Sociable Robot 'Lometh': Exploring Interactive Regions of a Product-Promoting Robot in a Supermarket

Nethmini T. Weerawarna[1,*], Udaka A. Manawadu[2] & P. Ravindra S. De Silva[3]

[1]Department of Information and Communication Technology, Faculty of Technology, University of Colombo, Sri Lanka
[2]Robot Engineering Laboratory, Graduate School of Computer Science and Engineering, University of Aizu, Aizu-Wakamatsu, Fukushima, Japan
[3]Department of Computer Science, Faculty of Applied Sciences, University of Sri Jayewardenepura, Gangodawila, Nugegoda, Sri Lanka
*E-mail: nethmi@ict.cmb.ac.lk,

Abstract. The robot 'Lometh' is an information-presenting robot that naturally interacts with people in a supermarket environment. In recent years, considerable effort has been devoted to the implementation of robotic interfaces to identify effective behaviors of communication robots focusing only on the social and physical factors of the addresser and the hearer. As attention focus and attention target shifting of people differs based on the human visual focus and the spatiality, this study considered four interactive regions, considering the visual focus of attention as well as the interpersonal space between robot and human. The collected primary data revealed that 56% attention shifts occurred in near peripheral field of view regions and 44% attention shifts in far peripheral field of view regions. Using correspondence analysis, we identified that the bodily behaviors of the robot showed the highest success rate in the left near peripheral field of view region. The verbal behaviors of the robot captured human attention best in the right near peripheral field of view region. In this experiment of finding a socially acceptable way to accomplish the attention attracting goals of a communication robot, we observed that the robots' affective behaviors were successful in shifting human attention towards itself in both left and right far-peripheral field of view regions, so we concluded that for far field of view regions, designing similar interaction interventions can be expected to be successful.

Keywords: *attention shifting; communication robot; human-robot communication; interpersonal distance; peripheral field of view.*

1 Introduction

Creating and sharing information can be considered a necessity in the business world. Presenting information to customers is a growing challenge faced by many industries. When promoting their business in order to compete in the marketplace, many entrepreneurs think of different methods to convey their business promotions to potential customers. Promotional messages can be used to improve the purchase decisions of the customer and if it is possible to make the customer

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buy products, it would be a winning situation in the competitive marketplace when running a business. Cleary & Lopez [1] state that researchers have frequently concentrated on how to make the information-presenting process more creative and attractive to the customer in a cost-effective manner. According to recent research, promoters use public places like supermarkets, exhibitions, conferences, and expos to publish information about their products and services to gain visibility in the marketplace. They use posters, leaflets, billboards, information boards, and interactive walls as promotion delivery methods [2-5]. A range of communication aids like text, images, multimedia, gestures, audio, video, animations, and touch experiences are used to attract customers' attention in these methods [6-9]. Since it was discovered that there are different downsides to each method of carrying out promotional activities, researchers and entrepreneurs have tried to find better ways of attracting human attention towards their promotional activities. Researchers combined the above communication aids with human sales agents to introduce human-friendly solutions to product promotion [4,10]. Usually, verbal communication, non-verbal communication, physical interactions, and social interactions are used by human sales agents for promotional activities.

These activities did not show the expected success, as customers complained about their shopping experience being disturbed and the cost of guidance for sales agents made entrepreneurs look for more effective ways to convey promotional material in a humanizing manner. Hegel, *et al*. [11] discusses the use of robots to implement communication with humans using social and physical interactions, introducing the idea of a social robot having socially acceptable communication attempts to overcome the disadvantages of the other methods used for product promotion.

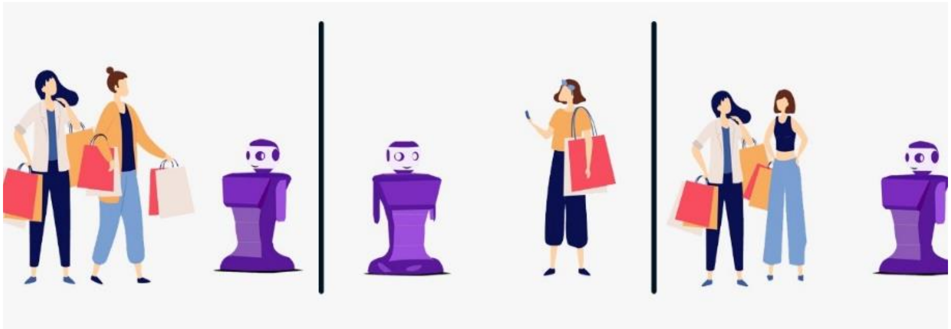

Figure 1 (a) Robot gets the attention of a customer passing by. (b) Smooth message delivery to the hearer. (c) Switching behavior to manage interruptions.

The present research attempted to design an interactive sociable robot called 'Lometh' that behaves as a product promoter in a public environment, like a supermarket. Lometh is supposed to attract customers who pass by and deliver promotional messages to them. This communication process can be divided into three main steps, as shown in Figure 1(a). Initially, the robot attracts the customer's attention to initiate the communication process. Secondly (Figure 1(b)), when the robot receives the awareness of active participation of a person towards itself, it delivers a promotional message.

