Exploring Customer Trust and Satisfaction in AI Chatbot Interactions on Amazon Marketplace Case in Ireland.

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Project Submission Sheet

Student Name:	Brandy Guerrero ………………………………………………………………………………………………………
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Hi! I'm currently working on my research which is about this: Exploring Customer Trust and Satisfaction in AI Chatbot Interactions	Of course, here is a list of links of sources corresponding to your request: 1. https://doi.org/10.1007/s12525-020-00414-7 2. https://doi.org/10.1016/j.chb.2010.03.013 3. https://doi.org/10.1145/3236669 4. https://doi.org/10.1057/s41599-024-03212-0 5. https://doi.org/10.1016/j.chb.2018.08.048

on Amazon Marketplace Case in Ireland, can you give any up to date papers that can be relevant for my dissertation	6. *https://doi.org/10.1080/10447318.2020.1841438* 7. https://doi.org/10.1016/j.jbusres.2018.10.004 8. https://doi.org/10.48550/arXiv.2207.01596 9. https://doi.org/10.17705/1thci.00143 10. *https://doi.org/10.1186/s40359-024-02083-z* 11. https://doi.org/10.1016/j.jbusres.2006.02.006 12. https://doi.org/10.1145/3085558 13. https://doi.org/10.1007/s41233-020-00033-2 14. https://doi.org/10.1007/s41233-021-00046-5 15. https://doi.org/10.48550/arXiv.2008.13534 16. https://doi.org/10.5465/annals.2018.0057 17. https://www.researchgate.net/publication/320015931 I hope this list helps you with your research. If you need additional assistance organizing these sources by topic or integrating them into your work, please don't hesitate to ask.

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Additional Evidence:

[Place evidence here]

Additional Evidence:

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Submission of Thesis and Dissertation

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(Thesis/Author Declaration Form)

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Acknowledgement

I would like to start by expressing my sincere gratitude to the National College of Ireland for providing me with the opportunity, resources, and environment to pursue and complete my Master of Science in Management. The academic community and facilities have been instrumental in supporting my learning journey. My heartfelt thanks go to Dr. Jonathan Lambert, Mathematics Development and Support Officer, for his patience, clear explanations, and willingness to guide me through challenging areas. Your dedication and encouragement have been invaluable in strengthening my skills and confidence.

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Abstract

Background: This research examined customer trust and satisfaction in AI chatbot interactions within Amazon Marketplace Ireland, aiming to extend understanding of both functional and emotional dimensions of user experience. Specially, the research explored how attribute such as competence, empathy, fairness, and transparency shape trust and satisfaction, and whether trust serves as a mediator between chatbot attribute and overall customer satisfaction. **Methods:** A cross-sectional online survey was conducted with Amazon Marketplace Ireland users (final analytic sample n=42, after excluding non-users of chatbot system). Multi-item scales measured constructs of trust and satisfaction, while single-item measures captured privacy concerns and fairness perceptions. Descriptive statistics, correlation analysis, and regressions based in mediation model were employed to test hypotheses. **Results:** Findings revealed that fairness perceptions significantly predicted customer trust, while empathy and transparency played a weaker but notable role. Trust was positively associated with satisfaction and partially mediated the relationship between chatbot attributes and satisfaction. However, the relatively small sample size limited statistical power, especially in categories such as complaint and returns. **Conclusion:** The study highlights that customer trust is fragile yet essential in chatbot interactions, with competence and fairness emerging as key drivers in the Irish Amazon Marketplace context. These insights contribute to the growing literature on AI customer service by showing how platforms dynamics shape trust and satisfaction, offering implications for both theory and practice in relational marketing.

Keywords: Customer trust, satisfaction, AI chatbots, Amazon Marketplace Ireland, mediation analysis.

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Chapter 1: Introduction

1.1. Context and Relevance

Customer service has undergone in a fast digitalisation over the last decade, with AI-driven chatbots becoming a core interface between firms and consumers. Implemented across websites, apps, and messaging channels, and scalable support high volumes of queries, promising faster responses, reduced costs, and scalable support in e-commerce settings (Adam et al., 2021; Gnewuch et al., 2017). Yet the same qualities that make chatbots efficient in automation, scripted flows, and standardisation also raise questions about warmth, empathy, and the ability to respond with flexibly, emotionally charged issues. Prior studies suggest users appreciate speed and availability, but remain sensitive to cues of authenticity, empathy, and fairness when evaluating service quality (Brandtzaeg and Følstad, 2018; Hill et al., 2015; Diederich et al., 2021; Zhou et al., 2023). Understanding how these functional and affective dimensions combine to shape trust and satisfaction is therefore essential for platforms that are both high-volume and high stakes.

1.2. Research Problem

Evidence on chatbots' impact remains mixed. While some work finds that chatbots can match or even exceed human support for routine tasks, concerns persist about perceived empathy deficits, rigid escalation paths, and the opacity of automated decisions (Chattaraman et al., 2019; Xu, Zhang and Deng, 2022; Raamkumar and Yang, 2022). Critically, much of the literature is derived from laboratory settings or from large non-Irish markets, limiting its transferability to localised, real world platforms. In highly intermediated marketplaces such as Amazon, where third party sellers vary widely in processes and quality, the customer experience is shaped not only by chatbot design but also by platform governance, escalation policies, and institutional safeguards (GDPR), all of which may alter how trust and satisfaction are formed.

1.3. Purpose and Objectives

The purpose of this study is to evaluate how IA-chatbot interactions on Amazon Marketplace Ireland influence customer trust and satisfaction, and to identify the antecedents that best explain these outcomes. Specifically, the study examines functional (fairness, transparency) and affective (empathy) perceptions alongside usage context (query type, frequency), to establish which factors most strongly predict trust and satisfaction in a real-world, regulated marketplace.

1.4. Expected Contributions

First, the theoretical contribution, the current study adds contextual shade to human-computer trust models by testing, in a GDPR governed marketplace, whether institution-based assurances shift the relative importance of privacy, fairness, and empathy for trust and satisfaction (McKnight et al., 2011; Nordheim et al., 2019). It also probes the debated role of empathy by evaluating trust as a mediator between empathy and satisfaction, clarifying when relational cues matter relative to justice evaluations (Følstad and Brandtzaeg, 2020; Chattaraman et al., 2019). Second, a practical contribution through the findings is intended to guide chatbot design and operations on platforms like Amazon, prioritising transparent rationales, consistent escalation thresholds, and fairness signalling over purely anthropomorphic styling; and tailoring flows for users who may be more sensitive to friction (Adam et al., 2021; Zhou et al., 2023).

1.5. Conceptual Lens

The analysis is grounded in three complementary lenses. First, Human-Computer Trust and trust in technology, distinguishing institution-based trust, trusting beliefs, and trusting intentions (McKnight et al., 2011; Kohn et al., 2021). Second, Disposition, learned and situational trust in conversational agents, which recognises contextual variability in trust formation (Nordheim et al., 2019). And third, service and justice evaluations (procedural and distributive fairness, transparency), positioned against socio-emotional cues such as empathy (Go and Sundar, 2019; Chattaraman et al., 2019). These lenses allow the study to test whether, in a mature, regulated marketplace, justice-related appraisals dominate over anthropomorphic cues in shaping trust and satisfaction.

1.6. Methodological overview

Adopting a positivist, deductive, cross-sectional design (Saunders et. Al.,2019; Bryman and Bell, 2022), the study collected primary data via a self-administered online questionnaire distributed to adult residents in Ireland (N = 91 responses; analytic N=42 after eligibility filtering). The 21-item instrument measured demographics and Amazon usage, prior chatbot interaction, and key constructs (trust, satisfaction, empathy, fairness, transparency, data concern) using Likert-type items adapted from validated sources. Analyses were conducted in SPSS and included descriptive statistics, hierarchical regressions, one-way ANOVA, and a mediation test using PROCESS Model 4 with bootstrap confidence intervals (Hayes, 2017). Reliability checks (Cronbach's alpha) supported the internal consistency of composite scales used in the inferential tests.

