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Full Paper

Robot Lometh: Exploring the Influence of Attentional Cueing Behaviors of a Product Promoting Social Robot on Attention Shift of a Passing by Human

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Abstract

Applications of social robots appear to be growing in many industries worldwide. Researchers in the field of human-robot interaction (HRI) explore how to implement a robot in a socially accepted manner and explore methods of building a successful social robot that can accomplish its expected behaviors. There will be more social robots for human representations in the future. Hence, interacting with a social robot should feel natural and humanized more than ever. The main challenging task of a product-promoting social robot is to make humans aware of the robot in the field and notify humans passing by of the robot's presence. This study attempts to identify the effect of different attentional cueing behaviors that robots can perform in capturing the attention of passing by humans to make the human aware of the robot and make the human interact with it using the anthropomorphic social robot "Lometh". Researchers of this study used three categories of attentional cueing behaviors and their combinations to analyze the influence of cueing behaviors in a supermarket environment where the robot performs the role of a product promoter. Studies are carried out to capture human attention by a robot when a human engages in some activity. At the same time, humans are immobile, but the influences of attention cueing behaviors of a robot towards passing by humans are yet to be explored. In this study, pre-defined robot behavioral combinations were experimented with, and the successful interaction initiations were recorded to analyze the influence of each attentional cueing combination. The outcome of this study recommends that behavioral combinations shift human attention and include verbal cues that highly motivate the human attention shift. The findings will contribute to configuring the procedures for the attentional goals of social robots to achieve their communication goals.

Keywords: Attentional cueing, Attention shift, Human-robot interaction, Anthropomorphic social robot

Introduction

Developing a robot with human-like behaviors should involve multiple research disciplines. The primary concern of researchers in the field of social robotics is to create an experience where people feel like they are interacting with a fellow human rather than a machine. Today and in the future, humans should be able to engage with a robot comfortably, the same as human-human engagements, as a variety of tasks will be handed over to robots in everyday human activities, ranging from domestic assignments like vacuum cleaning to empathic necessities like companionship and caregiving.

When considering human-human communication, initiating an interaction between multiple parties requires mutual attention. Similarly, in human-robot communication, capturing the target human's attention towards the robot is the initial stage of the communication process. Mavrogiannis *et al.,* (2023) in the study reveal that the attention control process must be designed carefully, considering various human factors, such as personal space, visual focus, and human acceptance, as capturing attention is a core behavioral challenge of social robots [1]. According to Hoque *et al.,* (2012) capturing the attention of a human by a robot who does not face the human involves more effort than capturing the attention of a human face to the robot because it requires the robot to perform significant behavior which can make the human's peripheral vision focused on the robot [2]. Hoque *et al.,* (2013) suggested that the attention shift passing by a human can be achieved with verbal and non-verbal cueing behaviors of the robot, such as eye gaze, head turn, change in body orientation, pointing gesture, or with verbal behaviors focusing on the target person who needs to be addressed [2, 3]. Foulsham *et al.,* (2011) suggest that though many experiments were carried out to explore the attention-capturing attempts of a robot of an immobile human, capturing the attention of a passing by human was not explored [4]. In this research, the robot Lometh was designed to explore attention-capturing methods that can be used by a robot toward a passing by human [5].

Figure 1. (a) Robot shifts the attention of a customer and (b) delivers promotions after an attention shift

As shown in Figure 1(a), when it detects a passing by human after a successful attention shift, as in Figure 1(b), it initiates communication, and the Robot delivers product promotion to achieve its promotional assignments [5].

The continuation of this paper will present information on the related background work, the experimental setup, the findings, the discussion, and the conclusions drawn. Finally, based on the results and gathered experiences, researchers suggest the identified future works to be done.

Background Study

Product Promotions

Researchers and industrialists, especially in the marketing discipline, struggled with different product promotion techniques, including distributing leaflets, promotion displays, advertising billboards, information boards, ambient displays, human agents, location-based mobile apps, and simple screens to deliver promotional messages to the customer [6].

Table 1 provides an overview of the different product promotional methods and techniques that researchers experimented with different promotion delivery channels.

