Does Repetition Affect Acceptance? A Social Robot Adoption Model for Technologically-Savvy Users in the Caribbean

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Abstract

There is little research on use and adoption factors for social robots in the Caribbean. In one pilot study, the Zenbo companion robot was used to evaluate potential social robot use in a Caribbean setting. An informal observation from that study was the existence of communication failure–participants frequently repeated commands to the robot. Based on this observation, we have undertaken this study to identify the factors that affect robot adoption among technologically-savvy Caribbean users (undergraduate Computer Science and Information Technology (IT) students) and create a technology adoption model for this type of user. Our model shows that communication failure, manifested as repetition, has no effect on technology acceptance. Additionally, social attitudes towards robots, like the perception of competence and warmth, also have no effect on adoption. This social robot adoption model is the first of its kind for the Caribbean and helps contextualize factors that can affect social robots' adoption in the region.

Keywords: Human Robot Interaction (HRI), conversational repetition, Caribbean, technology acceptance, communication failure.

1. Introduction

For decades, Caribbean manufacturers, service providers and food producers have been slow to adopt technologies in their product and service delivery (Cimoli et al., 2005; Hansen et al., 2002). Despite studies by multiple international developmental agencies advocating for rapid adoption of technologies across multiple sectors to achieve social and economic advancement, Caribbean adoption of new technologies has lagged the rest of the world (African Development Bank Group et al., 2018; Ahmed et al., 2021; Staff Writer, 2021; Valencia, 2020).

Governments and other stakeholders realize that technology adoption needs to be accelerated so that small island developing states can succeed and effectively compete in this new global era. However, the wide adoption of new technologies to fuel innovation and economic growth generally continues to lag. Caribbean companies have developed mobile and desktop applications, but the population has not purchased and/or used these applications to a significant degree. Meanwhile, other technologies, such as data analytics and machine learning, are rarely used in the development of business and consumer-oriented solutions (Williams, 2014).

Recently, there have been signs of a growing exception to slow technology uptake, and this is in mobile technology. While mobile phones have been in the Caribbean for decades, the adoption of smartphones and web-enabled tablets has seen significant uptake in the consumer market, where each person in the Caribbean possesses at least one smartphone subscription (Mobile Cellular Subscriptions, 2018). Due to the rapid diffusion of mobile technologies in the Caribbean, some research has been undertaken to understand how the technology is being used–primarily within an educational context (Ahmad, 2019, 2020; Thomas et al., 2020).

Another technological area that is experiencing slow uptake in the Caribbean is robotics. While Caribbean manufacturers use industrial robots to automate some of their processes, hospitals, hotels, banks, elder care facilities and households rarely use service or social robots. Consequently, there are no studies or reports that have been done on either the adoption or use of service or social robots within the Caribbean context. Our work contributes to this area.

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A social robot is composed of a physical robot hardware component designed to interact with people and a network architecture that acts as a cyber-physical computing system backed by cloud services. Social robots have been extensively studied and benefits have been demonstrated for their use in areas like elder care, education, and retail. In fact, they are being incorporated in global corporations and in many homes in North America, Europe and Asia. Given this rapid adoption of social and service robots, the Caribbean is at risk of once again missing out on the adoption of a new technology that can benefit its constituent societies. This work investigates the factors that may affect its adoption in the Caribbean.

Human-Robot Interaction (HRI) is the study of understanding, creating, and appraising robots for use by or with people. HRI research is essential if social robots are to be considered a part of our society. HRI, as a synthetic science, seeks to address issues around cognitive AI and its related technologies, psycho-social effects, cognition, human behaviour, perceptions, and attitudes toward robots. As a result, the aim of HRI is to discover, build, and test robots to create seamless human interactions.

