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How Do Humans Adjust Their Motion Patterns in Mobile Robots Populated Retail Environments?

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***Abstract*— In the retail environment, mobile robots start to serve as customer helpers and human worker assistants, which necessitates a safe, seamless, and affective human-robot interaction. Individuals' physical responses during those interactions become crucial factors to consider in order to improve robots' functionality and system productivity. The purpose of this study was to assess individuals' physical responses to mobile robots in a typical retail environment. Eight participants were recruited to complete shopping tasks (i.e., cart pushing, item picking, and item sorting) with and without a mobile robot. Biomechanics analysis showed that participants spent more time walking between shelves with a reduced walking speed and they demonstrated deteriorated walking stability with the mobile robot in the same space. Meanwhile, the mobile robot induced more posture adaptation in participants' distal segments (knee and ankle) during cart pushing and more posture adaptation in their proximal segments (hip) during item searching and sorting tasks. In addition, this study revealed that the mobile robot had a greater impact on participants' locomotion activities (walking) rather than other activities (item searching and sorting).**

Keywords*— *Human-Robot Interaction, Safety, Retail Environment, Biomechanics Analysis, Locomotion

I. Introduction

Robots have been increasingly omnipresent in work and life, as evidenced by its $ 43.8 billion worldwide global market share (for industrial robots) in 2021 [1]. Manufacturing [2], [3], agriculture [4], [5], healthcare [6], [7], and customer service [8], [9], are among the major fields for which robots and robotics technology are being developed. Historically, human workers have been physically separated from robots by safeguards (e.g. physical barriers or sensor-based systems) [10]. The designated physical safeguards, however, have hampered the utilization of robots in industries that demand frequent and direct interactions between humans and robots in shared space and close proximity. Collaborative robots (cobots) emerge as the times require in industries where direct human-robot interaction is mandatory. The warehousing, wholesale, and retail trade (WRT) industry [11]–[13] is one of the good examples in which the system efficiency can be best achieved using cobots, when the cobots take charge of repetitive and mundane tasks (e.g., cleaning, disinfection, inspection, delivery) and the human workers focus on tasks that need advanced environment perception, decision making, or object manipulation that beyond the capability of current robotic technologies [14], [15]. In this case, a safe, seamless, and affective human-robot interaction (HRI) becomes a critical research topic and the whole human-robot system can only be embraced if the safety of human workers and the productivity of the system are well ensured and perceived.

A large body of literature put focuses on the psychological aspects of HRI, for example, in terms of trust [16], [17], acceptance [14], [18], and other safety bounds [19], to calibrate humans' perception of the advanced technology. However, working with cobots may not only cause individuals' psychological adaptations but also induce their physical responses to some extent, especially when the cobots share space with them in close proximity. The purpose of this study was to fill current research gaps by investigating individuals' physical responses to mobile robots that work closely with them. A retail environment was chosen as the specific application domain. Individuals' physical responses (i.e., gait and posture) to the interaction were measured and compared by their motion patterns with and without a cobot in the same working environment. The following are the research question and the corresponding hypotheses:

Research Question: What aspects of personal physical responses can be induced by a mobile cobot in a robot-populated environment?

Research Hypothesis 1: The mobile cobot can alter personal gait and posture in a robot-populated environment, as indicated by individuals' spatiotemporal and kinematics parameters.

Research Hypothesis 2: The influence of the mobile cobot on individuals' gait and posture differs depending on the tasks that humans undertake in a robot-populated environment.

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II. METHODS

A. Participants

Eight adults (three females, 19.4 ± 2.0 years old, 176.7 ± 10.2 cm in height) were recruited from the surrounding community. Participants who had no injuries that required medical attention in the last six months were scheduled for the experiment. Seven of the eight participants claimed to be right-handed, while one reported being ambidextrous. The University of Florida Institutional Review Board authorized this study (IRB202002765).