Table 1. Promotional Delivery Modes Used in Supermarket Environments

Method	Mode of Delivery	Results
Posters	Text, Pictures	Customers are getting prejudgments about the text on the mounted poster [7].
Distributing Leaflets	Text, Pictures	Customers tend to overlook and form prejudgments about the text in the leaflet [8, 9]
Billboards	Text, Multimedia	The promotional message is not at eye level, making it difficult for customers to notice [10, 11].
Information Boards	Text, Multimedia	No interactions with the board lead to decreased customer attraction towards the information [12-14].
Artificial Intelligent Bots	Text, SMS	No verbal communication, no access to complete information [15].
Instrumented Shopping Cart	Visual outputs	Visual outputs with touch screen [16].
Interactive Walls	Text, Gesture, Audio, Video, Animation, touch	The absence of human-like interaction (both social and physical) results in an ineffective delivery of the message [17-19].
Human Sales Agents	Verbal and Non-verbal communication Physical and social interactions	Social & physical interactions are necessary and effective [20]. Disturbance to the shopping experience [21]. Come to prejudgments on the message to be delivered [16]. Gender Bias [21]. Less influence to listen continuously [22].
Robots at Stores	Verbal and Non-verbal communication Physical and social interactions	Implements social & physical interactions [21]. - Attracted by children [23]. - Not get bored even at work 24×7 [24]. - Not demotivated by negative customer feedback [25, 26].

Even though the methods discussed were used inside the supermarkets, there is doubt about accepting those methods in successful promotion delivery. Human-to-human promotion was found to be more effective with physical interactions, which means physical and social interactions remain more important in product promotions [27].

A summary of the above information reveals the different viewpoints on promotion delivery methods in supermarkets, including human sales agents and the involvement of robots in product promotional activities in supermarkets. Shop owners had a negative influence on human sales agents because of facts like time to train, taking breaks, salary, leaves, and humans getting bored by repeating the same promotional activities and getting negative feedback from the customers and then shop owners have shown interest in considering digital platforms and trusted the human issues can be addressed by a robot sales agents [24]. To use a robot for this purpose, the robot should have the ability to grab customers' attention and retain attention during the promotion delivery. Robot Lometh focuses on the initial stage of establishing communication between customers and robots.

Attention Shift of a Human

Hoque *et al.,* (2013) describe the shift of human attention as switching the current direction of the human attention to a specific goal direction, and in his studies about the human attention controlling process in human-robot interaction, he suggests the robot seeks to attract the target person's attention before starting the attention control procedure [28]. Iwasaki *et al.,* (2022) suggest that human attention is essential in real-life social interactions. The ability to give and take attention via eye gazing is fundamental to the human socio-cognitive system. Engagement in attention and shifting the attention to follow the gaze-at direction indicate the focus of attention, which is called gaze cueing [29]. Human attention via covert measures (without eye movements) is also reflected commonly in the real world when eye movements are restricted. These engagements are less studied and measured compared to the attention via overt measures (with eye movements), which is often tested within a constrained laboratory environment as opposed to the real-world environment [30].

Influence of Robot Behaviors on the Attention Shift of a Human

The studies of Hoque *et al.,* (2012) proposed behaviors like head turning or head shaking, gaze awareness, and blinking eyes that can shift the target person's attention and confirmed the proposed methods were effective in human-robot communications [28]. Valuch *et al.,* (2022) found that repeated visual content is another motivating factor in capturing human attention and continuing the attention toward the goal direction [31]. Li *et al.,* (2015) revealed that robotic or human appearance and motion effects positively capture the social attention towards the robot, and whether the robot is static or moving also influences the unconscious attentional capture process of human-robot communication [32]. Urakami *et al.,* (2023) Nonverbal stimuli such as body (shape, size, colors), movements (behavior, patterns, proxemics, chromatics), gestures (pointing, etc.), face (eyes, facial expressions), voice (paralinguistics), sounds (system sounds), surface structures, body smell, the taste can shift human attention towards a robot unconsciously [33].

Capturing Attention in Human-Human Interaction

Luciana *et al.,* (2018) identified that human attention in social and real-world environments is affected by the person's social knowledge and social behavior. Humans can choose which social cues they pay attention to in real-life settings. People detect both verbal and non-verbal gestures displayed by others in social contexts and select whether to respond or not depending on their social interest for creating an opportunity for social interaction. His study shows that social attention is sensitive to evaluating the value of other people's behavior. This social affordance is conveyed by both verbal and non-verbal signals [34].

Capozzi and Ristic(2018)identify perception, interpretation, and evaluation as three core processes in the social attention system that effectively filter many stimuli from the environment and direct social beings to select and manage their social interactions [35].

