Social Robots in Retail: Emotional Experiences a Critical Driver of Purchase Intention

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Abstract

The purpose of the current study is to explore whether emotional experiences prompted due to human-social robot interaction in retail environments significantly influence consumers' purchase intentions. This present study focuses primarily on emotional experience, comprising factors, namely, enjoyment, arousal, and emotional involvement. The study tests the conceptual model on a sample of 229 respondents using the PLS-SEM (Partial Least Squares – Structural Equation Modeling) approach. The results reveal that emotional experiences significantly impact consumers' purchase intentions in retail settings. All three emotional experiences, including enjoyment, emotional involvement, and arousal were significant in shaping consumers' purchase intentions. The study findings offer unique insights for manufacturers developing social robots for the retail sector. The present research extends the current body of work exploring hedonic predictors of consumers' purchase intentions in novel socio-technical contexts, such as social robotics.

Keywords: Social Robots, Emotional Experiences, Retail, Purchase Intentions, Hedonic Consumption

1. Introduction

A social robot is an autonomous agent that carries the capacity to communicate with humans through social actions (Jiang & Arkin, 2015). Similar to other robots, social robots vary in the type of features they possess; some robots are humanoid whereas other social robots have fewer anthropomorphous attributes (Duffy, 2003). Social robots are essentially social agents that house synthetic cognitive capacities, which aim to emulate human-like social characteristics (Lazzeri et al., 2018). Since the 1950s, robots have been purposely designed with social qualities however the field of social robotics is a relatively new branch of research inquiry (Breazeal et al., 2016). Based on Gartner's hype cycle, a tool that predicts how technologies evolve over time, social robots demonstrate immense potential (Kunz et al., 2019). There has been a rapid increase in the development of social robots in different sectors. Social robots have immense utility in healthcare (Breazeal, 2011), applications involve assisting patients with disabilities to help reduce depressive symptoms; social robots are employed in education (Belpaeme et al., 2018), to augment learner engagement and enthusiasm; social robots are also common in the consumer adult industry (Scheutz & Arnold, 2016), with applications ranging from platonic companionship to physical intimacy; and social robots are extensively used in the services industry (Čaić et al., 2019), with widespread utility in retail outlets, hospitality, tourism, banking sectors, etc. The current research focuses on social robots in the retail sector.

It's critical to understand that a social robot in retail is not only a productivity-oriented system but also a pleasure-oriented one (De Graaf & Allouch, 2013). Pleasure-oriented agents must embody hedonic attributes to truly simulate human behavior. Generally, the acceptance and usage of purely utilitarian systems rest on two critical factors, which have been identified by the Technology Acceptance Model (TAM) (Bröhl et al., 2016); these factors include the perceived usefulness and the perceived ease of use of a system. However, pleasure-oriented agents, such as social robots, must embody social factors, which are not solely captured through TAM predictor variables (De Graaf & Allouch, 2013). These factors are often ignored in the design of social robots, resulting in compromised user experience.

Robotics research in the retail and services industry demonstrates an incredible opportunity for growth. The market share for the robotics industry in retailing was valued at 19 billion in the year 2018, however, this is anticipated to rise by at least 30% by

URI: https://hdl.handle.net/10125/102819
978-0-9981331-6-4

2026 (De Gauquier et al., 2021). While there has been abundant research on how companies can utilize robots in the retail industry and reap maximum benefits in terms of business outcomes; an issue that has attracted less academic interest is the nature and impact of perceived experiences due to associated human interaction with social robots. Due to the complex requirements of social robots in the retail sector and the impulsiveness of customers, experience is paramount. Most shoppers anticipate a seamless human-robot experience; this is often met with dismay due to unsatisfactory implementation of critical features.