B. Apparatus

The experiment environment: A high-fidelity retail environment was simulated (Fig. 1A). The facility is equipped with configurable walls, shelves, and essential accessories (e.g., 100+ grocery items, one checkout machine, and one shopping cart) that can be reconfigured to meet the most of the layout adjustment demands seen in a retail store.

Motion capture system: A wireless wearable motion capture system (MVN Awinda, Xsens Technologies BV, Enschede, The Netherlands) was employed to record participants' positions and body postures during the experiment. This system includes a total of seventeen Inertial Measurement Unit (IMU) sensors (~ 10 g per sensor) that can be affixed to the top of participants' outfits in accordance with the manufacturer's instructions (Fig. 1B) [20]–[23]. Throughout the study, the sampling rate of the motion capture system was set at 60Hz.

The mobile robot platform: The retail robot was custom-built with a Fetch Freight Base (Fetch Robotics, Inc., San Jose, California) and a UR5 robot manipulator (Universal Robots, Odense, Denmark), measuring 0.508 × 0.559 × 1.295 m (Fig. 1C). The platform incorporated a 2D LiDAR sensor, a webcam, a 6D IMU sensor, and two wheel-encoders; and its base was controlled by the Robot Operating System (ROS) with an Intel i3 CPU, 8 GB RAM, and a 120 GB SSD. The robot was programmed to drive autonomously between predefined waypoints, avoiding obstacles and rerouting paths. The maximum speed of the robot was set at 1.0 m/s for the experiment, with the UR5 powered off and stayed retracted.

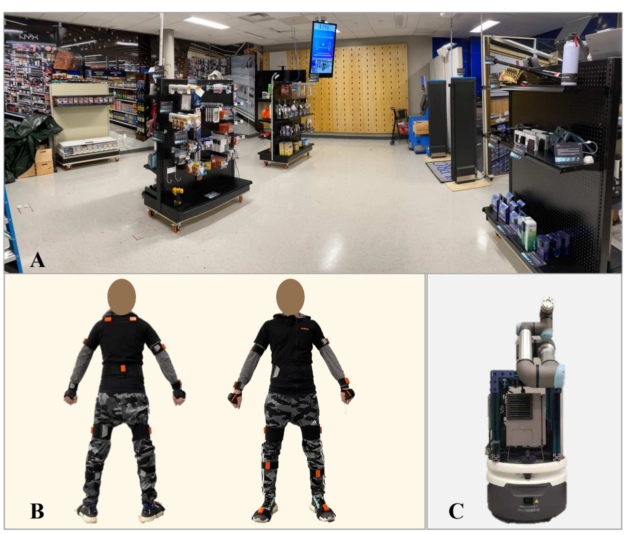

Fig. 1. Experiment site (A), sensor setup (B), and robot apperance (C).

C. Experimental Design

The study employed a within-subject design to evaluate the influence of a retail robot on customers' motion patterns during grocery shopping. The independent variable was the robot condition ("no robot" vs. "with robot"). The dependent variables of interest in this article contained measures that depict the motion patterns of each participant, including features of task efficiency, stability, and posture while grocery shopping. During the experiment, participants were instructed to complete ten grocery shopping tasks with (#:5) and without (#:5) the retail robot. The grocery shopping task was designed as a series of continuous actions, which included: (1) pushing a shopping cart between shelves (i.e., cart pushing task), (2) scanning and picking eight items, one from each shelf (i.e., item picking task), and (3) sorting the items into two bins at the checkout machine (i.e., item sorting task) (Fig. 2). At the beginning of each trial, a new list including all the items of target was given to the participants. And the participants were asked to pick up items in the correct sequence using their dominant hand.

During the trials in which the participants performed the grocery shopping task alongside the mobile robot (i.e., the "with robot" condition), the retail robot was designed to circle the "store", representing a platform realizing functions (e.g., disinfection, cleaning, and inventory management) in retail environments. The waypoints of the robot were predefined to ensure a frequent interaction between the robot and the participants (Fig. 2). And the order of the robot condition was presented at random to prevent systematic errors.