Capturing Attention in Human-Robot Interaction

In human-robot interactions, robots are required to influence human behavior to gain their attention and carry out smooth and effective interactions, just as magicians manipulate the spectators [36]. Urakami *et al.,* (2023) present the viewpoint of their studies on nonverbal cues in human-robot interaction, exposing that adapting human nonverbal codes for HRI is essential to becoming a robot as a socially embodied agent, and he reveals human receives the nonverbal codes through human sensory channels vision, Auditory, Haptics, Olfactory, Gustatory [33]. Individual and collective movements in gaze, eyes, and hands are key factors in catching the attention of humans and keeping them engaged in a particular target. Proposes a model for human attention by integrating a saliency map, which is a model of saliency-based visual attention for rapid scene analysis that captures the saliency of images with a manipulation map that projects the relationship between collective movements of face, eye, and hands in magician-spectator interactions [37]. Furthermore, the results indicated that their model, which incorporates the manipulation map, achieved a higher evaluation index compared to relying solely on the saliency map. The results from the experiment using the proposed model showed that the movement of hands is a key influential factor in guiding the attention of the spectator [36].

Eye contact is crucial in attention and interaction with a robotic framework. Turning the gaze towards the human itself is insufficient for establishing eye contact by the robot in human-robot interactions (HRI). When the human is engaged in a task, the robot cannot immediately establish eye contact with the human by turning the gaze [38]. Hoque *et al.,* (2012) illustrate a model for attention that the robot's shaking of the head after turning the head towards the target person successfully gets the target person's attention. In his model, blinking is taken as another successful cue in establishing gaze awareness. The act of blinking by the robot acknowledges the human that they exchange eye contact with each other and are ready to initiate an interaction. The head orientation of the target person is captured to evaluate whether the person is making eye contact or not. This method has proven to be a better substitute for monitoring eye movements because the head is a more significant visual stimulus and is easily recognized in peripheral vision [3, 28]. In summary, cues like eye gazing, turning the head, body movements, pointing hands, and verbal cues have been successfully used to direct the attention of the target person toward an object of interest [39].

Equipment and Sensors Used in Existing Social Robots Operate in Public Places

Saksena *et al.,* (2024) believe that the implementation of Hyper-Personalization in the retail industry is evolving with time [40]. An empirical investigation on product suggestion strategy employing two robots by Dani et al., (2020) used an ultra-wide-angle webcam to collect footage in real-time and a controller unit that worked together to allow the operators to regulate the robot's behavior [41]. Song et al., (2024) and Edirisinghe et al., (2024) their studies on human-mobile robot interaction in the retail environment, used 2D Lidar Sensor with a Logitech C920 webcam to scan the range, an Inertial Measurement Unit to capture localization and body posture information, and a Tobii Pro Glasses 2 eye tracker to capture human trajectories, robot movements, body posture, eye gaze data, and overall interactions in the retail environment [42,43].

Saksena *et al.,* (2024) in their study of computer vision technologies for in-store retail automation, created a robot called Tally with eyes developed using many Intel RealSense depth cameras. Tally uses depth data from cameras to map shelves and find out-of-stock items through gaps. Tally's multiple Intel RealSense depth sensors enable safe navigation around obstacles like as retail carts, displays, and humans. Tally may avoid crowds and focus on customer safety [40]. Dani *et al.,* (2020) in their study, used the Kinect sensors in the robot system to capture human arm joint position trajectories during reaching motions. These sensors gave RGB-depth (RGB-D) data, which allows the system to correctly monitor human movements and intentions. The Kinect sensors were critical in collecting demonstrations of joint position trajectories labelled with actual intentions, which are then used to train neural network models for human intention prediction in collaborative activities [41].

The most common sensors found in social robots in retail and supermarket environments to implement Hyper-Personalization include a range of equipment and sensors such as RGB cameras for colour image capture [42]. Chen *et al.,* (2022) used Kinect sensors for depth and colour image data with tasks such as facial and gesture recognition; depth cameras for obstacle avoidance and identifying perception [41, 43]. LIDAR sensors for mapping the environment 360 degrees [44]; ultrasonic sensors for short-range obstacle detection; infrared sensors for proximity sensing; microphones for audio input and voice command detection [40, 45].

Applications and Effectiveness of Social Robots in Public Places

Applications of social robotics in day-to-day activities are very diverse. They include caregiving social robots, learning robots, rehabilitation robots, entertainment robots, robots for elderly care, and personal robots as companions. Robots are currently being used in stores for various tasks related to logistics, inventory management, customer service, and product promotions [46]. Some of the best-known robots used in retail stores are Best Buy's Chloe, Amazon's Kiva, Tally in Target, the shelf-scanning robot in Walmart, and Pepper, a semi-humanoid robot utilized in Japanese stores [47]. These robots have demonstrated their effectiveness in performing roles traditionally carried out by humans [26].