We follow up on earlier HRI studies that evaluated a methodology for conducting HRI user studies in the Caribbean during the COVID-19 pandemic (C. Gittens, 2021; C. L. Gittens, 2021) and another HRI study using video conferencing software to undertake HRI studies in the Caribbean (C. L. Gittens & Garnes, 2022). These studies indicate that while the Caribbean participants positively perceived social robots, there may be some potential issues that could affect adoption. One issue identified in C. L. Gittens (2021) was the problem the robot had in recognizing its wake-up command. The authors believe that this was related to the data set used to train the voice recognition system. The robot was made in Taiwan and likely trained using Mainstream English or American English speakers as well as Asian speakers. Additionally, the participants in the study spoke English with strong regional accents. The authors suggest that this could be one of the causes of the frustration noted in the results because a social robot that ignores basic commands may annoy users and, result in non-adoption of social robots.

We carried out this study to develop an adoption model for technologically-savvy Caribbean users to determine whether communication failure–in the form of conversational repetition–would negatively affect social robot adoption in the Caribbean. We decided to focus our analysis on potential early adopters in the form of computer science and IT students at a Caribbean university. Such students will be most likely to develop and use social robots because of their education and deeper knowledge of technology. As Wozniak (1987) indicated, people who are more educated about innovation are more like to adopt it. This outcome was also noted in Baudier et al. (2020), where students were observed to be more likely to adopt smart home technologies because they were highly educated in technological areas.

Consequently, if potential early adopters–such as these students–have a poor perception of social robots because of communication failures, it will be a harbinger of low adoption, or no adoption, of the technology by the wider population.

2. Related Work

In the area of social robot adoption, Kalisz et al. (2021) studied the adoption and diffusion of social robots in the healthcare sector using the Delphi technique. The results showed that the ambiguous nature of social robots would create interactive experiences to increase their adoption and diffusion. Next, Khaksar et al. (2020) investigated the role of social robots in the education sector and identified the Critical Success Factors (CSFs) for social robot adoption from the following perspectives: (1) Perceived ease of use, (2) Perceived usefulness, (3) Student experience, (4) Assimilation with curriculum, (5) Self-learning skills, and (6) Student vulnerability. Then, (Chang, 2019) conducted three studies on implementing social robots in the eldercare sector by a theoretical framework of Social Shaping of Technology (SST) in the Science and Technology Studies (STS) field.

In the area of conversation with social robots, Vázquez et al. (2017) described a perception system to track participants and control the social robot's orientation and gaze during group conversations with a social robot. The results showed that robot gaze and body motion should be designed and controlled jointly. Next, Skantze (2017) investigated participation equality in terms of age, gender, and speaking time in multi-party human-robot conversations by the robot's verbal and non-verbal behaviours. Further, Cruz-Sandoval et al. (2017) created a conversational corpus based on Human-Robot Conversation (HRC) in terms of the language used as input for training a dialogue system that might affect the quality of the responses from a robot. Then, Isaka et al. (2018) found that humans appear to have difficulty ending their conversations with robots due to verbal and nonverbal cues in robot behaviours. Lastly, Shi et al. (2015) established a participation state model for measuring communication participation by guidelines for a natural way of initiating conversation.