1.7. Scope, Delimitations, and Assumptions

The empirical scope is Amazon Marketplace Ireland during July 2025, focusing on adult users residing in Ireland. The current study examines self-reported perceptions of interactions with the platform's chatbots; it does not analyse vendor side logs, conversation transcripts, or operational metrics. Findings are therefore most applicable to regulated European E-commerce platforms with similar governance and may not directly generalise to sectors with different risk profiles (e.g., healthcare) or to less regulated markets. The design assumes that composite Likert measures validly capture latent constructs such as trust, satisfaction, and fairness; steps were taken to use established items and to assess internal constancy, but unmeasured third variables (e.g., brand attitudes, prior seller experiences) may also shape outcomes.

1.8. Structure of the thesis

The current research is structure as follow, Chapter 2, literature review critically reviews scholarship on chatbots in customer service; examines trust and satisfaction frameworks; synthesises evidence on empathy, personalisation, and humanisation; and surveys applied studies with a focus on Amazon and Alibaba and European Irish contexts, concluding with identified gaps. In Chapter 3, research question states the primary research question and formulates hypotheses H1-H3. In Chapter 4, methodology justifies the positivist, deductive, cross-sectional survey design, details sampling, instrument construction, ethics, reliability and validity procedures. Chapter 5, analysis of Results and Main Findings. Presents descriptive and inferential results (regressions, ANOVA, mediation model 4) and summarises key findings relative to the hypotheses. Chapter 6, discussion interprets results against theory and prior evidence, elaborates implications for design and governance, future research.

Chapter 2: Literature Review

This chapter critically reviews the existing literature on AI chatbots use in customer service, focusing on their functional capabilities, emotional responsiveness, and the impact on customer trust and satisfaction. The chapter begins with and overview of how AI chatbots have been introduced and evolved in digital customer service, particularly within the E-commerce sector (Section 2.1). Then explores theoretical and empirical insights into customer trust in automated systems (Section 2.2). In Section 2.3 address Satisfaction outcomes in AI mediated interactions, including comparisons of chatbot use. Section 2.4 focusing on empathy, personalization, and user perceptions of humanization, especially in culturally sensitive contexts like Ireland. In Section 2.5 turns to applied studies from global platforms such as Amazon and Alibaba, alongside European and Irish case studies that illustrates how context influences chatbots effectiveness. Finally, section 2.6 identifies key gaps in the literature, particularly the lack of research centred on the Irish digital marketplace and limited platform specific studies using quantitative approach. Together, these sections establish the theoretical grounding of the current research.

2.1. Introduction of AI chatbots in Customer Service

The integration of AI-driven chatbots into customer service environments has revolutionized how businesses engage with customers, these systems are designed to simulate human conversation, these systems provide automated responses to customer queries, offering 24/7 availability and operational efficiency (Adam et., 2021). As digital channels have overtaken traditional modes of service delivery, chatbots have emerged as essential tools for managing high volumes of customer interactions while reducing operational costs, though the widespread implementation of chatbots, customer reaction remain varied (Gnewuch et al., 2017). While many users appreciated the speed and convenience offered by AI systems, other express concerns about the lack of empathy, authenticity, and personalization in this interactions (Brandtzaeg and Følstad, 2018).

Researches show that the effectiveness of chatbots is often judged not only by their functional performance but also by the emotional and psychological experience they provide, this duality balancing efficiency with emotional intelligence is at the core of customer service innovation and serves as a central theme of the current thesis (Hill et al., 2015; Diederich et al., 2022). The relevance of this topic lies in the growing reliance on AI Systems in customer facing roles, as human agents are increasingly supplemented or replaces by chatbots, understanding how these systems affects trust and satisfaction becomes a pressing concern (Zhou et al. 2023). The existing literature often emphasizes technical capabilities and adoption metrics but provides less insight into actual users engagement, especially in complex customer service environments such as Amazon Marketplace Ireland, whereas qualitative dialogue analysis offers richer understanding of response relevance and satisfaction (Følstad and Taylor, 2021).

2.1.1. Evolution and adoption in E-commerce

In the E-commerce sector, AI chatbots have transitioned from basic rule based scrips to sophisticated natural language processing (NLP) systems capable of understanding significant queries and delivering dynamic responses (Kvale et al., 2020). This evolution has been driven by advances in machine learning, user demand for immediacy, and the need for scalable solutions (Li and Wang, 2023). Platforms like Shopify, eBay and Amazon have integrated chatbot solutions to improve customer service efficiency, streamline issue resolution, and reduce customer attrition (Monjur et al. 2023). Customer adoption of chatbots, however, remains uneven, while many studies highlight the potential for improved satisfaction and loyalty through chatbot use (Xu et al., 2022). Trust in chatbots can be significantly reduced by systems errors, which negatively affect perceived competence and user responses, while higher social presence supports stronger trust belief (Toader et al., 2020). Particularly in scenarios requiring emotional intelligence such as complaint resolution or problem escalation, chatbots often fall short, leading to frustrations and decrease satisfaction (Raamkumar and Yang, 2022).

Within the context of E-commerce, the literature has identified several critical success factors for chatbot implementation, including accuracy, transparency, data privacy, and conversational coherence; yet, while these factors are well documented, fewer studies focus on the emotional aspects of the customers experience (Chattaraman et al., 2019; Følstad et al., 2028). Moreover, the literature tend to treat chatbot adoption as a homogenous process, with little regard for platform specific dynamics, in the case of Amazon Marketplace presents a unique case due to its vast seller network, heterogeneity in service quality, and varying chatbot implementations, this adds a critical dimension to the study, as it allows exploration of how context specific variable influence user responses (Dey and Bhaumik, 2022).

2.1.2. Example of Usage in Amazon Marketplace

Amazon's customer service infrastructure has increasingly relied on AI chatbots, a key technology behind is Amazon Lex which manage routine interactions, such as order tracking, return processing, and product inquiries, these systems are designed to reduce the burden on human agents and maintain high levels of responsiveness (Amazon Web Service, n.d.). In Amazon Marketplace, chatbots systems often serve as the first point of contact for customer issues, positioning them as key influencers of overall customer experience, by incorporating chatbots into these everyday support functions, Amazon demonstrates the platform's shift toward fully automated service environments (Kramer, 2020). However, while this automation improves operational efficiency, it raises important concerns regarding personalization, empathy, and trust in customer experiences particularly in cases where users face complex or emotionally charged issues (Xu et al., 2022).

2.2. Customer Trust in Automated systems

As AI chatbots become integral to digital customer service, understanding how they influence customer trust is increasingly important. Trust is a central component of user acceptance in automated systems, particularly in high stakes environments like E-commerce, where perceived risks, expectations, and the absence of human agents intersect (Nordheim et al., 2019). In the context of the Amazon Marketplace Ireland, where automated systems often act as frontline agents, that why in this section we will explores the factors that foster or erode trust, and the theoretical frameworks used to conceptualize it.

