Evaluation of Laban Effort Features based on the Social Attributes and Personality of Domestic Service Robots

by

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A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Systems Design Engineering

Waterloo, Ontario, Canada, 2022

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Today, it is not uncommon to see robots adopted in various domains and environments. From manufacturing facilities to households, robots take over several roles and tasks. For instance, the adoption of robotic vacuum cleaners has drastically increased in the recent decades. During their interaction with these embodied autonomous agents, humans tend to ascribe certain personality traits to them, even when the robot has a mechanoid appearance and very low degree-of-freedom. As the social capabilities and the persuasiveness of robots increase, design of robots with certain personality traits will become a significant design problem. The current advancements in AI and robotics will led to development of more realistic and persuasive robots in the foreseeable future. For this, it is crucial to understand people's judgment of the robots' social attributes since the findings can shape the future of personality and behavior design for social robots. Therefore, using only a simple and mono-functional robotic vacuum cleaner, this study aims to investigate the impact of expressive motions on how people perceive the social attributes and personality of the robot. To investigate this, the framework of Laban Effort Features was modified to fit the needs and constraints of a robotic vacuum cleaner. Expressive motions were designed for a simple cleaning task performed by iRobot's Create2. The four movement features that have been controlled for robot include path planning behavior, radius of curvature at rotational turns, velocity, and vacuum power. Next, participants were asked to rate the personality and social attributes of the robot under several treatment conditions using a video-based online survey. Participants were recruited through the crowd-sourcing platform, Amazon Mechanical Turk. The results indicated that people's ratings of personality and social attributes of the robot were influenced by the robot's movement features. For social attributes, there were two main findings. First, velocity influenced robot's ratings of warmth and competence. Second, path planning behavior influenced robot's ratings of competence and discomfort. In terms of robot personality, the results indicated three main findings. First, random path planning behavior was associated with higher Neuroticism ratings. Second, high velocity yielded higher Agreeableness ratings. Third, vacuum power with higher duty cycle yielded higher Agreeableness and Conscientiousness ratings. In conclusion, this study showed the framework of Laban Effort Features can be applied to fit the cleaning task of a domestic service robot, and that the framework's application makes a difference in how humans perceive the personality and social attributes of the robot. Overall, the findings should be considered in human-robot interaction when incorporating expressive motions and affective behavior into domestic service robots.

Acknowledgements

Thanks to my supervisor Dr. Catherine M. Burns for her invaluable guidance, support, and role-modeling. I also appreciate my colleagues and friends from the Advanced Interface Design Lab (AIDL) including Ece Uereten, Fan He, Ryan Tennant, Ramtin Lotfabadi, Yeti Li, and Murat Dikmen, who never hesitated to offer help when I needed it, guided me with their feedback, and generously provided both technical and emotional support.

Research reported was supported by Natural Sciences and Engineering Research Council of Canada (NSERC) under the Discovery Grant with award number RGPIN-2020-07026. The content is solely the responsibility of the authors and does not necessarily represent the official views of NSERC.

Dedication

This work is dedicated to my parents, Nuray and Veli Kamis, my sister, Selin Kamis, and my husband Gorkem Emir.

I am grateful to my parents for loving me unconditionally, putting my education above everything, and encouraging me to stay curious and adventurous.

I am thankful to my sister for her unfailing support, her sharp sense of humor, for backpacking with me in Europe, for our camping adventures, and for keeping me sane during the Covid-19 pandemic lockdown.

I am thankful to my husband for always being there when I needed moral support, patiently listening to my complaints, and believing in me when I had self-doubts.

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Chapter 1 Introduction

In the last few decades, robots of various functionality and appearances have been employed in our everyday lives. Today, robots are used at manufacturing facilities, warehouses, agricultural farms, and offices. There are robotic arms collaborating with humans at industrial facilities, robotic lifters running around in warehouses, robotic assistants being used at offices and households, companion and educational robots aimed for children with special needs, and domestic service robots taking on the responsibilities of household's chores.

The main purpose of domestic service robots is to help humans with menial household chores. Their tasks can range from cooking and kitchen preparation to vacuuming and mopping, from answering the door to serving food or drinks. As a common example of domestic service robots, robotic vacuum cleaners (RVCs) have been widely adopted by families and facilities in the last two decades. Market analysis by Fortune Business Insights (2021) revealed that there has been a 22.5% increase in the global market size for RVCs during 2020. The market size for domestic consumer robotics was estimated to reach USD 6.8 billion in 2025 (Loup Ventures, 2019). With the sales and adoption rates constantly increasing, many households now own an RVC.

As a result, humans are frequently in close contact with these domestic service robots, sharing their environment and interacting with them almost daily. In addition to these functional mechanoid robots, humans are adopting assistant or companion robots equipped with advanced social communication skills. As a result of the rapid introduction of robots into our everyday lives, research in human-robot interaction (HRI) and social robotics has recently gained momentum.

Anthropomorphism is an intriguing phenomenon that gained interest in the HRI community. It is defined as attributing "humanlike properties, characteristics, or mental states" to non-human entities, such as animals, machines, or robots (Epley et al., 2007, p. 865). This phenomenon is significant because humans' judgment of the robot's social attributes impacts their acceptance and adoption in the long run. It has been shown that people tend to anthropomorphize robots irrespective of the intelligence or technical capabilities of the robot (Złotowski et al., 2014). This fact allows the investigation of the phenomenon using simple and mechanoid robots with low degree of freedom (dof), such as iRobot's Create2 (iRobot Education, 2021).

As Knight and Simmons (2014) claimed in their paper, motion holds the power to enable natural collaboration, building rapport, and fair sharing of mutual space between humans and robots. Body language plays a crucial role in communication between humans, and its power can also be harnessed in this domain as well. Therefore, designing expressive robotic motions can facilitate effective communication of the robot’s intentions and affective states to humans, improving the overall quality of human-robot interaction. The main purpose of this study is to investigate the impact of expressive robotic motion on how humans perceive the social attributes and personality of domestic service robots.

Laban Movement Analysis (LMA) is a framework developed by Rudolf von Laban, who was a dance practitioner as well as a movement theorist (Hodgson, 2016). This framework aims to study human movement and to understand meaning embedded in those movements. LMA has been applied to several fields, from dance and drama studies to psychology and robotics. Inspired from the LMA, Knight and Simmons (2016a) suggested the Laban Effort Features, a framework for expressive motion design for mobile robots. To design and incorporate expressive motions into RVCs, the framework of Laban Effort Features was used in this study. It has been used in several studies before to design expressive motion for mobile robots.

Designing robots with personality holds huge potential since robots live alongside humans, share a mutual environment, and interact closely with humans. Responding to users' preferences in terms of robot personality will be in demand, considering the broad application areas from education for autistic children to domestic services like cleaning and cooking, from care and companionship for seniors' houses to personal assistantship. Expressive motions based on the framework of Laban Effort Features can provide an intuitive way to reflect robot personality, and to convey the robot’s inner states and intentions more effectively to humans.

1.1 Objectives of the Thesis

The major research question addressed in this dissertation is “Can personality be allocated to robotic vacuum cleaners (RVCs) based on the framework of Laban Movement Analysis (LMA) to enhance legibility of robot’s inner states and intentions?”.

There are several objectives associated with the major research question:

1. Analyze how the framework of Laban Effort Features has been applied to robots in the literature.
2. In line with the framework of Laban Effort Features, design and code movement features for the simple cleaning task performed by a robotic vacuum cleaner.
3. With an experimental study, determine how the expressive motions impact ratings of robot's personality and social attributes.

1.2 Structure of the Thesis

This thesis is organized in six chapters, described as follows:

Chapter 1 Introduction. This chapter makes an introduction to the problem space and the motivations for the research topic.

Chapter 2 Background. This chapter presents findings from the literature review on related terms and areas, such as Laban Effort Features, robot personality design, and robotic social attributes.

Chapter 3 Methods. This chapter explains the methods used for design and development of the robot's expressive motions, as well as the experimental study consisting of an online survey. Also, the participants and their demographics are discussed at the end of this chapter.

Chapter 4 Results on Robot's Personality. This chapter presents the conference paper accepted for presentation at the 66th HFES International Annual Meeting. The conference paper demonstrates the statistical analysis conducted using the data from the robot personality questionnaire and summarizes the findings.

Chapter 5 Results on Robot's Social Attributes. This chapter presents the conference paper accepted for presentation at the 31st IEEE International Conference on Robot & Human Interactive Communication. The conference paper demonstrates the statistical analysis conducted using the data from the robotic social attributes questionnaire and summarizes the findings.

Chapter 6 Conclusion and Future Research. This chapter makes a conclusion to the thesis. This chapter highlights the significance and implications of the research topic, discusses the limitations of the study, and makes suggestions for future research.

Chapter 2 Background

2.1 Laban Movement Analysis

Laban Movement Analysis, abbreviated as LMA, is a reliable and well-established framework used to analyze human movement and to interpret the meaning behind those movements (Laban & Ullmann, 1975). The framework of LMA has been developed by Rudolf von Laban, who worked as a dance practitioner and movement theorist (Hodgson, 2016). Since then, it has been widely used in the study of dancing and acting. While the framework was original developed for analysis of a dancer's movement, it's been applied to various other fields including theater, psychology, and computer science (Bernardet et al., 2019).

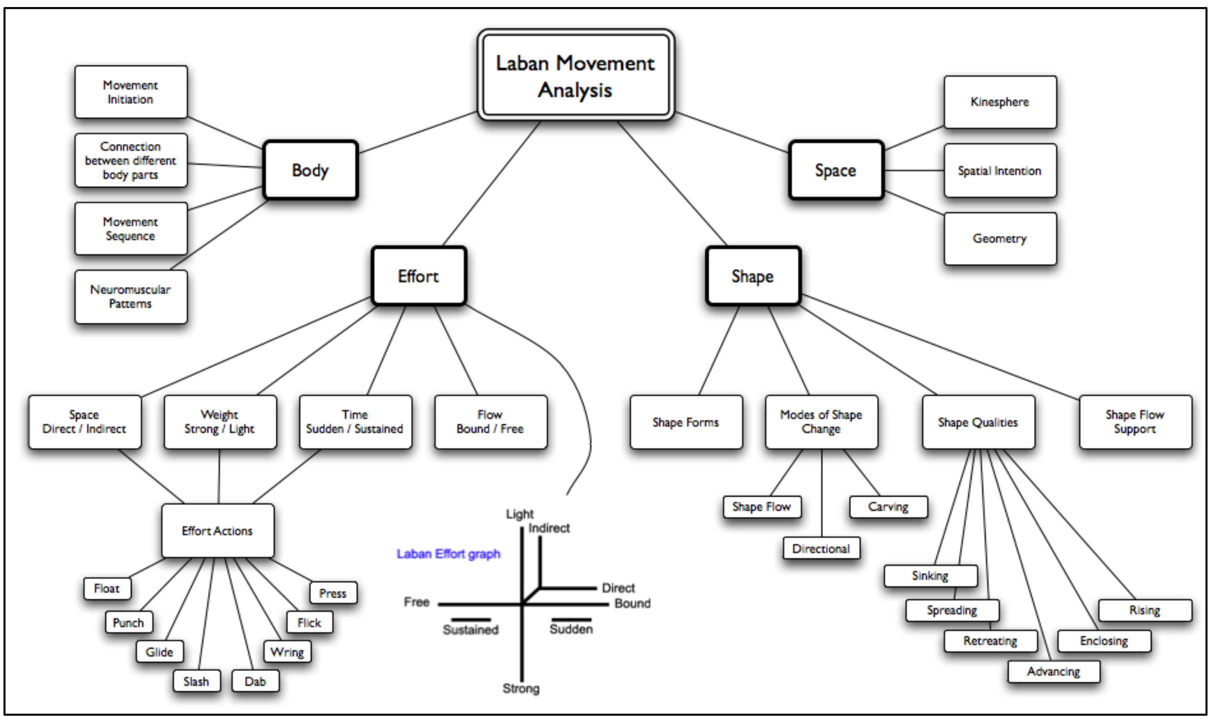

Figure 2.1 Laban Movement Analysis with all its components and subcomponents (Bernstein et al., 2015; Groff, 1995)

In this framework, human movement is described in four components: Space, Body, Shape, and Effort. As seen in Figure 2.1, four main components are each branched into several sub-components.

For instance, Space is defined using three aspects: kinesphere, spatial intention, and geometry. Effort component defines movement with regards to the intentions and internal states of the agent. There are four sub-components of Effort, including Flow, Space, Time, and Weight. Each of these sub-components define a unique expression of the movement using two polar levels. The polar levels for the sub-components of Laban Efforts are demonstrated in Figure 2.2 below.

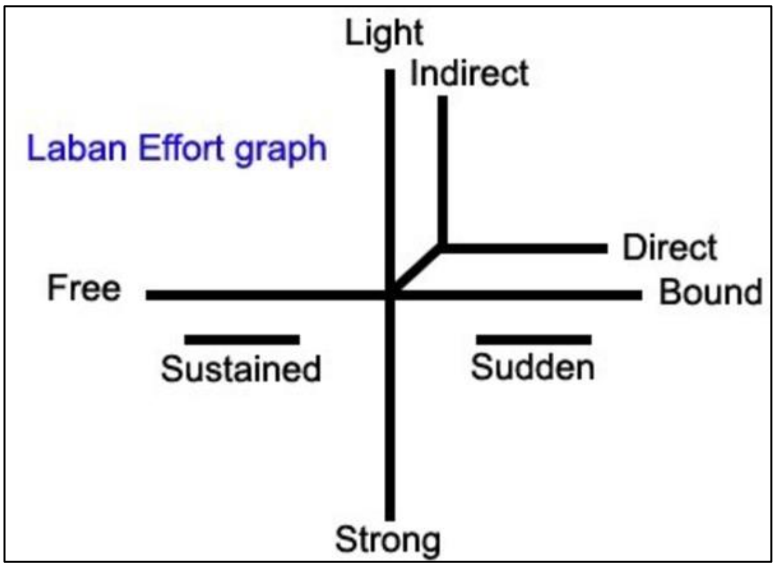

Figure 2.2 Laban Effort graph showing the polar levels (Bernardet et al., 2019)

As seen in Figure 2.2, there are four sub-components of Laban Effort, and each sub-component is measured in two polar levels. The polar levels are referred as “inducing pole” and “fighting pole”. Space Effort defines the human’s attitude towards its target; the human’s movements can be either direct or indirect. Time Effort defines the human’s attitude towards time; the human’s movements can be either sustained or sudden. Flow defines the human’s sense of restriction, where its movements can be either bound or free. Weight defines the human’s attitude towards force; human’s movements can be either light or strong.

The LMA has been applied in computer science in various contexts. One example is that Bernstein et al. (2015) used the framework of LMA in detection and classification of human movement using the Microsoft Kinect. In the field of human-robot interaction (HRI), there are several studies exploring the potential of the framework of LMA. Researchers implemented the framework of LMA to design expressive motions for mobile robots, companion robots, as well as flying robots (Knight & Simmons, 2014; Knight et al., 2016b; Agnihotri et al., 2020; Sharma et al., 2013).

Knight and Simmons (2014) investigated the application of LMA to a mobile robot, named CoBot. By manipulating the position (x, y) and the orientation (θ) of this mobile robot, they were able to design and analyze expressive motion path trajectories. The results indicated that humans performed very similar to the classifier algorithm in labeling different paths according to the Laban Efforts. The authors concluded their paper that the parametrized expressive motion features proved to be effective in robots with low degree of freedom. In a later study, Knight and Simmons (2016a) investigated the implementation of Laban Effort features using two robots with low degree of freedom, Nao's head and Keepon. Only head motions of these two robots were manipulated, and both robots were tested for two tasks: simple dance task and look-for-someone task (Knight & Simmons, 2016a). They conducted an online survey through Amazon Mechanical Turk, where participants were shown two side-by-side videos of the robot performing the same task and were asked to rate which of the video displayed more of the characteristics. Their results proved that implementing all four Laban Effort components (flow, space, time, and weight) provided statistically significant legibility results for robots with low degree of freedom. This research study is unique because it suggested an application order for the implementation of Laban Efforts, as well as developing a framework of feature vectors to operationalize each Effort component in terms of movement features.

Agnihotri et al. (2020) used the two components of Laban Efforts (Time and Space) to construct three robot personas. Inspired from the Seven Dwarfs, the personas were named happy, sleepy, and grumpy. Drawing upon the prior work in Laban Effort implementation, the researchers added a new variable called "interest-in-people" which defined whether the robot liked to be around people (Agnihotri et al., 2020). An in-person study with 24 participants revealed that the intended personas were correctly distinguished by the participants. More specifically, robot with grumpy persona was rated to have the lowest score of politeness and friendliness, while robot with happy persona was rated to have the highest score of friendliness and intelligence. Another surprising finding was that intelligence ratings of the robot were strongly influenced by the motion styles. They concluded their paper by suggesting potential use cases, where intelligence can be manipulated to mitigate the risks of over-trust in autonomous systems.

Another study by Sharma et al. (2013) investigated the implementation of Laban Efforts to design expressive robot locomotion paths in flying robots. In their study, the researchers adapted the Laban Effort System to a flying quadrotor and suggested a list of movement features that could be parametrized to design expressive locomotion paths. Using Russell's circumplex model of affect, participants rated the quadrotor's affect in two dimensions, known as valence and arousal. The results indicated statistically significant impact of Laban Efforts on both valence and arousal ratings, except for the combination of Flow and valence rating. The results from post-trial interview analysis revealed some interesting findings. For example, the robot with indirect Laban Space was described as "looking for something, little bit happy" while the robot with light Laban Weight was described as "calm, thinking something". The robot with sudden Laban Time was described as "excited, energetic, happy, enthusiastic" while the robot with free Laban Flow was described as "playful". It was concluded that the adaption of Laban Effort System for designing expressive locomotion paths was successful in communicating affect in flying robots (Sharma et al., 2013).

2.2 Framework of Laban Effort Features

The framework of Laban Effort Features has been developed by Knight and Simmons (2016a). In their paper, only the head motions were manipulated in two robots, Nao and Keepon. This paper was the first in the literature to suggest a framework that systematizes the implementation of Laban Efforts into movement features for expressive motion design in mobile robots.