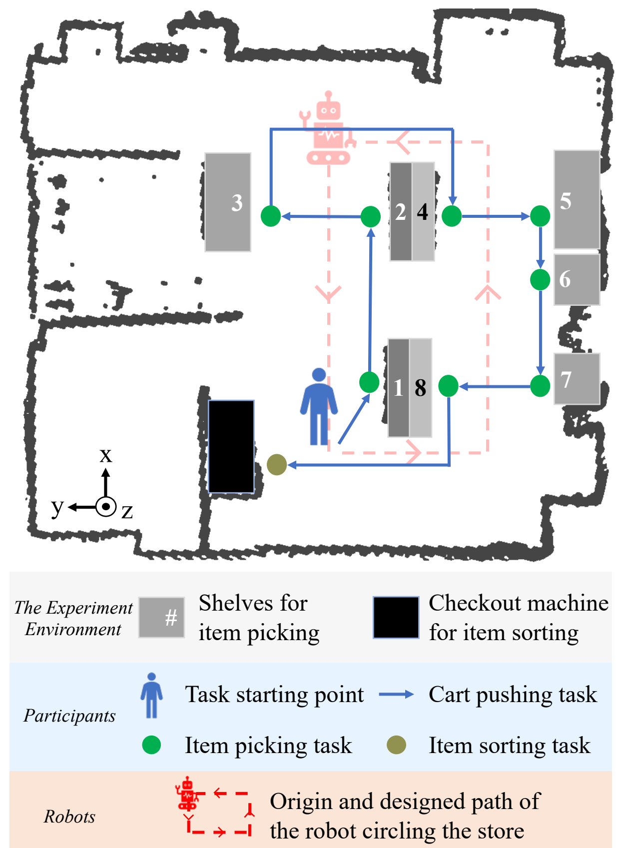

Fig. 2. Illustrations of the simulated retail environment, participants' grocery shopping tasks, and the path robot took to circle the store.

D. Procedures

The participants were first asked to sign the informed consent form and provide demographic information including their age, gender, weight, and height (shoes on). Following that, the motion capture sensors were attached to the participant's body and the system was calibrated [24]. The participants were then given ten grocery shopping tasks to complete. To avoid fatigue, a mandatory rest was designed between each trial.

E. Data Analysis

Data processing: Motion data collected by sensors was processed using custom MATLAB code [25], [26] to derive three categories of gait and posture features (i.e., task efficiency, stability, and posture) from the cart pushing, item picking, and item sorting tasks. The task efficiency measure included task completion time (i.e., the period of time to accomplish the action) and walking speed (i.e., the distance traveled retrieved from the pelvis sensor divided by task completion time). In terms of stability measures, the sample entropy of the resultant acceleration was extracted from the pelvis motion data [27]–[29]. Another stability measure, spectral arc length measure (SPARC), was chosen to describe the motion smoothness of the trunk [30], [31]. The average values of the participants' right hip, knee, and ankle flexion angles in the sagittal plane were calculated for each of the three shopping tasks and treated as posture measures [32].

Statistical analysis: Using R studio (R version 3.6.0), one-way repeated ANOVAs were performed if ANOVA model assumptions (e.g., normality and homogeneity of the model residuals) were satisfied. The robot condition was set as the independent variables, with motion pattern measures being the dependent variables, and the participant being the random effect. In case of unsatisfied model assumptions (e.g., the model residuals were not normally distributed), the Friedman tests for repeated measurement (participant being the blocking factor) were applied using the package "muStat" [33], [34]. The significance level of $\alpha = 0.05$ was used across all tests.

