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AI agent personality and purchase intention in expectation-discrepant transactional offers

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Abstract

This research explores the role of AI anthropomorphism, specifically agent personality, in shaping consumer purchase intentions toward expectation-discrepant offers. Through an experimental design, we investigate how consumers respond to purchase opportunities in the context of aftermarket ticket sales, where expectation-discrepancy is operationalized and validated via a pretest. Our analysis reveals that when confronted with a negatively discrepant offer, consumers are more likely to proceed with a purchase if the AI agent is anthropomorphized with a sociable personality. However, no effect significant effect was observed in the case of positively discrepant offers. With these findings, marketers can better tailor agent personalities to align with desired outcomes and decide which tasks are better suited to an AI or human agent. Furthermore, future researchers can decide what form of anthropomorphism to apply based on the transactional context.

Keywords– artificial intelligence**,** anthropomorphism, personality, expectations, transactions, purchase intention

Contents

1 Introduction

An e-commerce startup, Dukaan, has cut 90% of its customer support team, replacing them with AI agents, and ostensibly reducing costs by 85% and improving resolution time from two hours to -three minutes (Business Insider, 2023). The startup's CEO expressed the difficulty of the decision but also its necessity. However, netizens did not appreciate his explanation. The CEO's brutal declaration that the bot's superior intelligence, speed, and cost made the decision a "no-brainer". The article also quotes a report that "around 300 million jobs globally could be disrupted by the technology". Social media users criticized the decision harshly, as one framed the layoff decision as exchanging 'quality' for 'quickness'. However, another user stated that the layoffs happened because "-business is failing, and funding is dry. Not because of AI". In this period of technological transition, managers will have to decide when an AI agents be preferred over a human, and vice-versa. In 2023, Meta announced their next line of chatbots will have "personality", think "wisecracking sports debater" or "a big brother who 'roasts' you" (BBC, 2023). An agent's personality impacts the relationship users develop with them (Pal et al., 2023), with certain personality dimensions that contribute to a more pleasant user experience. An agent in the "interpersonal sales transaction" context refers to the role of administering a "product and service offer" (Garvey et al., 2023, p. 11). Customer service and front-facing businesses are examples of where AI agents are commonly used, supporting the importance of understanding the differences between AI and human agent interactions in transactional contexts.

A study has found that an AI agent can influence a consumer's response to an offer worse than expected through increased purchase likelihood and satisfaction (Garvey et al., 2023). Conversely, consumers will respond more positively to a human agent, if the offer was better than expected. The authors explain that consumers infer that AI agents lack selfish or benevolent intentions, "thereby dampening the extremity of consumer responses". Cammy et al. (2021) explored how humanizing AI agents, or how anthropomorphism (in the form of names and avatars) influences customer responses. The authors uncovered that the effect of chatbot anthropomorphism has a negative effect on customers who "enter a chatbot-led service in an angry emotional state". It was found that for these 'irate customers', expectancy violations were the driving this negative effect, and that it was absent within "customers in nonangry emotional states". Both articles express that their findings have practical implications for managers, and state that human agents serve their own role in this setting. Some suggestions include "AI bad cop / human good cop" or transferring angry customers to live persons, "avoiding an anthropomorphic chatbot-based expectancy violation entirely". Another interesting study by Tsai et al. (2021) revealed that consumer engagement outcomes are influenced by "chatbots' high social presence communication" and mediated by "perceived parasocial interaction and dialogue". The authors suggested among other things that chatbots should be designed to express emotions, use emojis, humor to improve the interaction's social presence, thereby improving consumer engagement.

Most existing research on AI agent personalities on consumer outcomes focuses heavily on chatbots. The majority of existing literature explores how forms of AI anthropomorphism positively influences specific consumer outcomes such as service satisfaction and customer (re)engagement. Though, the study by Garvey et al., (2023) suggest otherwise. Another interesting study by Pal et al., (2023) identified eight (8) distinct personality dimensions of AI agents and how these traits lead to formation of love and a pleasant user experience. The authors recommend that 'artificial' and 'offensive' personality traits in agents should be reduced in order to maximize their 'naturalness'. Another study explored the efficacy of AI agents utilizing humor to address service failures (Liu et al., 2023), however the authors concluded that its general efficacy was still unclear. Furthermore, agent demeanor is an interesting design factor to study in the context of administering offers because human-likeness is generally seen as a positive aspect of AI agents in other contexts, such as customer engagement. However, to date no studies on AI agent personality and purchase likelihood, have emerged. Moreover, the ways in which transactional offers are presented through an AI agent's manner of speech have not been explored. A reasonable moderation mechanism to study therefore is personality, in particular AI agent personality as a form of anthropomorphism. This results in the following research question: "How does an AI agent's personality (sociable vs. artificial) in expectation-discrepant transactional offers affect purchase intention".