Developing social robots which are intuitive and sociable, and function similar or superior to human workers is a top priority for robot manufacturers in the retail space. Therefore, practitioners require support tools, which can help designers assess critical features needed in social robots that appeal to consumers' hedonic needs (Rehman et al., 2021) and enhance the overall perceived experience of the customers. In retail settings, the human experience resulting from human-robot interactions carries far-reaching implications on end-user decision-making. Human-robot engagements would have an impact on variables, such as purchase intention, product desirability, and overall quality of consumer shopping experience. This present study focuses on a certain type of perceived experience, namely emotional experience, and investigates its impact on consumers' purchase intentions in retail outlets.

2. Literature Review

The presence of social robots in the retail and services sector is an emerging area of research inquiry. With a focus on retailing sector, we divide the review of literature into the following broad themes.

2.1 Functionality of Social Robots in Retail

Social robots in retail outlets are autonomous and flexible agents and are often tasked to fulfill customer service roles. These service responsibilities fulfilled by robots can be further classified into front-end customer-facing roles and back-end support roles (Wirtz et al., 2018). Generally, customer-facing responsibilities involve welcoming, advertising, informing, assisting, and entertaining customers (De Gauquier et al., 2020). A major chunk of research has focused on investigating the utility of social robots in informing customers, such as offering strategic in-store assistance on product offerings (Kamei et al., 2010; Zibafar et al., 2021). The use of social robots for advertising tasks has also been investigated in great depth (Nakagawa et al., 2013; Shi et al., 2016; Shiomi et al., 2013). Other roles that social robots carry out, such as greeting and assisting customers (Iwasaki et al., 2018; Nakagawa et al., 2013; Shiomi et al., 2013), have also been examined by researchers. There have been relatively fewer research studies that focus on the use of social robots for entertainment-related tasks in the retail sector (Aaltonen et al., 2017; De Gauquier et al., 2018).

2.2 Design Characteristics of Social Robots in Retail

Another area of research that has garnered considerable attention focuses on the design of the social robot. The appearance of social robots for client-facing roles carries significance because social robots are tasked to augment customer engagement and interest (Doering et al., 2015; Gee et al., 2005). Different research studies highlight the benefits of robots that possess human-like morphology; these robots are categorized as humanoids (De Gauquier et al., 2018; McBreen & Jack, 2001). Prior research highlights the impact of social robots comprising human-like features and traits, such as appearance, gestures, and emotions (Chiang et al., 2022; Gonzalez-Jimenez, 2018; van et al., 2019). Such features are found to boost customer trust and engagement. On the other hand, there have been studies that highlight the negative impact of social robots with too many human-like characteristics (Mende et al., 2019; Onnasch & Roesler, 2019).

Anthropomorphism can be described as ascribing human-like features to nonhuman entities (Duffy, 2003). Most research at the intersection of anthropomorphism and social robots is limited to the physical attributes of robots whereas there is a paucity of research on the effects of trait-based anthropomorphism (De Graaf & Allouch, 2013). The human tendency to anthropomorphize aspects such as affect, mood, and emotionality to non-human entities such as social robots has serious implications for consumer acceptability in retail (Chuah & Yu, 2021). For instance, perceiving a robot to encompass human-like psychological traits would compel users to contemplate whether that robot can socially interact, be independently accountable for its actions and be worthy of human regard.

We anthropomorphize social robots due to unconscious thinking processes as opposed to deliberative processes (Caporael, 1986). In essence, we apply certain heuristics to understand non-human agents, such as social robots (Dacey, 2017). Anthropomorphism is a type of cognitive bias which occurs due to the activation of the same brain

components which are activated when we interact with humans (Airenti, 2015; Varella, 2018). Anthropomorphic characteristics within social robots allow them to better assimilate to retail environments and engage in meaningful interactions with customers (De Gauquier et al., 2021). Also, people prefer to affix human-like traits to social robots to humanize them and engage with them on a deeper level since the practical utility of a social robot lies in its capacity to seamlessly interact with humans (Giger et al., 2019; Richert et al., 2018).