III. RESULTS

A. Data Description

This study included a total of 77 trials from eight participants, 40 of which were collected in the "no robot" condition and the remaining 37 in the "with robot" condition (motion data of three trials were discarded because of poor data quality). In general, during the grocery shopping task, the participants walked 21.31 ± 3.01 meters when there was no robot and 21.82 ± 3.15 meters in the "with robot" condition. Fig. 3 depicts the trajectories of one sampled participant (#3) under both robot conditions for demonstration purposes, while other participants showed consistent patterns.

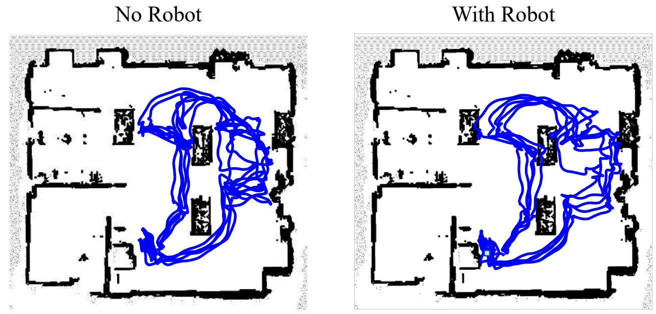

Fig. 3. The trajectories of one participant (#3) under both robot conditions.

The average time to complete the grocery shopping task was 129.58 ± 55.04 and 124.46 ± 31.83 seconds, respectively in the "no robot" and "with robot" conditions. In the "no robot" condition, the time spent on cart pushing, item picking, and item sorting tasks accounted for roughly 34 %, 41 %, and 25 % of the total time spent on the shopping task (Fig. 4). When the robot was on duty, an average of 36 %, 40 %, and 24 % of the time was spent on cart pushing, item picking, and item sorting (Fig. 4).

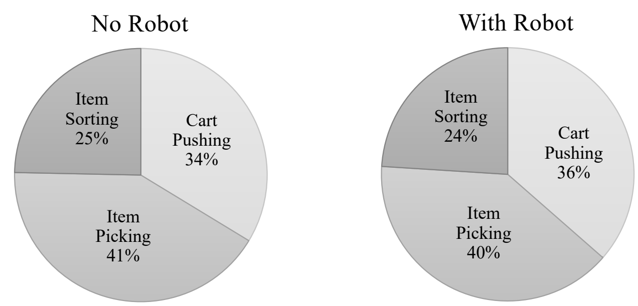

Fig. 4. Amount of time spent on tasks of cart pushing, item picking, and item sorting in two robot condition.

TABLE I. COMPARISON OF EFFICIENCY, STABILITY, AND POSTURE MEASURES (MEANS AND STANDARD DEVIATIONS) IN THREE GROCERY TASKS (WALKING, ORDER PICKING, AND CHECKOUT).

Measures \ Tasks		Cart Pushing			Item Picking			Item Sorting		
		No Robot	***With Robot***	***p-value***	***No Robot***	***With Robot***	***p-value***	***No Robot***	***With Robot***	***p-value***
Efficiency	Task Completion Time (s)	**40.20 (7.06)**	**44.14 (8.01)**	**0.002** ^{np}	59.44 (49.24)	50.82 (21.67)	0.615 ^{np}	29.94 (7.77)	29.51 (6.83)	0.908 ^{np}
	Motion Speed (m/s)	**0.51 (0.04)**	**0.49 (0.04)**	**0.014**	**0.16 (0.04)**	**0.14 (0.03)**	**0.040** ^{np}	0.14 (0.04)	0.14 (0.04)	0.969 ^{np}
Stability	Sample Entropy	**0.79 (0.08)**	**0.82 (0.09)**	**0.010**	0.51 (0.13)	0.55 (0.11)	0.061	0.53 (0.17)	0.50 (0.17)	0.202
	SPARC	**-3.05 (0.21)**	**-3.15 (0.23)**	**0.006** ^{np}	-3.88 (0.59)	-3.89 (0.54)	0.969 ^{np}	-4.10 (0.63)	-4.21 (0.76)	0.523
Posture	Hip Flexion (°)	16.76 (6.38)	15.57 (9.58)	0.511 ^{np}	**18.74 (8.69)**	**15.74 (10.93)**	**0.010** ^{np}	**14.45 (9.48)**	**11.25 (11.81)**	**0.010**
	Knee Flexion (°)	**21.27 (4.96)**	**19.19 (5.67)**	**0.002**	15.07 (7.30)	11.69 (7.16)	0.058 ^{np}	10.21 (6.29)	8.62 (7.88)	0.134
	Ankle Flexion (°)	**7.53 (2.51)**	**6.74 (2.06)**	**0.004**	5.47 (3.18)	5.12 (3.71)	0.671 ^{np}	5.15 (5.17)	4.57 (4.13)	0.235