According to this framework, each Laban Effort component defines a certain characteristic of motion, and each component is measured in two polar levels. For Time, the fighting pole is called sudden while the inducing pole is called sustained as demonstrated in Table 2.1 below. For Space, the fighting pole is called direct while the inducing pole is called indirect. For Weight, the fighting pole is called heavy while the inducing pole is called light. For Flow, the fighting pole is called bound while the inducing pole is called free.

Table 2.1 The descriptions of polar levels for Laban Efforts (Knight & Simmons, 2016a)

	Fighting Pole	**Inducing Pole**
Time	Sudden:	Sustained:

	rushed, hurried, “now, now now!!!”	lingering, relaxed, waiting for the perfect time to act.
Space	Direct: linear, pinpointed, laser-like.	Indirect: expansive, flexible, meandering.
Weight	Heavy: compressed by gravity, collapsed, overcome.	Light: delicate, buoyant, lifted-up, floating.
Flow	Bound: contained, controlled, rigid, clear.	Free: abandoned, released, outpouring, out of control.

They also suggested an application order for the implementation of Laban Efforts, as seen in Figure 2.3. According to the framework, task and degree of freedom are constraint inputs. After the constraints, Flow is the first Laban Effort to be applied to determine the range of possible motion for the robot. Then, Space is applied to determine motion goal and path. Finally, Time and Weight components are applied to specify the full trajectory for the robot.

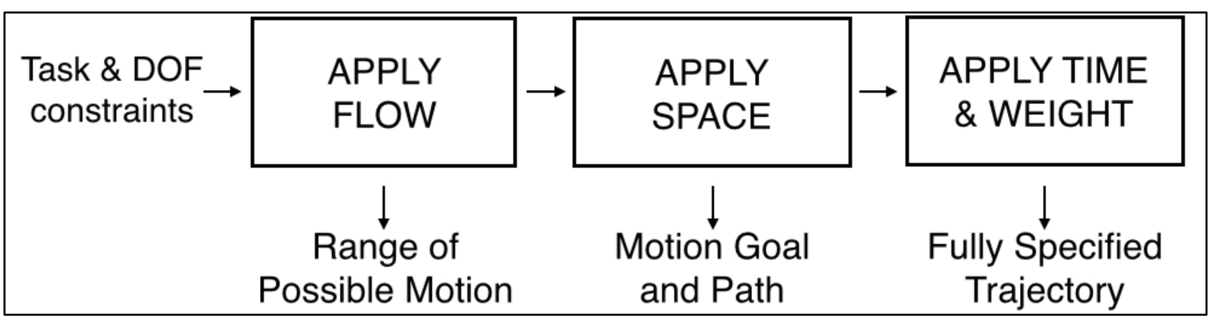

Figure 2.3 The application order of Laban Efforts (Knight & Simmons, 2016a)

According to the framework of Laban Effort Features, each Laban Effort corresponds to a specific vector of motion features. Table 2.2 below shows the feature vectors corresponding to each Laban Efforts, as determined by Knight and Simmons (2016a) in their paper. For Flow, they manipulated the range of motion for yaw, pitch, and tilt. For Space, the feature vector contained the target(s) based on the starting position of the robot. For Time, the researchers manipulated both robot's velocity and abruptness of motion, which directly impacted the robot's arrival time to the target(s). The feature vector for Weight contained acceleration, head pitch, and vertical compression of the robot's head.

Table 2.2 Feature vectors defined for each Laban Effort (Knight & Simmons, 2016a)

Laban Efforts	Features Vector
Flow	Yaw range of motion, Pitch range of motion, Tilt range of motion
Space	Starting position, Target Gaussian(s)
Time	Velocity, Abruptness, Arrival Time
Weight	Acceleration, Vertical compression, Head pitch

2.3 Rationale behind Laban Effort Features

The rationale behind the selection of Laban Effort Features is that it is rooted in the well-established framework of Laban Movement Analysis (LMA). As stated by Bernardet et al. (2019), LMA is a boiling pot of "theory, experience and movement knowledge representation". LMA suggests a reliable system to analyze human movement and describe it using a notation method. In their study, Bernardet et al. (2019) compared the number of citations for different movement coding systems, including Kinesics, LMA, Bernese, Labanotation, Benesh and Eskhol-Wachman. It was found that LMA gained attention in the literature and outnumbered other systems in terms of citations as of 2000s (Bernardet et al., 2019). Compared with the movement framework Kinesics, LMA was found to be used more frequently in computer science (Bernardet et al., 2019).

The second reason behind the selection of Laban Effort Features is that this framework has been used before in several research studies involving both mobile and flying robots (Knight & Simmons, 2016a; Knight et al., 2016b; Knight and Simmons, 2014; Agnihotri et al., 2020; Sharma et al., 2013). These studies reported positive results indicating that the framework is effective in communicating effective motions using simple movement features. More specifically, research by Knight and Simmons (2016a) suggests that it is possible to express robot's intentions by manipulating only X, Y, and theta variables for a mobile robot. Since the findings from the literature indicate that Laban Effort

Features is a reliable and promising framework for designing robot motion, it was preferred to provide the guidelines for expressive motion design in this study.

Another system for motion design in robotics is called animation techniques. Animation techniques are helpful in designing motion for robots because they leverage the principles of animation in films and computer graphics (Schulz et al., 2019). Previous literature on animation techniques in HRI mostly focused on robots with humanoid and animal shapes. There's only one study using the robotic vacuum cleaner, Roomba, to test the impact of animation techniques on human-robot interaction (Young et al., 2014). Due to its lack of application to monofunctional and mechanoid robots such as the one used in this study, iRobot's Create 2, the animation techniques approach was not preferred.

2.4 Literature on Robot Personality

Literature on robot personality has been rich, but very scattered. There are several studies but each focused on different robots, tasks, personality assessment scales, fields of application, as well as design frameworks and methods. There is not a well-accepted framework for design and evaluation of robot personality yet. This gap in the literature was partially answered by Knight and Simmons (2016a) in their paper where they suggested the framework of Laban Effort for expressive motion design. This framework covered the need of a systematic method for expressive motion design, whereas there is still need for a framework to evaluate robot personality.

An extensive literature review by (Robert et al., 2020) indicated that research on personality in HRI focused on four areas: 1) human personality, 2) robot personality, 3) human and robot personality match, 4) factors that influence robot personality. Sections 2 and 4 are relevant to our study.

There is diverse range of studies focusing on different aspects of robot personality. The most common research questions were "What forms a distinct robot personality?", "How does robot personality impact people's attitudes towards robots?" and "Whether people can perceive the designed robot personality" (Robert et al., 2020). Several measures of personality were used, including Big Five Inventory (BFI), International Personality Inventory Pool (IPIP), Ten-Item Personality Inventory (TIPI), NEO Personality Inventory Revised (NEO-PIR), and Wiggins Personality Test. Some studies measured all five dimensions of personality while others focused on three or less dimensions. The most popular dimension of personality tested for robots was extraversion. Personality traits were sometimes used as indicator measures, and they were used as outcome measures other times. The most preferred settings for experimental studies involved home environment, healthcare, and workplaces (Robert et al., 2020).

Windhouwer (2012) showed that the perceived intelligence of the robot was impacted by the extraversion dimension of robot personality, as well as the robot's roles. It was shown the perceived intelligence of CEO robot was higher for extraverted personality whereas the perceived intelligence of pharmacist and teacher robots was higher for introvert personality. Another study investigated the impact of robot's extraversion on the acceptance of healthcare robots (Tay et al., 2014). Their results indicated that people preferred healthcare robots to be extroverts while they preferred security robots to be introverts. Similarly, another study by Sundar et al. (2017) revealed that senior adults preferred different personalities for different robot tasks (assistant vs. companion). More specifically, for companion robots a serious attitude was preferred over a playful attitude, whereas for assistant robots a playful attitude was preferred over a serious attitude.

There are also numerous studies aimed at investigating different factors impacting personality design in robots. Several independent variables (e.g., robot's behavior, appearance, and role) were tested to understand if they had a significant impact on how people rated robots' personality (Robert et al., 2020). Robot's behavior was categorized in two, those are physical and communicative behaviors. Physical behaviors were manipulated using robot's gestures, body positioning, movement patterns, gaze, and facial expressions. Communicative behaviors were manipulated using voice speed, tone and pitch, voice gender, and linguistic style (Robert et al., 2020).

Research conducted by Birnbaum et al. (2016) found that responsiveness of a personal robot increased the frequency of non-verbal approach behaviors in humans. It was shown in another study that parenting styles of robots (authoritative or permissive) had an impact on how humans rated their effectiveness and acceptability (Johal et al., 2014). A video-based HRI study by Weiss et al. (2012) showed that the context of use of robot as well as people's cultural backgrounds had an impact on how people rated the robot's personality. Another study by Hoffman and Vanunu (2013) investigated the effect of robot's dance moves on people's perceptions of the robot. Their findings revealed that robots that danced as a reaction to music were attributed more positive traits than robots that gave no response to music. Yamashita et al. (2016) tested if touch sensations of robots had an impact on how people rated the personality impressions of these robots. Their factor analysis indicated that robots with preferable and natural touch sensations were perceived to be more likeable while robots with smooth and natural touch sensations were perceived to be less mighty.

Groom et al. (2009) investigated the effect of robot's form and assembler on people's perceptions of the robots. Their results indicated that self-assembled robots were perceived as more friendly and less malicious than the robots assembled by others. It was also found that car robots were perceived as having more integrity and as being less malicious than humanoid robots (Groom et al., 2009).

2.5 Literature on Social Attributes of Robots

There are several studies investigating robot's social attributes. Some of those are focused on measuring human's ratings of robotic social attributes, some are focused on the design and testing of social behavior and attributes in robots.

In a study by Sundar et al. (2017), the impact of robot task on people's ratings of robotic social attributes was investigated. Their results indicated that companion robots with a serious attitude were perceived to be more intelligent and socially attractive. Assistant robot with a playful attitude were perceived to have lower anxiety (Sundar et al., 2017). Another study by Tay et al. (2014) investigated the impact of robot's role and personality on ratings of user acceptance. The findings indicated that people preferred healthcare robots to be extroverts while they preferred security robots to be introverts. Chidambaram et al. (2012) investigated the impact of non-verbal communication cues (vocal and bodily) on robot's persuasiveness ratings and compliance with the robot's suggestions. Their results indicated that bodily cues were more persuasive on participants than the vocal cues, and that compliance with robot's suggestions increased with the use of non-verbal cues in robots (Chidambaram et al., 2012).

2.6 Literature on Robotic Vacuum Cleaners

The literature on robotic vacuum cleaners (RVCs) have been rich; there are several studies exploring the adoption of these robots in the domestic ecology. However, the literature on personality of RVCs has been very limited because they were rarely used in studies of social robotics and human-robot interaction due to their highly mechanoid and mono-functional nature.

The ethnographic study by Forlizzi and DiSalvo (2006) investigated the effects of adopting a domestic service robot. One finding was that people had low expectations of Roomba robotic cleaners, they had high expectations of other robots used in research and science. Another finding was that RVCs changed how people approached cleaning; for instance, rate of multitasking increased, people started doing decluttering activities before cycles. Lastly, it was found that people changed their home layout to adapt to robot's needs (Forlizzi & DiSalvo, 2006).

Sung et al. (2007) conducted an empirical study of iRobot Roomba, investigating its influence on the home environment. The empirical study consisted of reviewing posts in a forum of Roomba users and interviewing some of the comment owners. There are a few insights highlighted in their paper, including "people started enjoying the cleaning process" and "people strived to fit Roomba in their homes" (Sung et al., 2007). Later, the design implications related to these findings were discussed, such as a) select robot form appropriate to its function, b) utilize ambiguity in robot's behavior to engage users, c) provide supportive experience to build intimacy with users (Sung et al., 2007).

A study by Saerbeck and Bartneck (2010) investigated the impact of non-verbal communication, more specifically motion behaviors, on how people attributed affect to service robots used in domestic environments. The researchers used two robots, iRobot Roomba and iCat, and manipulated the parameters of acceleration and curvature. Acceleration was defined as the variance in robot's speed, and curvature was defined as the variance in direction. Their results indicated that robot's body shape did not impact while acceleration and curvature had a significant impact on people's attribution of affect. More specifically, acceleration was correlated to arousal and curvature was correlated to all three measures (arousal, valence, and dominance). In conclusion, it was shown that people attributed affect to both domestic robots depending on the motion behaviors while the robot's embodiment did not matter (Saerbeck & Bartneck, 2010).

Another study by Hendriks et al. (2011) investigated the user experience of RVCs, particularly how people anthropomorphize and attribute personality traits to these domestic service robots. After conducting interviews, the researchers were able to understand an ideal robot personality. They tested if the participants could distinguish the designed personality traits in RVCs using a video prototype. The results showed that it was indeed possible to recognize certain personality traits from robot behavior. The study suggested several modalities of expression including motion, sound, and light (Hendriks et al., 2011).

Research by Joosse et al. (2013) aimed to understand the impact of task context on people's perceptions of robot's personality. In literature, there are contradicting findings regarding human-robot personality match and mismatch. Some studies showed that people preferred interaction with a robot of similar personality, while others showed that people preferred interaction with a robot of opposite personality. Joossee et al. (2013) investigated the effect of robot's task on people's preference of robot personality. Nao robot was used in the context of cleaner robot and tourist guide robot. Their results indicated that participants preferred the complementary personality for a cleaner robot, whereas participants preferred the similar personality for a tourist guide robot.

The study by Agnihotri et al. (2020) aimed to understand whether it was possible to convey robot personality using simple motion behaviors. A robotic vacuum cleaner, Neato Botvac which had LiDAR sensors and a bump sensor, was used to convey three personas from the Seven Dwarfs. Their findings suggested that participants were able to distinguish the robot's personality only from its path, velocity, and its interest-in-people behavior (Agnihotri et al., 2020).

2.7 Chapter Conclusion

In his chapter, the literature on relevant concepts were presented. The relevant concepts involved Laban Movement Analysis (LMA), the framework of Laban Effort features and Human-Robot Interaction. Previous research on robot personality, robotic social attributes, and robotic vacuum cleaners (RVCs) were reviewed. Significant findings from these studies were presented.

Overall, it can be deduced from the literature review that Laban Efforts was used before in several studies primarily for designing expressive motion in humanoid robots. Mechanoid robots such as iRobot Roomba were infrequently utilized in human-robot interaction studies regarding robot personality and social attributes. This study is the first of its kind to implement the framework of Laban Effort features developed by Knight and Simmons (2016a) to RVCs specifically for the investigation of people's perception of robot personality and social attributes.

Chapter 3 Methods

To investigate the implementation of Laban Effort features and the impact of Laban Effort features on ratings of robot's personality and social attributes, the following methods were conducted in four stages (see Figure 3.1). The first stage was the mapping of Laban Effort Features to a robotic vacuum cleaner (RVC) for a simple cleaning task. The second stage was the implementation stage, which involved code development and testing. Next stage was the study design, which involved selection of the appropriate questionnaires and the production of robot's videos. The last stage was the administration of the online survey through Qualtrics.

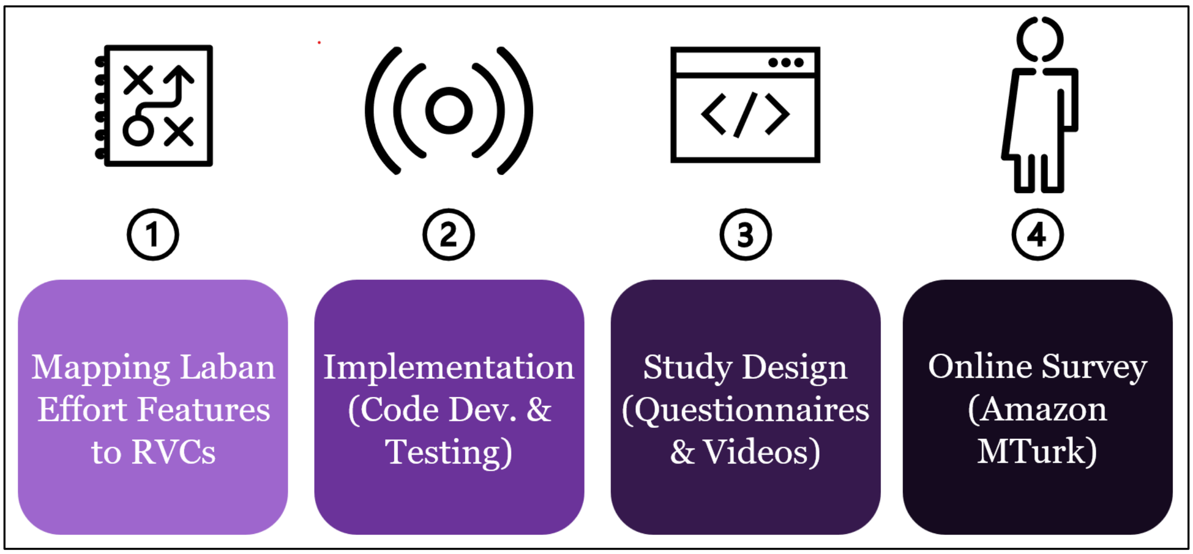

Figure 3.1 The Methods shown in Four Stages

3.1 Stage 1: Mapping Laban Effort Features

First, the Laban Effort Features were mapped to appropriate feature vectors for an RVC performing a simple cleaning task. The mapping was mostly informed by the literature, but we adjusted some of the feature vectors in the original framework. These changes were necessary because some movement features (range of motion for yaw, pitch, and tilt) were not applicable to an RVC and some feature vectors (vertical compression, and head pitch) did not successfully meet the mechatronic constraints of a non-humanoid cylindrical robot with very low degree of freedom. Thus, we replaced some of the movement features with other features that were more relevant for an RVC performing a cleaning task at a domestic environment. These changes interested the Flow, Space and Weight components. Specifically, 1) path planning behavior was added to the feature vector of Flow, 2) radius of curvature was selected as the movement feature for Space, and 3) vacuum power replaced the acceleration, vertical compression, and head pitch for Weight.

Table 3.1 below shows the movement features corresponding to each Laban Effort, and the parameters defined under each polar level.