2.3 Placement of Social Robots in Retail

The strategic placement of social robots can be critical to drawing customers' attention and stopping passersby, interacting with customers, and influencing their purchase decisions. Studies have investigated the efficacy of robots in different locations within a retail store, such as adding these to product shelves or in-store corridors, while some studies have investigated the efficacy of social robots outside the shopping store (De Gauquier et al., 2021). The ideal location for social robot placement to increase purchase intentions in a retail store is still undetermined (De Gauquier et al., 2021). Additional research is needed to comprehensively assess the impact of robot placement on different business outcomes, such as customer purchase decisions, customer engagement, customer retention, etc.

3. Research Objectives

The above-discussed topics have attracted considerable research attention, however, research that seems to be limited revolves around the impact of perceived emotional experiences associated with human-social robot interaction in retail settings. Since social robots are used for services other than pure productivity therefore social robots are designed to influence human emotional quotients (De Graaf & Allouch, 2013). Emotion is an affective response whereas emotionality is an experiential construct, comprising a multitude of factors (Barrett et al., 2007). Emotional experiences in the current context are essentially customers' feelings and moods in response to encountering, engaging, or soliciting help from a social robot in a retail setting.

Enhancing the perceived emotional experience of customers in retail settings carries importance for retail outlets because it leads to a significant impact on business outcomes. The emotional needs of customers of retail stores were traditionally addressed by human staff. While human staff cannot be fully replaced, social robots can complement human workers and improve the shopping experience for customers. While there is a push to move towards automation in different sectors (Shah et al., 2022), retail settings in particular are looking for ways to reduce on-site human capital through autonomous technologies. The reduction of human capital can significantly improve associated costs and result in a tangible increase in retail revenue. More importantly, it's critical to understand that there is an economy of scale gap between the emotional needs of retail customers and the human resources required to address these needs. Human resources cannot be present with every retail customer through every facet of their shopping experience. Social robots can leverage their social and affective attributes to increase customer engagement, enhance the customer shopping experience, significantly influence purchase intention and lead to long-term customer retention.

Perceived emotional experience due to customer interaction with social robots can have a profound impact on business outcomes, such as purchase intentions, etc. If the presence of social robots leads to an increase in business outcomes, then social robots offer retailers a strategic competitive advantage. There are different kinds of emotional experiences that customers may experience when interacting with social robots. Experiences such as enjoyment, arousal, and emotional involvement are investigated in the current research study. The goal of the current study is to assess whether emotional experiences due to social robots influence customers' purchase intentions in retail settings.

4. Theory and Hypothesis Development

We postulate that customers' emotional experiences associated with social robot interaction in a retail setting would significantly influence their purchase intentions. In the context of the current study, we investigate three facets of emotional experience, mainly enjoyment, emotional involvement, and arousal (Abbasi et al., 2019; Hollebeek et al., 2022). Refer to figure 1 for the conceptual model.

4.1 Stimulus-Organism-Response

Based on the Stimulus-Organism-Response (SOR) framework offered by Mehrabian & Russell (1974), one can account for the effects observed in a built environment due to the nature of that environment. According to the SOR framework, physical stimuli in the environment can influence users' internal states, which can play a facilitating role in shaping behavioral intentions and influencing consumer decisions. Prior research offers evidence

that high degrees of emotional experiences prompted by environmental stimuli in retail outlets can positively influence customer satisfaction and purchase intention (Ha & Lennon, 2010). Therefore, we posit that emotional experiences prompted due to social robots in retail environments will positively influence customers' purchase intentions.

4.2 Situational Involvement

Customers deeply involved in certain situations may indulge in different behaviors as opposed to those in less engaging situations (Wells & Prensky, 1996). An approach to enhance a customer's situational involvement in a retail context is through augmenting customers' emotional experience, which may shape their behavioral intentions and motivate them to undertake deliberate purchase decisions (Ha & Lennon, 2010). We, therefore, postulate that in retail situations, customers' purchase intentions may bolster due to emotional experiences associated with human-social robot interactions.

