they have received from foreign cultures, especially as young adults who can easily access information via the internet. It was also unknown how well the remaining 14.1% participants have integrated into a foreign society (e.g., Chinese international students who have studied in the US for years). In addition, all three countries included in this study have rich and diverse internal cultures across large population sizes, and participants may come from distinct families and religious backgrounds. The participants recruited were not very balanced: among the 115 US participants (85 females, 30 males), most responded through the university participant management system (SONA), representing college students with a mean age of 20.7 (SD=3.1). Among the 35 Chinese participants (26 females, 9 males), some were contacted through emails (6) while others responded through SONA, with a mean age of 26.1 (SD=4.9). Among the 41 Indian participants (6 females, 35 males), the majority responded through MTurk with a mean age of 29.7 (SD=4.9). This difference in recruitment platform may have partially contributed to the significant results observed in the Indian participant sample, which needs to be explored further. In addition, the scenario constructed for the online survey was based on a living and working space within the home, the results may not generalize to other domestic spaces, and participants may be thinking about their own personal space and use cases while answering the surveys. Similarly, we included only young adults for this study, so the results may not generalize to other age groups. For older adults who might have different exposure and acceptability toward technology and who might better represent the more traditional aspects of their cultures (versus more global tendencies), we anticipate the results and lessons might be very different.

C. Future Work

The variables we included in this paper only represent a small portion of all possible parameters relevant in a human multi-robot interaction study. We will propose and incorporate additional dependent measures in future experiments such as robot feedback and animistic group behaviors. We will also expand our study to include other age groups, cultures, and spatial contexts. For our own team and others in the research community, additional psychology theories may also need to be studied systematically and introduced to human multi-robot interaction to formulate new hypotheses. We also intend to fabricate a larger group of SORT robots to be used in an in-person lab study. To account for selection bias and influences from foreign cultures on some participants, we will apply additional filters to further control the recruitment process, such as including participants who have never travelled outside of their home countries.

D. Conclusion

In this paper, we conducted a study exploring the impact of cultural differences on participants' preferences and perceived usefulness of a multi-robot assistive organizer system. With so few studies investigating the role of culture in human multi-robot interaction at home, our early results reported here can provide insights for other researchers working in the domain of non-humanoid domestic robots. We also investigated mediation effects by using SEM, which has been an under-utilized tool for HRI studies. Introducing an assistive MRS into the home environment would require understanding of users' cultural backgrounds and preferences, which could have direct impacts on perceived usefulness of the system. More broadly for HRI design, culture is a necessary factor to consider in developing assistive robots as they become ubiquitous in the everyday lives of people around the world, especially in populous but under-studied regions.

REFERENCES

[1] C. McGinn, M. Cullinan, D. Holland and K. Kelly, "Towards the design of a new humanoid robot for domestic applications," 2014 IEEE International Conference on Technologies for Practical Robot Applications (TePRA), Woburn, MA, USA, 2014, pp. 1-6, doi: 10.1109/TePRA.2014.6869155.

[2] S. Kawazoe et al., "Development of standing assistive walker for domestic use," 2017 IEEE International Conference on Industrial Technology (ICIT), Toronto, ON, 2017, pp. 1455-1460, doi: 10.1109/ICIT.2017.7915580.

[3] J. Piasek and K. Wieczorowska-Tobis, "Acceptance and Long-Term Use of a Social Robot by Elderly Users in a Domestic Environment," 2018 11th International Conference on Human System Interaction (HSI), Gdansk, Poland, 2018, pp. 478-482, doi: 10.1109/HSI.2018.8431348.

[4] W. Jo, J. H. Park, S. Lee, A. Lee and B. Min, "Design of a Human Multi-Robot Interaction Medium of Cognitive Perception," 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Daegu, Korea (South), 2019, pp. 652-653, doi: 10.1109/HRI.2019.8673188.

[5] C. H. De Aguiar et al., "The networked, robotic home+ furniture suite: A distributed, assistive technology facilitating aging in place," 2016 IEEE International Conference on Automation Science and Engineering (CASE), Fort Worth, TX, USA, 2016, pp. 1067-1072, doi: 10.1109/COASE.2016.7743522.