As can be seen in Figure 1(c), during the message delivery, if the communication is interrupted, the robot switches its behavior to direct the hearer's attention back to the message delivery. Finally, the robot leads the communication towards a proper ending. The goal of this paper is to present experiments done in the first step of the communication process related to attracting the attention of people passing by the robot, as shown in Figure 1(a), by considering the spatiality between the robot and people passing by as well as their visual focus of attention. Blending social characteristics and social interactions in a robotic system can make them sociable robotic systems, which encourages humans to communicate with the robot in an interactive manner [2,11]. Research works have been carried out to understand the effect of the customers' social, physical, psychographic, and demographic information in human-robot communication [11].

The Lometh robot was developed to make human-robot communication more realistic and natural in an attempt to explore the impact of spatiality on successful information presentation by communication robots. This study was designed to identify optimal interaction sequences to be implemented in a sociable robotic platform for promotional activities, which has not been studied thoroughly before. The outcomes of this research will help find the most suitable robot behaviors for each identified interactive region to influence humans to communicate with it. This study explored the optimal initial robotic behavior in grabbing the attention of a customer passing by and making them communicate with it for each interactive region, considering the spatiality and peripheral viewing situations of the robot. The rest of this paper will present information on related research works, the design of the robot, the experimental setup, and finally, the results obtained and their discussion along with our conclusions based on the results.

2 Related Works

Researchers and marketing specialists continually experiment with attracting human attention and study human attention in order to find successful attention shifting mechanisms. This section on related works discusses the results of each method used previously as a communication aid by entrepreneurs and the problems of the alternative human sales agent approach. The study of Laurent & Monsone [12] shows the idea of Industry 4.0 with innovation processes in industries using available technologies that combine IoT, digital twins, co-bots, drones, artificial intelligence, and the cloud as components. This revolution has had a significant effect on many innovations, including the application of robots in social environments and drawing attention towards robots in stores and its application in human robot communication.

2.1 Human Attention Towards Product Promotions

To promote products to potential customers, capturing the attention of the customer towards an advertisement can be considered the first step. Once the attention is captured, keeping that attention for a period as long as it takes to convey the least possible information about the product to the customer is as important as getting the initial attention and is the most challenging step. Product advertising and promotional activities are the key efforts towards the product purchase rate of many business models that depend on the way of presenting promotional messages. This can be seen as having a positive or a negative effect on customers' communicative experience [4,13]. According to previous studies, giving value to interactive media such as gestures, audio-video, haptic, animation, touch, and behavioral interactions in delivering product promotion have shown to be effective in promotional activities [5,14,15]. When the most popular screens and displays were replaced with interactive media, it did not encourage social or physical engagement [16,17]. Different experiments have been carried out on the usage of screens as promotion displays without involving human-like interactions. Those attempts failed to make the customers attentive to the product promotions [18,19].

Prante, *et al.* experimented with an interactive ambient display called '*Hello.*Wall', which emits information via light patterns [20]. The interactions were defined for the target audience depending on their identity and the distance between the wall and people passing by. The interactions of *Hello.Wall* were limited to one interactor at a time. Vogel, *et al.* [21] from the University of Toronto experimented with another sharable and interactive public ambient display, which can communicate with more than one person at a time. GestureTec, a computer vision technology-based company, introduced the product 'ScreenXtreme', which gave a full-body immersive experience to motivate passers-by in a hospital environment to keep interacting with it but over time people developed prejudices and started avoiding the interacting wall and lost their interest in it [22]. Rubegni, *et al.* [18] experimented with social interactions around public displays with a product called 'Yearbook', which was a gesture-based interactive wall that helps strangers to overcome natural diffusion of interaction in public places, but the users were strongly concerned with their privacy [18]. The Korea Advanced Institute of Science tested the so-called ‘Photo Polling Wall’ on which users were allowed to share their ideas on a public display [23]. This Photo Polling Wall interacted with the users through a mobile device and social network services, but they had second thoughts about using it, as they were sensitive about the privacy of the content they shared. The University of Augsburg in Germany developed a public wall, called ‘Media Wall’, to examine different adaptation strategies and their impact on user preferences in interactions with the wall [24]. They figured out that there is a huge concern about privacy protection with interactive walls. Gentile, *et al.* [25] looked at issues related to public displays in-the-wild. They found that the usage of technology-based vocabulary, display blindness, prejudices about the content on the display, and interaction blindness are the main drivers of low social acceptability of public displays for any purpose.

Chamberlain, *et al.* [26] carried out a survey on a projected touch surface for the community in a rural context and found there should be more interactional possibilities on such systems if they are to be used in real-world settings. The Design Criteria for People’s Perception of Advertising introduced by O’Donnell, *et al.* [27] describes engagement and taste in adding content are essential in influencing customers. The Social Media Research Lab in the USA conducted research to find reasons for the lack of response to public displays. It was found that non-interactive vertical public displays, images, and texts did not change the walking path of customers moving towards the display, but eye-level mounted displays with short video clips did attract the attention of people passing by [18].

Romero-Garcés, *et al.* [28] experimented with a robot to attract passers-by and discovered that store managers have an interest in using robots in stores. This study discussed the intention and design requirements that store managers expected a robot to have. A robotic salesman was used in the experiment, to investigate its limitations and to identify future improvements. According to the available studies, researchers are still working on finding better ways to communicate promotions and sales messages to customers and seeing how customers are influenced by product promotions, which has led to the goal of finding better mechanisms to influence customers and make them attentive to product promotions.