Table 3.1 The mapping of Laban Effort Features to a Robotic Vacuum Cleaner

Laban Efforts	Movement Features	Level 1 (Low)	Level 2 (High)
Flow	Path planning behavior Range of motion	Linear $\theta = 90°$	Random $60° \leq \theta \leq 180°$
Space	Radius of curvature	0 mm	165 mm
Time	Velocity at direct drive Velocity at rotational turns	100 mm/s 80 mm/s	200 mm/s 160 mm/s
Weight	Vacuum power	50% duty cycle	100% duty cycle

For Flow, the feature vector involved path planning behavior and range of motion for the robot base. For low level, we used linear path planning behavior and range of motion fixed at 90 degrees. For high level, we used random path planning behavior and range of motion between 60 degrees and 180 degrees.

For Space, the feature vector involved radius of curvature, which defined the size of the arc that the robot makes when it takes a turn. Low level of this feature was 0 millimeters, meaning the robot spined in place when it turned. High level of this feature was 165 millimeters, meaning the robot make a slight arc with a radius of 165 millimeters when it turned.

For Time, the feature vector involved velocity at direct drive and velocity at rotational turns. Low level of this movement feature was selected as 100 millimeters per second for direct drive and 80 millimeters per second for rotational turns. High level of this movement feature was selected as double the velocity for low level, 200 millimeters per second at direct drive and 160 millimeters per second at rotational turns.

For Weight, the feature vector corresponded to vacuum power. Vacuum power is measured in duty cycle, which is defined as the ratio of the machine's active time to the total time in percentages (Karygiannis et al., 2007). Low level of this movement feature was selected as 100% duty cycle, and high level was selected as 50% duty cycle. The difference between the two levels of vacuum power was distinguishable from the robot's noises in the video recordings. As a side note, participants were asked to turn on their speakers at the beginning of the online survey.

As an example, the difference between the two polar levels of Space is demonstrated in Figure 3.2 below. The left-hand side of the image shows the path that a robot with high level of Space would take, where the radius of curvature equals to165 millimeters. The right-hand side of the image shows the path that a robot with low level of Space would take, where the radius of curvature equals to 0 millimeters. The robot on the left-hand side makes a slight arc when turning, but the robot on the right-hand side spins in place when turning.

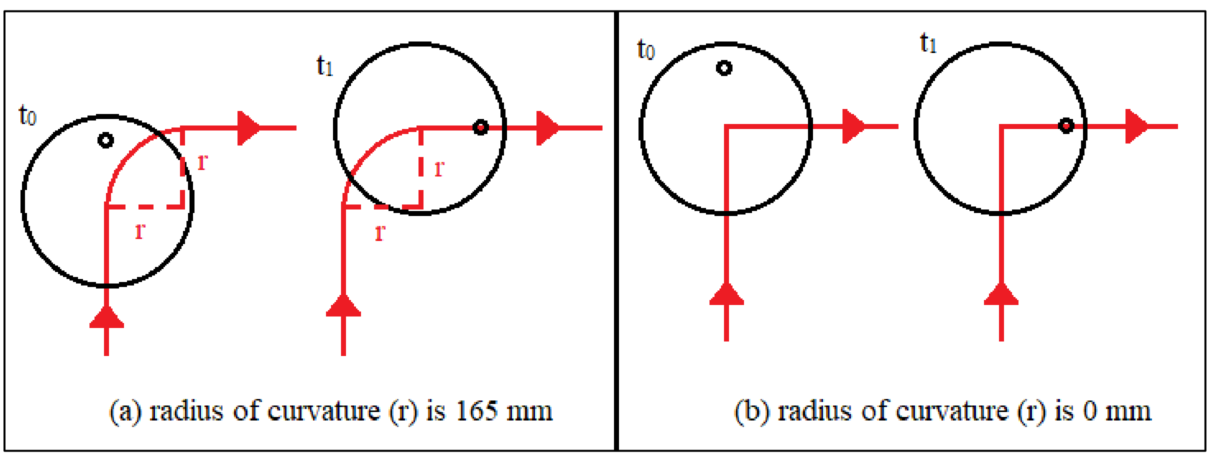

Figure 3.2 The comparison of the two polar levels of Space Effort

3.2 Stage 2: Implementation

During the second stage, the mapping of Laban Effort Features was implemented to an RVC. We used iRobot's Create2, because it is a programmable robot, aimed for educational purposes (iRobot

Education, 2021). “Pycreate2” library in Python was used to manipulate the movement features of the robot (Walchko, 2020). The library which is protected under an MIT license was forked and modified on GitHub. The link to the open-source code can be found in the references (Emir, 2021). The library was forked because we made some necessary changes in the library code, such as defining new functions and using different commands.

For the robot’s setup, we used a microprocessor and a portable charger as shown in Figure 3.3. Raspberry Pi4 as the microprocessor allowed wireless mobility and remote connection to the robot, so that the robot would travel freely while the code script was running. The portable charger provided power to run the Raspberry Pi 4 microprocessor. In addition, the robot’s faceplate was originally green-colored; it was painted black to avoid confusion and to provide a finished look to the robot.

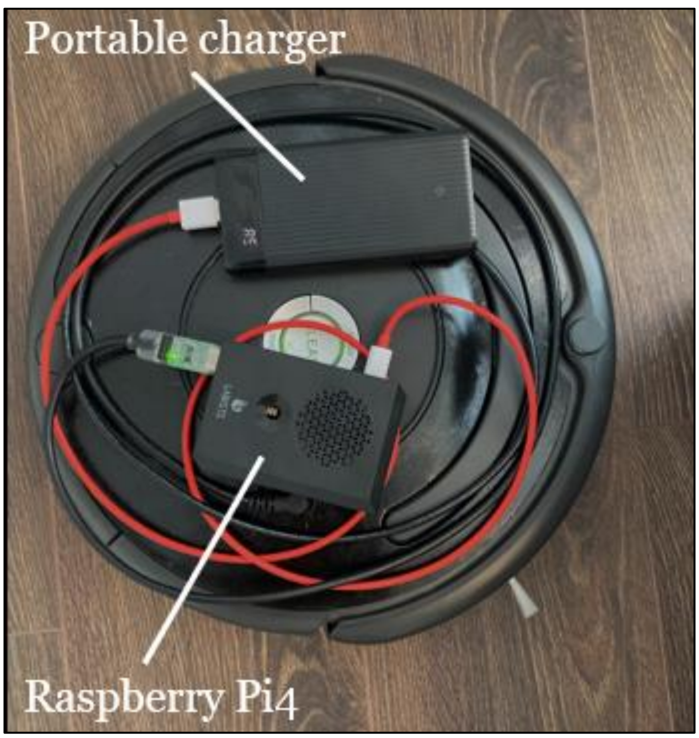

Figure 3.3 The robot’s setup used in the experimental study

This setup to was used to record videos of the robot, but since the robot was seen from a distance, the details of the equipment placed on top of the robot were not visible. To create a naturalistic environment, we preferred a living-room setting with a coach, two coffee tables and a few house plants as shown in Figure 3.4 below. The robot performed a simple cleaning task in the empty area between these objects. We used bird's eye view for the video recordings because it allowed the participants to have an objective and omniscient perspective on the scenarios being observed. Furthermore, it was shown in a recent study that the perspective of the robot's videos (bird's eye view of robot's point of view) did not have a statistically significant impact on how positively people rated the robot (Smith et al., 2021). GoPro Hero 7, which is an action camera with high resolution, was used to shoot the videos. Later, the video recordings were uploaded to an online survey in Qualtrics.

Figure 3.4 A screenshot of the video recordings showing the living room setting

3.3 Stage 3: Study Design

The next stage was concerned with the design of the experimental study and the online survey. We used within-subjects approach to evaluate the impact of movement features on how people rated the robot's personality and social attributes. Within-subjects design was preferred because we wanted to attribute some of the error to subject variability.

There were four factors with two levels each, meaning we had a total of $2^4 = 16$ treatment conditions in total. A folded fractional factorial design with two blocks was used in this study. Each block was a 2^{4-1} fractional factorial design of Resolution IV. Block 1 was the basic design with the defining relation $I = ABCD$. Block 2 was the folded design with the defining relation $I = -ABCD$.

The fractional factorial design was demonstrated in Table 3.2 below. There are two blocks, and each participant was randomly assigned to either block 1 or block 2. The basic fractional factorial design (block 1) was folded on factor D to generate the folded fractional factorial design (block 2). Participants in each block were shown half of the treatment conditions, in other terms participants were exposed to only 8 treatment conditions. Table 3.2 shows which treatment conditions were assigned to which block. The treatment conditions were randomly shown to participants, so the order effect was counterbalanced and minimized as much as possible.

Table 3.2 Design of experiment using fractional factorial design with two blocks

	Treatment Condition #	A (Flow, 0: bound, 1: free)	B (Space, 0: direct, 1: indirect)	C (Time, 0: sudden, 1: sustained)	D = ABC (Weight, 0: strong, 1: light)	Factors combination
Block 1	1	0	0	0	0	0-0-0-0
	2	1	0	0	1	1-0-0-1
	3	0	1	0	1	0-1-0-1
	4	1	1	0	0	1-1-0-0
	5	0	0	1	1	0-0-1-1
	6	1	0	1	0	1-0-1-0
	7	0	1	1	0	0-1-1-0
	8	1	1	1	1	1-1-1-1

	Treatment Condition #	A (Flow, 0: bound, 1: free)	B (Space, 0: direct, 1: indirect)	C (Time, 0: sudden, 1: sustained)	D = ABC (Weight, 0: strong, 1: light)	Factors combination
Block 2	9	0	0	0	1	0-0-0-1
	10	1	0	0	0	1-0-0-0
	11	0	1	0	0	0-1-0-0
	12	1	1	0	1	1-1-0-1
	13	0	0	1	0	0-0-1-0
	14	1	0	1	1	1-0-1-1
	15	0	1	1	1	0-1-1-1
	16	1	1	1	0	1-1-1-0

The rationale behind selecting the fractional factorial design was to avoid respondent fatigue in participants because they were expected to fill out the post-treatment questionnaires several times after each video. As defined in the *Encyclopedia of Survey Research Methods* (Ben-Nun, 2008), respondent fatigue is a phenomenon that causes a decrease in the response quality of participants. This decrease in response quality might be caused by several factors, such as lengthy questionnaires, frequent use of open-ended questions, boring survey topic, or repetitive questions. It is recommended that the items in a self-report questionnaire should be randomly presented to counterbalance the effect of respondent fatigue (Ben-Nun, 2008). For this, every questionnaire, including the pre- and post-trial questionnaires, were randomly presented to participants.

A power analysis was conducted to estimate the total number of participants needed for the study. The results from previous studies regarding the Big Five Inventory (BFI) were used. Using the mean and standard deviation values, a rough estimate of the effect size was calculated to be approximately 0.29. When the significance interval is selected to be $\alpha = 0.05$ and the power is selected to be 95%, a priori power analysis via G*Power software suggests a total sample size of 120. Since we used a fractional factorial design with two blocks, we needed around 120 participants per experimental block. In total, the sample size was estimated to be 240 participants.

Participants were recruited though Amazon Mechanical Turk, an online crowdsourcing platform commonly used by researchers. Only adults of age 18+ were recruited for participation in the online survey. Since Amazon Mechanical Turk contains verified users of age 18+, we did not use a pre-screening questionnaire. There was no inclusion or exclusion criteria aside from the age requirement. For compensation, participants received $8.00 (USD) for one hour of their time. Since the crowdsourcing platform, Amazon Mechanical Turk, does not provide personal information of their users and each user is assigned a worker ID only; we did not collect any data that could be personal identifiers in this study.

In a period of two months, the online survey received a total of 286 responses though Amazon Mechanical Turk. After filtering the responses using the three criteria shown in Figure 3.5 below, we were left with 240 responses. The filtering criteria were 1) the survey duration should be at least 12 minutes, 2) bot detection score determined by the survey should be at least 0.5, 3) the participants should provide a valid survey code on Amazon Mechanical Turk or via email.

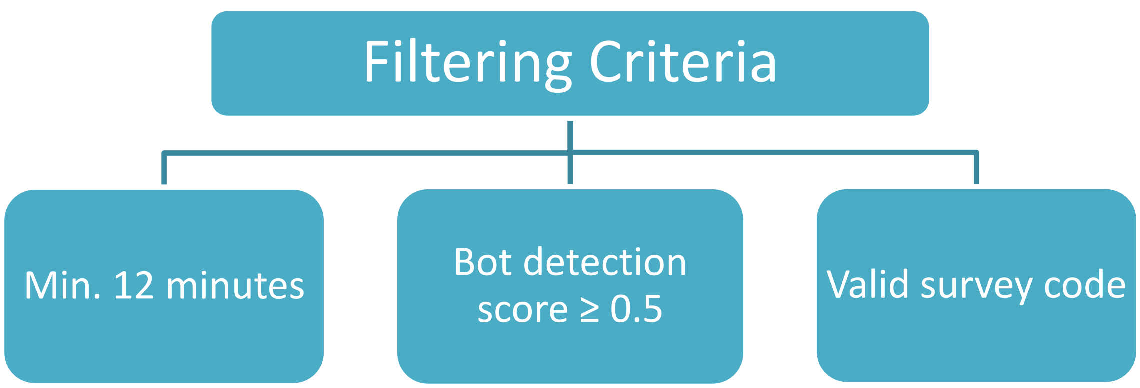

Figure 3.5 The filtering criteria used for survey responses

The first criterion was determined to make sure participants watched the robot's videos before answering the questionnaires. Considering there were eight treatment conditions exposed to each participant, they would need approximately 12 minutes to watch the video recordings. This requirement on the survey duration ensured participants watched the videos before filling out the questionnaires and that we did not involve any low-quality or rushed responses in the analysis.

The second criterion aimed to eliminate bot responses. The bot detection score was based on Google's reCAPTCHA v3. technology (Qualtrics XM Support, 2022). This score takes values from 0 to 1, where 0.0 should be interpreted most likely a bot response and 1.0 should be interpreted most likely a human response (Google Developers, 2021).

The last criterion was that participants submitted a valid survey code, which is a 4-digit code assigned to survey respondents by the survey platform. Participants were expected to provide this survey completion code when submitting their work on Amazon Mechanical Turk. This helped us track the study participants, associate responses with actual users in Amazon Mechanical Turk, and to make the necessary compensation payments. Thus, Amazon Mechanical Turk users submitting work without a valid survey completion code did not receive compensation. Also, there were some survey responses we could not associate with an Amazon Mechanical Turk user. These responses were filtered and not included in the statistical analysis, as well.

3.4 Stage 4: Online Survey

The online survey was constructed using the digital survey platform Qualtrics. The online survey consisted of six sections in total. Figure 3.6 below demonstrates an overview of the online survey.

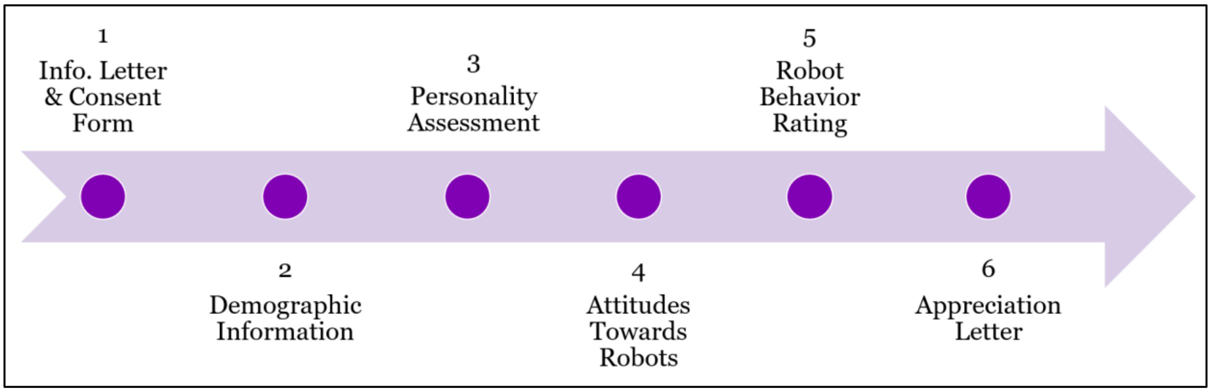

Figure 3.6 Overview of the Qualtrics online survey

In Section 1, the participants were provided with the Information Letter and Consent Form (see Appendix A). Section 2 was Demographic Information, which involved questions about age, gender, educational background, experience with robotics, RVC ownership and the length of ownership. Details of the demographic questions were reported at Appendix B.

Section 3 consisted of a self-report personality assessment, using Mini-IPIP (International Personality Inventory Pool) scale which was developed by Donnellan et al. (2006). This is a short version of the inventory pool IPIP, and it aims to measure five dimensions of personality (extraversion, agreeableness, conscientiousness, neuroticism, and intellect) using only 20 items. There are four items per dimension. This questionnaire was used to understand how participants perceived their own personality, as well as to develop familiarity with the scale. The items of the Mini-IPIP scale are shown in Figure 3.7 below. The items denoted with an "R" needs to be reversed before analysis.

20-Item Mini-IPIP

Item	Factor	Text	Original Item Number
1	E	Am the life of the party.	1
2	A	Sympathize with others' feelings	17
3	C	Get chores done right away.	23
4	N	Have frequent mood swings.	39
5	I	Have a vivid imagination.	15
6	E	Don't talk a lot. (R)	6
7	A	Am not interested in other people's problems. (R)	22
8	C	Often forget to put things back in their proper place. (R)	28
9	N	Am relaxed most of the time. (R)	9
10	I	Am not interested in abstract ideas. (R)	20
11	E	Talk to a lot of different people at parties.	31
12	A	Feel others' emotions.	42
13	C	Like order.	33
14	N	Get upset easily.	29
15	I	Have difficulty understanding abstract ideas. (R)	10
16	E	Keep in the background. (R)	16
17	A	Am not really interested in others. (R)	32
18	C	Make a mess of things. (R)	18
19	N	Seldom feel blue. (R)	19
20	I	Do not have a good imagination. (R)	30

Note. E = Extraversion; A = Agreeableness; C = Conscientiousness; N = Neuroticism; I = Intellect/Imagination; (R) = Reverse Scored Item. Original 50-item IPIP-FFM available at http://ipip.ori.org/newQform50b5.htm.

