The Influence of a Robot Recommender System on Impulse Buying Tendency

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***Abstract*—The present study examines the influences of a robot recommender system on human impulse buying tendency in online e-commerce contexts. An empirical user study was conducted, where different marketing strategies (limited quantity vs. discount rate) were applied to the products and intimate designs were utilized for the robotic agent. To appropriately investigate participants' real-time cognitive perceptions toward different experimental conditions (i.e., marketing plans and robotic agents), an electroencephalogram (EEG) headset was used to capture users' brain activities. Our preliminary results reveal that marketing strategies and robot recommender applications can trigger impulsive buying behavior and contribute to different cognitive activities.**

***Keywords*—human-robot interaction, impulsive buying, electroencephalogram (EEG), decision-making, empirical study**

I. Introduction

Social robots have attracted significant research attention and business interests in recent decades [1]. With advances in technology, a social robot is capable of satisfying most customers' needs and performing a series of social interactions in commercial contexts, such as greeting customers, introducing products, recommending alternatives, or promoting additional goods to customers. As the social robot market is drastically growing and its value is estimated to reach 700 million by 2023 [2], it is critical to investigate how a social robot may impact the operation of different marketing strategies and vary customer purchase intentions and behavior. The use of marketing strategies (such as the discount rate or perceived scarcity of an add-on product) heavily influences consumer needs as well as the perceived benefits of a product (Moser et al., 2019), which may encourage customers to purchase products or services that were not planning in advance (i.e., impulse buying). Without careful deliberation, an impulse purchase often leads to negative outcomes, such as financial difficulties and feelings of regret [4].

The present study aims to investigate the influences of marketing strategies on customers' purchase intent and the resultant impulse buying tendency. In addition, by using a robot recommender system, we aim to examine whether a robotic agent can encourage customers to deliberate their purchase intent and alternate their impulsive buying decisions. The research questions and the associated hypotheses are listed as follows:

RQ1: How do different marketing plans (discount rate vs. limited quantity) affect customers' impulse buying tendency?
H1: Both adopted marketing strategies will trigger customers' impulsive buying behavior, but the resultant cognitive activities would differ.

RQ2: Can a robot recommender system change customers' impulsive buying behavior?
H2: A robotic agent is able to alter users' impulse buying decisions. This effect would become more robust when the participants experience more robot recommendations.

To examine these research questions and validate the hypotheses, in this late-breaking report, we recruited seven participants for the empirical studies. The experiments included a variety of shopping tasks to investigate participants' rational and impulse buying behavior, and a social robot was used to recommend alternative products to change the participant's purchase intent. Additionally, an electroencephalogram (EEG) headset was used to collect human brain activities to examine the cognitive perceptions toward the robot assistant as well as different marketing options. By integrating participants' initial impulse buying tendencies, semi-structured interview results, and real-time neurophysiological evidence, the present study allows us to collect and explore the relationship between robot recommendations and marketing strategies on human impulse buying tendencies.

II. Related works

Social robots have been widely used in various commercial contexts, where the designs involve intricate human-robot collaboration (HRC) schemes to satisfy the rapid growth in task complexity. To enhance the effectiveness of HRC in different commercial services, a variety of robotic applications have been developed. For example, Robo-advisors are used in the financial industry to guide customers through investment advisory processes [6]. The designs of a robotic agent can significantly impact user acceptance and the resultant task outcomes. For example, a robot with intimate designs can significantly affect participant perceptions of robots and the resulting HRC experience [7].

Prior studies [3] indicate different marketing strategies (such as limited-time offers or discount rates) can heavily impact users' purchase decisions and even contribute to impulsive behavior for subscribing to a product or service. Impulse buying can be defined as an unplanned buying behavior involving quick decision-making process with little deliberation [8], [9]. Dholakia [10] indicated that impulsive buying behavior could be triggered by external cues (i.e., marketing stimuli), internal factors (i.e., impulsivity trait), and environmental variables (i.e., situational influencers).