2.2 Spatial Factors and Visual Focus for Human Attention Shifting

The spatial factors and their relationship with the visual focus and attention of humans are crucial aspects in developing ways for robots to attract attention. The study by Frijns, *et al.* [29] on communication models for human-robot interaction revealed that the space surrounding the addressor and the addressee is important for analyzing human attention and they suggest that factors concerning the environment such as embodiment and physical space deserve more attention [29]. As shown by Hall [30], space is used as a communicative function by humans. To interact with people, it is important to consider their focus of attention and their visual focus. Human visual focus and attention shifting have been explored only in immobile situations and not explored in passing-by situations [31]. Subramanian, *et al.* [32] explored the problem of the shrinking attention span of humans and the challenge of promoting products in the digital era. They highlight that due to the digitalized lifestyle of humans who are constantly being bombarded with various promotional messages and advertisements, their attention span has been skewed considerably, hence, more creative and innovative approaches need to be developed to seek customer attention and to make customers engage in promotional activities effectively.

Attracting the attention of a person is the first step to initiating an interaction. Several studies have been done on evaluating different methods for shifting attention in humans. The study by Das, *et al.* [31] presents an approach to attracting attention by analyzing a person's visual focus of attention (VFOA). The study was carried out on the basis of a real-life environment in which someone has their attention on a task they are involved in (e.g., reading, writing, using a computer). In order to start an interaction, it is first necessary to shift their target of attention to the addresser. It was identified that a person loses focus on their task and diverts their VFOA from time to time, depending on their level and intensity of concentration on the task. The robot can track visual cues like head pose, head movements, and face stability to recognize a person's VFOA and identify when to interrupt the person and establish a communication channel [31]. This method has been performed successfully in attracting attention, but it is limited to situations where the human is involved in a particular task with a fixed field of view. In an environment where humans are constantly on the move and not involved in a particular task for a long time at the same location, the above approach has not been tested.

2.3 Robots in Stores

Huttenrauch *et al.* [33] have shown that in human-human communication, both parties involved have the social capability of using the space actively during a conversation. According to Okafuji, *et al.* [34], in-trouble behavior may cause pedestrians to halt more often and remain in one place longer. The performance of robots is comparable to that of humans in providing information tasks in a constrained environment, making it possible to assess the effectiveness of the robot in a real environment. As a result, it is expected that service robots will function effectively in the real world as a labor support technology. Service robots need to use verbal and non-verbal expressions in human-robot interaction, like humans move their body, make eye contact, and various other exchanges in human-human interaction. A robot is a physical entity that is capable of dealing with spatial interactions with a human user and the orientation of the robot and the spatial distance between the robot and human are considered to play a major role in HRI [31,33]. Neggers, *et al.* [35] investigated the size of personal space when passing by a robot, calculated for both humanoid and non-humanoid robots. The findings showed that comfort improves with distance and individuals are less comfortable with robots that pass by them. According to the above research studies, eye contact, non-verbal cues, body language, and social/physical engagement are considered to have a significant influence on interaction in successful attention shifting.

It is impossible to achieve these factors only with a digital device. Therefore, it is necessary to explore the robot platform, enabling concepts of social and physical interactivity and rich engagement experiences to instigate social and physical interactions in product promotions. In this research, a robot called Lometh was implemented considering the modalities of posture and position in HRI based on Hall's proxemics theory [30] and the human visual focus system [36]. We experimented with customer behavior towards the robot in different interactive regions for robot different behaviors targeted towards shifting the attention of customers passing by towards the robot.

3 Design of the Robot

3.1 Appearance of the Robot

Futurism was one of the most experimental trends in the art of the early twentieth century's pre-war period. Technology, speed, and all other forms of progress were to be seen as truly contemporary, whereas tradition needed to be rejected as conventional and outdated. In rejection of creativity by conventional notions, futurism was attracted to the pace of contemporary life. All of the futurists' efforts were directed at providing a fresh perspective and a conceptualization that adds originality and innovation to culture and daily life [37]. To give a modern appeal to the Lometh robot, we used curves and sharp yet smooth cut edges in the head, body, and arms of the robot. Color selection was done by thinking beyond the traditional black and white colors, using a mix of white and purple colors to give a modern look to the robot.

A minimalistic design provides a reduced mental and physical workload to the user while interacting with a robotic system [38]. The body of the Lometh robot was designed with only the most necessary parts, like arms, head and integrated body, in order to implement the most required robot behaviors, which makes users only concentrate on the most necessary human-robot interactions. Reducing human-like hands, fingers and using integrated legs draw human attention to the most visible parts, that is, the head and the screen placed on the upper body of the robot, which leads human attention to focus on communication with the robot through affective behaviors performed using the eyes along with the head, upper arms, and full body movements. The mechanical structure and the finalized appearance of the robot are represented in Figure 2.

Figure 2 (a) Mechanical structure of the robot. (b) Finalized appearance.