^{np}: Instead of ANOVA, non-parametric analysis (Freidman test with participant as the blocking factor) was employed.

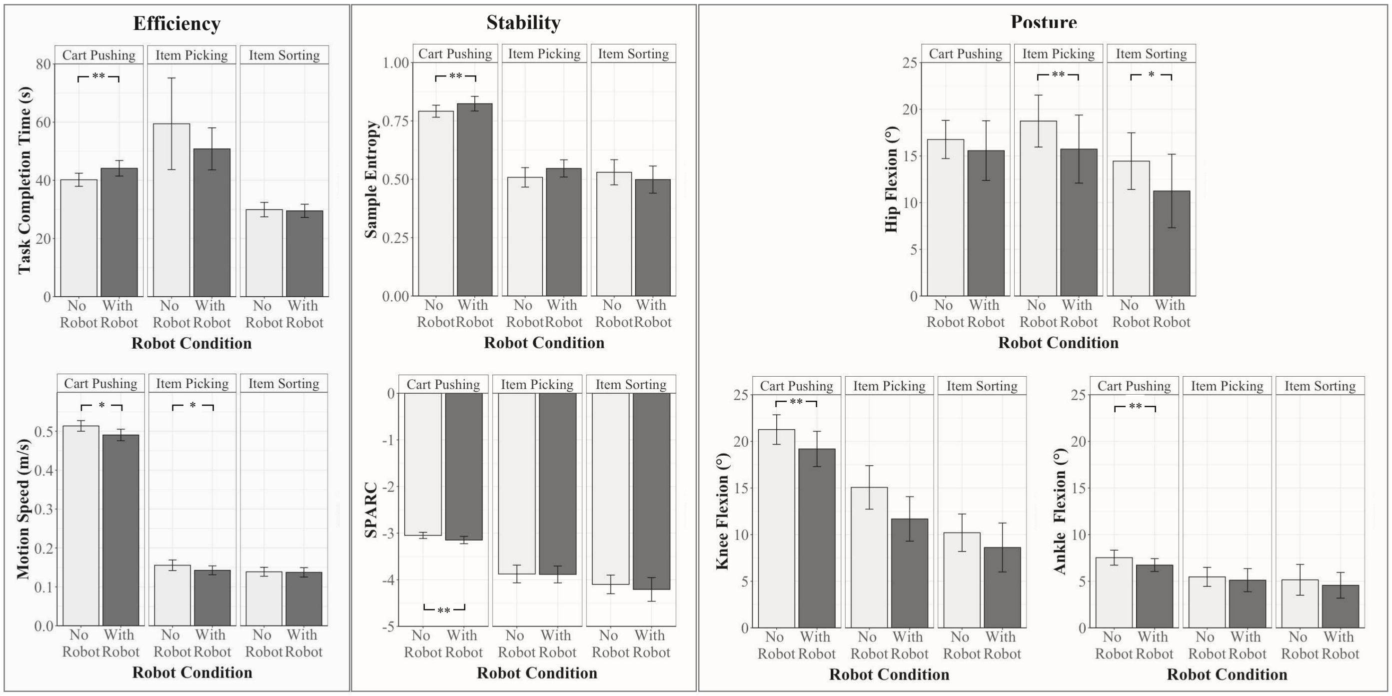

Fig. 5. Participants' efficiency, stability, and posture changes caused by the collaborative robot. Data were presented as means and 95 % confidence intervals.