To examine factors affecting impulse buying decisions, our study constructed an online shopping website (as the environmental factor), applied the intimate attributes to develop a robot recommender application, and adopted different marketing strategies (as the external factors). In addition, to capture human's real-time cognitive activities, the EEG assessments are adopted in this study to collect users' brain signals and measure users' mental states during HRC.

III. Methodology

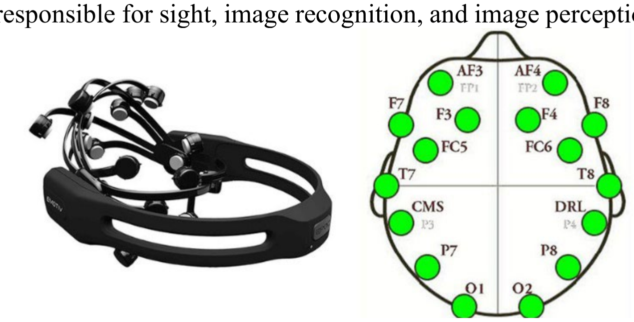
A. Apparatus

The testbed systems include a website and a robotic agent. The website was developed to simulate an e-commerce environment and create an online shopping experience, and the robotic agent was built to provide recommendations to customers while purchasing commercial goods. The participants were instructed to browse and purchase the planned and unplanned (i.e., add-on) products. During the process, the participants received product recommendations from a robot recommender system. The intimate behaviors were adopted and applied to the robotic agent to positively influence customers' purchase intent and subsequently engendered changes in user behavior [7]. For example, the robot used the active voice to convey shared opinions and comprehensive information to a participant to increase the intimacy of the human-robot relationship [11]. It is worth noting that the robot recommendations were provided to half of the add-on products in order to examine the influence of a robot recommender system on impulsive buying behavior.

Fig. 1. Our experimental website and robot recommender system.

B. EEG Headset

The EMOTIV EPOC X, a 14-channel wireless EEG Headset, was used to collect the participant's brainwave patterns (figure 2a). Fourteen electrodes were used to measure participants' cognitive states and decision-making processes during the experiments (figure 2b). Eight electrodes (AF3, F7, AF4, F8, F3, FC5, FC6, and F4) were placed in the frontal cortex to capture cognitive-related brain activities. Two electrodes (T7 and T8) were placed in the temporal lobe, responsible for short-term memory, equilibrium, and emotion. Two electrodes (P7 and P8) were placed in the parietal lobe, mainly for sensory perception and integration. The last two electrodes (O1 and O2) were placed in the occipital lobe, responsible for sight, image recognition, and image perception.



(Fig. 2a) (Fig. 2b)

Fig. 2. EMOTIV EPOC+ EEG headset and the electrodesplacement.

C. Participants and Procedures

The experiment followed a within-group design. Seven student participants were recruited from the university community, balanced among conditions for gender. Due to the system malfunction, two of the participants were removed. The experiments were conducted in a usability lab that supported a quiet atmosphere. Earplugs were provided to the participants to minimize any unforeseen environmental noise that might affect brain activities. The participants were first asked to complete the IBT questionnaire [5] to measure their initial impulsive buying behavior. In the following experimental sessions, participants were instructed to purchase different products accompanied by marketing strategies and robot recommender applications. At the conclusion of the sessions, semi-structured interviews were conducted to collect participants' decision-making strategies.

The experiments were divided into two sessions, each including five rounds of purchase tasks, figure 3. A participant was first requested to buy a planned product based on the required specifications (such as the display size and the number of cores in a laptop). Then, another four rounds of purchase tasks regarding the add-on options were followed. Each round included two similar items with either a discount rate (e.g., shown on the left in figure 1) or a limited quantity (e.g., shown on the right in figure 1). For the add-on options, the participants may first buy the discounted product, buy the limited product, or refuse to buy any add-on products. Afterward, a robot recommender system was used to advise the participants on the add-on products and provide an opposite option compared to the participant's first decision. For example, in figure 1, the participant first chose the limited product; then, the robot provided the benefits of the discounted product and recommended the participant change her original decision. However, the participant can decide to either switch or keep the same decision. After brief breaks, the other session was run, accompanied by repeated experimental conditions; however, different products were provided in different sessions.