This experiment largely follows the conceptualization and operationalization from Garvey et al. (2023); specifically their "resale ticket" scenario, pretest methodology, and their method of incorporating establishing expectations in the experiment. This prediction of this study is that anthropomorphizing an AI agent through its sociable (vs. artificial) personality will disproportionately affect responses (in the form of purchase intention) to expectation-discrepant offers. For example, if an offer is better-than-expected, an AI agent with a sociable personality will result in a higher purchase intention. The experiment will be a 2 (agent personality: 'sociable' AI, 'artificial' AI) x 2 (offer type: worse vs. better) group, between-subjects design. The studied context is administering expectancy-discrepant offers in an online aftermarket ticket-selling scenario. The operationalization of offer types will be validated with a pretest in order to check for a significant difference in price expectations between the two offer type conditions.

In this study, I hypothesize that an AI agent's personality (sociable vs. artificial) can significantly influence the impact of expectation-discrepant transactional offers on purchase likelihood. Specifically, I propose that when an AI agent delivers an offer, a sociable demeanor will lead to a higher purchase likelihood when the offer exceeds expectations, and a lower purchase likelihood when it falls short. This hypothesis draws inspiration from the study by Garvey et al. (2023), which revealed that AI agents can play a critical role in influencing consumer reactions in marketing transactions.

2 Theoretical Framework

2.1 Purchase intention

For this study, we must first clarify our understanding of purchase intention, as our definition will guide how we measure it and the conclusions we can draw. Purchase intention is generally understood as the subjective likelihood or probability of one purchasing a product (Dodds et al., 1991; Li et al., 2022).

Purchase intentions are a component of consumer behavior and can be utilized as a sales predictor or a consumer outcome (Schiffman & Wisenblit, 2019; Morwitz et al., 2006). Furthermore, marketing managers use data on purchase intentions to inform strategic decisions regarding both new and existing products, as well as the marketing initiatives that support them, understanding these intentions is essential (Moritz, 2012).

Noteworthy is the emergence of online consumers as its own consumer type, and the importance of trust, perceived risk, attitude, and personal innovativeness in consumers' online purchase intentions (Akar & Nasir, 2015). Thus, our focus lies in observing the purchase intentions of individual online consumers.

Juster (1966) was one of the first to study the prediction of consumer behavior and the empirical measurement of purchase intentions; aiming to test his hypothesis that explicit purchase probabilities predict future purchase rates more accurately than purchase intentions. Morrison (1979) later developed a more rigorous calculation of purchase intention from data from Juster's (1966) study, and a three-step transformation model. The model has since been widely accepted as a means for measuring consumer purchase intentions, alongside his differentiation between stated intentions, true intentions, and purchase probabilities (Rydin, 2021).

2.2 Expectation-discrepant offers

Expectation-discrepant offers are transactional offers that diverge from anticipated, thereby triggering an internal comparison against their expectations (Evangelidis & Van Osselaer, 2018; Oliver & DeSarbo, 1988). For instance, a potential guest at a hotel anticipating a rate of €80 per night based on past bookings, might receive a rate offer of €100 (worse-than-expected) or €60 (better-than-expected).

Expectation-discrepant offers can be understood as an application of the Expectancy-Disconfirmation Model, developed by Oliver (1977) for the purpose of consumer behavior research. The core idea of the model is that satisfaction and dissatisfaction arise from comparing perceived performance against a referent or standard (Oliver 1980). Positive disconfirmation occurs when performance exceeds expectations, leading to satisfaction, while negative disconfirmation occurs when performance falls short of expectations, resulting in dissatisfaction (Spreng et al., 1996).

These expectation-discrepant offers give us an opportunity to analyze how deviations from anticipated outcomes affect consumer satisfaction and decision-making. Hence, when exploring expectation-discrepant offers, we observe the individual consumer engaged in transactions.

Originating from the domains of marketing research and psychology, among the first to study expectation disconfirmation/confirmation as a theory was Oliver (1980). Motivated by earlier studies that suggested that consumer satisfaction is directly related to the ratio of product performance to consumer expectations, he recognized the lack of empirical evidence to substantiate this conclusion. In the following decades, according to Shukla et. al. (2023), consumer satisfaction, loyalty, and retention have been a central theme in marketing literature built upon the Expectancy-Disconfirmation Model (Churchill & Suprenant, 1982; Rust & Zahorik 1993).