B. *Task Efficiency Measures*

There were significant differences found in the task efficiency measures. According to Table 1 and Fig. 5, when the robot was present in the same working space, participants spent a longer period of time (mean: 44.14 s) pushing the cart and walking between shelves, compared to the baseline "no robot" condition (mean: 40.20 s) ($\chi^2(1) = 9.34$, $p = 0.002$). During the "with robot" condition, their motion speed was also observed to decrease in both of the cart pushing (0.51 m/s vs. 0.49 m/s, $F(1,68) = 6.36$, $p = 0.014$) and item picking tasks (0.16 m/s vs. 0.14 m/s, $\chi^2(1) = 4.20$, $p = 0.040$), compared to the baseline. No significant differences in task efficiency measures were identified between the two robot conditions during the item sorting task.

C. *Stability Measures*

Significant changes in two stability measures revealed the effect caused by different robot conditions. Specifically, when compared to the "no robot" condition, the "with robot" condition induced an increase in sample entropy (0.79 vs. 0.82, $F(1,68) = 7.11$, $p = 0.010$) and a reduction in SPARC (-3.05 vs. -3.15, $\chi^2(1) = 7.54$, $p = 0.006$) during the cart pushing task. The stability measures showed no significant changes during the item picking and sorting tasks.

D. *Posture Measures*

In terms of posture measures, when the participants pushed the cart and walked between shelves with the robot on duty, their average knee (mean: 19.19 $\circ$, $F(1,68) = 10.79$, $p = 0.002$) and ankle (mean: 6.74 $\circ$, $F(1,68) = 8.77$, $p = 0.004$) flexion angles (in the sagittal plane) were lower than the corresponding flexion angles under the "no robot" condition (knee mean: 21.27 $\circ$; ankle mean: 7.53 $\circ$).

When conducting the item picking task with the presence of the robot, participants displayed a decreased hip sagittal flexion (mean: 15.74 $\circ$, $\chi^2(1) = 6.72$, $p = 0.010$), when compared to the baseline "no robot" condition (mean: 18.74 $\circ$).

During the item sorting task, participants reduced their sagittal hip flexion (mean: 11.25 $\circ$, $F(1,68) = 6.96$, $p = 0.010$) under the "with robot" condition, when compared to the "no robot" condition (mean: 14.45 $\circ$).

IV. Discussion

The purpose of this study was to investigate individuals' physical responses to robots that work closely with them in the retail environment. Participants' physical responses in terms of task efficiency, motion stability, and lower-body posture can be revealed by comparing the motion data between two robot conditions when completing the grocery shopping tasks.

A. *Effect of the Retail Robot*

Preliminary results show that participants spent more time traversing between shelves ($p = 0.002$) with a reduced walking speed ($p = 0.014$) when the robot was presented in the same working space (Fig. 5). One possible explanation can be: upon perceiving the robot, participants slowed down or even stopped their shopping cart, either subconsciously or intentionally, to plan/adjust their path in accordance with the moving robot. This statement is corroborated by the differences in the percentage of time participants spent "slow walking" (<0.05 m/s) during the cart pushing tasks: participants' motion speed was less than 0.05 m/s around 1.3% of the time in the "with robot" condition, compared to 0.8% in the "no robot" condition. And interestingly, when moving from shelf 3 to shelf 4 and from shelf 4 to shelf 5, the amount of time that participants' motion speed was less than 0.05 m/s was observed to be 1% more in the "with robot" condition than in the "no robot" condition. When walking from shelf 3 to shelf 4, participants' vision (i.e., the sight of view) may be obscured by shelf 4 for a short period of time, causing them to slow down and verify the position of the robot. And when traveling from shelf 4 to shelf 5, the interactions between participants and the retail robot may be the most frequent, forcing them to slow down or stop to avoid the passing robot.