Figure 3.7 Mini-IPIP Scale used in the online survey (Donnellan et al., 2006)

In Section 4, we used the Multi-dimensional Robot Attitudes Scale (MDRAS) to measure participants' attitudes towards robots in general, not in particular to RVCs. This scale has been developed by Ninomiya et al. (2015). It aims to measure people's attitudes towards robots under 12 dimensions. Only a subset of this scale was used in this online survey, including the five dimensions Familiarity, Interest, Negative attitude, Self-efficacy, and Utility. This questionnaire was used in the pre-study assessment, to get a baseline of the individual’s attitudes towards robots in general. Participants were instructed to answer the items based on their experiences with and/or expectations of domestic robots. No specific robot name was provided. Names of the dimensions were not visible to participants since they might have caused bias in participants, as in the example of “Negative attitude”. This questionnaire was filled using a 5-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). The order of the items was randomized for each participant.

One small modification done on the MDRAS questionnaire was that, for the second statement under the Interest dimension, phrase “children and grandchildren” was replaced with “family” as seen in Table 3.3 below. With this modification, the purpose was to avoid situations where the statement would not apply to some participants.

Table 3.3 Subset of the Multi-dimensional Robot Attitudes Scale used in the online survey

Dimension	Question items
1. Familiarity	If a robot was introduced to my home, I would feel like I have a new family member. I would feel relaxed with a robot in my home. I like that a robot can encourage me. I think a robot can be a communication partner. I want to converse with a robot.
2. Interest	I would want to boast that I have a robot in my home. If a robot is introduced to my home, I think my family ~~children or grandchildren~~ will be pleased. If my friends use robots, I will also want one. I want to use robots if I can use them with my friends. Robots are neo-futuristic and cutting-edge. It is good if a robot can do the work of a human.

	I feel easy around robots because I do not need to pay attention to robots as I do to humans.
3. Negative attitude	It would be a pity to have a robot in my home. The movements of a robot are unpleasant. It is unnatural for a robot to speak in a human language. I feel like I also become a machine when I am with a robot. I feel scared around robots.
4. Self-efficacy	I have enough skills to use a robot. I can make full use of a robot. It is easy to use a robot. I can easily learn how to use a robot.
5. Utility	Robots are practical. Robots are user-friendly. Robots have functions that I find satisfactory with. Robots are convenient. I feel the necessity for robots in my daily life.

Section 5 focused on robot behavior rating, and the questions in this section formed the bulk of the experimental study. Participants were asked to watch video clips showing the robotic vacuum cleaner iRobot Create2, displaying different combinations of movement features. The video clips were embedded into Qualtrics, meaning participants could watch the videos without leaving the survey window. After each video, participants were asked to answer the following: 1) manipulation check questions, 2) Mini-IPIP scale, and 3) Robotic Social Attributes Scale (RoSAS). Manipulation check questions were aimed to understand the effectiveness of the manipulation and to see if these manipulations could be determined by participants. Mini-IPIP scale was used to measure the participants' rating of robot personality in each video. RoSAS scale was used to measure the participants' rating of robot's social attributes in each video.

The movement features being manipulated were path planning behavior, radius of curvature, velocity, and vacuum power. Participants were given instructions "Please rate the robot's behavior with regard to each item below". The items were the movement features based on the framework of Laban Effort features, as seen in Figure 3.8 below. Participants were asked to select one of the three options "low", "medium", or "high". As a side note, radius of curvature was rephrased as "degree of turn" to make it easier for people with a non-technical background to visualize this movement feature.

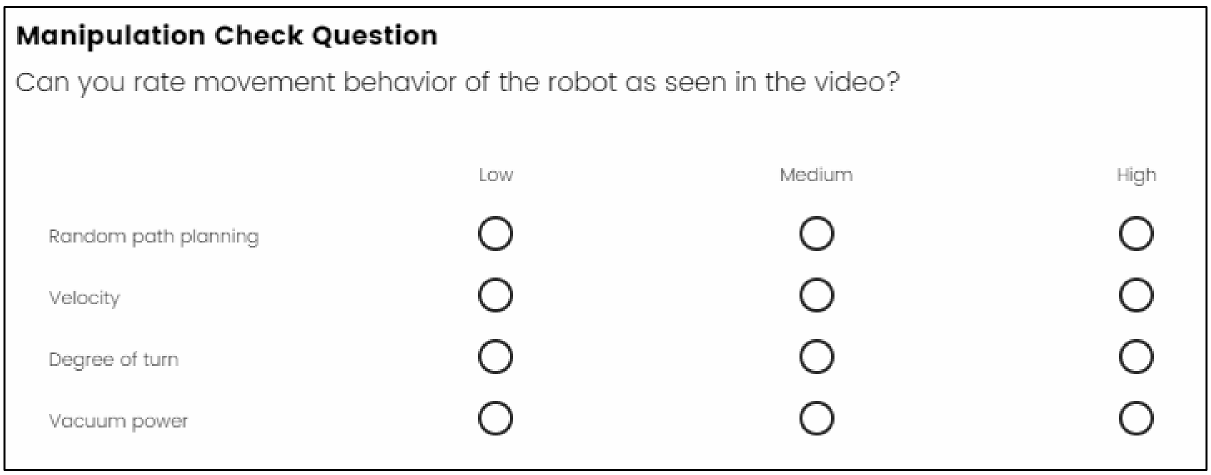

Figure 3.8 Manipulation check questions used in the online survey

RoSAS questionnaire was developed by Carpinella et al. (2017). It has a total of 18 items, which were categorized in three main factors, as seen in Figure 3.9 below. The three main factors affecting people's perception of social robots were "warmth", "competence", and "discomfort", respectively. Participants were asked to rate the RVCs in the video recordings using these unidirectional items on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The order of the items was randomized for each participant.

Variable	Factor 1	Factor 2	Factor 3
Happy	**.831**	-.013	-.009
Feeling	**.811**	-.154	.043
Social	**.793**	.125	-.176
Organic	**.784**	-.149	-.022
Compassionate	**.778**	-.039	.030
Emotional	**.776**	-.204	.050
Capable	-.210	**.706**	-.052
Responsive	-.141	**.680**	.040
Interactive	-.225	**.652**	-.006
Reliable	-.061	**.651**	-.028
Competent	-.111	**.646**	-.040
Knowledgable	-.007	**.620**	-.021
Scary	.052	-.012	**.693**
Strange	-.053	.150	**.601**
Awkward	.049	.037	**.601**
Dangerous	-.035	.024	**.597**
Awful	.360	-.250	**.555**
Aggressive	.265	.009	**.547**
Eigenvalue	22.031	9.336	5.047
Percent variance explained	26.54%	11.25%	6.09%

Figure 3.9 Robot Social Attributes Scale used in the online survey (Carpinella et al., 2017)

Lastly, in Section 6, participants received the appreciation letter and the contact information of the researchers (see Appendix C).

3.5 Participants

The participants in this study involved adults of age 18 and more. The online survey on Qualtrics received a total of 286 responses. After filtering the responses using the three criteria described in Section 3.3, there were 240 participants in total taking part in this study. Out of the 240 participants, 76 were females and 164 were males. Figure 3.10 below shows the distribution of gender among participants. Although there were other gender options (non-binary, third gender, and others) listed in the demographic question, those options received no responses.

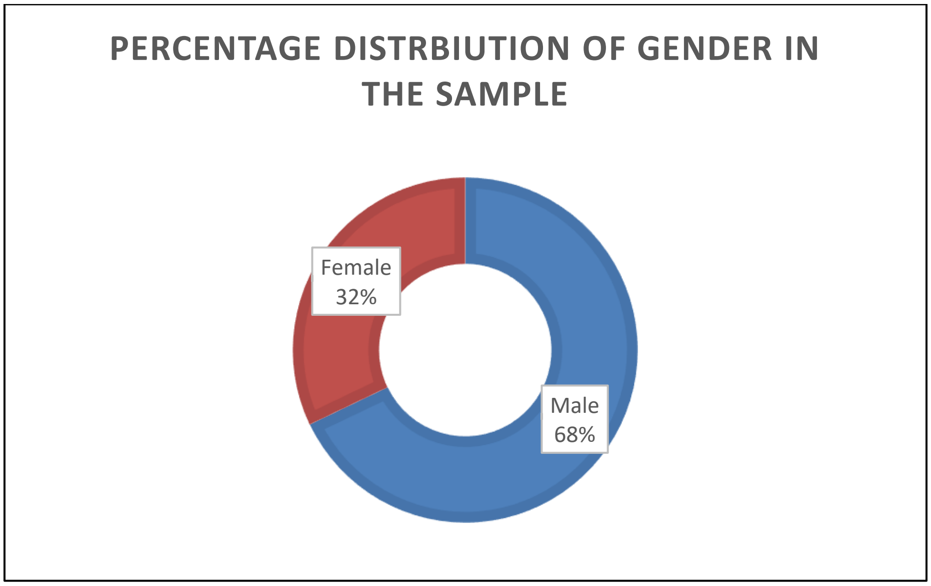

Figure 3.10 Pie chart showing the percentages of gender in the sample

The median age category was "35-44", with the minimum age category of "18-24" and the maximum age category of "85 or older". Figure 3.11 below shows the count for each age category. As a side note, there were nobody in the age category "75-84" so it was not included in the distribution chart.

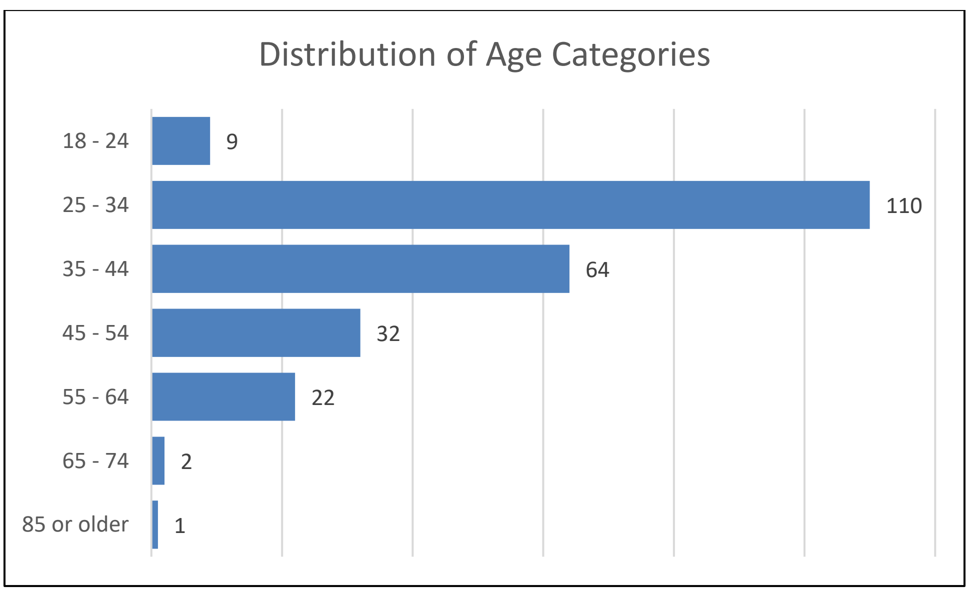

Figure 3.11 Distribution of Age Categories in the sample

The chart shown in Figure 3.12 below visualizes the distribution of sample in terms of age and gender. As seen in the chart, female participants were more uniformly distributed among different age categories, while male participants cumulate around only 1-2 age categories. For male participants, the percentage of age category “25-34” was 50% and the percentage of age category “35-44” was around 32%. This means most of the male participants (around 82%) were aged between 25 and 44.

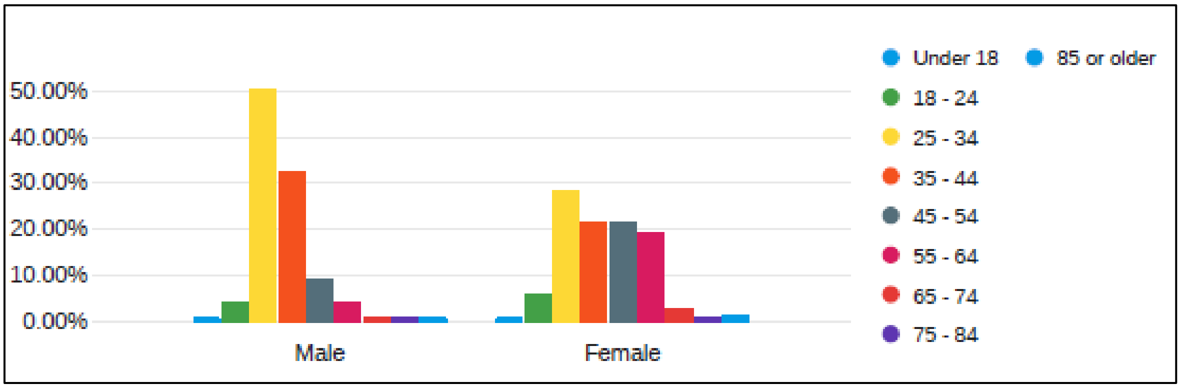

Figure 3.12 Distribution of participants in terms of age and gender

The distribution graph of educational background in Figure 3.13 indicated that “Computer Science” was the most frequently observed academic discipline among participants. Following this, “Engineering and Technology” and “Economics” were respectively the second and third academic disciplines with the highest count of responses. The academic disciplines with the least responses were “Anthropology” with 3 responses, “Theology” with 4 responses, “Law” and “Chemistry” both with 6 responses. From this graph, it is inferred that approximately one quarter of the participants received education in technical fields such as computer science, engineering, and technology. It is fair to claim that the sample was not evenly distributed with regards to academic background.

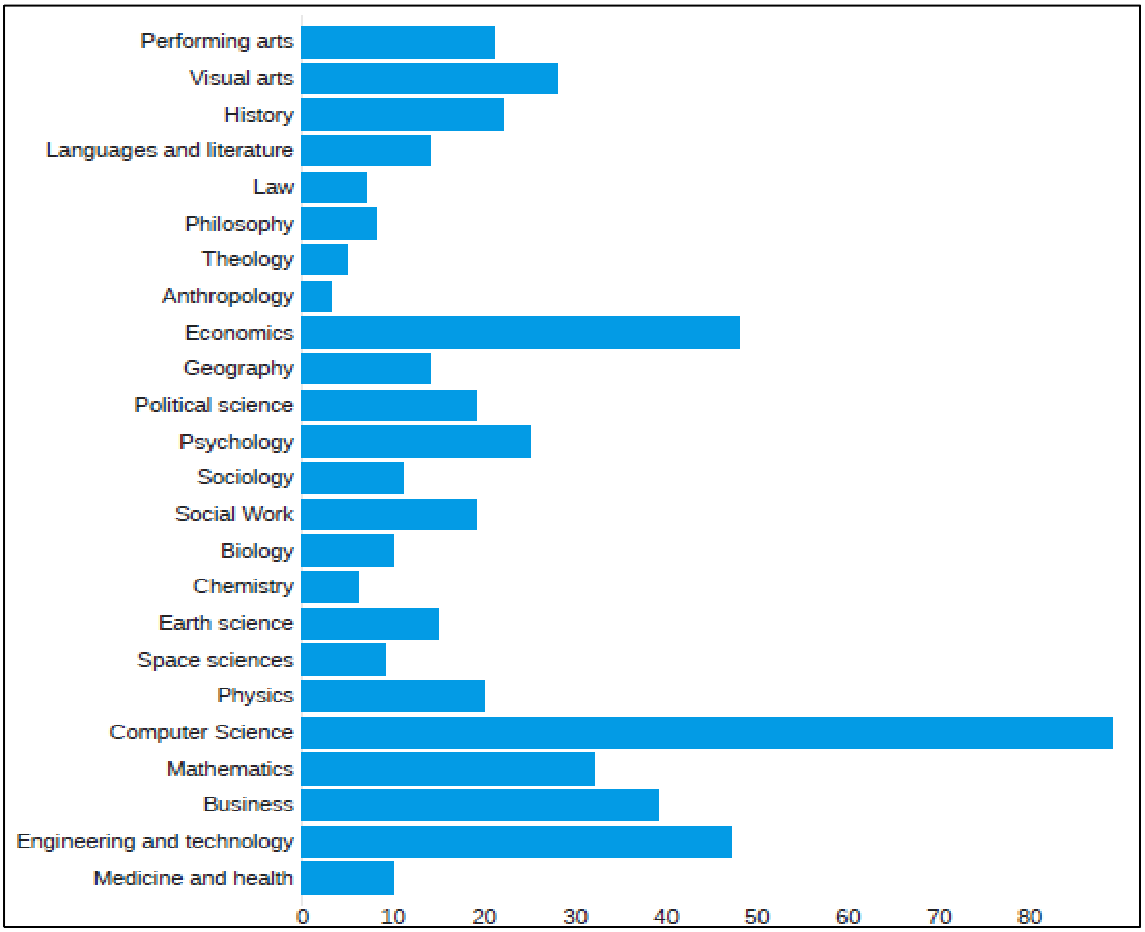

Figure 3.13 The distribution graph for the academic discipline question in demographics section

The participants were asked if they have ever taken courses or workshops related to the study of robotics. Fields related to robotics include Artificial Intelligence, Automation, Mechatronics, Computer Vision, and Human-Robot Interaction. The responses were visualized in a pie chart in Figure 3.14 below. 67% of the participants indicated that they took courses or workshops related to the field of robotics, meaning the majority was familiar with the terminology and the frameworks taught in robotics. Two thirds of the sample was interested in learning more about robotics, they took the initiative to register for technical courses and/or to attend workshops related to this field.

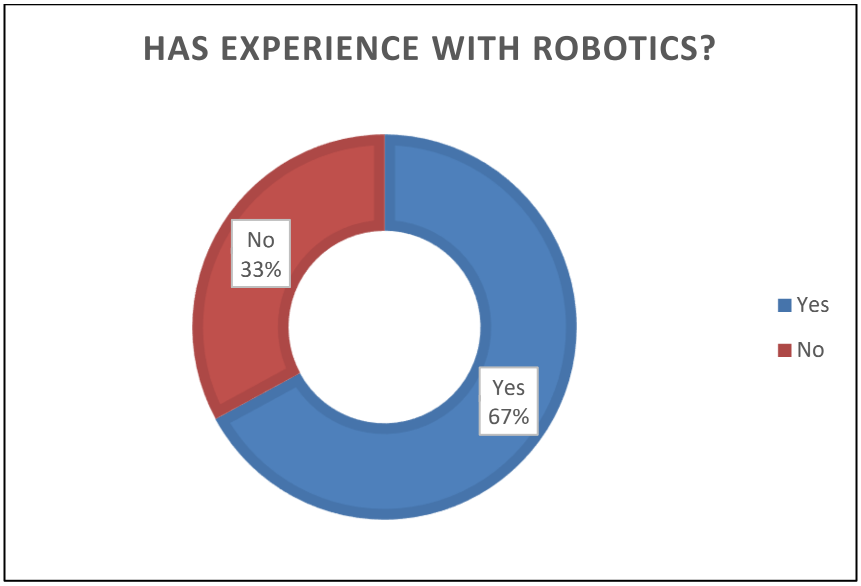

Figure 3.14 Pie chart showing the percentage distribution for the question about robotic experience

63% of the participants indicated that they owned a robotic vacuum cleaner (RVC), meaning 181 of the 240 participants owned an RVC at the time of taking the survey. The graph in Figure 3.15 below shows the percentage distribution of RVC ownership.