2.3 Relationship: purchase intention & expectation-discrepant offers

Similar to purchase intention, consumer outcomes towards expectation discrepancies have been explored across various transactional contexts (Darke et al., 2009; Evangelidis & Van Osselaer, 2018; Oliver et al., 1994; Yoon & Kim, 2000; Hsu & Lin, 2015). The broad body of existing research agrees that negative expectancy disconfirmation adversely affects consumer outcomes such as satisfaction, brand perception, loyalty, and purchase intention. Conversely, better-than-expected offers yield higher purchase likelihoods and reengagement with sales agents (Spreng et al., 1996).

To our knowledge, only Garvey et al., (2023) has investigated the implications of using AI agents as transactional administrators. In their research, consumers respond more positively to AI agents delivering worse offers, in the form of higher purchase likelihood and satisfaction. Furthermore, AI agents were demonstrated to be perceived by consumers as having weaker intentions than human agents and this was presented as the primary driver of the aforementioned effect.

Overall, the current literature is consistent in terms of the relationship between expectation discrepancy and purchase intentions, however, there remains a gap in the research surrounding AI administered expectation discrepant offers. We replicated the "resale ticket" scenario design by Garvey et al., (2023) and adapted it to be more suitable for respondents in the Netherlands. Thus, we expected individuals who are presented a worse-than-expected offer to exhibit lower purchase intentions compared to those presented a better-than-expected offer.

2.4 The moderating role of AI anthropomorphism

It is widely known that AI functionalities are often anthropomorphized, as well as previous studies on customer receptiveness towards anthropomorphism, and anthropomorphic design approaches (Bartneck et al., 2009; Epley et al., 2007). Anthropomorphism is defined as the attribution of human-like behaviors and characteristics upon non-human entities (Waytz et al., 2010). Thus, anthropomorphism can be understood as a design approach with the purpose enhancing the user experience in human-computer interactions (Blut et al., 2021; Chaves & Gerosa, 2021).

Research has shown that consumers interpret positive and negative outcomes differently when administered by AI agents (Crolic et al., 2021; Garvey et al., 2023). Furthermore, research by Garvey and associates suggests that anthropomorphism can have a negative effect on preference, engagement, and purchase likelihood. Additionally, it is important to note that extant research has suggested contrasting results, highlighting the positive effects of anthropomorphism on consumer engagement and trust (Longoni et al., 2019; Liu et al., 2023).

Anthropomorphizing AI agents may affect a user's perception of its intentions, thereby influencing trust and engagement. This would have the effect of moderating the extent to which offers deviating from expectations affect consumer purchase intentions. A transactional agent perceived to have good intentions may receive better credit for delivering a positive offer than an agent perceived to have no intentions at all. Stated differently, a consumer would be more likely to accept a subpar offer from a robotic agent than a human-like one. In summary, we intend to test the following hypothesis: **H1**: anthropomorphism of an AI agent moderates a consumer's purchase intention in response to expectation-discrepant offers.

3 Data & Methodology

Due to the limited timeframe for conducting the experiment and the challenge of reaching a broad range of respondents as an undergraduate student, we used a combination of convenience and snowball sampling. This approach is inexpensive and simple; however it will be difficult to produce generalizable results given that the sample is unlikely to be representative of the population from which it is drawn from.

3.1 Main experiment

Adapted from Garvey et al., (2023) a 2 (**offer type**: 'worse' vs. 'better') by 2 (**agent personality:** sociable vs. artificial) between-subjects experiment was conducted and distributed using a mixture of snowball and convenience sampling. A link to the online experiment was distributed from June 2024 to July 2024, obtaining a sample size of 78. Respondents completed the experiment in return for monetary compensation in the form of a raffle. Participants during this period ranged in age from 18 to 80 years, with the majority (approximately 70%) falling within the 18 – 34 age group. The percentage of male and female participants was roughly equal (51% versus 49%).

This experiment aimed to test for the moderating effect of anthropomorphism on the purchase intentions of consumers towards expectation-discrepant offers. Built on top of the study by Garvey et al., (2023), we explored anthropomorphism in the form of **personality** given the widespread use of text-based service agents (Komiak & Benbasat, 2006; Völkel et al., 2019). Agent **personality** was manipulated through the wording used in presenting an offer in a text description and the inclusion (or exclusion) of emojis in order to enhance human-likeness (Tsai et al., 2021; Chaves & Gerosa, 2021).