2.2.1. Factors that Build or Weaken Customer trust

Trust in AI systems is influenced by both functional and emotional components. On the functional side, factors such as accuracy, consistency, transparency, and data privacy protection play pivotal roles (Diederich et al., 2021). Users are more likely to trust a chatbot that respond reliably and aligns with their expectations (Følstad et al., 2018). For instances, clear and consistent messaging enhances perceived competence, while transparency about limitations or escalation protocols increase user confidence (Ok, 2025). Equally critical, however, are affective and relational factors such as empathy, warmth, and conversational coherence have been shown to significantly affect trust perceptions, especially in situations involving emotional or complex inquiries (Xu et al., 2022). Customers may distrust a chatbot even when it perform well functionally, if it fails to convey attentiveness or human like understanding (Raamkumar and Yang, 2022). These emotional dimensions are particularly relevant in contexts like Ireland where service culture emphasizes politeness and personalization (Wallace and de Chernatony, 2011).

Moreover, previous experiences, brand reputation, and users' general predisposition to trust technology shape how they interpret automated service. According to Chung et al (2020), negative prior interactions or lack of familiarity with AI systems can hinder trust developments, even when the chatbot behaves correctly, this highlights the need to design interaction that not only resolve issues but foster trust building over time. Additionally, chatbot errors or failure significantly undermine trust, even, minor communication breakdowns can trigger perceptions of incompetence or deception, especially when not followed by appropriate recovery strategies (Diederich et al., 2021; Toader et al., 2020). Although many studies prioritize technical capabilities and adoption metrics, limited attention has been given to real world platforms such as Amazon Market Place Ireland, in this environment characterized by diverse vendors, varied service protocols, and heterogeneous chatbot implementations which creates expectation for fast, flawless service, yet chatbot interactions can differ significantly from controlled or generic environments (Wang et al., 2023).

2.2.2. Theoretical Models of Trust

To evaluate customer trust in automated systems, several conceptual models have been proposed, one of the most widely applied is the Human- Computer Trust (HCT) model, which outlines trust as a function of system attribute (e.g., reliability, helpfulness) and user related factors (e.g., propensity to trust, prior experience) (Kohn et al. 2021). The model helps differentiate between cognitive trust (based on the performance and logic) and emotional trust (based on comfort and relationship), a distinction that aligns closely with the aims of the current study (Sousa et al., 2014). Another foundational framework is McKnight et al., (2011) Trust in Technology model, which distinguishes between institution based trust (e.g., brand reputation), trusting beliefs (competence, benevolence, integrity), and trusting intentions (willingness to rely on the system), this layered approach is useful when examining trust in AI chatbots deployed by large platform like Amazon, which carry strong institutional reputations but delegate service roles to autonomous systems. Recent models specific to conversational agents, such as the one proposed by Nordheim et al (2019), emphasize the role of dispositional trust (general attitude toward technology), learned trust (based on direct use), and situational trust (influenced by context). These models are particularly relevant in the case of Amazon Marketplace Ireland, where customer trust may fluctuate depending in the nature of the issue (simple tracking vs product complaints), or even by time of day (e.g., late night automated responses vs daytime hybrid support). Despite these theoretical advances, most frameworks are either too general or have been tested in highly controlled environments (Wang et al., 2023).

2.3. Customer Satisfaction in Interactions with AI

As AI-powered customer service tools, particularly chatbots, become more prevalent in e-commerce, understanding customer satisfaction in these interactions is essential. Satisfaction serves as a key indicator of service quality, influencing customer loyalty, retention, and overall trust in the platform (Xu et al., 2020). However, while much of the current literature focuses on performance metrics such as response time and accuracy, less attention has been paid to the subjective experience and expectations of customers engaging with these automated systems (Chung et al., 2020; Zhou et al., 2023). This section explores how customer satisfaction is shaped in AI mediated service, comparing anticipated versus actual experiences, and contrasting AI support with human led service. This discussion is particularly relevant in the context of Amazon Marketplace Ireland, where platform standardization intersects with local service expectations, Irish consumers are culturally accustomed to interpersonal warmth and politeness in service interactions (Wallace and de Chernatony, 2011). Therefore, assessing how AI aligns or misaligns with these expectations offers insights into both functional and emotional dimensions of satisfaction, despite the increasing adoption of chatbots in e-commerce, few studies explore customer satisfaction with AI tools in specific marketplace or cultural settings.

2.3.1. Expectations vs Experiences

Customer satisfaction with AI systems is strongly influences by the alignment between initial expectations and actual experiences, users often approach chatbots expecting fast, convenient, and efficient service, especially for low-complexity tasks like order tracking or FAQs (Chung et al., 2020). These expectations are rooted in the common marketing narrative of chatbots as 24/7, instant-response agents that reduce wait times and resolve issues autonomously (Gnewuch et al., 2017). When these expectations are met or exceeded, users typically report high levels of satisfaction (Go and Sundar, 2019). However, satisfaction declines rapidly when chatbots fail to address user needs accurately, repeat information, or provide limited options (Xu et al., 2022). Emotional aspects also matter, when users seek empathy or acknowledgement, a scripted or overly functional response can feel dismissive or robotic (Raamkumar and Yang, 2022).

This gap between expected emotional intelligence and the often limited emotional responsiveness of chatbots contributes to dissatisfaction, particularly in high stakes or emotionally loaded scenarios such as complaints or returns (Zhou et al., 2023). While some chatbots incorporate affective cues, their success depends on how well these cues align with the user's cultural and contextual expectations (Brandtzaeg and Følstad, 2018). In Ireland, where interpersonal politeness is emphasized, generic or interpersonal responses may be perceived as poor service (Wallace and de Chernatony, 2011). Although chatbots succeed in handling transactional or repetitive queries, the lack of adaptability to emotional needs is a persistent shortcoming (Zhu et al., 2023).

2.3.2. Comparison between Human Support vs Chatbots

A core question in the literature is whether chatbots interactions can match or exceed the satisfaction levels typically associated with human support, with studies suggesting that for routine and low involvement tasks, satisfaction with chatbots can equal or even surpass that human agents, primarily due to speed and convenience (Hill et al., 2015; Adam et al., 2021). However, the scenario changes in more complex or emotionally charged interactions, for instances human agents are generally perceived as more empathetic, flexible, and context sensitive, especially when customers express frustration or confusion (Xu et al., 2022). In contrast, users often report that chatbots lack empathy, provide rigid responses, and struggle with out of scope queries (Chattaraman et al., 2019). This contrast reduces perceived service quality in chatbots interactions and highlights a critical limitation in AI based systems (Cheng et al., 2025).

Another point of divergence lies in the escalation process, as users who realize that a chatbot cannot solve their issue often experience greater dissatisfaction when there is no seamless transfer to a human agent(Gnewuch et al., 2017; Li and Wang, 2023). In marketplaces like Amazon, where vendor level support varies, inconsistent service experience can exacerbate user frustration, particularly among older users or those with lower digital literacy who often find chatbot interfaces challenging, leading to lower satisfaction even when functionally is adequate (Brandtzaeg and Følstad, 2018). Conversely, younger users may value speed over human warmth and prefer chatbots for transactional efficiency, while chatbots offer measurable operational advantages, human support still provides a more emotionally responsive experience, which is particularly important in building long term satisfaction (Chung et al., 2020).

2.4. Empathy, Personalization and Emotions

As AI chatbots increasingly mediate customer service interactions, the absence of human warmth and emotional intelligence has become a major point of contention, while these systems are optimized for efficiency and scalability , users frequently report dissatisfaction when emotional or personalized engagement is lacking (Raamkumar and Yang, 2022). In the context of Amazon Marketplace Ireland, where cultural expectations prioritize politeness and human courtesy, emotional gaps in chatbot communications may significantly decrease the user experience (Wallace and de Chernatony, 2011).