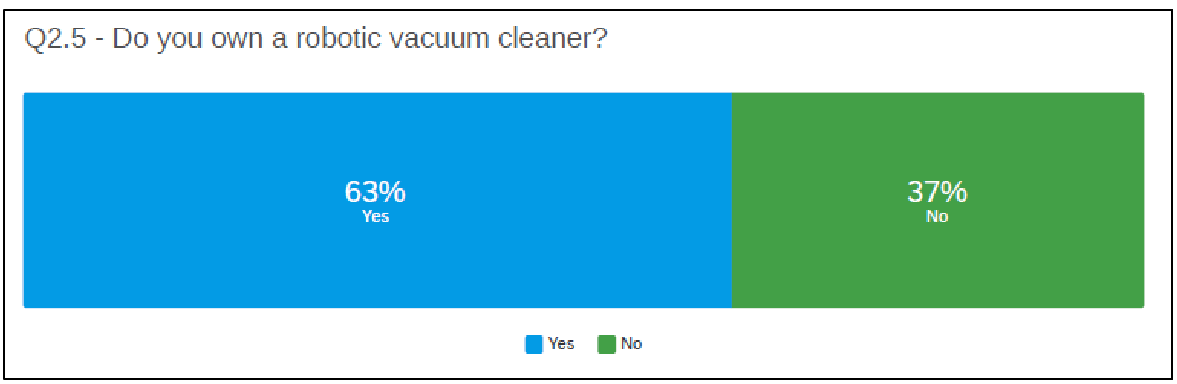

Figure 3.15 The answers to the RVC ownership question under demographics section

The distribution for the length of RVC ownership were visualized in Figure 3.16 below. The graph indicated that the mean length of ownership is around 1-2 years, with the minimum length of "less than 1 month" and the maximum length of "11-19 years". Out of the participants who owned an RVC, approximately 35% owned their device for 1-2 years and 21% owned their device for 3-5 years.

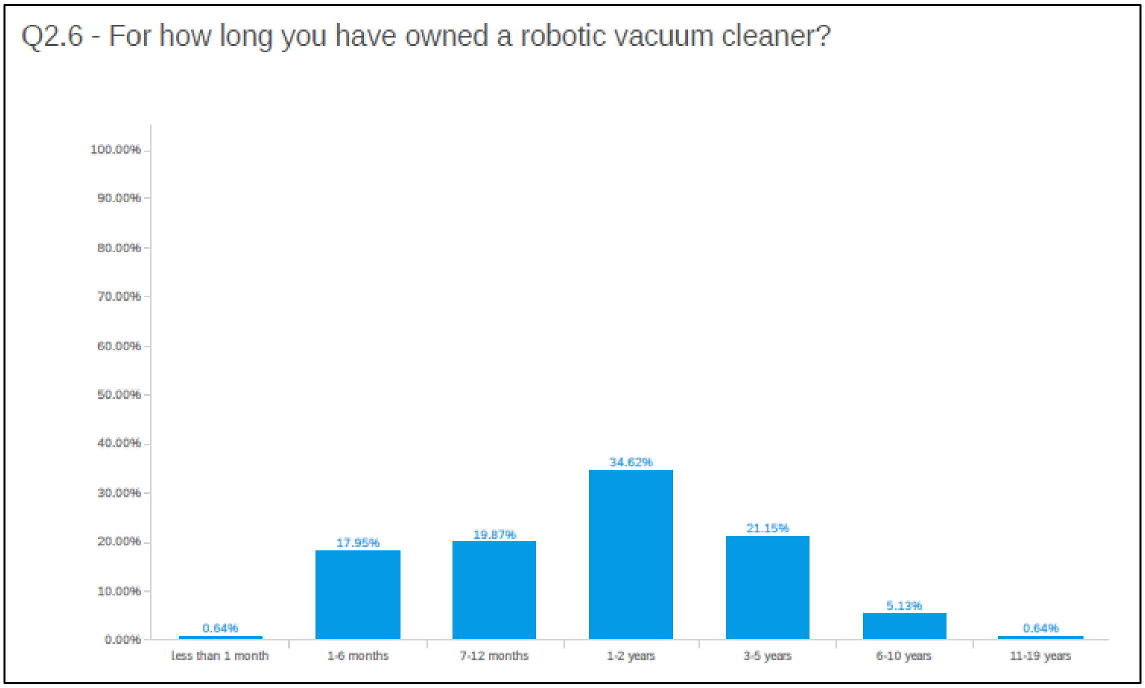

Figure 3.16 The distribution of the length of RVC ownership question in demographics section

3.6 Chapter Conclusion

In this chapter, the methods used during the experimental study were listed and described in detail. The rationale behind most of the design choices such as the movement feature vectors applied to simple cleaning task of a robotic vacuum cleaner (RVC), the selection of questionnaire items, and the selection of video perspective were explained. In addition to the methods, the profile of the participants was explained. The results of the demographics section were presented and their implications on the study sample were discussed. The findings indicated that majority of the sample was males and owned an RVC. The mean length of RVC ownership was between 1-2 years. One quarter of the sample was from technical academic disciplines, including Computer Science, Engineering and Technology. It was also found that two thirds of the sample took courses or workshops in the field of robotics.

Chapter 4 Results on Robot's Personality

4.1 Chapter Introduction

The following conference paper has accepted for presentation at the 66th International Annual Meeting of Human Factors and Ergonomics Society (HFES) in Atlanta, Georgia, US. This paper presents and discusses the results related to the impact of Laban Effort features on ratings of the robot's personality (Emir & Burns, 2022b). The complete paper was reported in the next section.

4.2 Conference Paper: A Survey on Robotic Vacuum Cleaners: Evaluation of Expressive Robotic Motions based on the Framework of Laban Effort Features for Robot Personality Design

Ebru Emir, Catherine M. Burns

Department of Systems Design Engineering, University of Waterloo

4.2.1 Abstract

The adoption of robotic vacuum cleaners (RVCs) has drastically increased. During interaction with these embodied autonomous agents, humans tend to ascribe certain personality traits to them even when the robot has a mechanoid appearance and low degree of freedom. As the social capabilities and the persuasiveness of robots increase, the design of robot personality will become important. This paper investigates the impact of expressive motions on people's perception of robot personality. The framework of Laban Effort Features was implemented for a simple cleaning task. Movement features were programmed in iRobot Create2, and participants were asked to rate the robot's personality in an online survey. The results indicated that Flow factor was closely associated with neuroticism ratings, Weight factor impacted both agreeableness and conscientiousness ratings, while Time factor impacted only the agreeableness ratings. Movement characteristics should be considered when designing personality into domestic service robots like RVCs, which are expected to operate in highly social settings.

4.2.2 Introduction

In the last two decades, robotic products have been employed increasingly in our everyday lives. Many households adopted personal assistance or domestic service robots. One common phenomenon in human-robot interaction (HRI) is that people tend to anthropomorphize and ascribe certain personality traits to robots regardless of the robot's technical capabilities, intelligence, and social skills. This phenomenon is significant because it can be utilized to improve the quality of HRI. Body language plays a crucial role in communication between humans, and its power can also be harnessed in this domain. Designing expressive robotic motions can facilitate effective communication of intentions and inner states to humans, improving the quality of human-robot interaction. It is important to study the design of robot personality because robots live alongside humans, share a mutual environment, and interact closely with humans. Responding to users' preferences for robot personalities might be highly valuable considering the broad domain of applications from education for autistic children to domestic services like cleaning and cooking, from care and companionship for seniors' houses to personal assistants.

4.2.2.1 Laban Movement Analysis

Laban Movement Analysis is a reliable and widely used framework of human motion and expression (Laban & Ullmann, 197). It has been applied in several domains, including theatre, dancing, psychology, and computer science (Bernardet et al., 2019). In this framework, human movement is described in four categories, one of which is Effort. Laban Efforts define movement with regard to intentions and internal states. There are four sub-categories of Laban Efforts, including Flow, Space, Time, and Weight. Several researchers implemented the framework to design expressive motions in mobile and companion robots and flying robots (Knight & Simmons, 2014; Knight et al., 2016b; Agnihotri et al., 2020; Sharma et al., 2013).

Knight and Simmons (2014) claimed that motion holds power to enable natural collaboration, to build rapport, and to contribute to fair sharing of mutual space between humans and robots. In a later study, Knight and Simmons (2016a) proved that implementing all four Effort components (flow, space, time, and weight) provided statistically significant legibility results for robots with low degrees of freedom. Agnihotri et al. (2020) found that participants could recognize the robot's intended personality. In their study, motion style was designed using Space and Time sub-components from the Laban Efforts System. Another study investigated the implementation of Laban Efforts in the design of expressive robot locomotion paths in flying robots (Sharma et al., 2013).

4.2.2.2 Personality in Robotics

Literature on robot personality is very scattered and disconnected. There is not an established framework of robot personality design or a common ground among scholars for how to measure robot personality. While some studies investigate the factors impacting robot personality, others focus on assessing the interaction quality resulting from human or robot personality. As revealed in the literature review by Robert et al. (2020) various personality scales have been used, including Big Five Inventory, NEO-Five Factor Inventory, International Personality Inventory Pool, Ten-Item Personality Inventory, and Myers-Briggs Type Indicator.

Personality research in robotics has mostly focused on measuring either human or robot personality (Santamaria & Roberts, 2017). A few studies investigated the impact of personality match between humans and robots on the quality of HRI. These studies resulted in inconsistent findings; some indicated that personality match leads to positive experiences (Tapus & Matarić, 2008) while others found the opposite (Celiktutan & Gunes, 2015).

Only two studies have investigated the intersection of the two concepts, namely Laban Efforts and robot personality (Agnihotri et al., 2020; Sonlu, 2021). A gap in understanding leads to two research questions: 1) How can the framework of Laban Effort Features (parametrized features for Laban Efforts: flow, space, time, and weight) be adapted to design motion for robotic vacuum cleaners? 2) To what extent do a robot's expressive motions affect how humans perceive the robot's personality?

4.2.3 Method

4.2.3.1 Study Design

The framework of Laban Effort Features, described by Knight and Simmons in their paper (2016a), was used to operationalize efforts into movement features. Combining these four movement features enabled us to generate expressive motions for iRobot Create2 while it was performing a simple cleaning task. Four factors correspond to different movement features with two levels (see Table 4.1).

Table 4.1 Implementation of Laban Efforts as movement features

Factor	Movement Feature	Level 1 (low)	Level 2 (high)	Laban Effort
A	Path planning and range of motion	linear path and θ = 90°	random path and θ in [60°, 180°]	Flow
B	Radius of curvature at turns	0 mm	165 mm	Space
C	Velocity (Direct drive & rotational turns)	200 mm/s & 160 mm/s	100 mm/s & 80 mm/s	Time
D	Speed of vacuum	100% vacuum duty cycle	50% vacuum duty cycle	Weight

The Flow Laban Effort was implemented through the robot's path planning and range of motion. The two levels of path planning involved linear for the low level and random for the high level. The range of motion was fixed at 90 degrees for low level and between 60-180 degrees for high level. The Space Laban Effort was implemented through the radius of curvature at rotational turns. The low level of this feature was 0 millimeters, meaning the robot would spin in place to change its orientation. The high level was equal to the robot's radius 165 millimeters, meaning it made a slight arc during the rotational turns. For the Time Laban Effort, the movement feature used the robot's velocity for both direct drive and rotational turn. The direct drive velocity was 200mm/s for low level, and 100mm/s for high level. The rotational turn velocity was 160mm/s for low level, and 80mm/s for high level. For the Weight Laban Effort we used the speed of the vacuum motor, where higher speed meant a higher vacuum power displayed by the robot during the cleaning task. The low level was set at a 100% duty cycle while the high level was set at 50% duty cycle. The higher speed of the vacuum motor caused the robot to make louder noises, and the change in these noises were distinguishable in the video recordings. Participants were asked to unmute their audio while viewing the videos at the beginning of the survey.

The "pycreate2" library in Python (Walchko, 2020) was modified to code the movement features with desired parameters. The robot was connected to a microprocessor computer, Raspberry Pi 4, and a power bank to provide wireless mobility. A simple action camera, GoPro Hero 7, was used to capture the robot's motions from a bird's view. With this setup, the code program was run simultaneously as the video recordings were made.

This design meant that there were $2^4 = 16$ combinations of robot behavior in total. However, we decided to proceed with a fractional factorial design instead of a full factorial design to mitigate the risk of respondent fatigue (Ben-Nun, 2008). A 2^{4-1} fractional factorial design of Resolution IV with defining relation I = ABCD has been used. Each participant was assigned to 8 treatment conditions. This basic design was folded on factor D, which gave us another fractional factorial design with the defining relation of I = -ABCD.

4.2.3.2 Participants

Participants were recruited through Amazon Mechanical Turk, an online crowdsourcing platform. The participants were required to be over 18 and received $8 (USD) compensation to participate when their work got accepted. Acceptance of work was determined by three criteria explained below.

Criteria 1. The survey duration should be equal to or greater than 720 seconds (12 minutes) so that participants who did not watch the robot's video recordings are eliminated.

Criteria 2. The reCAPTCHA V3 score, a metric captured automatically by Qualtrics, should be equal to or greater than 0.5 so that bot responses are eliminated.

Criteria 3. The participants should provide a valid completion code to match their work with a survey response.

Although 286 participants initially signed up for the study, 240 participants (76 Female, 164 Male) qualified to be included in the analysis according to the criteria above. The mean age was 38.37 (*SD* = 11.02). Of the 240 participants, 115 participants were randomly assigned to group 1, while 125 participants were randomly assigned to group 2.

4.2.3.3 Online Survey

After the participants were recruited, an online survey via Qualtrics was conducted. The online survey consisted of five sections: 1) Information and consent, 2) demographics, 3) personality self-rating, 4) attitudes towards robots, and 5) video ratings. The order of videos, as well as the questionnaire items, was randomized.

The demographics section included gender, age, academic background, robotics knowledge, and robotic vacuum ownership. In the next section, the Mini-IPIP (International Personality Inventory Pool) questionnaire (Donnellan et al., 2006) was administered to rate participants' personality in five dimensions: extraversion, agreeableness, conscientiousness, neuroticism, and intellect. There were four questions for each dimension, for a total of 20 questions. The following section measured participants' attitudes towards robots using the Multi-Dimensional Robot Attitudes Scale developed by Ninomiya et al. (2015).

The last section involved video recordings of the iRobot's Create2, showcasing a cleaning task in different combinations of movement features. Participants were asked first to watch these videos and then answer a manipulation check question, followed by Mini-IPIP and Robotic Social Attributes Scale (RoSAS). The manipulation check questions measured how well each participant perceived the operationalization of Laban Efforts. The manipulation check question was "Please rate the robot's behavior with regard to each item below," and the items were Path Planning, Radius of Curvature, Velocity, and Vacuum Power. The participants were asked to select one of the three options "low," "medium," and "high." Participants were instructed to answer the Mini-IPIP questionnaire regarding each robot they observed in the video recording. Participants filled out this questionnaire eight times, once for each treatment condition. The RoSAS scale provides a reliable measurement of how people perceive the social attributes of robots. The questionnaire classified the social perception of robots in terms of three dimensions: warmth, competence, and discomfort (Capinella et al., 2017).

4.2.4 Results

This paper focused on participants' rating of the robot's personality after observing expressive motions. The results related to ratings of the robot's social attributes are reported in another article (Emir & Burns, 2022a).

First, the accuracy rate of participants in manipulation check questions was calculated for each factor of Laban Efforts. The error rate was calculated by finding the differences between participants' ratings and the actual ratings, later taking the average for all treatment conditions. For instance, assuming the actual rating was low for a video, participants gained 1 error point if they selected medium, 0 point if they selected low and 2 points if they selected high. The accuracy rate was then calculated by the formula (*1-ErrorRate*). Accuracy rate values range from 0 to 1, inclusive. As observed in Figure 4.1, Flow factor had the highest mean accuracy rate M_f = .556 (*SD* = .201) while Time factor had the lowest mean accuracy rate of M_t = .422 (*SD* = .13).