3.2 Technologies

Kinect for Windows SDK v1.7 was used to detect humans and calculate interpersonal distance, which are the initial signals captured by the robot. The AFFDEX SDK Cross-Platform Realtime Multi-Face Expression Recognition Toolkit was used to detect the attraction level of the customer interacting with the robot. Dynamixel.dll was used to implement the head and arm movements of the robot. The Roomba Open Interface (OI) was used to control and manipulate Roomba's behavior to implement the robot's bodily behaviors.

3.3 Action Sequence of the Robot

The program of the robot was written in the C# programming language. There are three main modules connected together in the software system to identify the optimal robot behavior in attracting people passing by as represented in Figure 3, an input module, a processing module, and am output module, which together are programmed to initiate interaction between the robot and the customer. The robot uses four interactive regions in managing the spatiality of the communication:

R1 = Left near peripheral field of view, social space
R2 = Right near peripheral field of view, social space
R3 = Left far peripheral field of view, social space

R4 = Right far peripheral field of view, social space

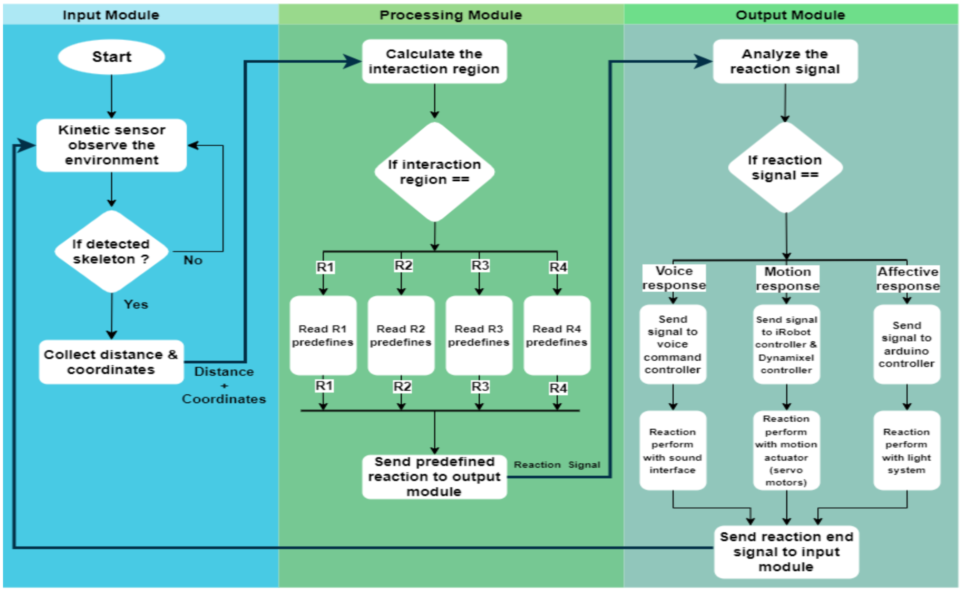

Figure 3 Action sequence of the Lometh robot.

When the Lometh robot is placed within a 366 cm radius, a circular area centered from the robot in the supermarket environment, the system starts up the kinetic sensor that observes the environment, as shown in Figure 5. If it senses a person, it measures the distance between the center of the robot and the identified customer and calculates where the person is by using the coordinates of the detected person. After receiving the coordinates and the distance, the input module sends the distance and the coordinates to the processing module. The processing module calculates the interactive region where a human figure was detected. Based on the region the person is in, it reads the predefined responses of the robot and sends the filtered response to the output module as a response signal.

By receiving the response signal, the output module then analyzes the mode of the response signal and identifies whether it is a voice response, a motion signal, or an affective response. Depending on the selected signal type, a response will be executed by the robot. If it is a voice response, the voice command controller transfers the command to the voice interface of the robot to perform a voice response. If the response is a motion, it coordinates with the servo motors of the iRobot platform and then moves the arms or the full body to the front and back or rotates them accordingly. If an affective behavior response has to be performed, the robot communicates with its light system and performs the programmed affective response accordingly. After performing any response, it sends the response end signal to the input module, notifying to get the environment monitored by the robot until another customer is detected to initiate communication between the person and the robot.

4 Experimental Protocol

The objective of this research was to identify what is the optimal set of robot behaviors to capture the attention of humans passing by based on the spatiality in human-robot interaction. The method to test the robot was to observe it in a real-world supermarket environment promoting products to customers passing by. The robot was equipped with a mounted camera to observe human interactions in order to analyze them using the video footage and the log records from the robot system per each interaction session, as shown in Figure 4.

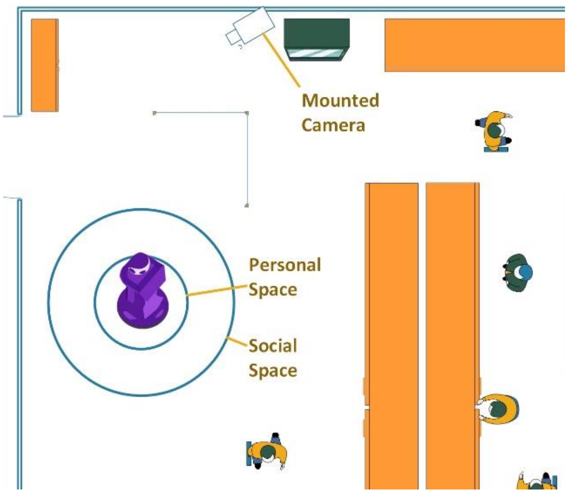

Figure 4 Experimental setup in the supermarket environment.