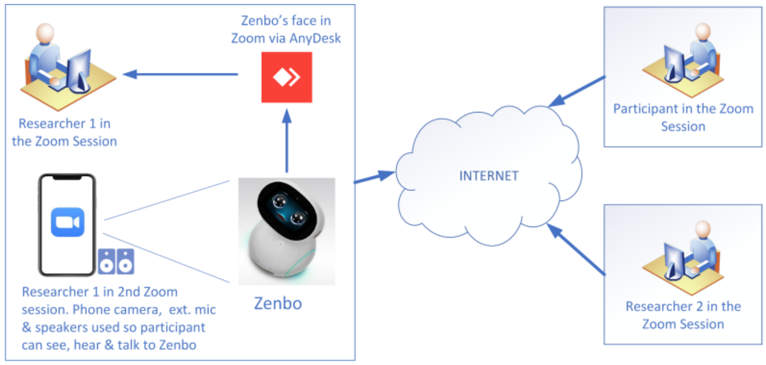

Figure 1. Experiment setup

2.1. Technology Adoption Studies in the Caribbean

There are few technology-adoption studies that focus solely on the Caribbean. The studies that focus on the Caribbean community have been predominantly on adopting technologies to improve education. Some of the more recent studies have also examined technology use—specifically mobile technologies by undergraduate students (Ahmad, 2019, 2020). However, the traditional approach to studying technology adoption in the Caribbean is to investigate its impact on improving learning outcomes or improving the learner's experience. The most recent work that undertakes such a study is Thomas et al. (2020), which evaluated the adoption of mobile technologies for mobile learning. The outcome of the study showed that the Unified Theory of Acceptance and Use of Technology (UTAUT) model was inadequate at modelling mobile adoption for learning. The research involved five institutions in the four Caribbean territories of Guyana, Barbados, Jamaica and Trinidad and Tobago.

Table 1. Part of the Zenbo scripted conversation and the list of commands. ME – Mainstream English; BD – Bajan Dialect

User Questions / Responses	Zenbo Responses / Follow-ups
Start the Conversation	
Say: "**Hey Zenbo**"	*[The wake command. Zenbo goes into listening mode]*
Say: "**Talk to me**"	BD: "Ok, everything bless fam, what going on with you?"
Say: "I am good" / "I am ok"	ME: "Ok, what is your name?" BD: "That easy, so wha you name?"
Say: "My name is..."	ME: "Ok, there are a lot of things that I like, what would you like to know about me?" BD: "Safe, dey got a lotta stuff dat I like wha you wann know about me fam?"
⋮	
Ask: "Where are you from?"	ME: "I am from Taiwan, but I've been living here for a while. Where are you from?" BD: "I from Taiwan, but I did bout here for a good while now, which part you from?"
Resp: "I am from..."	
⋮	
End Conversation	
Say: "Goodbye" / "Bye"	

3. The Method

3.1. The Experiment Conditions

The experiment conducted to create our model was a pre-scripted conversation between the participant and the Zenbo robot (Table 1). Our study focused on the repetition of the first two commands that started the conversation. Once the conversation started, the other statements and questions were not significantly repeated. The Zenbo companion robot used can manage smart home systems and even contact emergency services. In addition, it can generate a work schedule, remind users of upcoming tasks, and set alarms. Its personality profile, as a companion robot, suggests a polite, active, and eager little boy of about five years of age (ASUSTek Computer Inc., 2018). We used this robot because it should be perceived as pleasant and willing to please so any frustration that arises should not be due to its design but to the human-robot interaction.

We conducted the experiment online using Zoom® video conferencing software. The online session was designed so that one researcher had two concurrent Zoom sessions: one for displaying the robot's face and another for displaying the robot's body to the participants. The session's second researcher was tasked with describing the experiment to participants with short instructions on how to communicate with the robot, see Figure 1.

Participants used two instructions to initiate the pre-scripted conversation. "Hey Zenbo," was used to activate the robot's listening mode where it waits for additional instructions. Then "Talk to me" was used to start the pre-scripted conversation. Participants were told to repeat these and the other commands or questions as many times as needed if the robot did not react.

3.2. The Participants

The participants were 38 undergraduate student volunteers from a Caribbean institution, 26 men (μ_{age}=22.65, σ=3.97) and 12 women (age μ_{age}=21.6, σ=3.82). The study occurred during the school year, and participants were recruited from the second-year cohort that was enrolled in at least one course in the Information Technology or Computer Science program. Volunteers received an assignment credit for participation. The participants represented 8.5% of the students enrolled in the Computer Science and Information Technology major. 85% of participants had never used a social robot, and 55% have never heard of or interacted with one before participating in the study.

4. The Theoretical Model and Hypotheses

Work done by Lugrin et al. (2020) on the effect accents have on the perception of robots showed that if a robot speaks with a standard accent (German in that case), then it is perceived as more competent than a robot that speaks with a regional variation of the language. However, if the participant spoke with the same accent as the robot, the robot was considered more competent by the dialect-speaking participant than those who did not speak the dialect. Other research has shown that participants preferred robots to speak with a specific kind of accent–in this case, the Standard Southern British English (SSBE) accent (Torre & Le Maguer, 2020). The Zenbo robot speaks with a slightly synthesized voice and uses what may be best described as a standard American-English accent. This can be considered an out-group accent since the study participants were Caribbean nationals with regional accents.