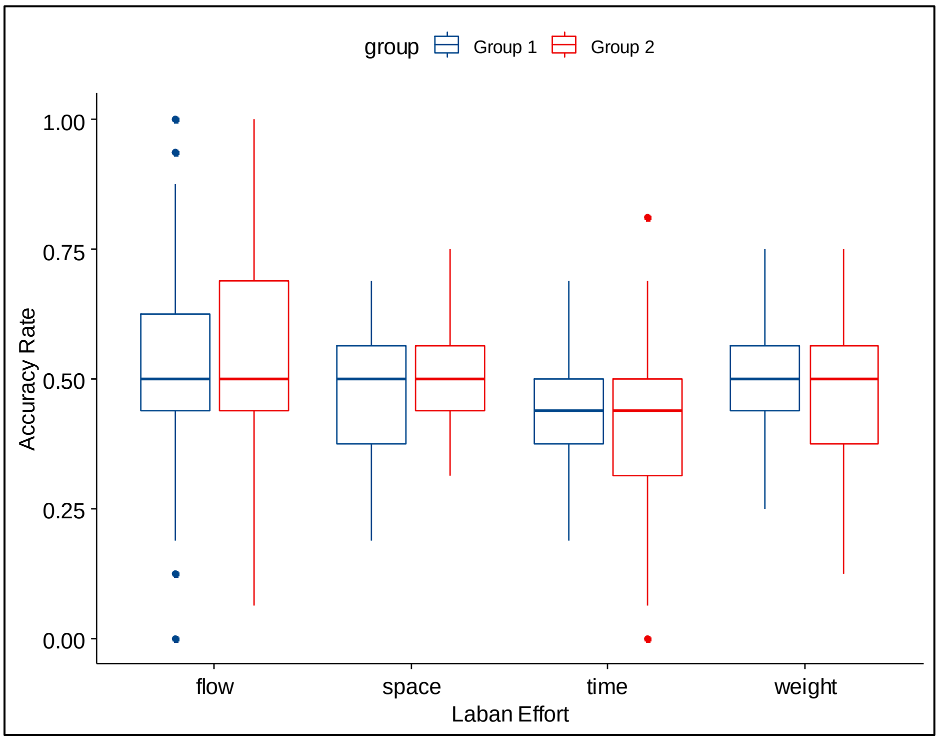

Figure 4.1 Accuracy rate of manipulation check questions for each Laban Effort, shown by experimental groups (referring to blocks)

A four-way repeated measures ANOVA was performed to evaluate the effects of four factors from the Laban Efforts (flow, space, time, and weight) on the robot's personality score measured in 5 dimensions (extraversion, agreeableness, conscientiousness, neuroticism, intellect). There were no extreme outliers, as assessed by the box plot method. The results from Shapiro-Wilk's test of normality (p > .05) indicated that data were not normally distributed for the most part. However, Howell states that ANOVA test is robust to the assumption of normality and that "homogeneity of variance assumption can be violated without terrible consequences" (2010, p. 334). Homogeneity of variances ($p > .05$) was observed for most of the data, as assessed by Levene's test of homogeneity of variances. Since the assumption of sphericity is tested internally by the "anova_test" function in R, no separate test was conducted (Anova Test, n.d).

Extraversion. There was a statistically significant three-way interaction between flow, space, and time, $F(1, 114) = 4.698$, $p < .05$. The partial eta-squared was .04, indicating a small effect size. A Bonferroni adjustment was applied for the simple two-way interactions and simple main effects, leading to statistical significance being rejected at the $p < .0018$ level. There was a statistically significant simple two-way interaction between flow and time for space:low group ($F(1, 114) = 5.35$, $p = .023$). The simple main effect of flow on extraversion was statistically significant for the condition where space:low and time:low ($F(1, 114) = 5.94$, $p < .05$).

Agreeableness. There were two statistically significant main effects for time, $F(1, 114) = 5.870$, $p < .05$, and weight, $F(1, 114) = 5.146$, $p < 0.05$. The partial eta-squared was .049 for time and .043 for weight, indicating small effect sizes for both. The simple main effect of time on agreeableness score was statistically significant for the condition where flow:high, space:low and weight:low ($F(1, 114) = 4.64$, $p < .05$). The simple main effect of weight on agreeableness score was statistically significant for the condition where flow:high, space:high and time:high ($F(1, 114) = 4.83$, $p < .05$).

Conscientiousness. There was a statistically significant three-way interaction between flow, space, and time, $F(1, 114) = 4.038$, $p < .05$. The partial eta-squared was .034, indicating a small effect size. A Bonferroni adjustment was applied for the simple two-way interactions and simple main effects, leading to statistical significance being rejected at the $p < .0018$ level.

There was another statistically significant three-way interaction between flow, time, and weight, $F(1, 114) = 4.759$, $p < .05$. The partial eta-squared was .04, indicating a small effect size. A Bonferroni adjustment was applied for the simple two-way interactions and simple main effects, leading to statistical significance being rejected at the $p < .0018$ level.

There was a statistically significant two-way interaction between flow and weight, $F(1, 114) = 5.938$, $p < .05$. The partial eta-squared was .05, indicating a small effect size. A Bonferroni adjustment was applied for the simple main effects, leading to statistical significance being rejected at the $p < .008$ level.

There was a statistically significant main effect of weight, $F(1, 114) = 5.516$, $p < .05$. The partial eta-squared was .046, indicating a small effect size. The simple main effect of weight on conscientiousness was statistically significant for the condition where flow:high, space:high, and time:high ($F(1, 114) = 4.85$, $p < .05$) as well as the condition where flow:low, space:high, and time:low ($F(1, 114) = 4.49$, $p < .05$).

Neuroticism. There was a statistically significant main effect for flow, $F(1, 114) = 6.565$, $p < .05$. The partial eta-squared was .054, indicating a small effect size. The simple main effect of flow on neuroticism score was statistically significant for the condition where space:high, time:low and weight:low ($F(1, 114) = 6.91$, $p = .01$).

Intellect. There was a statistically significant four-way interaction between flow, space, time and weight, $F(1, 114) = 4.172$, $p < .05$. The partial eta-squared was .013, indicating a very small effect size. For the simple three-way interactions, simple two-way interactions and simple main effects, a Bonferroni adjustment was applied, leading to statistical significance being rejected at the $p < .00125$ level.

4.2.5 Discussion

The goal of this study was to investigate the impact of expressive motions in robots on people's subjective rating of the robot's personality. The results of this paper contribute to the existing literature on robot personality by addressing this question and highlighting the potential of Laban Efforts framework for motion design in domestic service robots including robotic vacuum cleaners.

The results suggested that expressive motions designed using the Laban Effort Features have an impact on the robot's personality ratings. Summary of results in Table 4.2 indicated that there are four main effects in total while the interaction effects could not pass the post-hoc tests. We discuss the three main findings related to personality ratings of the robot next.

Table 4.2 Summary of results from ANOVA and post hoc tests

Personality Dimension	ANOVA test ($p < .05$)	p-value	Partial eta-squared	Post hoc test
Extraversion	Flow:space:time	.032	.040	✕
Agreeableness	Time	.017	.049	-

	Weight	.025	.043	-
Conscientious-ness	Weight	.021	.046	-
	Flow:weight	.016	.050	✕
	Flow:space:time	.047	.034	✕
	Flow:time:weight	.031	.040	✕
Neuroticism	Flow	.012	.054	-
Intellect	Flow:space:time:weight	.043	.013	✕

F1: Agreeableness. Agreeableness ratings were closely associated with time and weight components of Laban Efforts. As mentioned earlier, time factor determines robot's velocity for both direct and rotational drive, while weight factor determines its vacuum power. Robots with low velocity were rated by participants to have lower agreeableness. This finding was surprising because one would expect the robot with lower velocity to seem milder and more easygoing, suggesting higher agreeableness. High agreeableness ratings are reflected through "characteristics like altruism, compliance, sympathy, and mild-mindedness" (He, 2019). Participants rated the robots with higher vacuum power and louder noises to have higher agreeableness. Potentially, robots making louder noises were perceived to be working harder.

F2: Conscientiousness. Conscientiousness ratings are influenced by the main effect of weight. Since weight factor corresponds to the speed of the vacuum in the robot, it is possible that the louder noises coming from the robot's vacuum unit created the illusion that the robot was showing much greater effort to clean the space. This finding is intuitive in the sense that when traditional vacuum cleaners do not make any noises, people assume they are either broken or not turned on.

F3: Neuroticism. Neuroticism ratings of the robot were influenced by the main effect of flow. Considering the mapping of flow factor as path planning and range of motion of the robot, this finding is predictable. When the robot used a random path planning algorithm and moved erratically during the cleaning task, participants were more likely to perceive the robot's personality to show high neuroticism than the scenario where the robot used a linear path planning behavior. This finding is important because it implies that the robot's path planning behavior has an evident impact on how people perceive neuroticism dimension of its personality. When roboticists or engineers aim to design a robot with low neuroticism, they should try to avoid navigation algorithms using random path planning. In fact, RVCs that navigate based on random path planning algorithms are slowly getting replaced by versions that navigate in a linear path using advanced technology like VSLAM and LIDAR (Bennett, 2021). Careful and deliberate selection of the robot's navigation strategy is crucial to the interaction. This decision will influence people's perception of the robot's personality traits; therefore, influencing overall acceptance of domestic service robots.

4.2.5.1 Limitations

The limitations of this study are mainly concerned with experimental design and technical constraints related to the programmable robot, Create 2. For technical constraints, robot's low degree-of-freedom and highly mechanoid body were the main constraints limiting the pool of potential robotic motions. These kinematic constraints prevented accurate replication of the Laban Effort Features framework suggested by Knight and Simmons (2016a). Some of the movement features were replaced by other features that are more relevant to a robotic vacuum cleaner. For instance, the weight component of the Laban Efforts was changed from ‘range of motion of joints’ to ‘path planning behavior’ because the latter is more relatable to a mechanoid robot lacking a jointed body.

For experimental design, limitations involve unbalance of gender in the sample and administration of demographics questionnaire at the beginning of the survey. The number of female participants was less than half of the male participants. This limitation might have impacted the results since there is a potential difference between males and females in their interaction with social robots as demonstrated in a study by Wonseok et al. (2021). It is not recommended to administer the demographics questionnaire since it has been shown that doing so primes the participants and causes them to embrace fully their "self-relevant stereotypes" (Rydell et al., 2009). To minimize the priming effect of demographics for future research, demographics questionnaire will be administered at the very end of the experimental study.

The results from statistical tests yielded significant results and small effect sizes for the relationship between robot's expressive motions and the robot's personality ratings. However, the low accuracy rate of participants means the manipulations were not easily observed by them. It is approximately equal to the chance line 0.5, meaning the participants were not successful in detecting the movement features of the robot in videos. The manipulation check questions were highly valuable, because they reveal if the desired manipulation on the robot's behavior was correctly perceived by the participants. The factor with the highest accuracy rate was flow, whereas the factor with the lowest accuracy rate was time. This indicates that the path planning combined with range of motion was the easiest, while the robot's velocity was the hardest feature to be distinguished by the participants. For future studies, scale of the difference between two levels of velocity needs to be studied to understand if the low accuracy was caused by the small scale or the operationalization of independent variables.

Overall, it is shown that designing expressive motions in robotic vacuum cleaners influenced how people ascribed personality traits to them. Three personality dimensions including agreeableness, conscientiousness, and neuroticism had statistically significant results. The most intuitive finding was that random path planning was associated with a high neuroticism rating. The framework of Laban Effort Features was implemented to design expressive motions by operationalizing the independent variables into tangible movement features. Investigation of accuracy rates proved that manipulations did not yield a high rate of detection among participants and further research is needed to ensure the findings are caused by the designed expressive motions. These findings will hopefully benefit researchers and engineers when designing robots with specific personality traits for various scenarios and in different domains such as domestic service, personal assistantship, and robot companions for elderly.

4.2.6 Acknowledgements

Research reported was supported by Natural Sciences and Engineering Research Council of Canada (NSERC) under the Discovery Grant with award number RGPIN-2020-07026. The content is solely the responsibility of the authors and does not necessarily represent the official views of NSERC.

4.3 Chapter Conclusion

To sum up, the purpose of this study was to understand the impact of Laban Effort Features on how people rated the personality of domestic service robots. iRobot's Create2, a robotic vacuum cleaner, was used to manipulate robot behavior and to implement movement features based on the framework of Laban Effort features. Using an online survey, where participants watched videos of different robot behavior, we aimed to investigate how people's perceptions of the same robot changed. The results indicated that the dimension of agreeableness was influenced by both velocity and vacuum power, the dimension of conscientiousness was influenced by vacuum power, and the dimension of neuroticism was influences by the path planning behavior.

Chapter 5 Results on Robot's Social Attributes

5.1 Chapter Introduction

The following conference paper was accepted for presentation at the 31st IEEE International Conference on Robot & Human Interactive Communication in Naples, Italy. This paper presents and discusses the results related to the impact of Laban Effort features on ratings of the robot's social attributes (Emir & Burns, 2022a). The complete paper was reported in the next section.

5.2 Conference Paper: Evaluation of Expressive Motions based on the Framework of Laban Effort Features for Social Attributes of Robots

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5.2.1 Abstract

In today's world, it is not uncommon to see robots adopted in various domains and environments. Robots take over several roles and tasks from manufacturing facilities to households and offices. It is crucial to measure people's judgment of robots' social attributes since the findings can shape the future design for social robots. Using only a simple and mono-functional robotic vacuum cleaner (RVC), this paper investigates the impact of expressive motions on how people perceive the social attributes of the robot. The Laban Effort Features, a framework for movement analysis that emerged from dance, was modified to design expressive motions for a simple cleaning task. Participants were asked to rate the social attributes of the robot under several treatment conditions using a video-based online survey. The results indicated that velocity influenced people's ratings of the robot's warmth and competence, while path planning behavior influenced people's ratings of the robot's competence and discomfort. Limitations of this study include the kinematic constraints of the robot, potential issues with survey design, and technical constraints related to the open interface provided by the robot's developer. The findings should be considered when incorporating expressive motions into domestic service robots operating in social settings.

5.2.2 Introduction

Robots of various functionality and appearances have been employed in our everyday lives during the last decade. Robots are used at manufacturing facilities, warehouses, agricultural farms, and offices. It has become common to see robotic vacuum cleaners or floor scrubbers in households. These service robots perform menial and tedious tasks that humans do not prefer. In addition to these functional mechanoid robots, humans are adopting assistant or companion robots equipped with advanced social communication skills. As a result of the rapid introduction of robots into our everyday lives, research in human-robot interaction (HRI) and social robotics has recently gained momentum.

Anthropomorphism is an intriguing phenomenon that gained interest in the HRI community. It is defined as attributing "humanlike properties, characteristics, or mental states" to non-human entities, such as animals, machines, or robots (Epley et al., 2007, p. 865). This phenomenon is crucial for HRI because humans' judgment of the robot's social attributes impacts robot acceptance and adoption rate. It has been shown that people tend to anthropomorphize robots irrespective of the intelligence or technical capabilities of the robot (Złotowski et al., 2014). This fact allows the investigation of the phenomenon using very simple and mechanoid robots with low degrees of freedom (dof), such as iRobot's Create2 (iRobot Education, 2021). Designing expressive motions into the robot can increase the quality of HRI by facilitating nonverbal communication norms. Expressive movements based on the Laban Effort Features can provide an intuitive way to convey the robot's inner states and intentions that humans easily perceive.

5.2.2.1 The framework of Laban Effort Features

The framework of Laban Movement Analysis (LMA) is a reliable and widely used method to analyze human movement and expression (Laban & Ullmann, 1975). Over the years, it has been applied to several domains such as dancing, theater, computer science, and psychology (Bernardet et al., 2019). This framework has been used in computer science to train human detection algorithms (Bernstein et al., 2015) and to design expressive motions for robots. LMA classifies human movement into four categories: Body, Effort, Shape, and Space. The Effort category focuses on the intentions and emotions conveyed through movement. There are four components of Laban Efforts, including Flow, Space, Time, and Weight. Table 5.1 demonstrates that each element of Laban Efforts defines a different feature and is represented with two polar levels (Knight & Simmons, 2014).

Flow defines the agent's sense of restriction, where the agent feels bound or restricted at the fighting pole, free or relaxed at the inducing pole. Space defines the agent's attitude toward its target, where its motions are direct at the fighting pole, indirect or meandering at the inducing pole. Time defines the agent's attitude toward time, where its movements are sudden or hurried at the fighting pole and sustained or lingering at the inducing pole. Weight defines how much force the agent feels on itself, where it feels compressed or collapsed at the fighting pole, floating or light at the inducing pole.

Knight and Simmons (Knight & Simmons, 2014) used this framework to develop a systematic method to parametrize the four factors of Laban Effort into motions. Their implementation of Laban Effort features has inspired this study and their Laban Effort feature vectors has been modified slightly to fit a simple cleaning task of a robotic vacuum cleaner. They suggested an application order for these Laban Effrot features, which follow as Flow, Space, Time, and Weight.

Table 5.1 Laban Efforts with Two Polar Levels

Laban Effort	**Fighting pole**	**Inducing pole**
Flow: *sense of restriction*	Bound	Free
Space: *attitude toward target*	Direct	Indirect
Time: *attitude toward time*	Sudden	Sustained
Weight: *force or apparent inertia*	Strong	Light

A few studies investigated this framework's impact on how humans interact with mobile robots and companion robots (Knight & Simmons, 2014; Knight et al., 2016b; Agnihotri et al., 2020), and flying robots (Sharma et al., 2013). Implementing all four Laban Effort features in a robot with low dof yielded statistically significant results for the legibility of its intentions (Knight & Simmons, 2016a).

Participants successfully detected the intended personalities in Neato Botvac, a vacuum cleaning robot (Agnihotri et al., 2020). These studies show that Laban Effort features can impact human-robot interaction. Expressive robotic motions can enhance natural collaboration between humans and robots and facilitate the fair use of mutual space in office environments or houses (Knight & Simmons, 2014).

5.2.2.2 Literature on Social Attributes of Robots

There are several scales to measure the perceived social attributes of robots. The Godspeed questionnaire is a widely used scale measuring people's attitudes towards robots in five dimensions, including anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety (Bartneck et al., 2008).

The Robotic Social Attributes Scale (RoSAS) is another survey that categorizes people's perceptions of the social attributes of robots. This scale uses three dimensions: warmth, competence, and discomfort (Carpinella et al., 2017; Fiske et al., 2007). Pan et al. (2018) used the RoSAS scale to measure people's perception of the social qualities of robots in a handover scenario with varying arm position, grasp type, and speed levels. In their study, the scale was found to show high internal consistency. Their findings indicated that the competence ratings of the robot were primarily affected by the grasp type. In contrast, the discomfort ratings of the robot were affected mainly by the interaction between grasp type and speed (Pan et al., 2018).

5.2.2.3 Overlap of the Two Concepts

Currently, only two studies have investigated the implementation of Laban Effort features for robot personality design (Agnihotri et al., 2020; Sonlu et al., 2021). However, Laban Effort features have been implemented in designs. A study by Arent et al. (2017) found that the facial emotions embodied in the Nao robot using the framework of LMA were recognized by participants.

This study aims to determine the factors impacting robot personality and social attributes of robots using the Laban Effort framework. We are interested in: 1) How can the Laban Effort framework be adapted to design motion for robotic vacuum cleaners? 2) To what extent, if any, do expressive motions impact how humans perceive the social attributes of robots?

5.2.3 Method

5.2.3.1 Study Design

The implementation approach suggested by Knight & Simmons (Knight & Simmons, 2016a) was used to operationalize Laban Effort into movement features, determining the order of implementation, as shown in Figure 5.1. However, their suggested feature vectors corresponding to each Laban Effort were simplified and modified to fit the movement constraints of a low-dof vacuum cleaner robot. The revised version of this mapping between Laban Effort and movement features for a simple cleaning task is presented in Table 5.2.