2.4.1. Lack of empathy as a Barrier

A key limitation of AI-driven systems lies in their inability to simulate empathy at a human level, for instances empathy involves not just recognizing user emotions but responding with sensitivity and appropriateness skills that most chatbots, even advanced ones, struggle to execute effectively (Chaves and Gerosa, 2021). When users feel emotionally dismissed, especially in cases involving complaints or service failure, the result is a decline in both trust and satisfaction (Xu et al., 2022). Recent research indicates that users are more forgiving of functional errors that of emotionally tone deaf interactions, particularly when they expect human like attentiveness (Zhou et al., 2023). This mismatch between expectation and reality creates friction and fosters perceptions of cold, transactional service, even when the chatbots performs its informal duties correctly (Chung et al., 2020). Moreover, emotionally neutral or repetitive responses can exacerbate user frustration, particularly in cultures like Ireland's where emotional engagement is an expected aspect of service (Wallace and de Chernatony, 2011).

Go and Sundar (2019) also indicates that even when affective computing features such as sentiment analysis or emotion tagging are present, users remain sceptical of the authenticity of these expressions, this suggests that technical approximations of empathy may fall short in producing genuine rapport. As a result, many users prefer to speak with human agent when facing emotionally sensitive or high stakes issues, although technological progress, the affective shortcomings of chatbots remain a consistent barrier to deepening user trust and satisfaction (Zhang et al., 2024). In Amazon Marketplace Ireland, where vendors may implement divergent chatbot protocols, inconsistent empathy cues further contribute to user dissatisfaction, this platform specific challenge makes the Irish case particularly compelling for examining how empathy or the lack of it shapes customer experience (Cheng et al., 2024)

2.4.2. User Perception of "Humanization of Chatbots"

To counteract the empathy deficit, many chatbot systems are designed with anthropomorphic or "humanized" features such as names, avatars, informal speech patterns in order to enhance emotional relatability (Go and Sundar, 2019). These features are intended to stimulate social presence and trust, drawing on users' natural tendencies to attribute human characteristics to non-human agents, though the effectiveness of such strategies remains contested (Chattaraman et al., 2019). Some users appreciate humanized features when they align with conversational flow and problem resolution, while others perceive them as superficial or manipulative, especially when emotional responses are scripted and non-contingent (Følstad et al., 2020). The credibility of humanization depends on contextual coherence; if a chatbot uses a friendly tone but fails to resolve the issue or escalates ineffectively, the mismatch it can make even worse user frustration (Adam et al., 2021).

Humanization is also culturally variable, in markets like Ireland, overly casual language or excessive cheerfulness from bots can come across as insincere or inappropriate, further undermining user confidence (Wallace and de Chernatony, 2011). As Raamkumar and Yang (2022) argue, humanization must be balanced with functional competence to be perceived as genuine rather than performative so that customer can feel satisfied; in addition personalization in adapting chatbot responses to individual users based on history, preferences, or emotional tone has shown promise in enhancing satisfaction. Recent research caution that without robust data governance and transparency, personalization can raise concerns about surveillance and misuse of personal information, these concerns are especially relevant in the EU context, where GDPR compliance adds another layer of user expectation and trust sensitivity (Li and Wang, 2023).

Ultimately, the literature points to some contradictions, while users seek human like qualities in chatbot interactions, they also expect transparency about the system's non-human nature, this findings reinforces the need for more detailed chatbot system design that are functionally competent, contextually adaptative, and emotionally aware without overstepping into the uncanny valley of artificial empathy (Rao Hill and Troshani, 2024). This discomfort is particularly evident when chatbots emulate human behaviour too closely without making their non-human identity explicit, leading to user unease and diminished trust (Lukasik and Gut, 2025). Moreover, Ma et al. (2025) emphasize that anthropomorphic visual design and perceiver intelligence only contribute positively to user experience when moderate by perceptions of empathy and trust, reinforcing the need for emotionally aware but clearly machine labelled chatbots system.

2.5. Applied Studies in E-commerce

The application of AI- powered chatbots in customer service is not just a theorical concept; it has been extensively trialled and deployed by major global E-commerce platforms such as Amazon and Alibaba, these real world implementations provide a critical lens through which we can evaluate the practical implications of chatbot systems on customer trust, satisfaction, and overall experience (Monjur et al., 2023). By examining applied studies, this section contextualizes the theoretical constructs discussed previously within functioning E-commerce ecosystems, it highlights both the technological affordances and limitations of chatbot interactions in live commercial settings. Moreover, special attention is given to cases in Ireland and comparable European markets, where cultural and regulatory environments play a significant role in shaping user perceptions of automation, the dual focus on international tech giants and regional European context ensures that the analysis remains relevant to the Amazon Marketplace Ireland.

2.5.1. Focusing on Amazon, Alibaba

Empirical studies on the application of AI chatbots in global E-commerce giants like Amazon and Alibaba highlight the strategic integration of automated agents to enhance customer service scalability and responsiveness, focusing in these two companies is a warranted because these platforms are the global reference cases for scaled, AI mediated customer service . Monjur et al. (2023) illustrates that both companies have employed AI tools, particularly chatbots, to manage high interaction volumes, streamline transactions, and reduce customer service costs. Amazon's implementation leverages systems such as Amazon Lex, capable of handling order related tasks, showcasing high functional efficiency, yet raising concerns about personalization in more complex customer (Amazon Web Services, n.d.) . On Amazon, chatbot design emphasizes speed and automation, but scholars have noted persistent gaps in empathy and emotional engagement, especially when dealing with complaints or products issues (Zhou et al., 2023). These limitations become evident in customer reviews and support ticket data, which reflect dissatisfaction when automated replies fail to provide adequate emotional cues or problem solving flexibility (Xu et al., 2022). Similarly, Alibaba integrates AI systems through its Dian Xiaomi chatbot, employing natural language processing and real time learning algorithms which handles inquiries in real time, but studies show that customer trusts is fragile when chatbots offer scripted or vague responses in emotionally sensitive cases which can leads to user frustration, even when the chatbots performs functionally well (Lui and Qi, 2022).

Even though both companies have experimented with anthropomorphising their bots through avatars, casual language, or emotive icons, informal tones to enhance social presence and boost relatability (Go and Sundar, 2019). Yet, research indicates mixed outcomes, while some users respond positively to human like tone, others find them superficial, especially when the systems fail to answer meaningfully to their needs (Chattaraman et al., 2019). In Amazon's case, the inconsistency across third-party seller support exacerbates these problems, especially when encounter varying levels of chatbots capability and responsiveness across vendors (Hill et al., 2015). In Alibaba's context, cultural alignment with customer expectation (e.g., high power distance and acceptance of automation in China) improves acceptance, whereas Amazon's international markets, including Ireland, may demand more emotionally attuned systems (Wallace and de Chernatony, 2011). Another critical distinction lies in escalation mechanism, Amazon users often express frustration when they are trapped in automated loops without clear pathways to human agents, a phenomenon linked to reduced satisfaction, lower trust and service quality declines sharply (Zhou et al., 2023). Alibaba, by contrast, offers more visible escalation options in its mobile ecosystem, which studies suggest contributes to higher perceived transparency, increasing trust and satisfaction, these differences underscore how chatbots success is not solely dependent on technical design, but also on ecosystem context, cultural expectations, and escalation policies (Fu et al., 2020).

2.5.2. Studies in Similar Context in Ireland- Europe

In Ireland and broader European markets, the integration of chatbots into customer service reflect both global digital trends and distinct regional expectation , Irish consumers, in particular, are accustomed to high level of interpersonal service marked by politeness and attentiveness (Wallace and de Chernatony, 2011). When chatbots fail to meet these cultural expectations, trust and satisfaction are undermined, regardless of functional performance, this cultural misalignment is critical in contexts like Amazon Marketplace Ireland, where vendors vary in how they implement AI support systems (Ding and Najaf, 2024; Cai et al., 2024). Recent in Irish E-commerce sector (2024) demonstrates a clear preference for hybrid customer support modes, while chatbots are appreciated for their availability and efficiency in handling routine tasks, customer overwhelmingly expect escalation to human agents for more complex or sensitive integrations. These findings aligns with the Human- Computer Trust Model, which underscores the importance of system reliability, emotional resonance, and user control in building trust (Kohn et al., 2021).