Respondents were first asked "Who is an artist or musician you would love to see perform live?" and were required to provide an answer. **Offer type** represents a price offer that would deviate from expectations either negatively ('worse') or positively ('better'). Respondents were first asked "Who is an artist or musician you would love to see perform live?" and were required to provide an answer. They then read a scenario where they are asked to imagine that all tickets for an upcoming concert to the artist or musician they previously answered have sold out, and that the only way to attend the concert was by purchasing a resale ticket online (e.g. Ticketmaster, TicketSwap). Each respondent was offered a ticket for €125, while the **offer type** was manipulated by informing them that a ticket of the same kind was recently sold at different price to another customer. Participants in the 'worse' ('better') condition were told that a different ticket was recently sold for €150 (€100). This approach towards eliciting negative expectation discrepancy is consistent with established practices (Fisk & Young, 1985). Given the lack of formal statistics, publicly listed prices on aftermarket ticket sites (e.g. TicketSwap) were used to establish a reasonable estimate for the offered price. Then, participants indicate whether they will purchase the ticket or not (yes/no). Finally, participants respond to background questions (e.g. age, gender).

To analyze the collected data we performed two separate logistic regressions on each **offer type** condition. Logistic regression is a statistical model used to predict the probability of a binary outcome based on predictor variables, hence its suitability given the binary nature of our outcome **purchase intention**.

3.2 Pretest

A two-item expectancy disconfirmation scale from Oliver (1980) adapted to our context was presented to 86 individuals who participated in the pretest survey. An online survey was distributed in June 2024, and the total sample was collected by July 2024. Survey links were initially distributed to students at Erasmus University Rotterdam. Respondents completed the pretest survey in return for monetary compensation in the form of a raffle. Participants during this period ranged in age from 18 to 70 years, with the majority (approximately 64%) falling within the 18 – 24 age group. The percentage of male and female participants was skewed towards females, with approximately 59% being female.

The pretest was done in order to test the operationalizations of **offer type** ('worse' vs. 'better'). Respondents were first asked "Who is an artist or musician you would love to see perform live?" and were required to provide an answer. They were then shown the same scenario as in the main experiment.

Each respondent answered the two-item expectancy disconfirmation scale from Oliver (1980) adapted to this context by Garvey et al., (2023): (1) "Describe your expectations for the ticket price offer" (1 = "I expected a much lower price", 4 = "The price was as I expected", 7 = "I expected a much higher price"); (2) "Think about what your expectations were for the price offer. How does the price that you were offered, compare to your expectations? (1 = "It was a much worse offer than expected", 4 = "The offer was as I expected", 7 = "The offer was much better than I expected"). The first scale assesses the respondent's expectations for the price offer, while the second scale evaluates the respondent's perception of the offer in relation to their expectations. Finally, participants respond to background questions (e.g. age, gender).

A composite score was calculated by averaging the responses to the two items. The reliability of this composite was assessed with Cronbach's alpha. To determine whether the worse and better **offer type** conditions were significantly different from the as-expected midpoint, two one-sample T-tests were conducted using the mean composite scores from each condition.

4 Results

4.1 Main experiment

The marginal effect of **personality** (0: artificial, 1: sociable) on **purchase intention** was estimated using a logistic regression. The results suggest that for our sample, in the case of a 'worse' **offer type**, switching from an artificial to a sociable agent **personality** has a positive and significant association. The marginal effect holding all other variables constant was a 31.15% increase in probability, or **purchase intention**. On the other hand, 'better' **offer types** had a negative and less significant association. The marginal effect was a 6.8% decrease, all else held constant.

	Purchase intention:	
	logit	
	worse	better
Personality	1.533**	-0.284*
	(0.747)	(0.656)
Female	-1.121	0.682
	(0.744)	(0.657)
Age	0.279	-0.146
	(0.267)	(0.212)
Constant	-1.313	0.406
	(1.036)	(0.914)
Observations	38	40
LR χ2	7.22	1.49
Prob > χ2	0.065	0.684
Note:		*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 1: Logistic regression results, separating each **offer type**. No control variables were found to be significant, and neither of the **personality** coefficients were highly significant ($p < 0.01$).