Applications of Social Robots in Retail and Supermarkets

The study by Keeling *et al.*, (2013) analyzed the impact of robots in retail markets and identified that robots are better than humans in terms of stability, physical capability fatigue, and accuracy [48]. The results of a survey showed that human-robot interaction is more task-oriented as opposed to human-human interactions, which further establishes the capability of robots to perform tasks in retail stores more reliably [48, 49].

Out of a variety of services performed by robots, Murakawa *et al.*, (2011) identified announcement services like sales and product promotions as the most effective and feasible services that a robot can perform in commercial facilities. The effectiveness of sales promotional services performed by robots was further examined in terms of the number of customers attracted to the promotion, and the number of sales increased as a result. The results showed that the robot's service outperformed both manned (salesperson) and unmanned promotional services, affecting increased customer attraction and sales [24]. The study concluded that robots' service in product promotion would be more useful in brand penetration of a specific product rather than promoting products to increase sales of individual products in the store in terms of cost-effectiveness. Hence, selecting a target person among other people who are already engaged in a task like walking, approaching and gaining attention to initiating an interaction with the person are the main tasks that a robot in a store should achieve to provide the service like delivering information, advertising or guidance [25, 26].

The above-mentioned studies have shown that non-verbal cues like eye gazing, body movement, and pointing are practical in seeking the attention of humans and setting off a human-robot interaction. This study, Robot "Lometh," is intended to explore the influence of attentional cues performed by the robot towards a person who is passing by the robot with the intention of shifting moving humans' attention toward the robot. In contrast, the past studies monitored the communication robots and the human when they are in situated environment.

Design of Robot Lometh

Minimalistic and Futuristic Design

The design of the Robot 'Lometh' considered the minimalist and futuristic appeal anthropomorphous [5, 50]. Bennett et al., (2013) suggest the minimalist approach could reduce the complexity of robots and artificial entities, resolving constraints connected to representing non-critical aspects of human anatomy [51]. To make the appeal less complex and to make the human interactors focus on communication, the arms and the body were designed minimalist only, including palms and the lower body with a combined leg shape, and it leads customers passing by less distracted by shifting and retaining the attention towards the robot.

Figure 2. (a) Initial sketch of the Robot design and (b) finalized appearance of the Robot

The height and the size of the robot were decided with ideation using the initial sketch as in Figure 2(a). Considering the visual merchandising principles used in product promotions based on the study of Sigurdsson *et al.,* (2009) retailers recommended placing the displays at the eye level of the customers to achieve the best results [52]. We placed the product promotional display on the body of the robot in a satisfactory level of eyesight for customers, as shown in Figure 2(b). The color selection of the robot was done, concentrating on the color biases of human attributes like gender or age groups. The study of Xin et al., (2007) focused on finding an electronic entertainment environment with the potential for social interaction. It was confirmed that the purple color gives a sense of physical presence through the exploration of physical interactions and demonstrated that the purple color shows feasibility, is closely associated with natural sociable behaviors, and can have a significant impact on the social meaning of entertainment [53]. To build aesthetically engaging appeal, we used a combination of white and purple color to the body of the robot "Lometh." Figure 2(b) shows the robot's finalized appearance.

Anthropomorphous Design

The Robot "Lometh" managed the uncanny valley's behavioral consequences in HRI by designing the robot with more humanized features. According to Wang *et al.,* (2015) studies uncanny valley phenomenon is a specific psychological reaction that people have when they interact with a robot or animated character, and their experiment presents there can be effects of the uncanny valley's phenomenon on human attention and retaining attention during interactions [54]. DiSalvo *et al.,* (2002) in their experiments, discuss the designers engaged with planning robot designs who have recently been interested in enabling anthropomorphic appearance for social robots and discovered the essential qualities in designing a robot to seem social and useful. Their findings were the dimensions of the head and the robot face were significant to the human responders and confirmed that humanlike robots would be perceived as more user-friendly [55]. Kwak (2014) discussed how oriented robots can make a human presence in HRI in their service evaluation of the impact of robot appearance types on social interactions [56]. Pinxteren *et al.,* (2019) reveal social functioning features like non-verbal communication cues and turn-taking cues, such as intonation, paralanguage, body motion, socio-centric sentences, pitch, or syntax, which can be implemented to make trust in humanoid robots in service marketing [57]. Dubois-Sage *et al.,* (2023) in their studies on mere appearance hypothesis and SEEK (sociality, effecting, and elicited agent knowledge) theory on anthropomorphism, present anthropomorphism has many factors vary according to the voice, behavior, and movement quality of the robot and not only the appearance [58, 59]. They identified that the context factors for robots could be a range of implementations from human-like appearance to human-like voice, human-like behavior, and movements [60]. Robot "Lometh" is designed with a humanlike design, having the visible head, body, arms, and movable body shaped in a modern look without disturbing the product promoter's human-like nature. Figure 2 (b) shows the initial pencil sketch and the modern design. Table 2 presents the implementation of non-verbal affective cues and verbal and bodily behaviors in Robot Lometh to support anthropomorphous Design.