4.1 Interpersonal Distance

How people use the space with others in many activities in public places including human-human communication has been investigated in several studies. Hall [39] studied the personal distance between the addresser and the hearer in communication and defined social interaction as based on four interpersonal distances, called ‘intimate space’, ‘personal space’, ‘social space’, and ‘public space’, respectively. For attracting attention, the same spatial classification can be used, as it is the earliest point of communication. Implementing the behaviors of the Lometh robot was designed considering spatiality in communication. As public places are often crowded, free space more than 366 centimeters (12 feet) between the robot and a person cannot always be found in public space. As shown in Figure 5, we considered only two interaction situations, i.e., personal space (45 cm to 122 cm) and social space (123 cm to 366 cm), between the robot and the person [36,39].

4.2 Viewing Situations

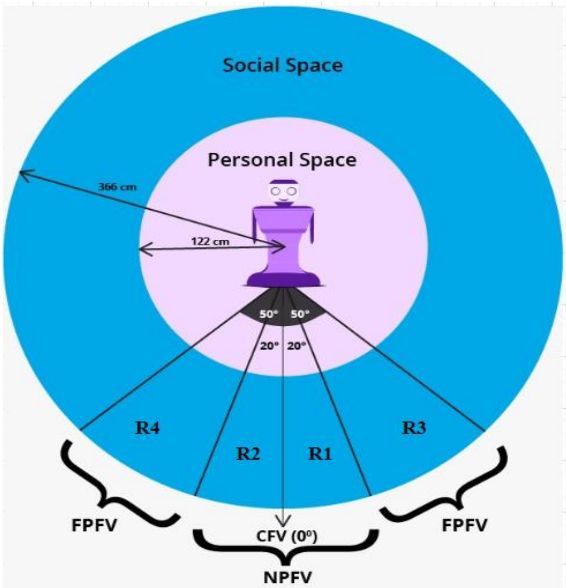

Figure 5 Interactive regions based on interpersonal distances and visual focus.

The Lometh robot uses the concept of visual focus of attention as discussed in the studies by Das, *et al.* [31,36]. It suggests categorizing viewing situations of a human to 'near', 'far', and 'out of the field of view' based on the area at the edges of the human visual field. Chakraborty, *et al.* [37] states that the intensity of the focus on a subject or situation can be measured according to the level of attention by exploring different levels of human attention. The center of the human view is where the central field of view (CFV) is located. The near peripheral field of view (NPFV) is the region on each side of the CFV zone. The zone known as the right near peripheral field of view is on the right side of the CFV, and the left near peripheral field of view is on the left side. The far peripheral field of view (FPFV) is the field of view that extends beyond the human view on both sides. The left near peripheral field of view refers to portion R1, the right near peripheral field of view refers to R2, the left far peripheral field of view refers to portion R3, and the right far peripheral field of view refers to portion R4 in Figure 5.

4.3 Interactive Regions

For the preliminary study, only four viewing situations were considered, consisting of near and far field of views. A near viewing situation means 20 degrees from the central viewpoint and a far viewing situation means 50 degrees from the central viewpoint. Both the left and the right side were considered in near and far viewing situations. The Lometh robot used four interactive regions, R1, R2, R3 and R4, as defined in 3.3 and as represented in Figure 5.

4.4 Experimental Predefined Actions

The Lometh robot was designed with body movements, sound cues, and affective cues as its behaviors. To develop the interaction in a pleasing manner, we designed a pool of interactive responses towards people passing by, categorizing them into three behavioral groups, called ‘bodily cues’, ‘affective cues’, and ‘verbal cues’. The details of the behavioral cues are presented in Table 1.

The robot monitors the viewing field and when it detects a human it identifies the interactive region where the human is in using the kinetic and sensor input and performs predefined robot behaviors, logs the actions performed, and tracks which action caused humans to shift their attention towards the robot.

Table 1 Behavioral groups and predefined actions.

Behavioral Groups	Predefined Actions
Bodily behaviors	Head turns up and down, head turns side to side, body moves side to side. Body moves back and forth, body rotates and stops, both arms move up and down, one arm moves at a time.
Affective behaviors	Head light changes color, head light blinks, head light fades, eye color changes Eye blinks
Verbal behaviors	Uttering reference terms, interrupting phrases, and turn-taking terms (e.g., Good Morning! Good evening! …)

If the person leaves the social space and reaches the personal space to interact with the robot, it counts as a successful human attention shift, after which the related actions performed by the robot and human are logged.

4.5 Experimental Setup and Participants

Customers passing by engaged in a shopping experience were participants in this study. We placed the robot in a supermarket for three consecutive days and monitored 212 customer interactions with the robot for the study. Customers, with an age range of 15 to 55, showed attraction to the robot, as shown in Figure 6.

Figure 6 Customer interactions with the Lometh robot in the supermarket.