Participants' motion stability during the cart pushing task was also influenced by the retail mobile robot, as evidenced by a larger sample entropy (p = 0.010) and a lower SPARC (p = 0.006). Sample entropy was used to describe human postural control, especially the regularity of human motion [28], [35]. When the value of sample entropy sits near zero, it indicates the corresponding motion has a high regularity and its future patterns are likely to be comparable to the previous observations [36]. And the SPARC measures the smoothness of the movement [37], with a lower value indicating less smooth movement. In this study, larger sample entropy and lower SPARC under the "with robot" condition implied that participants' moving patterns contained certain unpredictable and sudden (i.e., jerkier motion) components during cart pushing tasks, and these components were most likely caused by direct or indirect interactions between participants and the retail robot.

Additionally, when perceiving the mobile robot as active on duty, participants flexed less of their knees (p = 0.002) and ankles (p = 0.004) during the cart pushing task and less of their hips during the item picking and sorting tasks (p = 0.010 for both). Smaller knee flexion [38], [39] and ankle (dorsi-)flexion [40], [41] angles were reported during dual tasks that engaged walking/running and other concurrent cognitive tasks. The findings from this study were consistent with previous dual-task studies. Participants' dual tasks, which included walking and monitoring (and perceiving) the position and motion of the mobile robot, took an obvious influence on their body postures (the knee and ankle flexions). In addition to that, individuals flexed their hips less throughout the item picking and sorting tasks. A more erect standing posture can be one of the explanations for this observation. Participants may choose to stand as straight as possible in order to occupy the least amount of space in the environment, minimizing potential collisions with the retail robot.

B. *The difference in physical response between tasks*

Another noteworthy finding from this study is that the physical responses of participants to the robot varied between tasks. The mobile robot in a retail environment negatively affected participants' walking pace and motion stability during the cart pushing task but showed less effect on those during the item picking and sorting tasks. Meanwhile, when the mobile robot was presented in the same space, participants' posture adaptation focused more on the distal segments (i.e., knees and ankles) during the cart pushing task and focused more on the proximal segments (i.e., hip) during the item picking and sorting tasks. The difference in the nature of these tasks can be ascribed to the physical response distinction. The cart pushing task required participants to maneuver the cart between shelves and needed more locomotion control capability (i.e., walking) from them. Whereas the item picking and sorting tasks were conducted in a standing (or bending) posture, which demanded less locomotion control capability but more alternative skills (i.e., item searching and sorting skills).

C. *Limitations and Future Work*

Three limitations were highlighted here to aid in the interpretation of the results. First, the participants recruited in this pilot study only reflected a portion of the demographics of all retail customers. A sampling strategy to include people in a wider age range and a broader cultural background could better represent the population of retail customers, strengthening the study's generalizability. Second, due to the research interest of this pilot study, only motion patterns were examined between the "no robot" and "with robot" conditions. Follow-up studies could expand the research scope by looking into the effect of robots on individuals' other responses (e.g., task accuracy & attention allocation). And last, although the appearance of the retail environment (i.e., items display and shelf layout) was simulated in high fidelity, the experiment site was relatively quieter than the actual retail setting. More realistic background noise could be applied to the experiment site during the experiment in future studies.

V. Conclusions

In summary, the mobile retail robot negatively affected participants' walking pace and motion stability during the shopping tasks that required human locomotion. The frequent interactions between the robot and humans in the retail setting induced participants' posture adaptation in the distal segments (i.e., knees and ankles) during locomotion-involving tasks and in the proximal segments (i.e., hips) during tasks that demanded item searching and sorting skills.

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