4.1. Repetition and Social Attitude

Given that accents play an important role in robot perception, if a robot does not speak with either the mainstream accent or a regional accent of the participant's country and responds only after the participant has made repeated attempts at issuing commands, we hypothesize that:

H1a: Repetition of the wake command "Hey Zenbo" will have a negative effect on the perception of the robot's warmth.

H1b: Repetition of the wake command "Hey Zenbo" will have a negative effect on the perception of the robot's competence.

H2a: Repetition of the start conversation command "Talk to me" will have a negative effect on the perception of the robot's warmth.

H2b: Repetition of the start conversation command "Talk to me" will have a negative effect on the perception of the robot's competence.

4.2. Social Attitude and User Experience

All the scales used in this study are validated and have been used in other social robot perception studies. The variables in the Warmth and Competence subscales of the Robotic Social Attributes Scale (RoSAS) (Carpinella et al., 2017) align with the Pragmatic and Hedonic items of the short version of the User Experience Questionnaire (UEQ-S) (Schrepp et al., 2017) than the RoSAS Discomfort subscale–that is, they are related measures. So, we anticipate if a measure in RoSAS is rated highly, we should observe a similarly high rating in the related UEQ-S measure. The eight items in the UEQ-S and the twelve items of the RoSAS scales are shown in Table 2. Based on these items, we hypothesize that:

H3a: Warmth will positively affect Pragmatic.

H3b: Warmth will positively affect Hedonic.

H4a: Competence will positively affect Pragmatic.

H4b: Competence will positively affect Hedonic.

Table 2. UEQ-S and RoSAS Items

UEQ-S		RoSAS	
Pragmatic	**Hedonic**	**Competence**	**Warmth**
Obstructive / Supportive	Boring / Exciting	Capable	Happy
Complicated / Easy	Not Interesting / Interesting	Responsive	Feeling
Inefficient / Efficient	Conventional / Inventive	Interactive	Social
Clear / Confusing	Usual / Leading Edge	Reliable	Organic
		Knowledgeable	Emotional
		Competent	Compassionate

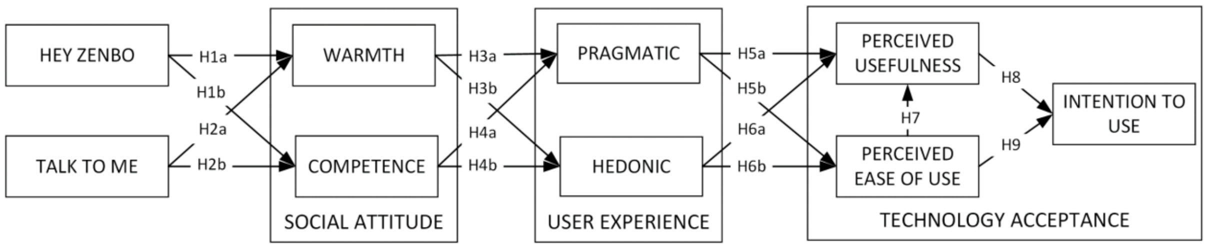

Figure 2. The hypothesized technology acceptance model for Caribbean early adopters.

4.3. User Experience and Technology Acceptance

Perceived ease of use (PEU) is the degree to which a person thinks that operating or adopting the system would be effortless. Perceived usefulness (PU) is a person's belief that adopting the system would improve his or her work performance (Venkatesh & Davis, 2000). These definitions align with the Hedonic and Pragmatic items in the UEQ-S because they appeal to both the usefulness and pleasure of using technology. That is, we consider these to be related measures. Based on this, we hypothesize that:

H5a: Pragmatic will positively affect Perceived Usefulness

H5b: Pragmatic will positively affect Perceived Ease of Use

H6a: Hedonic will positively affect Perceived Usefulness

H6b: Hedonic will positively affect Perceived Ease of Use

The final three hypotheses are based on the Technology Acceptance Model (TAM2) by (Venkatesh & Davis, 2000), which are:

H7: Perceived Ease of Use will positively influence Perceived Usefulness

H8: Perceived Usefulness will positively influence the Intention to Use

H9: Perceived Ease of use will positively influence the Intention to Use

The theoretical model based on our hypotheses is shown in Figure 2.