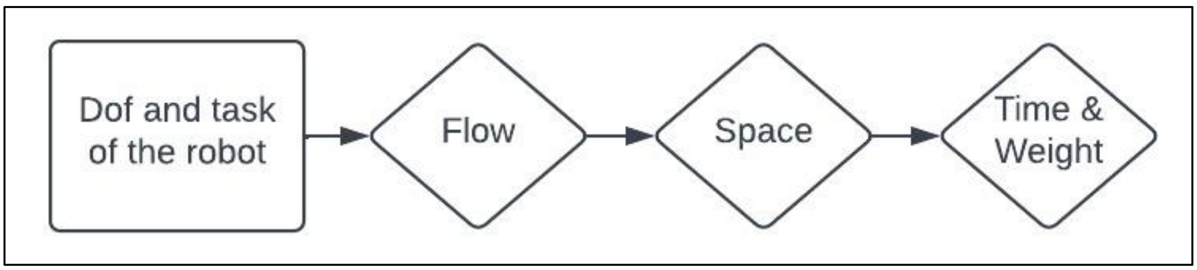

Figure 5.1 Application Order of Laban Efforts

For Flow, the original framework suggested "range of motion for every joint" as the movement feature (Knight & Simmons, 2016a). In our case, this was changed to 'path planning and range of motion' since the robot's path planning behavior directly impacts the robot base's range of motion (θ), which was our robot's only joint.

Table 5.2 Implementation of Laban Efforts for Cleaning Task

Factor	Laban Effort	Movement Feature	Level 1 (low)	Level 2 (high)
A	Flow	Path planning and range of motion	Linear path and θ = 90°	Random path and θ in [60°, 180°]
B	Space	Radius of circular arc during turns	0 mm	165 mm
C	Time	Velocity (direct drive & rotational turns)	200 mm/s & 160 mm/s	100 mm/s &

Factor	Laban Effort	Movement Feature	Level 1 (low)	Level 2 (high)
				80 mm/s
D	Weight	Speed of vacuum	100% vacuum duty cycle	50% vacuum duty cycle

For Space, the movement feature was suggested to be "target Gaussian(s) based on the starting position" in the original paper (Knight & Simmons, 2016a). Our study changed this to 'radius of circular arc,' which determines the robot's radius during rotational turns. As seen in Figure 5.2, the low level is 0 millimeters, meaning the robot spins in place, whereas the high level is equivalent to the robot's radius (165 millimeters), meaning the robot makes an arc.

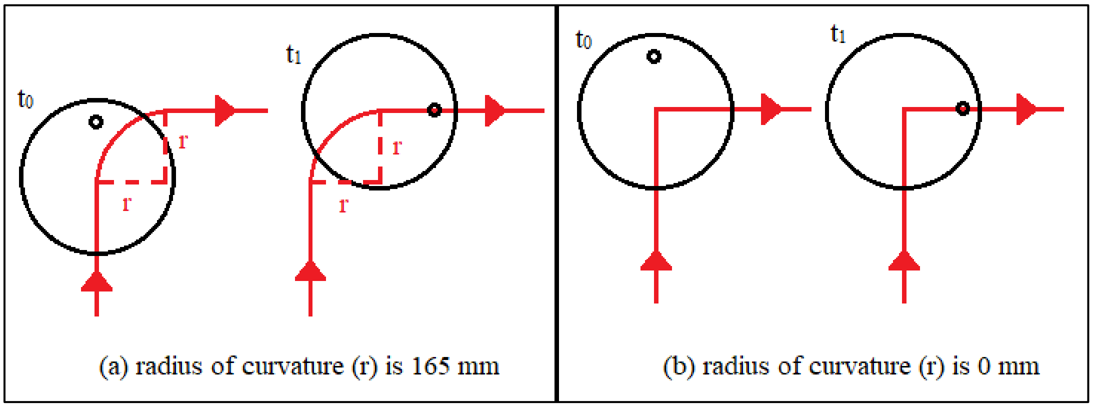

Figure 5.2 Two Levels for The Radius of a Circular Arc Defining Rotational Turn

For Time, the movement feature suggested was 'velocity', and it was not changed in our study. The low levels of 'velocity' are determined to be 200 mm/s for direct drive and 160 mm/s for rotational turns, while the high levels of 'velocity' are half these values, 100 mm/s for direct drive and 80 mm/s for rotational turns.

For Weight, the original framework suggested "acceleration and body position" as the movement features (Knight & Simmons, 2016a). Our study changed this to 'speed of vacuum' since body position does not apply to a robotic vacuum cleaner comprised of a cylindrical, mechanoid body. The speed of the vacuum determines the power displayed by the robot's vacuuming motor, where a higher speed creates louder noise. Thus, the change in the robot's noises indicated its weight feature. The high level for this feature used a 50% vacuum duty cycle, while the low level used the complete 100% vacuum duty cycle.

After designing the Laban Effort features, the movement features were coded in the robotic vacuum cleaner using the "pycreate2" library in Python (Walchko, 2020). The code for the library was forked and modified with some additional functions. The open-source code was uploaded to GitHub and can be accessed in (Emir, 2021). Raspberry Pi4, connected to the robot, allowed for wireless movement, facilitating mobility and liveliness. The robot's behavior for each combination was recorded in a realistic living-room setting, and a simple action camera, GoPro Hero7, produced video recordings from a bird's view (see Figure 5.3). The rationale behind using a bird's eye view shot was that it allowed the audience to have an objective and omniscient perspective as defined in cinematography (Lannom, 2021), allowing for neutral and unbiased assessments from participants. In addition, a recent study using a telepresence robot demonstrated that video perspective (either robot's point-of-view or overhead view) had no significant impact on how positively people responded to the robot (Smith et al., 2021).

Figure 5.3 Bird's Eye View Video Recording of the Robot

Different combinations of the LEs created a list of expressive motions for the robotic vacuum cleaner, iRobot's Create2. Since there are two polar levels for each Laban Effort there are $2^4 = 16$ combinations of movement features in total, corresponding to 16 treatment conditions. To prevent respondent fatigue (Ben-Nun, 2008), each participant was randomly assigned to one of the blocks, either block 1 or block 2. Participants in each block were exposed to 8 treatment conditions in total. Each block is a 2^{4-1} fractional factorial design of Resolution IV. The defining relationship for block 1 is I = ABCD, while the defining relationship for block 2 is I = -ABCD.

5.2.3.2 Participants

Amazon Mechanical Turk, an online crowd-sourcing platform, was used to recruit participants for this study. The only requirement for participants was to be over 18 and willing to spare one hour of their time. Participants received $8 USD compensation for their time when it was ensured that their work followed the three criteria explained below.

Duration Criteria. The survey duration should be at least 12 minutes to ensure participants watched the robot's video recordings.

Bot Score Criteria. The bot detection score based on reCAPTCHA V3 (Qualtrics XM Support, 2022), where 0.0 is very likely a bot and 1.0 means very likely a human (Google Developers, 2021), should be at least 0.5 to eliminate bot responses.

Survey Code Criteria. The survey completion code submitted by the Amazon Mechanical Turk workers should be valid and match with a survey response in Qualtrics.

In total, 286 participants signed up for the study, but the responses from 240 participants (76 Female, 164 Male) were included in the analysis after screening them using the criteria above. 115 participants were randomly assigned to block 1, while 125 were randomly assigned to block 2. The mean age was 38.37 (*SD* = 11.02).

5.2.3.3 Online Survey

Participants were directed via a URL link to the online survey in Qualtrics. The online survey was divided into five sections: 1) information and consent, 2) demographics, 3) personality rating, 4) attitudes towards robots, and 5) video ratings. Each section of the survey is explained below.

Section 1 informed participants about the study and collected informed consent from participants. Section 2 presented a demographic questionnaire about gender, age, academic background, prior knowledge about robotics, and ownership of a robotic vacuum cleaner. In section 3, Mini-IPIP (International Personality Inventory Pool) (Donnellan et al., 2006) was used to measure self-ratings of personality using a 5-point Likert scale where 1 is 'strongly disagree' and 5 is 'strongly agree'. Section 4 aimed to detect participants' attitudes towards robots using the Multi-Dimensional Robot Attitudes Scale using the same 5-point Likert scale (Ninomiya et al., 2015). This scale uses five dimensions to capture personality: neuroticism, intellect, agreeableness, conscientiousness, and extraversion.

Lastly, section 5 consisted of video recordings of the robot displaying different behavior combinations of movement features. Participants were asked to answer a manipulation check question after watching each video. The phrasing was as follows: "Please rate the robot's behavior with regard to each item below," The items included path planning, circular arc radius, velocity, and vacuum power. Through the manipulation check questions, the legibility of the manipulation was measured. High legibility meant validity of the operationalization of LEs.

Two surveys followed this, the Mini-IPIP and the RoSAS. Participants were asked to fill out the Mini-IPIP questionnaire for each robot video using the same 5-point Likert scale. The RoSAS was used to measure how people perceived the social attributes of robots (Carpinella et al., 2017). The RoSAS uses the same 5-point Likert scale, where 1 is 'strongly disagree' and 5 is 'strongly agree'. Participants filled out these two questionnaires after each treatment condition for a total of 8 times. The order of videos and the order of questionnaire items were randomized.

5.2.4 Results

This paper focuses on participants' rating of the robot's social attributes. Data analysis of participants' ratings of robot personality will be reported in another publication (Emir & Burns, 2022b).

A four-way repeated measures ANOVA was performed in Minitab to evaluate the effect of movement features mapped from the LEs (Flow, Space, Time, and Weight) on the participants' rating of social attributes measured in 3 dimensions (warmth, competence, discomfort) using the RoSAS scale. The four movement features corresponding to LEs were crossed, fixed factors with two levels, and 'subject_id' was a random factor with 240 levels. As assessed by the Grubbs' test at a significance level of .05, there were no extreme outliers for warmth and discomfort; however, the smallest data value was an extreme outlier for competence. The Anderson-Darling normality test at a significance level of .05 indicated that the data were not normally distributed. Homogeneity of variances at a significance level of .05 were observed for ratings of warmth and discomfort but not for ratings of competence, using Levene's test of homogeneity of variances. The ANOVA conducted for each response variable will be presented below.

5.2.4.1 Warmth

There was a statistically significant main effect for Time, $F(1, 1666) = 4.65$, $p = .031$, $\eta p^2 = .003$, indicating a very small effect size. Simple Bonferroni pairwise comparisons were conducted for the simple main effect of Time, confirming a statistically significant difference ($p = .031$).

5.2.4.2 Competence

There was a statistically significant main effect for both Flow, $F(1, 1666) = 55.28$, $p < .001$, $\eta p^2 = .032$, and Time, $F(1, 1666) = 9.18$, $p = .002$, $\eta p^2 = .006$. The partial eta-squared values indicated a small effect size for Flow and very small effect size for Time, confirmed following Bonferroni correction ($p < .001$ and $p = .002$ respectively).

5.2.4.3 Discomfort

There was a statistically significant main effect for Flow, $F(1, 1666) = 37.18$, $p < .001$, $\eta p^2 = .022$, indicating a small effect size. Simple Bonferroni pairwise comparisons were conducted for the simple main effect of Flow, leading to a statistically significant difference between high and low levels ($p < .001$).

There was also a statistically significant interaction effect between Space, Time, and Weight, $F(1, 1666) = 4.71$, $p = .03$, $\eta p^2 = .003$, indicating very small effect size. Simple Bonferroni pairwise comparisons were conducted for the interaction effect of Space, Time, and Weight for all combination treatments. The difference of means for discomfort ratings was not significantly different in any comparisons ($p > .05$).

5.2.5 Discussion and Limitations

The findings from the repeated measures ANOVA test are summarized in Table 5.3. For Space and Weight, no statistically significant effects were observed on any response variables. This finding might imply that changing the speed of vacuum power and the circular arc radius does not have a salient impact on how people perceive the social attributes of robots. This result might also mean that these two features' operationalization was not valid, or perhaps the scale of difference between the two levels was inconspicuous. The main effects of Flow and Time will be discussed in detail.

Table 5.3 Summary of Results from the ANOVA Test

Dimension	Significant Effect(s)	*P*-value	Partial eta-squared
Warmth	Time	.031	.003
Competence	Flow	< .001	.032
	Time	.002	.006
Discomfort	Flow	< .001	.022
	Space * Time * Weight	.03	.003

5.2.5.1 Main Effect of Flow

Flow was found to have a statistically significant effect on participants' ratings of competence and discomfort. As mentioned earlier, Flow determined the path planning behavior and the robot's range of motion. A low level of Flow corresponded to a linear path with a constant theta of 90 degrees, while a high level of Flow corresponded to a random path with a theta varying in the range 45-135 degrees, inclusive. Figure 5.4 displays the main effects plots for each dimension. Competence and discomfort ratings indicate that participants rated the robot with random path planning to have lower competence and higher discomfort than the robot exhibiting linear path planning behavior.

The competence ratings of the robot were not surprising because it is expected that participants associated the linear path planning behavior with the autonomy and intelligence of the robot. It was also assumed that the robot using random path planning algorithm would be perceived as more erratic and less competent.

The second finding suggests that participants rated the robot with random path planning to evoke greater discomfort. Participants were less comfortable with the random path planning. This result can be explained by the fact that humans feel secure and comfortable while they can predict others' behavior. Thus, the robot with random path planning behavior might have confused participants, causing discomfort during the interaction.

5.2.5.2 Main Effect of Time

Time was found to have a statistically significant effect on participants' ratings of warmth and competence. As indicated before, Time determined the velocity of the robot. There are two types of movement, thus two velocities at each level. For the low level, the velocity for the direct drive was 200 mm/s, and the velocity for the rotational turn was 160 mm/s. For the high level, the velocity for the direct drive was 100 mm/s and the velocity for the rotational turn was 80 mm/s. Technically, the maximum velocity of the robot was 500 mm/s, but it was too fast to manipulate the robot's movement accurately. When the main effects plots in Figure 5.4 are examined, it was observed that participants rated the faster robot to have more warmth and more competence than the slower robot.

This finding can be explained by the idea that higher velocity made the robot seem more animate, energetic, and agile. Since aliveness is usually associated with mobility, this finding is not unexpected. The robot's swift movements might have caused participants to perceive it as more alert, intelligent, and aware of its environment, which explains higher competence ratings.

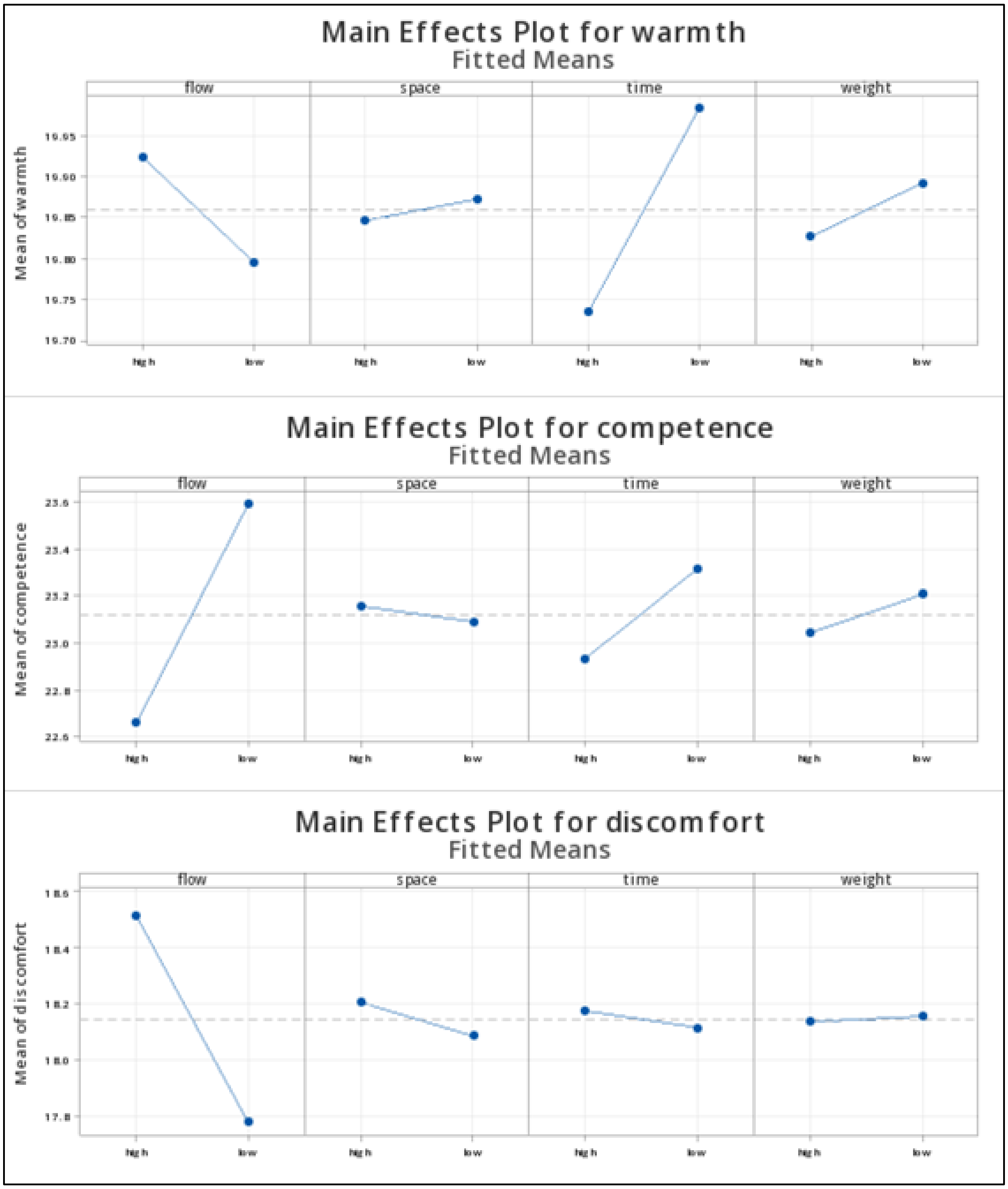

Figure 5.4 The Main Effects Plot for Response Variables (From Left to Right: Flow, Space, Time, Weight. At Each Graph: High to Low)

5.2.5.3 Limitations

This study has a few limitations, categorized under experimental design and the technical constraints. The first issue with experimental design is that no initial screening was used to ensure a balanced sample in terms of gender. Gender has been shown to influence preferences with social robots. For instance, it was found in a study that the trust towards the decisions made by robot umpires varied with gender, more specifically males expressed higher trust than females (Wonseok et al., 2021). The same argument can be claimed for age, as well. Age might have an impact on people's perception of the robot's personality and social attributes. The natural unbalance in the sample's age might have altered the findings. Another issue is that the demographic questionnaire was administered at the beginning of the study. It has been shown that asking demographic questions before the survey items cause participants to be reminded of their social identities, therefore pushing them to think and act in line with their "self-relevant stereotypes" (Rydell et al., 2009).