4.3 Hypothesis Development

Enjoyment in the current context would refer to customers tangibly experiencing delight in response to interaction with a social robot. Previous research has investigated human enjoyment in different contexts, such as gaming (Chen et al., 2016), online shopping (Kim et al., 2007), etc. Enjoyment as an experiential facet has not been investigated adequately in the context of human-robot interaction in retail settings. However, humans have had enjoyable experiences with social robots in other settings (Heerink et al., 2009). A step toward further humanizing social robots and equipping them with emotional intelligence will imply that humans can communicate with robots as they do with other humans and come across enjoyable experiences as a result of this interaction. In retail settings, these experiences could help customers formulate behavioral intentions to purchase products or services therefore we hypothesize the following:

H1: Enjoyment associated with human-social robot interaction will be positively related to consumers' purchase decisions

Emotional involvement in the current context would represent the capability of social robots to induce customers to psychologically involve themselves in the retail experience (Fridin & Belokopytov, 2014). This behavior may differ in terms of intensity and duration. Human emotional involvement has been investigated in different environments such as gambling in casinos (Ricketts* & Macaskill, 2003), shopping (Machleit & Eroglu, 2000), entertainment-related activities (Druin et al., 2000), etc. High emotional involvement in humans is often witnessed when they are engrossed in cognitively onerous activities, such as video gaming (Abbasi et al., 2019; Abbasi, Rehman, Fayyaz, et al., 2021; Abbasi, Rehman, Hussain, et al., 2021), etc., or when they are involved in undertaking strategic purchase decisions (Guo et al., 2020). Human experiences with social robots in retail environments have now emerged as a social and leisure activity, often involving potential shoppers emotionally (Parment, 2013). This emotional involvement can play a critical role in helping customers formulate purchase intentions due to the enhanced shopping experience, therefore we hypothesize the following:

H2: Emotional involvement associated with human-social robot interaction will be positively related to consumers' purchase decisions

Arousal is also an emotional state which varies in intensity based on circumstances and internal motivations (Branscombe, 1985). Humans can experience an aroused state as a result of interaction with a social robot, leading to sentiments such as alertness, emotional activation, and enthusiasm (De Graaf & Allouch, 2013). Arousal is both a physiological and psychological state, which is often triggered in response to internal or external impulses (Ha & Lennon, 2010). Human arousal has been investigated in different contexts such as driving (Ünal et al., 2013), aviation (Chittaro et al., 2014), etc. The state of arousal achieved as a result of interaction with artificial agents in retail settings has not been adequately explored in the literature. Customers aroused states can serve as an internal motivator concerning a purchase decision and play a critical role in the formulation of purchase intention (Ha & Lennon, 2010), therefore we hypothesize the following

H3: Arousal associated with human-social robot interaction will be positively related to consumers' purchase decisions

5. Method

5.1 Study Participants, Measure, Data Collection, and Data Analysis Approach

To investigate the research model, we sample participants who have encountered social robots in retail settings. We specifically target generations Z and Y due to their increased interactions with new forms of digital technology (Seemiller & Grace,

2018). We adapted previous questionnaires to fit the context of the current research study.

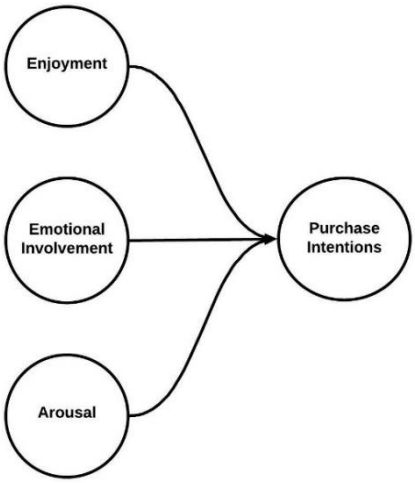

Figure 1. Theoretical Model of the Current Study

Table 1. Demographics

Gender	Percentage %
Male	72.1
Female	27.9
Age	
Generation Z	10.5
Generation Y	89.5
Shopping Frequency	
Daily	23.6
Weekly	69.4
Monthly	7.0
Social-Robot Interaction at Retail Store	
Rarely	16.2
Seldom	24.9
Often	33.2
Sometimes	20.5
Always	5.2