Experimental Procedure

The experiment was done in a real-world setting, in a supermarket. The behavioral responses of the participants, log records, and observation outputs were gathered and analyzed. Hoque et al., (2012) explain that to get people's attention, shaking your head may be a useful cue because people are motivated to notice moving objects [28]. The study further describes the visual stimuli provided by the robot's nonverbal behaviors cannot affect a person if they are in a position where they cannot see the robot [3]. It is also difficult to attract their attention with any physical movement because the human eyes cannot observe that movement cannot observe that movement due to the distraction of the attentional focus. Touch or voice can be used as an option in this case [61]. Based on past studies on attention controlling in HRI, the robot should perform strong behaviors when the robot is captured just in the human's far peripheral field of view; a single action is not sufficient [2, 62-64]. In that instance, head shaking may be an effective cue with verbal or nonverbal cues to attract human attention since object motion is particularly likely to attract attention. Based on the literature above, the Robot "Lometh" was selected to perform affective, verbal, and bodily behaviors in capturing the attention of passing by humans and the behaviors and the equipment and sensors used to implement them are presented in Table 2.

Table 2. Equipment and sensors used to implement the behaviors of Robot Lometh

Attentional Cueing Category	Robot Behaviour	Equipment and Sensors
Affective Cues B1	Headlight color change	RGB LED Strips, MS Kinect Sensor
	Headlight blinks	RGB LED Strips, MS Kinect Sensor
	Headlight fades	RGB LED Strips, MS Kinect Sensor
	Eye color change	RGB LED Strips, MS Kinect Sensor
Verbal Cues B2	Greetings	Speakers, MS Kinect Sensor, Web Camera
	Uttering reference	Speakers, MS Kinect Sensor, Web Camera
	Interrupting phrase	Speakers, MS Kinect Sensor, Web Camera
	Turn-taking terms	Speakers, MS Kinect Sensor, Web Camera
Bodily Cues B3	Body moves back and front	, MS Kinect Sensor, Web Camera, iRobot Base
	Body rotates and stops.	MS Kinect Sensor, Web Camera, iRobot Base
	Both arms move up and down.	MS Kinect Sensor, Dynamixel Servo Motors
	One arm moves at a time.	MS Kinect Sensor, Dynamixel Servo Motors
	Head turn up down	MS Kinect Sensor, Dynamixel Servo Motors

In this study, 230 interaction sessions were observed. When a random person passes by, the robot identifies the human and performs affective cues, waiting for a positive attention shift. If the person's body orientation and eye contact were established for interaction, that session was considered a successful attention shift of affective cues. The robot performed behavioral combinations of affective verbal and bodily cues if the attention shift failed towards a single cue. Once the robot and the person were at a social distance, eye gaze and other non-verbal cues were employed to retain the person's attention while conveying the promotional message.

Robot Behaviors

There were predefined sequences of robot attentional cueing behaviors categorised into three groups, as presented in Table 2, and performed to explore the customers' attentional behaviors towards the robot. The equipment and the sensors used to implement robot behaviors are labeled in figure 3.