[6] L. Wang, P. P. Rau, V. Evers, B. K. Robinson and P. Hinds, "When in Rome: The role of culture & context in adherence to robot recommendations," 2010 5th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Osaka, Japan, 2010, pp. 359-366, doi: 10.1109/HRI.2010.5453165.

[7] M. Zhang, J Hardin, J. Cai, J. Brooks and K. Green, (In press.) "Self-Organizing Robot Team (SORT): A Multi- Robot, Wall Climbing Organizer-and-Delivery System for Living Spaces," *Springer Series in Adaptive Environments*.

[8] K. S. Haring, D. Silvera-Tawil, T. Takahashi, M. Velonaki and K. Watanabe, "Perception of a humanoid robot: A cross-cultural comparison," 2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), Kobe, Japan, 2015, pp. 821-826, doi: 10.1109/ROMAN.2015.7333613.

[9] G. Cortellessa et al., "A Cross-Cultural Evaluation of Domestic Assistive Robots," 2008 AAAI Fall Symposium: AI in Eldercare: New Solutions to Old Problems, pp 24-31

[10] J. Bernotat and F. Eyssel, "Can('t) Wait to Have a Robot at Home? - Japanese and German Users' Attitudes Toward Service Robots in Smart Homes," 2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), Nanjing, China, 2018, pp. 15-22, doi: 10.1109/ROMAN.2018.8525659.

[11] C. Bartneck, "Who like androids more: Japanese or US Americans?," RO-MAN 2008 - The 17th IEEE International Symposium on Robot and Human Interactive Communication, Munich, Germany, 2008, pp. 553-557, doi: 10.1109/ROMAN.2008.4600724.

[12] Lim, V., Rooksby, M. & Cross, E.S. Social Robots on a Global Stage: Establishing a Role for Culture During Human–Robot Interaction. Int J of Soc Robotics (2020). https://doi.org/10.1007/s12369-020-00710-4

[13] M.R. Fraune, S. Kawakami, S. Šabanović, P. R. S. de Silva, M. Okada, "Three's company, or a crowd?: The effects of robot number and behavior on HRI in Japan and the USA," 2015 Robotics: Science and Systems. Rome, Italy, DOI: 10.15607/RSS.2015.XI.033.

[14] S. Woods, M. Walters, Kheng Lee Koay and K. Dautenhahn, "Comparing human robot interaction scenarios using live and video based methods: towards a novel methodological approach," 9th IEEE International Workshop on Advanced Motion Control, 2006., Istanbul, Turkey, 2006, pp. 750-755, doi: 10.1109/AMC.2006.1631754.

[15] M. Heerink, B. Krose, V. Evers and B. Wielinga, "Measuring acceptance of an assistive social robot: a suggested toolkit," RO-MAN 2009 - The 18th IEEE International Symposium on Robot and Human Interactive Communication, Toyama, Japan, 2009, pp. 528-533, doi: 10.1109/ROMAN.2009.5326320.

[16] M. Brysbaert, "How Many Participants Do We Have to Include in Properly Powered Experiments? A Tutorial of Power Analysis with Reference Tables." Journal of cognition vol. 2,1 16. 19 Jul. 2019, doi:10.5334/joc.72

[17] A.C. Bluedorn, C.F. Kaufman, P.M. Lane, "How many things do you like to do at once? An introduction to monochronic and polychronic time", 1992 The Executive 6, no. 4 (1992): 17-26.

[18] S. V. Gupta, "Metrology Through Ages", in Units of Measurement: Past, Present and Future. International System of Units, Springer Series in Materials Science: 122. R. Hull, J. Parisi, R. M. Osgood, H. Warlimont (Eds), 2010 Springer. pp. 6–9

[19] M. R. Fraune and S. Šabanović, "Negative Attitudes toward minimalistic Robots with intragroup communication styles," The 23rd IEEE International Symposium on Robot and Human Interactive Communication, Edinburgh, UK, 2014, pp. 1116-1121, doi: 10.1109/ROMAN.2014.6926401.

[20] ET Hall. 1976. Beyond Culture, New York (Anchor Press) 1976. Anchor Books, United States of America.