The items for emotional experiences were retrieved through the playful consumption experience scale (Abbasi et al., 2019) whereas purchase intent was adapted from the body of research on consumption behaviors (Abbasi et al., 2020). We also collected information concerning participants' demographic details, shopping frequency, and nature of interaction with the social robot in retail outlets. The data was collected through Amazon Mechanical Turk (Paolacci, 2010). We received a total of 240 responses, and data of 229 valid respondents were accepted for further analysis. Refer to table 1 for details. We applied the PLS-SEM approach, which is specifically useful for the explanatory and exploratory nature of studies (J. F. Hair et al., 2020). We applied the SmartPLS 3.3.2 version to perform PLS-SEM analysis in two phases, comprising the measurement model and structural model.

5.2 Evaluation of the Measurement Model

We considered the measurement model assessment (i.e specified as reflective constructs in our study) through reliability and validity by using Cronbach's alpha, outer loadings, average variance extracted (AVE), composite reliability (CR), and HTMT (J. F. Hair et al., 2011, 2019, 2020). The threshold for outer loadings must not be less than 0.40 or greater than 0.60 (Chin, 2010); Cronbach's Alpha should be greater than 0.70, the composite reliability (CR) must surpass 0.70, and for convergent validity the average variance extracted (AVE) should be larger than 0.50. Table 2 shows that all the given criteria of reliability and validity were achieved because all the values of composite reliability and convergent validity met the defined threshold. To analyze the discriminant validity, Henseler et al. (Henseler et al., 2015) proposed the HTMT criterion approach to quantify the correlation, with the suggested range value less than 0.90. Table 3 displays that no discriminant validity concerns were present in the study.

5.3 Structural Model

To examine the structural model and check the hypotheses, we apply SmartPLS with bootstrapping resampling technique of 5000 (J. Hair et al., 2017; J. F. Hair et al., 2019). Therefore, in our study, we run bootstrapping with a sample size of 229. These relationships present from H1, H2, and H3 can be quantified by the path coefficient effect size, standard error, p-value, f2, R2, and Q2. Table 4 illustrates that enjoy ($\beta = 0.248$, $p < 0.01$), einvolve ($\beta = 0.418$, $p < 0.001$), and arousal ($\beta = 0.288$, $p < 0.01$) carry a positively significant effect on purchase intention.

Table 2. Measurement Model Assessment

Construct	Items	Loadings	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Enjoyment	En-1	0.824	0.847	0.847	0.897	0.685
	En-2	0.844				
	En-3	0.827				
	En-4	0.815				
Emotional Involvement	EI-1	0.881	0.856	0.856	0.912	0.776
	EI-2	0.871				
	EI-3	0.891				
Arousal	Ar-1	0.875	0.84	0.842	0.904	0.759
	Ar-2	0.829				
	Ar-3	0.908				
Purchase Intention	PI-1	0.88	0.82	0.82	0.893	0.736
	PI-2	0.822				
	PI-3	0.871				

Table 3. Discriminant Validity Using HTMT

	Arousal	BI	Einvolv	Enjoy
Arousal				
BI	0.835			
Einvolv	0.862	0.872		
Enjoy	0.770	0.771	0.694	

Note: Best if HMTM values are below 0.85 or good if HTMT values are below 0.90

Table 4. Structural Model Assessment

Hypotheses	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	f^2	R^2	Q^2
H1: Enjoy -> Purchase Intention	0.248	0.084	2.97	0.001	0.09		
H2: EInvolve -> Purchase Intention	0.418	0.12	3.484	0.000	0.205		
H3: Arousal -> Purchase Intention	0.228	0.112	2.024	0.022	0.054	0.624	0.445

6. Discussion

This research study investigates how consumers' emotional experiences garnered through interactions with social robots impact their purchase intentions in retail settings. The results highlight that emotional experiences positively impact customers' purchase intention; all three emotional experiences, including enjoyment, emotional involvement, and arousal were significant in shaping consumers' purchase intention. The results are similar to existing findings concerning emotional experiences in other contexts (Abbasi et al., 2019; Abbasi, Rehman, Fayyaz, et al., 2021).