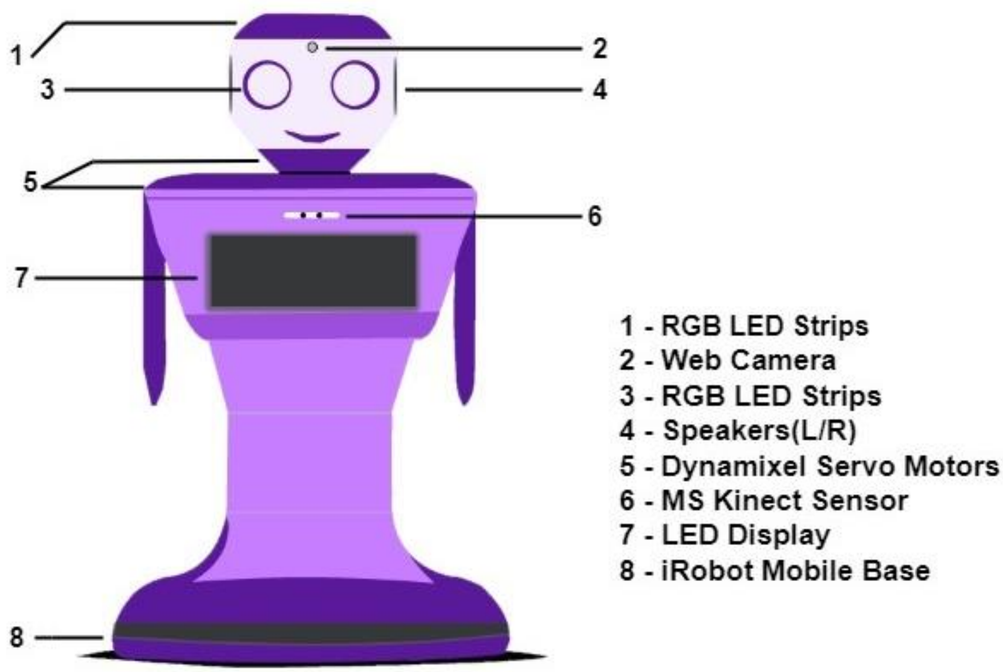

Figure 3. Equipment and sensors used in Robot "Lometh"

Behaviors of Robot Lometh

Kuzuok *et al.*, (2010) in their study on spatial formation arrangement by robot body orientation, conclude that rotating the whole body of the robot is more significant than rotating only the head [65]. Althaus *et al.*, (2004) shows robot's approach want to acknowledge nonverbally to the human [66]. Based on the background details on effectiveness of robot behaviors, predefined behaviors of the robot Lometh, implemented with three behavioral categories named affective behaviors, verbal behaviors, and bodily behaviors [61]. As labelled in Figure 3 and presented in Table 2, affective cues, verbal cues and bodily cues were implemented.

Affective Cues with Head and Eye: RGB LED strips were used as they were supported with separate data buzz to pass the signals on color changes and brightness. As in Figure 3, 1 represents the headlights, and 3 locates the eye lights. 1 and 3 purple color fading, blinking in purple, and changing the color from blue to purple were implemented as affective cues.

Verbal Cues: Speakers (4) located in the head providing verbal cues like uttering reference terms and Greetings. With the support of the LED display (7), the robot delivers the promotional message to the customer. A camera placed on the head (2) detects the attention level for delivering the message effectively. *Bodily Cues*: Followed with the human detection using the Microsoft Kinect sensor (6), Moving Arms, moving head, and Moving or Rotating body of the robot implemented with the support of the Dynamixel servo motors (5) and the iRobot base (8).

Behavioral Combinations

To explore the influence of the three behavioral cueing categories on attention shift of a passing customer, combinations of cuing behaviors were tested as shown in Table 3.

Table 3. Behavior combinations performed by Robot

Attentional Cueing Categories	Action Combinations
Affective Cue B1	Headlight color change Headlight blinks Headlight fades Eye color changes
Affctive_Verbal B1_B2	Headlight color change_Uttering reference terms Headlight blinks_Greetings
Affective_Verbal_Bodily B1_B2_B3	Headlight color change_Uttering reference terms_Head turns up and down/Side to side. Headlight blinks_ Greeting_Arms move up and down Eye color changes_Greeting_Body moves side to side

Experimental Setup

In this experiment, the robot was situated within a supermarket environment, with a surrounding space of a 12 ft radius. The participants involved in the study were customers who were actively engaged in their shopping activities.

The experiment spanned three consecutive days, during which a total of 230 customers passing by the robot had the opportunity to interact with it, as the experimental design represents in Figure 4. The focus of the experiment was to observe how the robot's behavioral cues influenced the attention of the customers, leading to a shift in their focus toward the robot.

The robot communicated information on today's promotions to the passing customers, and a mounted camera was used to monitor customers with the observer, as represented in Figure 4.