European wide research further suggests that privacy attitudes towards automation influence chatbot acceptance, for example, Nordheim et al (2019) argue that in European countries, where consumers are more privacy conscious and sceptical of AI decision making, trust is harder to earn and easier to lose. Raamkumar and Yang (2022) emphasize that emotional intelligence, affective cues, and respectful tone are critical in chatbot interactions, systems offering affect matching and empathic behaviours performs better in user satisfaction and trust. These shortcomings are further amplified in Ireland environment, as consumers are shown to value clarity, accountability and fairness, even in digital service interactions and where linguistic misinterpretation by AI can signal incompetence or disregard (Leonard, 2025).

Finally, research show that chatbot interaction judge as misaligned such as unexpected phrasing or rude tone often lead to user frustration, even when the chatbot performs its tasks correctly, these findings imply that culturally aligned communication styles such as calm, polite, reserved are vital, especially in service contexts where conversational norms matter. (Følstad et al., 2020). While this does not map directly onto Irish cultural expectations, it implies the argument that chatbot design must be locally adapted for optimal trust and satisfaction outcomes, as Ma et al. (2025) note, user confidence increases when AI systems are seen to respect boundaries and adhere to regional and local data ethics, suggesting that future chatbot research and design must account for these evolving legal frame work. Recent European policy shifts, including the AI Act and expanding digital service regulations, further compliance the deployment of chatbots in European Markets (European Parliament and Council, 2024).

2.6. Gaps Identified in the Literature

Despite increasing interest in AI chatbots for customer service, the literature remains uneven in its focus and scope, while numerus examine technical implementation, usability, and trust in digital agents, these are often conducted on generalized or simulated environments, lacking the platform specific analysis. This section outlines the limited availability of research contextualized in the Irish digital marketplace, which remains significantly underrepresented. Much of the existing literature draws from large markets such as United states, China, or cross-European regions, assuming a uniformity in user behaviour and service expectations, yet cross cultural studies suggests that chatbot perception and trust vary significantly by market and context, undermining the generalizability of findings to localized environments (Xu et al., 2022).

2.6.1. Lack of Specific Studies in the Irish Context

Ireland presents a unique service ecosystems shaped by bilingual communication, strong regulatory frameworks (GDPR) and distinct cultural norms in service interactions, customers often expect conversational tone, responsiveness, and a sense of relational closeness these elements that influence how they perceive and interact with AI-driven service system (Wallace and de Chernatony, 2011; Leonard, 2025). However, most chatbots design and evaluation frameworks fail to account for these culturally embedded expectations, leading to a research gap in how trust and satisfaction are formed in Irish specific digital contexts. Moreover, while platforms like Amazon implement advanced chatbot systems globally, little is known about how these tools perform and are perceived on the Amazon Marketplace Ireland, which operates under a different seller structure, service variation, and customer support experience compared to the U.S or UK (Wang et al., 2023). The lack of region specific studies restricts the ability to tailor chatbot design and policies to meet local customer needs.

This gap is especially critical given that trust and satisfaction with chatbots are highly context sensitive, studies have shown that customer expectation and trust building strategies vary significantly depending on cultural norms, platforms type, and service environment, for instance, a cross -cultural comparison showed that trust levels differ significantly between Germany and South Korea depending on content domain and how explanations are provided(Følstad and Brandtzaeg, 2020; Kang et al., 2025). Therefore, applying general findings to the Irish E-commerce market risks overlooking key emotional, social, and technical dynamics that shape user experience. By addressing this gap, this study contributes novel insight into users in Ireland interact with AI powered chatbots, offering both academic value and practical guidance for platform specific optimization in markets with distinctive cultural and structural characteristics.

Chapter 3: Research Question

As Artificial Intelligence (AI) becomes increasingly immerse in customers- facing services, understanding how these technologies impact customers experiences is essential. This study seeks to examine customer trust and satisfaction in interaction with AI chatbots, specifically within the context of the Amazon Marketplace in Ireland. The focus is on how consumers respond to automated customer service systems, particularly chatbots, which are now widely used vendors and customer support teams on the Amazon platform. The research aims to evaluate not only the perceived performance of AI chatbots but also the emotional and psychological factors that influence trust and satisfaction in these interactions. The core objective is to investigate how chatbot-driven communication affects customer trust, satisfaction, and overall experience on the platform. As AI continues to replace or complement human agents, it is critical to assess whether these systems meet customer expectations or fall short in delivering a meaningful service experience. To guide this inquiry, the following research questions and sub-questions have been developed:

3.1. Primary Research Question

How do AI chatbots interactions on the Amazon Marketplace Ireland influence customer trust and satisfaction?

This central question explores the relationship between automated customer service and key outcomes such as trust and satisfaction. It aims to uncover how customers perceive chatbot interactions in terms of reliability, responsiveness, personalization, and emotional tone, and how these perceptions translate into satisfaction with the overall service experience. In particular, the study investigates whether customers feel heard, respected, and understood during automated exchanges, or if the lack of human involvement undermines trust and rapport. This research also acknowledge that trust and satisfaction are complex constructs influences by both functional performance (empathy, transparency). The investigation seeks to strike a balance between these two dimensions in understanding user responses to AI systems. To support a better understanding, the following sub-questions are posed:

Sub-question 1: *What specific factors contribute to or interfere customer trust in AI chatbot interactions on the Amazon Marketplace Ireland?*

This question seeks to identify the elements that shape customers wiliness to rely in AI chatbots. Factors such as clarity of responses, consistency of communication, perceived fairness, and data privacy may all influence trust levels. The study will explore whether customers see chatbots as dependable and credible, or whether doubt automation and algorithmic decision-making affect their trust.

Sub-question 2: *which aspects of chatbot interactions have the most impact on customer satisfaction, and how do these vary across different types of customer service needs?*

Here, the focus is on satisfaction whether customer feel their issues are resolve efficiently, and whether the experience is smooth and pleasant. This sub-question also explores if satisfaction varies depending on the nature of the request (simple queries vs complaints) and how well the chatbot handles the shades of human communication.

Sub-question 3: *To what extend does the absence of human interaction affect customer perceptions of empathy and personalization in AI chatbot responses?*

This sub-question investigates emotional responses. While chatbots can simulate human dialogue, they often lack true emotional understanding. This question will explore whether the absence of human touch negatively impacts how customers experience support interactions, particularly when emotional sensitivity is needed.

3.2. Hypotheses

Based on preliminary observation and literature, the following hypothesis will guide the investigation:

H1: Customers with high concern over data privacy are less likely to trust chatbot systems.
H2: Customer satisfaction with chatbot agent interactions significantly differs depending on the nature of the service query.
H3: Trust mediates the relationship between perceived empathy and overall satisfaction with AI chatbots interactions.

Together, these research questions and hypotheses aim to capture both the functional and emotional dimensions of customer experience with AI chatbots on the Amazon Marketplace Ireland. By focusing specially on customer trust and satisfaction, the study contributes to ongoing debates about the roles of AI in consumer service environments and offers practical insights for improving automated support systems in E-commerce contexts.