5. Measurement Model Analysis

In this study, we used multiple linear regression to analyse our hypothesized model. Before hypotheses analysis, the items of measurement must first undergo reliability and validity tests. The reliability analysis can measure the stability and consistency of a measurement instrument (Kerlinger & Lee, 1999).

A generally accepted rule is that the Cronbach's α of the measurement items of a variable being greater than 0.6 and the composite reliability (CR) value of each variable also being greater than 0.6, indicates an acceptable level of reliability (J. Hair et al., 2017). As can be seen in Table 3, all the variables in this study have a Cronbach's α value greater than 0.6, indicating

Table 3. Reliability and validity analysis

Variable	Factor loadings		Cronbach's α	CR	AVE
Warmth	WA1	0.830	0.863	0.900	0.600
	WA2	0.776			
	WA3	0.731			
	WA4	0.794			
	WA5	0.797			
	WA6	0.715			
Competence	CO1	0.811	0.856	0.895	0.589
	CO2	0.737			
	CO3	0.791			
	CO4	0.838			
	CO5	0.691			
	CO6	0.727			
Discomfort	DI1	0.798	0.659	0.811	0.521
	DI4	0.575			
	DI5	0.710			
	DI6	0.782			
Pragmatic	PR1	0.699	0.748	0.842	0.572
	PR2	0.838			
	PR3	0.748			
	PR4	0.734			
Hedonic	HE1	0.847	0.847	0.897	0.686
	HE2	0.921			
	HE3	0.778			
	HE4	0.756			
Perceived Usefulness	PU1	0.851	0.852	0.901	0.694
	PU2	0.811			
	PU3	0.897			
	PU4	0.769			
Perceived Ease of Use	PEU1	0.803	0.833	0.889	0.667
	PEU2	0.789			
	PEU3	0.838			
	PEU4	0.835			
Intention to Use	IU1	0.968	0.933	0.967	0.973
	IU2	0.968			

the questionnaire scale used in this study meets the criteria of the reliability test.

Regarding the validity test, this study conducted both convergent and discriminant validity tests. In the convergent validity test, the factor analysis was conducted to examine whether multiple items under the same variable converged to the same factor. According to Hair et al. (2017), the factor loading of each measurement item under the same variable should be greater than 0.5. As can be seen in Table 3, the factor loading of each measurement item is greater than 0.5.

Table 4. Square root of AVE and correlation coefficients

	WA	CO	DI	PR	HE	PU	PEU	IU
WA	**0.775**							
CO	0.399	**0.768**						
DI	0.018	0.059	**0.722**					
PR	0.344	0.570	0.146	**0.766**				
HE	0.472	0.545	0.121	0.628	**0.828**			
PU	0.117	0.119	-0.291	-0.063	-0.081	**0.833**		
PEU	0.466	0.532	-0.200	0.444	0.431	0.382	**0.817**	
IU	0.239	0.094	-0.207	0.080	0.276	0.599	0.347	**0.968**

[1] WA: Warmth; CO: Competence; DI: Discomfort; PR: Pragmatic; HE: Hedonic; PU: Perceived Usefulness; PEU: Perceived Ease of Use; IU: Intention to Use.
[2] The values in bold type shown along the diagonal are respectively square roots of AVE of specific variables, while all other values are respectively Pearson correlation coefficients between two variables.

In addition, the convergent validity must also be measured by measured applying average variance extracted (AVE). The value of each variable should be greater than 0.5 to ensure that the measurement items have acceptable convergent validity (Fornell and Larcker 1981). As shown in Table 3, in this study, all the AVE and CR value of variables have higher than 0.5 and 0.6, indicating the measurement items used in this study has good convergent validity.