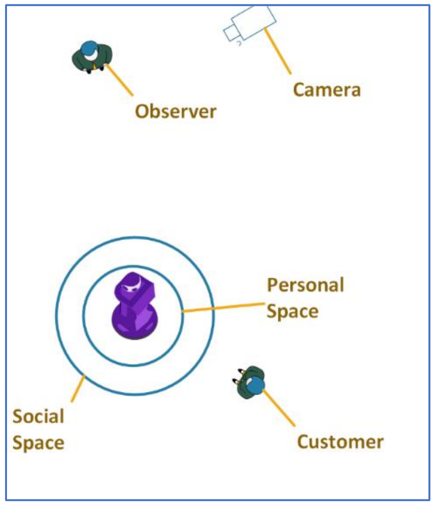

Figure 4. Experimental design

Suppose the customer changes the direction of their walking route by changing body orientation towards the robot by responding to the robot's attentional cueing performances. In that case, the observer marks that case as a successful attention shift achieved by the robot. The robot initiates promotional delivery when the customer enters the personal space (45 to 122 cm range), passing the social space (123 to 366 cm)as shown in the experimental design [5]. The implicit robot system tracked the human and kept records of performed robot behaviors and the status of the attention shifts of the customer. If the customer changes their body orientation and walking direction in response to the robot's behaviors, a log record is created as a successful attention shift. Figure 5 shows an interaction between the robot and a customer.

Figure 5. Experimenting with the Robot "Lometh" in a supermarket environment

The attentional queuing behavior performed by the robot for each passing by customer is also recorded in the system as a log. It used both log records and data gathered from the observations to finalize the data set. Collected data and the analyzed behavioral information on interaction sessions were presented in the results and discussion section.

Method of Analysis

Since it is challenging to obtain a clear sense of the data briefly, preliminary data analysis was conducted. The aim was to explore the influence of behaviors by statistically analyzing the collected data, to identify the effects of each attentional combination category. Upon reviewing the preliminary analysis results, potential hypotheses were identified and subsequently tested using the proportion comparison statistical testing method.

Results and Discussion

Collected data was visualized in preliminary data analysis, and three hypotheses were identified to discover the significance of behavioral cueing combinations.

Preliminary Data Analysis

Table 4. Summary of the data collected from observations and logs

Attentional Cueing Category	No. of Attention Shifts
Affective	89
Affective_Verbal	37
Affective_Verbal_Bodily	86
Not Responded	18

Though we expected growth in attention shift of a human when using combinations of attentional cues, it does not show the expected pattern of increasing attention shifts.

Another observation from visualized data was that combining verbal cues with affective cues shows less influence on the attention shift. But, combining bodily cueing behaviors shows a positive impact and amplifies human attention toward the robot. To test the observations from the sample data and analyze the impact of different types of combined cueing categories towards capturing human attention.

Hypotheses Testing

We tested the proportions of each attentional cueing group, aiming to answer the identified questions. To evaluate the significance of attributes, we used two sample Z tests of proportions testing methods to validate the hypothesis [67, 68]. Tests were performed with a one-tailed, two proportions Z test method using a significance level of 0.05.

Number of users tested with group 1: n_1
Number of users tested with group 2: n_2
The proportion of attention shifts of group 1: $\hat{p}_1$
The proportion of attention shifts of group 2: $\hat{p}_2$
Mean of both the samples; If x_1 is successes out of n_1, x_2 is successes out of n_2: $\hat{p}$
The test statistic: z

Under the assumption that $\hat{p}_1$, and $\hat{p}_2$, all estimate a similar proportion, the $\hat{p}$ can be calculated with the formula 1 and z with formula 2.

$$\hat{p} = (x_1 + x_2) / (n_1 + n_2) \quad \text{———} \; 1$$

$$z = \frac{\hat{p}1 - \hat{p}2}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_1}+\frac{1}{n_2})}} \quad \text{———} \; 2$$

In Table 4, we can see that the number of attention shifts caused because of only affective behaviors of the robot is 89 occurrences, 38.7%, and when performed the behavioral combinations, Affective_Verbal_Bodily, it shows the occurrence of 86, 37.4%. As the percentages seem close by, we need to test whether the difference is large enough to say that the behavioral combinations make an impact on attention shifts of passing by humans.

Test whether the difference in the proportion of attention shifts of passing by customers who faced Affective_Verbal_Bodily cueing combinations is the same/greater than the proportion of passing by customers who faced Single Affective cueing behaviors we formed hypothesis 1 and hypothesis 2.