5 Results and Discussion

Experiments were done to identify the optimal behavioral cues in four interactive regions considering the spatiality factor in human-robot communication connected with the human visual focus. Attention shifts of customers passing by based on three behavioral categories, namely affective, verbal, and bodily behaviors, were recorded from the 212 interactions. The data were categorized under two nominal variables, namely interactive region and behavior type. The interactive region variable had four values: R1, R2, R3, and R4. The behavior type variable had three values: affective, verbal, and bodily.

Studies in the social robotics research domain that explore the behaviors of humans and robots produce categorial data rather than continuous data. To analyze the categorical data, researchers use the statistical method correspondence analysis [40-42]. Behavioral category and interactive region are both categorical variables. We used correspondence analysis to examine their relationship and how each category relates to the other and variables, which was graphically illustrated using a correspondence plot. Generating the plot was done using the SPSS software [43].

The measure of correspondence can signify affinity, similarity, correlation, interaction, or confusion between the variables interactive region and behavior type, while the cells denote the frequency counts [44,45,46]. Table 2 shows the distribution of the three different behaviors in four different interactive regions.

Table 2 Contingency table of interactive region and behavior type.

Region	Behavior			
	Affective Behavior	**Verbal Behavior**	**Bodily Behavior**	**Active Margin**
R1	18	10	20	48
R2	19	20	32	71
R3	22	5	15	42
R4	30	2	19	51
Active Margin	89	37	86	212

There were 89 attention shifts because of affective behavior, 37 attention shifts because of verbal behavior, and 86 because of bodily behavior in the data set. In Region 1, 48 attention shifts were shown altogether, while 71, 42, and 51 attention shifts were shown in Regions 2, 3, and 4 respectively. Together, 212 participants showed attention shifts. According to the marginal row totals, the most common successful attention shifts happened because of the robot performing behaviors in the affective behavior category. Most of the attention shifts happened in Region 2 and the fewest number of attention shifts happened in Region 3.

5.1 The Mathematics of Correspondence Analysis

Correspondence analysis is an exploratory data approach used to investigate categorical data. It analyzes two-way or multi-way tables, with each row and column becoming a point on a multidimensional graphical map. The data analyzed in this study showed the relationship between the successfulness of behavior approaches for each interaction region. It is a contingency table, which means that each number in the table represents the number of attention shifts for each pair of categories. The computational methods used can be described with the following steps.

Step 1: Generating contingency table

The first step of processing data in correspondence analysis is to produce a contingency table, which is a two-dimensional table built to present categorical variables in rows and columns. For example, the cell in the top-left corner of Table 2 tells us that 18 customers showed successful attention shifts because of affective behavior of the robot in Region 1. Table 2 shows all the data for a sample of 212 interactions.

The contingency table incorporates the frequencies for each of the row and column categories given and produces a summation for each of the row and column categories called the ‘active margin.’ As an example, all of the frequencies for Region R1 across all behavior categories added up to 18 + 10 +

20 = 48. Similarly, the total frequency of the affective behavior category across all region categories came to 18 + 19 + 22 + 30 = 89. The generated contingency table is used to calculate standard residuals for each cell, which can be used to find the coordinates of the plot.

Step 2: Calculating each cell's standardized residual (Z)

The standard residual (Z) can be calculated by following Eqs. (1), (2) and (3) by calculating the residual (R) and the index residual (I).

The residual (R) is equal to:

$$R = P - E, \tag{1}$$

where (P) is the observed proportion of attention shifts (the value in a cell divided by the total sum of all values in the table) and (E) is the expected proportion for each cell. The residual is the difference between the actual and the predicted data proportions. The values for P and E are represented in Tables 3 and 4. The values for R are represented in Table 5.

Table 3 Observed proportions (P)

	Affective Behavior	**Verbal Behavior**	**Bodily Behavior**
R1	.085	.047	.094
R2	.090	.094	.151
R3	.104	.024	.071
R4	.142	.009	.090

Table 4 Expected proportions (E)

	Affective Behavior	**Verbal Behavior**	**Bodily Behavior**
R1	.095	.040	.092
R2	.141	.058	.136
R3	.083	.035	.080
R4	.101	.042	.098

Table 5 Residuals (R)

	Affective Behavior	**Verbal Behavior**	**Bodily Behavior**
R1	-.010	.008	.002
R2	-.051	.036	.015
R3	.021	-.011	-.010
R4	.041	-.033	-.008

R is then passed to calculate the indexed residual (I). The set of residual results obtained can be skewed towards rows/columns with bigger masses, so interpreting the results can be difficult. To address this, the residuals are divided as follows:

$$I = R / E, \tag{2}$$

This produces a table of the indexed residuals (I) and the residual (R) used here was taken from Equation (1).

The standardized residual (Z) can be calculated as follows:

$$Z = I * \mathrm{sqrt}(E) \quad (3)$$

where I is the indexed residual given by Eq. 2, and E is the expected proportion [45,46]. The standardized residuals are represented in Table 6.

Table 6 Standardized residuals (Z)

	Affective Behavior	Verbal Behavior	Bodily Behavior
R1	-.032909	.038504	.008223
R2	-.135946	.148446	.040928
R3	.071442	-.059111	-.033906
R4	.127495	-.158863	-.025498

The standard residual values give the input to generate singular values to generate the coordinates in the plotting regions and the success of each type of behavior [47,48].