Chapter 4: Methodology

4. 1. Introduction:

This chapter outlines the research methodology y employed to examine how AI chatbots interactions on the Amazon marketplace Ireland influence customer trust and satisfaction. While there is a growing body of literature exploring AI chatbots in customer service (Adam et al., 2021; Xu et al., 2022), much of the existing research is based on generalized or simulated environments, with a predominant focus on large markets such as the United States or Asia. This geographical and contextual bias creates a significant gap in localized, user centred investigations, particularly within the Irish E-commerce landscape. The methodological framework for this study was specifically designed to address this gap by capturing both attitudinal and behavioural insights from customers. It aligns closely with the research objectives, which focus on understanding trust, satisfaction, empathy, transparency, fairness, and related constructs in AI- driven customer service. To achieve this, the primary data collection instrument was a self- administered online questionnaire consisting of 21 questions, structured to quantitatively measure perceptions and experience with AI chatbots on Amazon Marketplace Ireland. The survey provide a comprehensive view of how users engage with AI-driven customer support systems.

This chapter is organised in five sections, Section 4.2. Research Design and Philosophy, explains the overall methodological approach adopted. In section 4.3. Mode of Data Collection and Sampling, outlines the target population, sampling method, recruitment strategy and data collection process. The next section 4.4. Questionnaire Structure, describes the design, content and measurement scales used in the survey, referencing existing validated instruments adapted for this study. In section 4.5. Ethical Consideration, discusses the ethical safeguards implemented to ensure participant privacy, informed consent, and data protection. And last, section 4.6. Validity and Reliability, presents the statistical test applied to evaluate the robustness and internal consistency of the survey instrument, including Cronbach's Alpha results.

4.2. Research Design and Philosophy

In alignment with the research onion framework proposed by Saunders et al., (2019), this study adopted a positivism philosophy, and deductive approach to theory development, and a mono- method quantitative research strategy using a cross-sectional survey design. The philosophical stance of positivism was selected because the research aims to produce objective, measurable, and generalise findings on the relationship between AI- chatbot interactions and customer trusts and satisfaction. Positivism assumes that reliability is external and can be measured through observables phenomena (Bryman and Bell, 2022), this philosophy aligns with the study's focus on quantifying user perceptions and testing theory-driven hypotheses rather than exploring subjective meaning in depth. The deductive approach was employed because the present research was grounded in well-established theories such as the Human- Computer Trust model (Kohn et al., 2021) and Trust in Technology frameworks (McKnight et al., 2011) and sought to test hypotheses derived from the literature review. Deduction is particularly suited to research where variables are clearly defined, relationship are theorises, and the aim is to confirm or refute existing theoretical propositions through empirical data (Saunders et al., 2019). This contrasts with inductive approaches, which are more appropriate for exploratory studies lacking a strong theoretical base.

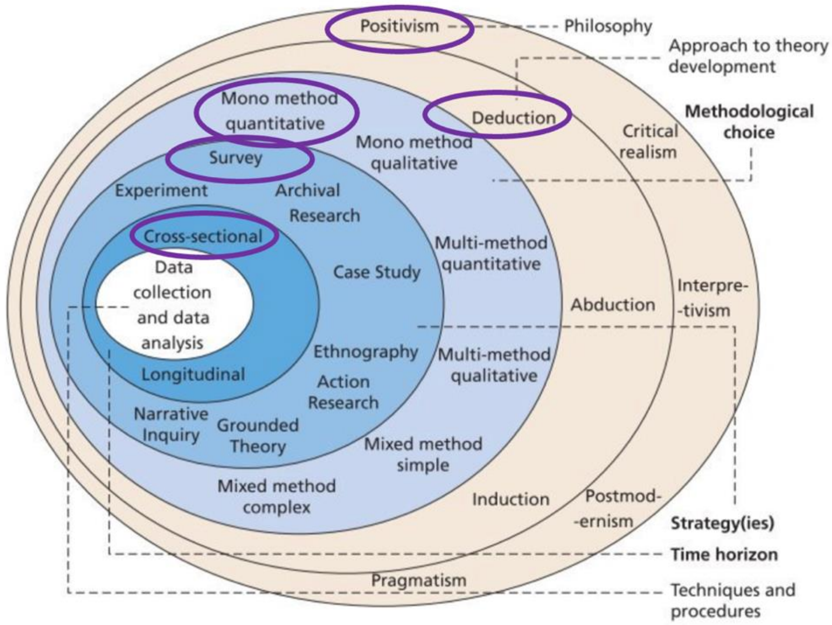


Figure 1: Research Onion, Saunders et al.,(2019).

A cross-sectional design was chosen to capture a ‘snapshot’ of user perceptions within a fixed time frame between 1 July and 28 July 2025, allowing the researcher to examine the relationship between trust, satisfaction, empathy, and other psychological constructs without the time and resource demands of longitudinal tracking. While longitudinal designs could offer insights into changes over time, they were deemed impractical for the present study due to time constraints and the research’s objective of assessing current, rather than evolving, attitudes. The study adopted a mono-method quantitative survey because it facilitates the systematic measurement of variables and allows for statistical analysis, such as descriptive statistics, correlation, and regression, using SPSS. This method provides a high degree of control over the measurement process and enables comparability with prior studies in the field (Følstad and Brandtzaeg, 2020; Xu et al., 2022).

Alternative designs such as mixed methods research, while offering richer contextual insights, would have required a longer data collection period and more complex integration of findings, exceeding the scope and time constrains of the current project. Purely qualitative designs, on the other hand, would not have allowed for the same level of statistical testing of hypotheses or generalisation of results. By adopting this methodological configuration, the research ensures a strong link between theory and empirical testing. The design support the analysis of relationship between functional (transparency, fairness) and emotional (empathy) dimensions of chatbot interactions, within the culturally specific context of Amazon Marketplace Ireland. This approach not only strengthens the reliability and validity of the findings but also contributes to filling the identified gap in the literature by moving beyond controlled settings to investigate real world user experiences.

4.3. Mode of Data collection and Sampling

The target population for this study compromised adult residents of Ireland, aged 18 years and above, regardless of whether they had preciously interacted with AI-powered chatbots on the Amazon Marketplace Ireland. This inclusive approach allowed the collection of a broad spectrum of perceptions, while subsequent filtering during the data analysis stage ensured that only relevant cases were included in the final statistical testing (as detailed in Section 4.5). The intended sample size was 100 respondent, a number deemed sufficient to generate preliminary insights while maintaining feasibility within the project's time constrains. However, due to time limitations, 91 completed responses were obtained, representing a 91% achievement rate of the original target. A simple random sampling strategy was initially intended to ensure equal selection probability for participants within the target population. Yet, in practice, the recruitment process also incorporated to share the survey link with acquaintances.

This pragmatic adjustment was necessary to increase the response rate within the fixed data collection period and is consistent with recommendations by Bryman and Bell (2022), who note that hybrid sampling approaches can be effective for niche population or time-constrained projects. The chosen method of data collection was a self-administered online questionnaire, designed to be completed without researcher assistance. This method was selected after evaluating alternative approaches such as face-to-face surveys or telephone interviews, which were dismissed due to higher costs, limited geographical reach, and lower expected response rates (Saunders et al., 2019). Online survey are widely regarded as efficient for consumer studies involving digitally literate populations, particularly when anonymity and convenience are priorities. The questionnaire was designed and hosted on Google Forms, selected for its secure data storage, compliance with the General Data Protection Regulation (GDPR), and cross-platform accessibility on both desktop and mobile devices. Its user friendly interface helped minimise participant burden and reduce the risk of incomplete submissions.