The purpose of the discriminative validity test is to measure whether different variables could be distinguished from each other to represent different concepts. According to Hair et al. (2019), in a correlation matrix of all variables, the square root of AVE along the diagonal should be greater than the correlation coefficients of all the rows and columns. As shown in Table 4, in this study, the square root of the AVE value of any variable is greater than the correlation coefficients between the variable and all other variables in the same column or row, indicating all the variables meet the required discriminant validity in this study.

In this study, the measurement items of the variables with a nine-point scale were "warmth", "competence" and "discomfort", and a seven-point scale was used on the items of other variables. Thus, this study also conducted a one-sample t-test to examine whether the mean of each variable is significantly different from the median value. The results indicated that the variables of WA, CO, and DI are significantly higher or lower than the median 5, and the variables of PR, HE, PU, PEU, and IU are significantly higher than the median 4. The mean of each variable can be seen in Table 5.

Table 5. Means of variables

	WA	CO	DI	PR	HE	PU	PEU	IU
Mean	3.16*	5.64*	2.01*	4.16*	4.37*	4.20*	4.53*	5.28*

* indicates significant at $p < 0.05$, the means of WA, CO and DI are compared to median 5, and other means are compared to median 4, N = 38

6. Regression Model Analysis

We first examined the effect of the repetition of commands on user experiences (H1a, H1b, H2a, H2b). Regression results showed that none of the repetition of command variables significantly influenced either Competence or Warmth ($p>.1$). Therefore, these hypotheses are not supported by our data.

Second, we examined the effect of Social Attitude on User Experience (H3a, H3b, H4a and H4b). When we regressed Pragmatic on Warmth and Competence, only the effect of Competence was significant (β=.51, $p<.05$), supporting H4a. Then, we regressed Hedonic on Warmth and Competence and both the effect of Warmth and Competence was significant (β=.3, $p<.05$; β=.42 $p<.01$), supporting H3b and H4b.

Third, we tested our hypotheses regarding the effect of User Experience on participants' Technology Acceptance (H5 and H6). We found that Pragmatic and Hedonic had no effect on either Perceived Ease of Use or Perceived Usefulness—as expected in our model—so there was no support for H5 or H6.

Finally, our analysis of Technology Acceptance showed, as expected, that Perceived Ease of Use significantly influenced Perceived Usefulness (β=.52, $p<.05$), supporting our hypothesis H7. Furthermore, Perceived Usefulness significantly affects Intention to Use (β=.55, $p<.001$), supporting hypothesis H8. However, Perception of Ease of Use did not significantly affect Intention to Use, so H9 is not supported.

Lastly, the hypothesized model of this study with five hypotheses passed the examination. The research model accounts for 62% (R2=0.62) of explained

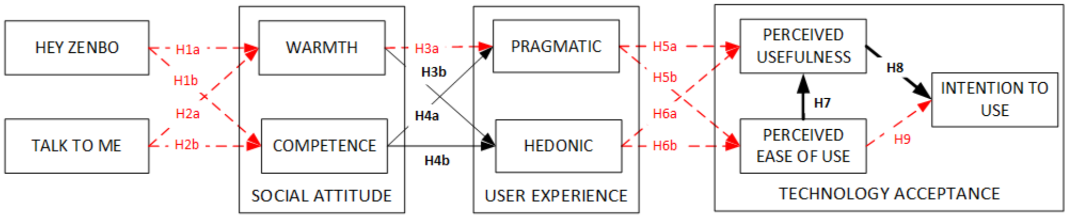

Figure 3. The regression model from our analysis. Dotted red lines are unsupported hypotheses

variances. The model based on our analysis is shown in Figure 3 and Table 6.

7. Discussion

The fact that repetition had no effect on our model was unexpected but not inexplicable. The accent used by the robot to interact with participants can be categorized as a Standard North American type of accent. Even though this accent is an out-group accent, it was acceptable because all participants were from the Caribbean with diverse accents and were more accepting of foreign accents. Work done by Bresnahan et al. (2002) has shown that groups with weak ethnic identities (not strongly affiliated with a social group) are more accepting of foreign accents. Since the Caribbean is a multicultural, multi-ethnic region, interactions with members outside of social and cultural groups are normal. Additionally, since the robot is using a type of Standard North American accent, this aligns with the formal language used in the region. Even though it was slow to respond, robots that speak with standard accents are always rated higher (Andrist et al., 2015; Fuertes et al., 2012; Torre & Le Maguer, 2020).