Hypothesis 1:

H_0: There is no difference in attention shifts when a robot performs combined behavioral cueing behaviors than when performing a single behavior. ($\hat{p}_{\text{Affective}} = \hat{p}_{\text{Affective\_Verbal\_Bodily}}$)

H1: There is a difference in attention shifts when a robot performs combined behavioral cueing behaviors than when performing a single behavior. ($\hat{p}_{\text{Affective}} \neq \hat{p}_{\text{Affective\_Verbal\_Bodily}}$)

$n_1 = 230$
$n_2 = 104$
$\hat{p}_{\text{Affective}} = 89/230$
$\hat{p}_{\text{Affective\_Verbal\_Bodily}} = 86/104$

The test, static 53.829, was generated using formula 2 with the statistical tool RStudio by two-sided sample proportion comparison test, and the output p-value of the test is 2.187e-13, which is less than the significance level 0.05, and it rejects the H0. We can validate that the proportion of the attention shifts of passing by human face to behavior combinations differs from the shifts of people who faced single robot behavior. So, we need to test whether the combinations are increasing the attention shifts or not with the following hypothesis.

Hypothesis 2:

H_0: The attention shift is not different or decreasing when combining verbal cueing behaviors.
($\hat{p}_{Affective} \geq \hat{p}_{Affctive\_Verbal}$)

H_1: The attention shift increases when combining verbal cueing behaviors. ($\hat{p}_{Affective} < \hat{p}_{Affctive\_Verbal}$)

$n_1 = 230$

$n_2 = 141$

$\hat{p}_{Affective} = 89/230$

$\hat{p}_{Affctive\_Verbal} = 37/141$

The test statistic, 5.503, was calculated with a one-tailed sample proportion comparison test, and the p-value of the test is 0.009492, which is less than the significance level of 0.05, and it rejects the H0. We can conclude that the proportion of attention shifts passing by humans is increasing when it combines verbal cues with affective behaviors.

According to Table 4, the occurrence of attention shifts for Affctive_Verbal combinations is 37, 16.1%and when combined with the bodily behaviors, it shows 86 occurrences, 37.4%. To test the impact of combining verbal cueing behaviors and bodily cueing behaviors, we formed hypothesis 3 and tested it.

Hypothesis 3:

H_0: Combining bodily behaviors does not have a more positive effect on attention shifts than combining verbal cueing behaviors. ($\hat{p}_{Affective\_Verbal\_Bodily} \leq \hat{p}_{Affctive\_Verbal}$)

H_1: Combining bodily behaviors has a more positive effect on attention shifts than combining verbal cueing behaviors. ($\hat{p}_{Affective\_Verbal\_Bodily} > \hat{p}_{Affctive\_Verbal}$)

$n_1 = 104$

$n_2 = 141$

$\hat{p}_{Affective\_Verbal\_Bodily} = 86/104$

$\hat{p}_{Affective\_Verbal} = 37/141$

The test statistic was 74.054, and the p-value is 1, which is greater than the significant value of 0.05. So, we can see the H_0 is not rejected, and we can interpret the result, combining bodily behaviors does not have a significant effect on attention shifts than combining verbal cueing behaviors.

Conclusions and Future Works

The experiments conducted with the developed Robot Lometh revealed a success rate of 92% (212 out of 230) when using attentional cueing behaviors. This suggests that the affective, verbal, and bodily behaviors of the robot had a significant impact on shifting the attention of passing customers. When we assessed the results obtained by exploring each attentional cueing category, it became evident that there was a significant difference in attention shifts when robots performed a single behavior compared to when they performed combined cueing behaviors. Observing the results from hypothesis test 2, we can conclude that grabbing the attention of a passing human increases when verbal cueing behaviors are combined with affective behaviors. In hypothesis test 3, we found that there is no significant effect on grabbing attention when bodily behaviors are combined with affective cues. The conclusions drawn from this experiment explain the impact of each attentional cueing behavior category on the attention shift of passing humans. We recommend using behavioral combinations rather than relying on a single behavior to attract human attention to a robot. Combining verbal and affective cues yields the best results in initiating human-robot interaction.

In this article, we have presented the results and findings regarding capturing the attention of a passing human to initiate human-robot interaction. In future studies, we will experiment with the influence of various robot behaviors on turn-taking and handling interruptions during human-robot communication. Another challenging aspect of this study was the process of targeting random individuals, identifying and selecting those likely to interact and easy to approach.

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