Step 3: Analyzing standardized residuals (Z) and deriving plot coordinates

The generated Z values in Table 6 were analyzed with Singular Value Decomposition (SVD) to generate singular values. The SVD method uses the theoretical insight of linear algebra and matrix transformation. SVD produces a rectangular matrix and converts it to the product of three matrices. Mathematical studies and sources with a detailed explanation on matrix transformation in SVD can be found in References [47] and [48].

The singular values relevant to this study are 0.310 and 0.027, as can be seen in Table 7.

Table 7 Summary of the correspondence analysis between region and behavior type.

Dimension	Singular Value	Inertia	Chi Square	Sig.	Proportion of Inertia		Confidence Singular Value	
					Accounted for	Cumulative	Standard Deviation	Correlation 2
1	.310	.096			.992	.992	.060	-.186
2	.027	.001			.008	1.000	.064	
Total		.097	20.504	.002	1.000	1.000		

5.2 Interpretation of Results

As can be seen in Table 7, two dimensions resulted from the collected data. The main thing to identify from the summary table is to know whether the results are statistically significant or not. In this study, the X2 value of 20.504 and the degrees of freedom value of 6 were correlated with a P value of less than 0.01.

This means that a chi-square value this large would occur simply by chance less than 1% of the time. Thus, our model was significant at the .002 level and had a chi-square value of 20.504. A canonical correlation between the two variables is displayed by the Singular Value column for each dimension.

The total inertia value represents the amount of variance attributed to the original contingency table by the total model. The inertia shown by a particular dimension can be evaluated by comparing it to the total inertia.

According to the Table 7, 99.2% (0.992) of the total inertia is shown for the first dimension, whereas the second dimension shows only 0.8% (0.008). The chi-square test examines the states for which the total inertia value is zero or not different than zero [44,48]. The significance value is 0.002, which is less than 0.05, indicating that the total value of inertia is significantly distant from zero. As the first-dimensional solution explains almost all of the total, it is not necessary to consider the second dimension, because it represents less than 1.0% of the total inertia.

This analysis only produces dimensions that can be interpreted, rather than taking all the dimensions that describe something about the model. For this reason, inertia does not always add up to 100%. The Inertia column gives the total variance defined by each dimension in the model. The total inertia (total variance explained) in our model was 9.7%. Dimension 1 explains 9.6% of the total 9.7% of the variance accounted for and Dimension 2 explains 0.1% of the total 9.7% of variance accounted for. This shows that knowing something about behavior type explains roughly 10% of something about a region and vice versa. This correlation is significant enough, as indicated by the chi-square statistic in our test, although it is a weak correlation.

Table 8 (Overview of the row points) provides information on how each row point is plotted in the final biplot. The Mass column in the table describes the proportion of each region with respect to each behavior type in the analysis. The score in the Dimension column represents the coordinates of each dimension (1 and 2), where each row category will be located in the biplot. Inertia reflects the variance. The Contribution field indicates how well each of the points contributes to each dimension.

Here, Region 2 and Region 4 are dominant points in the first dimension, contributing 87% (0.439 + 0.437) of the inertia. Region 3 is a dominant point in the second dimension, contributing 65% of the inertia. The first two dimensions contribute all of the inertia (100%) for all four regions.

Table 8 Overview of the row points.

Region	**Mass**	**Score in Dimension**		**Inertia**	**Contribution**				
					of Point to Inertia of Dimension		**of Dimension to Inertia of Point**		
		1	**2**		1	2	1	2	Total
R1	.22	-.19	-.01	.003	.027	.00	.99	.001	1.00
R2	.33	-.63	.05	.042	.439	.03	.99	.001	1.00
R3	.19	.38	-.30	.010	.096	.65	.95	.050	1.00
R4	.24	.75	.18	.042	.437	.31	.99	.006	1.00
Total	1.0			.097	1.00	1.0			

Table 9 gives information that was used for plotting the column points in the biplot. The affective and verbal behaviors are the dominant points in Dimension 1 and account for 96% of the total inertia. Bodily behavior is the dominant point in Dimension 2, accounting for 56% of the total inertia. The first two dimensions contribute all of the inertia (100%) for all three behaviors.

Table 9 Overview of the column points.

Behavior	**Mass**	**Score in Dimension**		**Inertia**	**Contribution**				
					Of point to inertia of dimension		**Of dimension to inertia of point**		
		1	**2**		**1**	**2**	**1**	**2**	**Total**
Affective behavior	.420	.560	-.101	.041	.425	.155	.997	.003	1.0
Verbal behavior	.175	-.981	-.211	.052	.542	.283	.996	.004	1.0
Bodily behavior	.406	-.158	.195	.004	.033	.562	.881	.119	1.0
Active Total	1.000			.097	1.000	1.000			

As in Figure 7(a), the row point plot shows that Region 1 is very close to the origin, indicating that it differs little from the average row profile. Three general classifications emerge. R1 and R2 are located left, so we can say there can be some similarities between them. The lower right contains R3 and the upper right contains R4. As regions R3 and R4 are not clustered, they are separated from each other. Hence, no similarities between regions R3 and R4 are observed. According to Figure 7(b) (Column point plot), bodily behavior is close to the origin, so it is similar to the overall centroid. Verbal behavior is in the lower left and affective behavior is in the lower right. None of the three behaviors are clustered together. Hence, none of the behaviors are similar to any other behavior in shifting human attention.