The survey link remained open from 1 July to 28 July 2025, during which responses were collected through multiple recruitment channels, including, first, direct invitations sent via personal and group message on WhatsApp, second, posts in relevant Facebook groups frequented by Ireland based consumers and third, email invitations to potential participants. To enhance participation, recipients were encourage to share the survey with family and friends, creating a secondary recruitment wave through peer-to-peer referrals. This approach extended the survey's reach beyond the research's immediate network, although it also introduced a non-probability element to the sample composition. Overall, the data collection process balanced methodological rigour with practical constraint, ensuring adequate coverage of the target population within the available timeframe while adhering to ethical and data protection standards.

4.4. Questionnaire Structure

The questionnaire was designed as self-administered survey to measure customer trust, satisfaction, empathy, transparency, and related constructs in interactions with AI-powered chatbots on the Amazon Marketplace Ireland. Its structure was informed by established measurement scales in the literature and adapted to the specific research context. Following the recommendations of Saunder et al., (2019) and Bryman and Bell (2022), the instrument was developed to ensure clarity, brevity, and alignment with research objectives, thus reducing respondent fatigue while maintaining measurement reliability. The final instrument consisted of 21 closed- ended questions organised into four main sections, first section was demographic information, which includes participant age, gender, and frequency of Amazon use to enable subgroup analysis. Second section, interaction with AI-chatbots, established whether participants had prior experience with Amazon Marketplace Ireland chatbots, as well as measured perception of satisfaction, empathy, frustration and issues with chatbots. The third section, measured perceptions of trust, transparency, fairness, and concern, using Likert-scale items adapted from validated instruments such as Customer Evaluations of service Complaint Tax et al., (1998) Measurement of Trust in Automation: A Narrative Review and Reference Guide (Kohn et al., 2021) and AI interaction framework (Følstad and Brandtzæg, 2020). A 5 point Likert Scale (1=Strongly Agree to 5=Strongly Disagree) was used for attitudinal question, allowing for quantitative analysis and statistical testing. This format is widely recognised in customer behaviour and service quality research for its balance between sensitivity and respondent comprehension. The full questionnaire can be found in Appendix 1.

Table 1: Below Summarises key questionnaire sections, example items, and their source references:

Section	Example	Measurement	Source/Adaptation
Satisfaction	Overall satisfaction with the AI chatbot interaction	5 Point Likert	Tax et al., (1998) Customer Evaluations of Service Complaint Experiences: Implications for Relationship Marketing.
Trust	I trust the information provided by the chatbot	5 Point Likert	Adapted from Kohn et al.,(2021). *Measurement of Trust in Automation: A Narrative Review and Reference Guide.*

Empathy	Compared to human agents, I feel that chatbot responses are less empathetic?	Multiple Choice	Adapted from Raamkumar and Yang, (2022), *Empathetic Conversational Systems: A Review of Current Advances, Gaps, and Opportunities.*
Transparency	I was clearly informed that I was interacting with an AI chatbot and not a human.	Multiple Choice	Adapted from Følstad and Brandtzæg (2020)

The instrument was pre-tested with a small sample (n=5) to ensure question clarity and logical flow before full deployment. Minor adjustments were made to wording to ensure accessibility for participants without technical knowledge. This structures approach ensured that questionnaire was content valid reliable, and capable of producing quantifiable insights aligned with the research hypotheses. The questionnaire was aligned with the study's hypotheses to ensure that each construct could be reliably measured and statistically tested.

4.5. Ethical Considerations

Ethical integrity was a central priority in the design and execution of this study. First, the current research was approved by the National college of Ireland Ethical committee. Second, No personally identifiable information or sensitive data was collected at any stage. Prior to participation, respondents were provided with a clear explanation of the study's purpose, ensuring informed consent. Participation was entirely voluntary, and individuals were free to withdraw at any point without consequence, consistent with ethical guidelines for voluntary participation (Saunders et al., 2019). To maintain anonymity, survey responses were recorded without any identifying markers. Access to the questionnaire was restricted to individuals with a valid email address to reduce the risk of duplicate submissions; however, no email data was stored or linked to responses. All research activities complied fully with the General Data Protection Regulation (GDPR) requirements applicable in Ireland and the wider European Union, ensuring that participant privacy, data confidentiality, and secure handling of information were upheld throughout the research process.

4.6. Validity and Reliability

Survey research is often subject to missing data or inconsistent responses, and sample bias (Quilan, 2011), in this study, the initial dataset consisted of 91 responses; however, to ensure validity, cases were filtered according to the study's scope. Specially, 46 respondents answered "No" to the question 'Have you ever interacted with an AI-powered chatbot on Amazon Marketplace Ireland? (Q2). These cases were excludes, as they did not meet the inclusion criteria for analysis. Three additional cases were removed due to incomplete data, resulting in a final sample size of 42 respondents (See table 2). To assess the internal consistency of the scale based items used in the questionnaire, Cronbach's Alpha was applied. This statistical test measures the degree to which items within a scale are correlated, with higher coefficients indicating stronger reliability (Heale and Twycross, 2015). This test is particularly suited to Likert-scale data, where responses are ordinal responses are treated as interval data for statistical purpose and analysis. In this present study, the questionnaire included 21 items, with nine variables groups assess constructs of satisfaction and trust, empathy, transparency, concerned, and fairness.

Table 2: Below Summarises Final Sample according to Criteria Analysis.

Case Processing Summary			
		N	%
Cases	Valid	42	93.3
	Excluded	3	6.7
	Total	45	100

4.6.1. Validity and reliability of Satisfaction.

The satisfaction construct was measured using eight items. Cronbach's Alpha for this set was 0.617 (See table 3), indicating an acceptable but moderate level of internal consistency. While values above 0.7 are generally considered satisfactory (Saunders et al., 2019), scales in exploratory research may yield lower coefficients yet still provide useful insights, particularly when dealing with small samples or complex constructs. Comparable findings have been reported in prior research on customer satisfaction with chatbot interactions. For example, Yun, J. and Park, J. (2022) in their study on The Effects of chatbot Service Recovery with Emotion words on Customer Satisfaction, reported alpha values in the 0.862-0.854 range when measuring satisfaction. Although these values are higher than those obtained in the present study, the difference can be attribute to factors such as sample size, measurement context, and scale refinement. Taken together, this comparison supports the credibility of the satisfaction measurement instrument used here, while acknowledging its moderate reliability level in an exploratory research setting.

Table 3: Reliability of Satisfaction.

Reliability Statistics (Satisfaction)	
Cronbach's Alpha	N of Items
0.617	8

4.6.2. Validity and reliability of Trust.

The construct of trust in chatbot interactions was operationalised through five survey items designed to capture participants' perception of the reliability, integrity, and competence of AI-powered customer service systems. The internal consistency of these items was evaluated using Cronbach's Alpha, which produced a coefficient of 0.877 (See Table 4) considered “good” and reflects a high degree of reliability, indicating that the items within the trust construct are strongly correlated and consistency measure the intended latent variable. The robustness of the scale is further supported by comparable findings in previous literature. For example, McLean and Osei-Frimpong (2019), in their investigation of trust in online live chat service, reported reliability coefficients exceeding 0.85 when measuring similar constructs, underscoring the methodological of the approach adopted in this study. The high alpha coefficient achieved here suggest that the trust measure can be considered both stable and dependable for assessing user perceptions in the context of AI chatbot interactions on the Amazon Marketplace Ireland. This reliability is essential for ensuring that subsequent statistical analyses such as regression model and mediation testing are based on measures that accurately reflect participant’ true attitudes, thereby strengthening the validity of any inferences drawn from the data.

Table 4: Below Reliability of Trust.

Reliability Statistics (Trust)	
Cronbach’s Alpha	N of Items
0.877	5

The results demonstrate that the survey instrument achieved a high degree of internal consistency for the trust construct and an acceptable level for satisfaction, consistent with findings in related literature. This supports the reliability of the measures used to address the study’s objectives. In the following chapter, the research questions and hypotheses will be examined through statistical analysis. This will include the application of linear regression, correlation analysis, and a mediation model to assess the relationship between key variables and test the proposed conceptual framework.