Purchasing the planned product allowed us to measure a participant's rational buying behavior and the associated brainwaves, whereas the add-on scenarios enabled us to examine how different marketing strategies and the robot recommender system determined customers' purchase intent. In addition, a plain white page was inserted after each round to provide a quick break (lasting for 5 seconds) to the participants and reset their brainwaves.

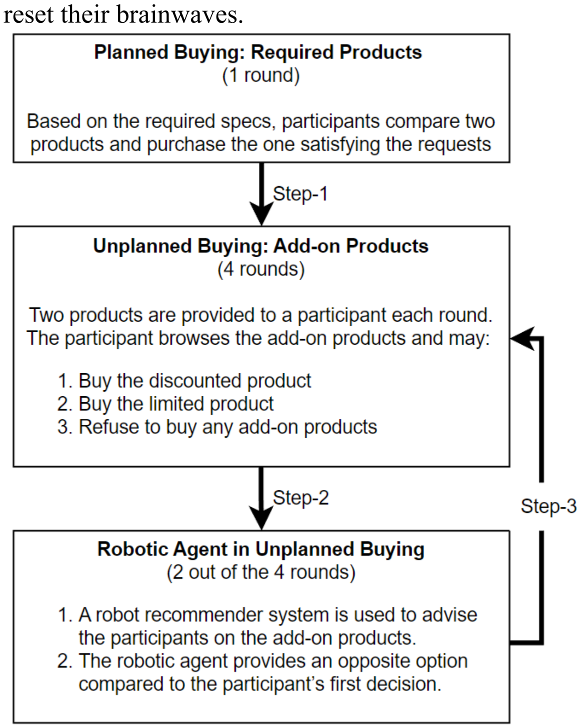


Fig. 3. Experiment procedures.

IV. Results and Discussion

The participants' EEG data are collected within a 256 Hz sampling rate. As different types of brainwaves are associated with distinct cognitive activities, previous neuroscience research suggests beta waves involve people's conscious thoughts and can appropriately represent their arousal states [12]. The beta wavelengths were therefore adopted to our analyses. To further determine the related cognitive activities, the beta brainwaves were categorized into three frequency bands, namely: low beta (12-15 Hz), mid beta (15-20 Hz), and high beta (18-40 Hz). The preprocessing procedures included a baseline normalization and a 5-second epoch extraction for each purchasing decision event. In other words, to appropriately assess the differences between rational and impulse buying intent, the EEG signals retrieved from the planned buying served as the baseline that enabled us to identify the cognitive changes resulted from the impulsive buying behavior (i.e., the add-on scenarios).

The frontal lobes (such as FC5, F4, F7, and AF3) are suggested to have a close relationship with human cognitive and emotional activities [13]. The band power of these channels was analyzed and the resultant changes were used to represent the impulse buying intent. Figure 4 reveals that participants had different cognitive patterns while deciding to buy discounted products, buy limited products, or reject to buy any unplanned products. A darker color on the EEG topographic map represented stronger power variations (e.g., figure 4, top left corner in the mid beta group of the reject condition). To compare the cognitive differences resulting from the marketing strategies, our EEG results showed that participants focused more on discounted products. These observations are consistent with the interview results, as the participants revealed that they paid more attention to discounted products. The mid-beta power of refusing to buy the unplanned product is significantly higher in the left dorsolateral prefrontal cortex, which is an indicator of making a low-risk decision.