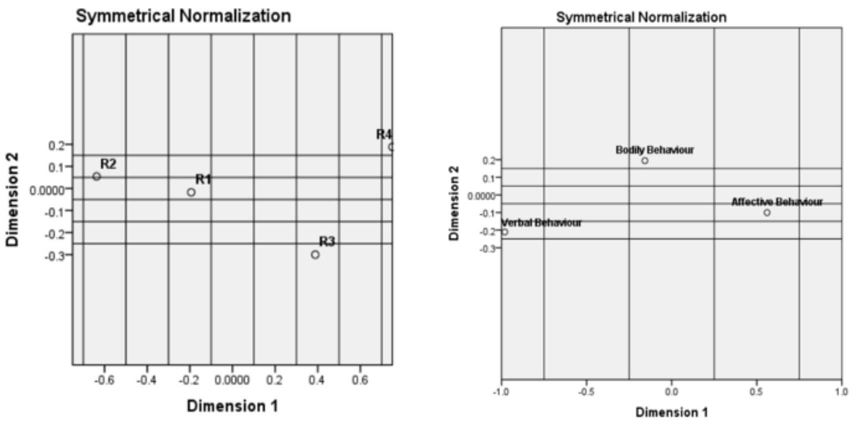

Figure 7 (a) Row points for region. (b) Column points for behaviors.

The correspondence map illustrates each category score in both dimensions for both region and behavior at once, as shown in Figure 8. These scores help us to compare between the categories across the variables in two-dimensional space. Correspondence is a standardized measure of relationship (in space/distance) between categories of multiple variables. The points for Region 1 and bodily behavior are situated close together, so that Region 1 appears to prefer bodily behavior. R2 is closer to the verbal behavior point, showing that verbal behavior is more significant for human attention shift. The affective behavior point is close to both Region 3 and 4, hence R3 and R4 both prefer affective robot behavior for human attention shifting.

Of all of the factors measured, R1 and bodily behavior are fairly average. Because they do not have anything distinguishing them, they end up in the middle of the map (near the origin), and that is all they have in common. It is clear that visualization reveals 10% of the diversity in the data and that this only accounts for 10% of the variation in the relationships. As a result, much of the information has been omitted from the summary. We need to explain a large fraction of the volatility in the data. The angles in the biplot are useful. As the chi-square test is significantly different (p 0.002 < 0.05) and the total inertia value is 99.2%, we have confidence in the ability of these data to offer conclusions about the general population.

It is hard to draw conclusions about the relationship between the row labels and the column labels based on the distance between them. Instead, a line linking the row and column labels to the origin is used in correspondence analysis to describe the relationships. The stronger the link, the sharper the angle. As a result, there is a stronger relationship between R1 and verbal behavior than between R1 and bodily behavior. Similarly, R2 is strongly correlated with verbal behavior, while

R3 and R4 are strongly correlated with affective behavior. If a row and column label have a 90-degree angle to the origin, they are most likely unrelated. As a result, there is no link between R3 and verbal behavior and R4 and bodily behavior. If a row and column label are on different sides of the origin, they are most likely negatively correlated. As a result, we can find a negative relationship between verbal behavior and R3 as well as between verbal behavior and R4. In other words, R1 and R2 are more strongly correlated with verbal behavior than R3 and R4.

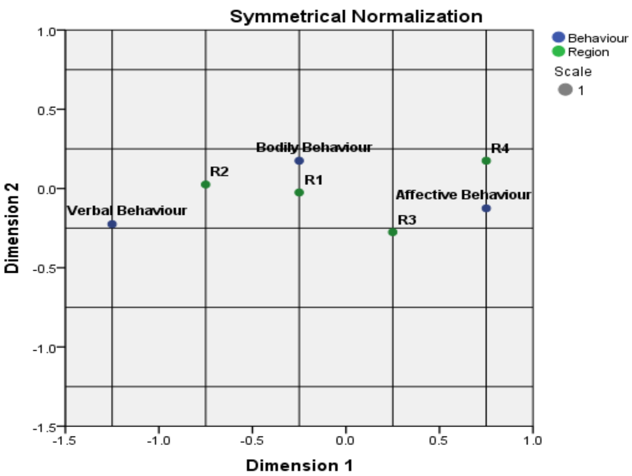

Figure 8 Row and column point correspondence map.

6 Conclusion

We can conclude that when a person is in Region 1 (Left Near peripheral field of view_Social Space), the bodily behavior of the robot is successful in capturing human attention. Also, if a person is in Region 2 (Right Near peripheral field of view_Social Space), successful attention capturing behavior is verbal behavior. When persons were in either Region 3 (Left Far peripheral field of view_Social Space) and Region 4 (Right Far peripheral field of view_Social Space) they shifted attention because of affective behavior of the robot. In this study, we observed that different robot behavior types were successful in capturing the attention of a person depending on the spatiality. Hence, consideration of human focus of attention and spatiality is critical when it comes to human-robot interaction and successfully shifting the attention of people depends on the region where they interact with the robot.

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