Another limitation concerns the technical constraints of the robot and the development software. The movement capability of the robot was restricted by its technical and kinematic constraints. More specifically, the kinematic constraints of the robotic vacuum cleaner involve its low dof, lack of flexible joints, and mechanoid body which restricts the vector of movement features. In our case, the only dof was the 360 degrees rotation in the robot base. These kinematic constraints prevented accurate replication of the Laban Effort Features framework suggested by Knight and Simmons (2016a). Some of the movement features were replaced by other features that are more relevant to a robotic vacuum cleaner. For instance, the weight component of the Laban Efforts was changed from 'range of motion of joints' to 'path planning behavior' because the latter is more relatable to a mechanoid robot lacking a jointed body.

In addition, the Python library "pycreate2" (Walchko, 2020) did not contain all the commands made available by the robot's developer. Some commands the robot's developer provided did not perform as expected, as it is stated in the OI specifications guide that there is still an ongoing effort to fix bugs for some commands found in earlier versions (iRobot Corp., 2020). Despite these challenges, researchers applied workaround solutions to code the desired movements into the robot, either by defining new functions or using the bug-free commands. Overall, all these constraints restrained the operationalization of Laban Efforts as movement features; therefore, it was not probable to replicate the implementation framework suggested by Knight and Simmons (Knight & Simmons, 2016a) precisely.

5.2.6 Conclusion

This study demonstrates that Laban Effort features can be modified slightly to fit the cleaning task of a robotic vacuum cleaner. It was also shown that the Laban Effort features changed people's perception of the robot's social attributes. It was observed that the robot's velocity and path planning behavior were the two factors that yielded statistically significant results. Specifically, doubling the robot's velocity (from 100 mm/s to 200 mm/s) caused an increase in people's ratings of its warmth and competence. Random path planning behavior caused people to rate the robot as being less competent and causing more discomfort than linear path planning behavior. These findings can be used by robotics engineers and designers when designing expressive behavior for robots to provide favorable and more effective interaction. The results of this study should not be restricted to robotic vacuum cleaners only, since they are potentially applicable to more complicated, humanoid, and social robots, which are anticipated to interact more closely with humans.

In conclusion, it is essential to study the design of expressive motions for domestic service robots such as robotic vacuum cleaners because it facilitates the communication of robots' internal states and intentions to humans, enhancing the quality of interaction. Using the nonverbal communication cues in robot behavior design helps us establish a common language between humans and social robots. These cues would increase the legibility of the robot's movements, providing a more effortless HRI experience and ensuring higher robot acceptance rates among the general society in the long run. The future of robotics promises robots equipped with social characteristics and personality traits customized to the requirements of the social environment they will operate in.

5.2.7 Acknowledgments

This research was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) under the Discovery Grant program. The content is solely the responsibility of the authors and does not necessarily represent the official view of NSERC.

5.3 Chapter Conclusion

To sum up, the purpose of this study was to understand the impact of Laban Effort Features on how people rated the social attributes of domestic service robots. A robotic vacuum cleaner iRobot's Create2 was used to manipulate robot behavior and to implement movement features based on the framework of Laban Effort features. Using an online survey, where participants watched videos of different robot behavior, we aimed to investigate how people's perceptions of the same robot changed. The results indicated that the warmth ratings of the robot were influenced by velocity, the competence ratings were influenced by path planning behavior and velocity, and the discomfort ratings were influenced by the path planning behavior.

Chapter 6 Conclusion and Future Research

6.1 Summary

The goal of this study was to investigate the impact of Laban Effort features on how people rated the social attributes and personality of domestic service robots. We used a robotic vacuum cleaner (RVC) called iRobot Create2 in this study. The results indicated that three out of four Laban Efforts had statistically significant impact on the participants' ratings of robot personality and social attributes. The radius of curvature was the only factor which did not yield statistically significant results on any of the output measures. This might indicate that this movement feature was not effective in communicating the Space component of Laban Efforts.

More specifically, path planning behavior (factor 1) had a statistically significant impact on the neuroticism dimension of robot personality, as well as competence and discomfort ratings. Velocity (factor 2) had a statistically significant impact on the agreeableness dimension of robot personality, as well as warmth and discomfort ratings. Vacuum power (factor 3) had a statistically significant impact on the agreeableness and conscientiousness dimensions of robot personality. These findings might be valuable for researchers and engineers in designing expressive motions for domestic service robots composed of a mechanoid body with very low degree of freedom.

6.2 Contributions

The findings in this paper are applicable to different types and forms of robots, including domestic service robots, personal assistant robots, and companion robots. All these robots are designed to operate in domestic environments, in proximity to humans. Thus, they are expected to interact closely and frequently with humans. The quality of this interaction depends on many factors, one being the legibility of the robot's intentions and affective states. It is important for the robot to be able to convey its intentions effectively because exchange of thoughts and feelings is a determinant of healthy communication for human-robot interaction as well as human-human interaction.

Domestic robots can take various forms. The robot that was tested in this study was iRobot's Create2, which is a monofunctional mechanoid robot with a circular wheelbase. For a robot with a wheelbase, all the findings regarding robot's locomotion can be easily applied. For a personal assistant robot that has humanoid form and works on top of a wheelbase, these findings related to velocity and path planning behavior can be relevant in this scenario. To make the personal assistant robot express higher warmth and higher competence, the direct drive velocity should be selected as 100mm/s instead of 200mm/s. For a companion robot that has an animal form and a wheelbase, the path planning behavior can be selected as random rather than linear to express a robot personality with high neuroticism. On the other hand, let us consider a humanoid robot with two legs instead of a wheelbase, these findings regarding robot locomotion cannot be applied. Since the kinematics of locomotion via two robotics legs are very different from the kinematics of locomotion via wheelbase, the findings regarding path planning behavior and velocity are not applicable in this scenario and more research is needed to make any claims.

Companion robots would be designed to exhibit a personality with higher extraversion and lower conscientiousness. In terms of social attributes, companion robots also need to have higher ratings of warmth and lower ratings of discomfort, so that they can respond to the demands of a compassionate companion. Similarly, personal assistant robots need to exhibit a personality with high conscientious and low neuroticism if the robot's main purpose is to assist humans with serious tasks such as scheduling, office work and planning.

The findings can also be applied to various scenarios, where a domestic service robot operates in proximity to humans and needs to communicate socially with humans. The RVC might require assistance from the human agent, where the two need to cooperate. In this scenario, the robot's behavior should reflect higher agreeableness in its personality traits. Another scenario might be that the robot could be programmed to act differently at different times. Specifically, the robot's behavior could show higher extraversion and warmth when there are people around, lower extraversion and warmth when nobody is home. Another scenario is that the robot might be programmed to match the owner's personality. It has been shown in previous studies that people preferred the interactions when there was a match of personality traits between humans and robots (Niculescu et al., 2013; Salam et al., 2017; Tapus & Matarić, 2008).

These preferences of robot behavior might change from person to person, so it might be valuable to program robots with personality and behavior adaptive to the preferences and needs of individuals. As mentioned earlier, humans prefer robots with matching personality traits sometimes, so it is possible to design domestic service robots with adaptable personalities and behavior. The robots might adapt their behavior in different use-cases too. For instance, a companion robot might be programmed to behave with higher warmth and higher neuroticism when it communicates its affective states, but it exhibits a personality with higher intellect and higher competence when building trust or completing difficult tasks.

RVCs hold a huge potential to improve the quality of life for people with either visual impairment or physical disabilities as well as for older adults. With just the click of a button or a vocal command, a household chore gets completed, and this makes it accessible and comfortable for these populations.

6.3 Limitations

The limitations of this study were categorized under two: *technical constraints* and *survey design*. Technical constraints were concerned with the kinematic properties of the robot of interest, and the development interface provided by the robot's manufacturer. Study design was concerned with how the study was designed, and the flow of the online survey.

Regarding technical constraints, there were two potential issues that have challenged us. The first issue was related to the robot's kinematic constraints. iRobot's Create2 that has been used in this experimental study was a robot with very low degree of freedom and a mechanoid body (iRobot Education, 2021). It did not resemble humans in any way, so it was harder to design expressive behavior compared to designing expressive behavior for a humanoid robot. We could not take advantage of the norms of non-verbal communication that have been widely accepted and utilized in behavior design for humanoid robots. The robot's kinematic constraints directly impacted the design and implementation of expressive robotic motion based on the Laban Effort features.

The second issue was concerned with the development interface. There were bugs in some of the commands in the Create Open Interface (OI) provided by the robot's manufacturer. The OI specifications document, where the descriptions of commands for actuators and sensors were explained in detail, has reported that "the Create2 firmware is still a wok in progress" (iRobot Corp., 2020, p. 41). Some of the bugs were fixed in newer software versions, but there are still a few issues in the older software versions. To overcome this challenge, the "pycreate2" library in Python has been forked and modified. The forked library shared publicly on GitHub (Emir, 2021) involved new functions that use different commands by the Create2 Open Interface.

In terms of study design, there were two issues that potentially impacted our findings. The first issue was that the sample was not balanced in terms of gender. The number of female participants was approximately half of the number of male participants. This might have impacted the findings, since it has been shown in previous studies that gender has a role in perception of social robots. For instance, Wonseok et al. (2021) studied the effect of gender on the interaction between humans and robot umpires. the results from their study indicated that males expressed more trust for the robot umpires than female participants.

The second issue with study design concerned the flow of the survey. The demographics section was filled out by participants before the experimental study. Asking demographic questions right before a study has been shown to cause “priming bias” in participants. Rydell et al. (2009) showed that participants who were given the demographic questions prior to a study were reminded of their social roles. This, in turn, caused the participants to express and act in line with the prototypes more frequently (Rydell et al., 2009). Thus, it is possible that the choice of survey flow, more specifically placing the demographics section before the actual study, might have caused “priming bias” in the participants, therefore influencing our findings.

6.4 Future Research

For future research, we plan on studying the different vectors of movement features. Three out of four factors yielded statistically significant results on the perceived personality and social attributes of robots. The only factor that did not have any influence on the dependent variables was the radius of curvature. It would be ideal to replace this factor with another movement feature, one that can better communicate the Space component of Laban Efforts.

Another improvement for future research would be to test the efficacy of each movement feature before conducting the online survey. This would be done using a preliminary study structured as a short survey of 5-10 minutes. In this case, manipulation check questions would be separated from the main study. After achieving promising results for the manipulation check questions, only then the designed movement features would be implemented to the robot for testing.

In addition, the online study would be repeated in-person at a lab. The setting would be a naturalistic environment, a space resembling living-rooms with a sofa, a few coffee tables and house plants. The in-person study would be structured in three sections, pre-trial, main study, and post-trial. In the pre-trial section, the demographics questions and self-rating personality questionnaire would be administered. The main study would involve participants observing the RVC perform different behaviors as experimental conditions and then rating the robot's personality and social attributes in the post-trial section.

It is not expected that the findings from the in-person study would be hugely different from the findings of the online study. The reason is that the proposed in-person study is planned to run very similar to the online study; participants observe the robot's behavior from a distance while it performs a simple cleaning task in a living-room setting. Due to the lack of free interaction between the humans and the robot, it is anticipated that the findings will not change drastically. However, if the proposed in-person study aims to study free interaction between humans and the RVC, then the results would change hugely due to measuring different outcome measures.

For future research, we plan to repeat the same experimental study on different scenarios or tasks for the RVC. In this study, we focused on a simple cleaning task only, where iRobot Create2 completed a spot cleaning in an empty area of a living-room setting. For our next steps, we would like to construct new scenarios requiring the RVC to perform a wide range of tasks. Some examples for the scenarios involve the robot getting stuck at a tight corner and escaping from there, the robot alarming the user that a filter change is needed, the robot performing obstacle detection and avoidance behavior, the robot navigating back to its home base.

Another opportunity for future research is studying the implementation of Laban Effort features on a different robot, possibly a humanoid robot such as Nao. When working with a humanoid robot, various factors come into play with regards to designing of expressive motions, therefore complicating the design process. However, these factors could also provide a wide range of possible movement features, including non-verbal communication cues like eye gaze, body positioning, facial and gestures.

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Appendices

Appendix A Information Letter and Consent Form

Title of Study: Robotic Vacuum Cleaners with Personality: Designing Expressive Robotic Motions based on the Laban Framework

You are invited to participate in a research study conducted by **Ebru Emir**, under the supervision of **Dr. Catherine Burns, Systems Design Engineering** of the University of Waterloo, Canada. The objectives of the research study are to **investigate the implementation of Laban Framework on movement behaviors of domestic robots, and to determine if different combinations of movement features can enable attribution of specific personality traits to domestic robots.** The study is for a master's thesis.

If you decide to volunteer, you will be asked to complete a **40-minute** online survey that is completed anonymously. There are four main sections including demographic questions, personality self-assessment test, robot attitudes scale, and robot behavior rating. Questions in the robot behavior rating section focus on **watching video clips of robotic vacuum cleaners displaying different behaviors and movement features, and later rating the perceived personality of the robot.** As a requirement, volume should be turned up while watching the videos, because sounds are a critical part of the displayed robot behavior.

Participation in this study is voluntary. You may decline to answer any questions that you do not wish to answer, and you can withdraw your participation at any time by exiting the browser window and by not submitting your responses. There are no known or anticipated risks from participating in this study. Although there are no direct benefits to you as a participant, you might appreciate the expansion of knowledge regarding both design and development of domestic robots that provide enhanced human-robot interaction capabilities.

In appreciation of your participation in this study, you will receive a total of USD $8.00 through Amazon Mechanical Turk. If you choose to withdraw from the study, you will still receive remuneration by clicking through to the end of the study to find the code.

Please allow 5-10 business days after your completion of the study for payment processing. Please feel free to contact any of the investigators listed below for questions about your remuneration payment.

It is important for you to know that any information that you provide will be confidential. All the data will be summarized, and no individual could be identified from these summarized results. Furthermore, the web site is programmed to collect responses alone and will not collect any information that could potentially identify you (such as machine identifiers).

You will be completing the study by an online survey operated by Qualtrics™. Qualtrics has implemented technical, administrative, and physical safeguards to protect the information provided via the Services from loss, misuse, and unauthorized access, disclosure, alteration, or destruction. However, no Internet transmission is ever fully secure or error free. Qualtrics temporarily collects your computer IP address to avoid duplicate responses in the dataset but will not collect information that could identify you personally.

When information is transmitted over the internet confidentiality cannot be guaranteed. University of Waterloo practices are to turn off functions that collect machine identifiers such as IP addresses. The host of the system collecting the data such as Amazon Mechanical Turk™ may collect this information without our knowledge and make this accessible to us. We will not use or save this information without your consent.

The data, with no personal identifiers, collected from this study will be maintained on a password-protected computer database in a restricted access area of the university. As well, the data will be electronically archived after completion of the study and maintained for a minimum of seven years and then erased.

Research data will also be deposited in an online public repository/database. You will not be able to be identified from this data. This process is integral to the research process as it allows other researchers to verify results and avoid duplicating research.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Board (REB 43362). If you have questions for the Board, contact the Office of Research Ethics, at 1-519-888-4567 ext. 36005 or reb@uwaterloo.ca.

For all other questions about the study, please contact either **Ebru Emir at** ekamis@uwaterloo.ca or **Dr. Catherine Burns at** catherine.burns@uwaterloo.ca. Further, if you would like to receive a copy of the results of this study, please retain this letter for your records and contact either investigator. The results of the study will be available by **January 1, 2022**.

Thank you for considering participation in this study.

Consent to Participant

By providing your consent, you are not waiving your legal rights or releasing the investigator(s) or involved institution(s) from their legal and professional responsibilities.

With full knowledge of all foregoing, I agree, of my own free will, to participate in this study.

"I agree to participate."

"I do not wish to participate (please close your web browser now)."

Appendix B Demographic Questions

1. What gender do you identify as?

- Male
- Female
- Non-binary / third gender
- Other: …….

2. What is your age?

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 - 74
- 75 - 84
- 85 or older

3. Which academic discipline best describes your educational degree? (Select at most 3.)

- Performing arts
- Visual arts
- History
- Languages and literature
- Law
- Philosophy
- Theology
- Anthropology
- Economics
- Geography
- Political science
- Psychology
- Sociology
- Social Work
- Biology
- Chemistry
- Earth science
- Space sciences

- Physics
- Computer Science
- Mathematics
- Business
- Engineering and technology
- Medicine and health

4. **Have you ever taken any courses/workshops related to the field of Robotics (such as Artificial Intelligence, Automation, Mechatronics, Computer Vision, Human-Robot Interaction, etc.)?**

- Yes
- No

5. **Do you own a robotic vacuum cleaner?**

- Yes
- No

6. **For how long you have owned a robotic vacuum cleaner?**

- Less than 1 month
- 1-6 months
- 7-12 months
- 1-2 years
- 3-5 years
- 6-10 years
- 11-19 years

Appendix C Appreciation Letter

Thank you for participating in our **Perception of Personality in Domestic Robots** survey! Your feedback is extremely valuable.

If you would like a copy of the results, please retain this letter for your records and contact any of the investigators. The results of the study will be available by **February 1, 2022**.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Board (REB 43362). If you have questions for the Board, contact the Office of Research Ethics, at 1-519-888-4567 ext. 36005 or reb@uwaterloo.ca.

For all other questions or if you have general comments or questions related to this study, please contact **Ebru Emir, Systems Design Engineering**, ekamis@uwaterloo.ca or **Dr. Catherine Burns, Systems Design Engineering,** catherine.burns@uwaterloo.ca.