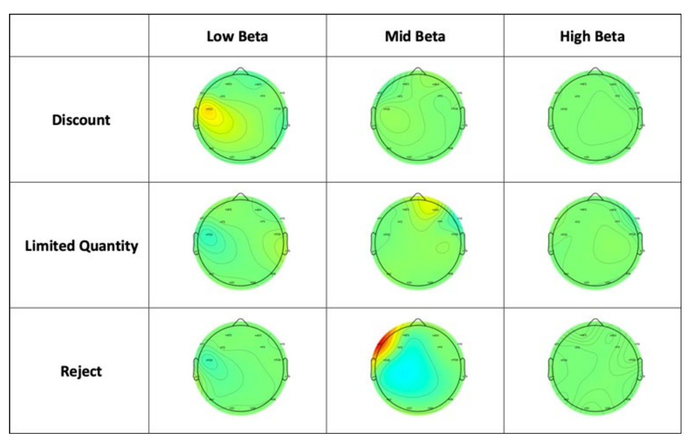


Fig. 4. EEG topographic maps for participants buying discounted products, buying limited products, and rejecting to buy any add-on products.

Prior research suggests that impulsive buying behavior often results in a host's feeling of regret [3]. To examine this phenomenon, we identify the EEG data into two groups, regretted purchases vs. unregretted purchases (figure 5). The classifications were based on our post-experiment interview results, where the participants had a chance to review all the purchased add-on products and point out the regretted items, if any. In total, seven regretted purchases were made, where three of the purchases were made with the robot recommender and the other four were made without the robot recommender. Interestingly, all participants regretted buying discounted products, which might be the reason that similar low beta patterns were observed in the topographic maps in the discount purchases (figure 4) and regretted purchases (figure 5). Meanwhile, the results revealed that making decisions more attentively does not necessarily reduce the likelihood of regret. In fact, customers' initial hesitations are highly related to their later regrets. Additionally, compared with the regretted purchase, the unregretted purchase pattern has little difference with the baseline condition (i.e., planned buying), implying that rational purchasing behavior is less likely to cause buyer regret. For instance, according to the post-experiment interview, #3 and #7 participants mentioned they didn't know if they needed to buy the TouchPad due to the uncertain demand for it; as a result, they thought twice and regretted it afterward.

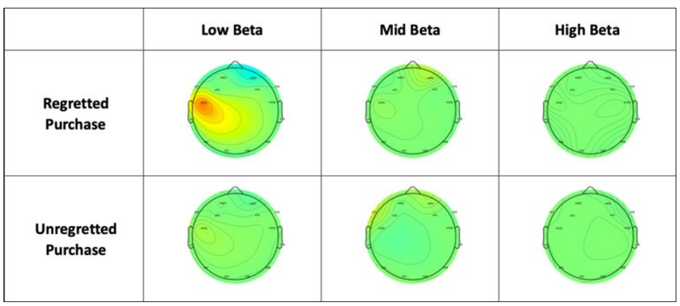


Fig. 5. EEG topographic maps for participants regretted product vs. unregretted product.

To study the influence of robot recommendations on consumers' buying behavior, figure 6 displays the brainwave changes during the decision-making process. The results show the differences between before and after receiving robot recommendations for the add-on products. Although the robot did not successfully change participants' purchase decisions, the low beta band power increased after participants received robot recommendations, which demonstrated the impact of the robot recommendations on elevating participants to further engage in the decision-making process.

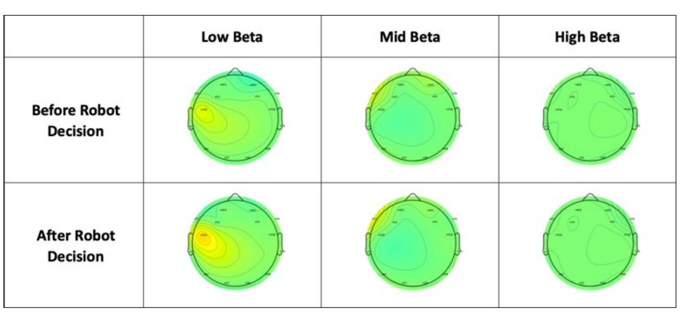


Fig. 6. EEG topographic maps for participants' decision process before robot's recommendation vs. after robot's recommendation.

The present research integrates neurophysiological, qualitative, and quantitative mechanisms to examine human-robot relationships across various experimental conditions, which supports a comprehensive understanding of human decision-making processes in commercial contexts.

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