Multiple factors serve as mediating variables in shaping consumer intention. Some of these factors are grouped under the classification of control beliefs (De Graaf & Allouch, 2013). In the current context, an individual's controlled beliefs are defined as salient factors, which enable or hinder the intention to

perform a particular behavior. Previous research has found, that experiences of enjoyment, arousal, and emotional involvement, are critical in the formation of positive control beliefs (De Graaf & Allouch, 2013). The current results suggest that the formation of positive control beliefs associated with the use of social robots in retail settings are critical drivers of consumers' purchase intention.

6.1 Arousal and Emotional Involvement

Previous research offers evidence that certain emotional experiences, mainly arousal and emotional involvement, increase consumers' affective and cognitive engagement (Abbasi et al., 2019). Scholars have discovered that arousal and emotional involvement lead to an increase in the intention to use mobile learning applications (Hsiao et al., 2018). Arousal and emotional involvement also serve as critical factors in shaping a user's behavioral intention to engage with pleasurable forms of information systems (Abbasi, Rehman, Fayyaz, et al., 2021). In the current setting, customers identify social robots as a distinct platform to acquire product-related information. Social robots offer a differentiated experience, to which customers are usually not accustomed as they routinely interact with human workers only. As a result, experiences of arousal and emotional involvement enhance attention and relevancy of product offerings in the retail context, which helps shape consumers' purchase intention.

6.2 Enjoyment

This research further discovered that enjoyable experiences through interaction with social robots are a strong predictor of customers' purchase intention. Previously enjoyment has been found to strongly influence a user's intention to use pleasure-oriented information systems (Abbasi, Rehman, Fayyaz, et al., 2021). Enjoyment also has a significant impact on TAM variables such as ease of use, intention to use, and actual usage (De Graaf & Allouch, 2013). Enjoyable experiences associated with the use of social robots in retail, may reduce consumer anxiety and allow people to self-confidently acquire product information that would have otherwise been difficult in one-on-one interactions with human workers. As a result, enjoyable experiences in retail settings would play a crucial role in the formulation of consumer purchase intentions.

6.3 Research Implications

While there has been adequate research geared towards investigating factors that influence purchase intention in different socio-technical contexts, hedonic variables, such as emotional experiences are seldom tested (De Graaf & Allouch, 2013). More specifically, research investigating emotionality as a driver of purchase intention in social robotics and retail contexts is limited. We extend the current body of work related to hedonic consumption and test novel predictors of consumers' purchase intention (Hirschman & Holbrook, 1982). The present research also has major implications for different technology companies, including, startups, growth stage, and mature (Shah & Guild, 2022), which aim to develop social robots for the retail sector. Utilizing the insights from the current research, companies can design social agents that embody design characteristics that particularly appeal to consumers' unique emotional quotients, as means to enhance purchase intentions.

6.4 Limitations

No distinct category of social robots was assessed in the current study and there is a likelihood that the results may vary based on the type of social robot employed in retail outlets. Therefore, to generalize the current findings, different social robots need to be investigated. Also, participants encountered social robots in several different retail outlets, and there is a possibility that the type of retail outlet may influence research outcomes. Furthermore, participants' experiences which social robots was not controlled in the current research; some participant had extensive experience whereas others were limited in terms of the nature of experience and the level of engagement with the social robot. Lastly, the sample employed in the study was fairly homogenous concerning age and gender therefore the findings of the current research may apply to male and generational Y customers only.

6.5 Conclusions

The goal of this research paper is to offer insights into the experiential facets of customer interaction with social robots in retail settings and investigate the impact it has on customers' purchase intentions. We also review major research issues at the intersection of social robots and retail environments. We highlight the lack of research focusing on the study of emotional factors associated with the use of social robots in retail environments. As a result, we focused on emotional experiences, namely, enjoyment, emotional

involvement, and arousal. The present study employs the PLS-SEM approach to assess the conceptual model. The study results reveal all constructs carried a significant positive impact on customers' purchase intention.

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