We confirmed some interesting results in our analysis. The first was that Competence had an impact on both Pragmatic and Hedonic measures. This may indicate that the participants expect that besides being accurate, capable, and responsive, a social robot should also be capable of delivering a fun or interesting experience.

The second interesting finding is that neither the Social Attitude or the User Experience variables influence either Perceived Ease of Use or Perceived Usefulness. These results might be because the participants did not ask the robot to complete a functional task, which made it difficult to judge its usefulness based on the social interaction task. That is, the Warmth and Competence judgment did not directly influence the usefulness judgment and neither did the Pragmatic or Hedonic judgments. However, as found in prior studies, Perceived Ease of Use, influenced Perceived Usefulness as discussed in (Venkatesh & Davis, 2000).

Table 6. Results of the Hypothesis Tests

Hypo-thesis	Path	Esti-mate	Result
H1a	Hey Zenbo → Warmth		Unsupported
H1b	Hey Zenbo → Competence		Unsupported
H2a	Talk to me → Warmth		Unsupported
H2b	Talk to me → Competence		Unsupported
H3a	Warmth → Pragmatic		Unsupported
H3b	Warmth → Hedonic	0.30*	Supported
H4a	Competence → Pragmatic	0.51*	Supported
H4b	Competence → Hedonic	0.42**	Supported
H5a	Pragmatic → Perceived Usefulness		Unsupported
H5b	Pragmatic → Perceived Ease of Use		Unsupported
H6a	Hedonic → Perceived Usefulness		Unsupported
H6b	Hedonic → Perceived Ease of Use		Unsupported
H7	Perceived Ease of Use → Perceived Usefulness	0.52*	Supported
H8	Perceived Usefulness → Intention to Use	0.55***	Supported
H9	Perceived Ease of Use → Intention to Use		Unsupported

Notes: *p-value < 0.05; **p-value < 0.01; ***p-value < 0.001 (two-tailed)

7.1. Limitations

The two limitations of this study are: (i) the sample size and (ii) the limited diversity in the participants. Regarding the sample size, we enlisted 38 participants. This sample size would have had an impact on the effects we would observed as we constructed our model and limit the power of the conclusions that can be drawn from the model. This is constrained by the number of students that are at the university. However, future studies will focus on enrolling a larger percentage of the eligible student population.

The reduced diversity of the participant group will affect the conclusions drawn regarding the technological acceptance of robots by technologically-savvy students. We did not collect nationality or ethnicity data but relied solely on the fact that the student's institution has a culturally and ethnically diverse enrolment. Therefore, we must undertake larger studies that is more representative of the student population and expand future studies that include other tertiary educational institutions in the Caribbean. This broader and more diverse set will then provide a better picture of the attitudes of technologically-savvy students with backgrounds that better reflect the demographics in the Caribbean.

8. Conclusions

Our study attempted to determine whether communication failure in the form of conversational repetition with a social robot negatively affected technology acceptance. We created a model that incorporated the repetition factors of concern, namely the "Hey Zenbo" robot activation command and the "Talk to me" conversation initialization command. We believed that these repetition factors would have had a negative impact on robot adoption and created a theoretical model to reflect this hypothesis. A benefit of the study that we did not discuss was that the experiment was conducted online. Work done in (C. L. Gittens & Garnes, 2022) indicates that such online experiments do not negatively affect the interaction. This is promising because it may imply that future HRI studies in the Caribbean can be conducted online.

Finally, our data analysis showed that repetition of the start-up command and the conversation initialization had no effect on any aspect of the model. This discovery is promising because it might indicate that the use of robots by early adopters in the Caribbean might not be hampered even if they must repeat commands during their interactions. This means that robots developed outside of the Caribbean may be adopted even if their responses are imperfect.

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