The 'worse' condition's model p-value of 0.065 indicates that despite the evidence of an improved fit compared to the null model, the evidence is not strong enough to meet the standard 0.05 significance level. The 'better' condition's model likelihood ratio Chi-Square statistic suggests that there is little evidence that the predictors improve the model fit. Additionally, its p-value is substantially higher than the conventional alpha level of 0.05, suggesting that the observed improvement in model fit is not statistically significant.

The lack of significant model fit may be partly due to the small sample size, which can limit statistical power and obscure true effects. Furthermore, our ineffective operationalization of the **offer type** conditions might have led to poorly measured predictors, further contributing to the model's inability to capture meaningful relationships.

4.2 Pretest

Analysis of the two-item 'worse' condition composite (α = .81) revealed it was not significantly below the "as expected" midpoint (i.e. 4). (M_{worse} = 3.9, SD = .228; t(39) = -0.439; p = .332). Furthermore, analysis of the 'better' condition composite revealed a questionable Cronbach's alpha (α = .69), however the composite score was found to be significantly higher than the "as expected" midpoint (M_{better} = 4.3, SD = .223; t(45) = 1.705; p = 0.048). The results suggest that the manipulation of the 'worse' **offer type** condition was not effective, whereas the 'better' condition was successfully manipulated.

4.3 Discussion

Given these disparate results, I find only partial support for the hypothesis which stated that anthropomorphism in the form of **personality** moderates the relationship between **purchase intention** and expectation-discrepant offers. While the 'worse' **offer type** model presents a somewhat significant result ($p < 0.05$), the 'better' **offer type** model does not. Additionally, our operationalization of the 'worse' **offer type** was unsuccessful as seen from the pretest results, making the model's coefficients even more questionable.

My results showed that anthropomorphism has a moderating effect towards the relationship between purchase intention and offers that trigger negative expectation discrepancy. This finding is different from a previous study by Garvey et al., (2023), which focused on anthropomorphism in a different form (physical appearance) and context (ridesharing app, Uber). We believe that the observed moderating effect in their results is partly unique to their specific context. Consumers have more direct interaction with a driver than with an online agent selling resale tickets, which likely influences consumer outcomes.

Furthermore, the results indicate that the moderating effect of anthropomorphism is positive. While this finding contrasts with Garvey et al. (2023), it aligns more closely with previous research by Chaves & Gerosa (2021) and Liu et al. (2023). This suggests that the impact of anthropomorphism as a moderator likely depends on its specific form and the transactional context.

5 Concluding Remarks

5.1 Limitations

A potential limitation of this study was the operationalization of offer types. The study's current approach was unable to trigger expectation discrepancy in the context of resale ticket prices. We observed that some respondents consistently expected significantly higher offers for tickets to specific artists, such as "Taylor Swift", which may have skewed the results. Therefore, we believe that future research would benefit from a deeper analysis of resale ticket prices in order to improve their operationalization of expectation-discrepant offers.

Unfortunately, the study's findings were limited by its sample size and representativeness as a considerable fraction of our data was not fit for use due to respondents not truthfully or improperly completing the online experiment. Potentially, future researchers could improve incentives to answer truthfully, by offering a monetary compensation that aligns better with the task (e.g. ticket vouchers).

5.2 Conclusion

In this thesis I have looked at the moderating effect of anthropomorphism on the relationship between purchase intention and expectation-discrepant offers. Previous research generally suggests that anthropomorphism improves consumer outcomes such as trust, loyalty, and purchase intention. However, these findings were from studies conducted in non-transactional contexts, with only some research undertaken to explore anthropomorphism in transactional contexts. Agent personality has been studied from a design perspective, highlighting the benefits of a humorous or casual personality design. Therefore, the question that was studied in this dissertation was: "How does an AI agent's personality (sociable vs. artificial) in expectation-discrepant transactional offers affect purchase intention".

To answer this research question, 78 respondents obtained through a mixture of convenience and snowball sampling participated in an online experiment. Additionally, a sample of 86 respondents completed a pretest survey about their perceptions and expectations of resale ticket price offers. The pretest results suggested that only the positively discrepant offers were successfully operationalized. Our analysis of the main experiment showed that a sociable personality increased purchase intention exclusively for negatively discrepant price offers.

This study therefore concludes that although the literature shows that anthropomorphism generally has positive effects in non-transactional contexts, in transactional contexts its effect depends on the form of anthropomorphism (e.g. appearance, personality) in relation to the transactional context. Together with findings from previous studies on agent design, this suggests that anthropomorphism should be applied selectively depending on the type of transaction.

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