Chapter 5: Analysis of the Results and Main Findings.

5.1. Introduction

This chapter presents the analysis of the empirical data collected for this present study and discusses the main findings in relation to the research questions and hypotheses. The purpose is to provide a detailed examination of how AI chatbot interactions on Amazon Marketplace Ireland influence customer trust, satisfaction, and perception of empathy, transparency, concerned and fairness. The dataset was obtained through a self-administered online questionnaire distributed to residents in Ireland, resulting in 91 responses, of which 42 were eligible for analysis after filtering. Following a deductive, quantitative, cross-sectional design, the analysis combines descriptive and inferential statistics to test the hypotheses developed in Chapter 3. This chapter is structure as follows: section 5.2 reports descriptive statistics of the sample and variables, section 5.3 reports the inferential statistics which analyses results for each research question and hypotheses, section 5.4 offers an integral interpretation of the findings in light of existing literature.

5.2. Descriptive Statistic

Descriptive statistics were calculated for all variables included in the final dataset (N=42) to provide an overview of participant characteristics and patterns of Amazon Marketplace Ireland usage. The demographic profile compromised both categorical variable (gender, shopping frequency) and continuous variable (age). The mean (M) age of participants was 33.53, with ages ranging from a minimum of 18 to a maximum of 50 years. In terms of gender distribution, the majority of respondent were female (80%, n=36), while 20% (n=9) were male. Regarding shopping frequency on Amazon Marketplace Ireland, 8.9% (n=4) reported using the platform weekly, 31.1% (n=14) reported monthly use, and 60.0% (n=27) indicated they shop rarely (See Table 5). With respect to prior chatbot experience, a filtering question determined whether participants had interacted with an AI-powered chatbot on Amazon Marketplace Ireland. Of the total sample, 31.1% reported monthly use of Amazon but did not necessarily engage frequently with chatbots, while 27 respondent 60% indicated rare use of the platform, which corresponded to fewer chatbot interactions. This distribution reflects a predominantly occasional user base, consistent with patterns observed in other European E-commerce adoption studies (Hajli et al., 2017; Luo et al., 2019). These descriptive insights provide important context for subsequence inferential analysis, as both demographic characteristics and usage frequency are likely to influence trust and satisfaction in AI chatbot interactions (McLean and Osei-Frimpong, 2019).

Table 5: Frequency of Amazon Marketplace Ireland Usage.

Frequency	N	%
Weekly	4	8.9
Monthly	14	31.1
Rarely	27	60
Total	45	100

5.3. Inferential Statistics Results

Inferential statistical analyses were conducted to examine the relationships differences, and predictive effects between the key constructs of this study, namely satisfaction, trust, empathy, transparency, fairness, and concern. The primary objective was to test the research hypotheses and determine whether the observe patterns in the sample could be generalised to the broader population of Amazon Marketplace Ireland user. While descriptive statistics provide an overview of the data, they do not permit statistical generalisation (Saunders et al, 2019). Inferential statistics were therefore essential, as they allow for the assessment of relationship and the testing of theoretical prediction derived from the literature review. This approach aligns with the study's deductive, positivism orientations, whereby hypotheses are derived from prior research and then empirically tests. A hierarchical multiple regression framework was employed to examine the predictors of Satisfaction and Trust, while ANOVA test were used to assess if the nature of the query and other categorical factors significantly influenced these outcomes, as well as a Mediation Model 4 and Spearman's rho analysis.

5.3.1. RQ1- / H1: Customers with high concern over data privacy are less likely to trust chatbot systems.

The first hypothesis aimed to examine whether heightened concern over data privacy negatively influences trust in AI powered chatbots on Amazon Marketplace Ireland. This directly addressed Sub-question 1, which sought to identify factors that contribute to, or interfere with, customer's willingness to rely on AI chatbots. While trust can be shaped by multiple elements such as clarity of responses, consistency of communication, and perceived fairness, this hypothesis, focused specially on the role of data privacy concerns as a potential barrier to trust formation.

Variable and Measurement

Two variables were used to test this hypothesis, first concern which was measured through a single item ('I am concerned about how my data is used during chatbot interactions"), assessed on a 5-point Likert scale (1=strongly disagree to 5= strongly agree). Trust was measured through a composite score of five Likert scale items capturing perception of chatbot reliability, honestly, and credibility. The use of Likert scales in consistent with established approaches in trust and privacy research (McLean and Osei-Frimpong, 2019; Glikson and Woolley, 2020).

Statistical Test Applied and Results

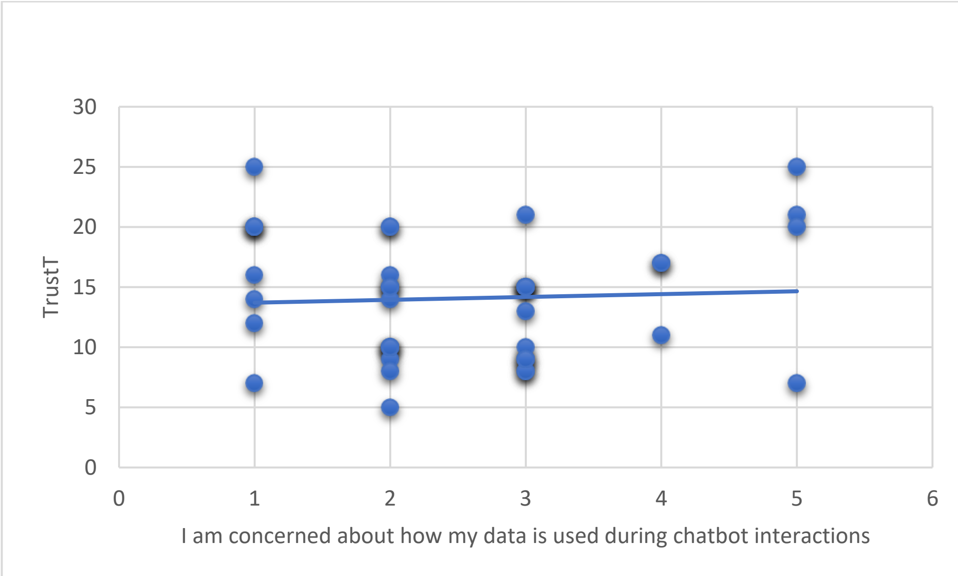
Given that preliminary normality checks indicated non-normal data distribution for at least one of the variables, Spearman's rho correlation was used. This non-parametric test is appropriate for ordinal data and detecting monotonic relationship without assuming normality (Field, 2018). The Spearman's rho analysis revealed a negligible and non-significant association between privacy concern and trust ($r_s = –0.007$, $p = .965$, $N = 42$)(See Table 6). This suggests that in this sample, participants' levels of concern over data use did not meaningfully correlate with their trust in AI chatbots systems. The lack of statistical significance means H1is not supported. This finding also has implication for H3 (trust as a mediator between empathy and satisfaction), as it suggests that privacy concern may not be a relevant antecedent in the mediation model for this context.

Table 6: Spearman's rho- H1

Correlations			TrustT	I am concerned about how my data is used during chatbot interactions
Spearman's rho	TrustT	Correlation Coefficient	1	-0.007
		Sig. (2-tailed)		0.965
		N	42	42
	I am concerned about how my data is used during chatbot interactions	Correlation Coefficient	-0.007	1
		Sig. (2-tailed)	0.965	
		N	42	43

Additionally, in the figure 2 below presents a scatter plot examining the relationship between participant's level of concern regarding data privacy during chatbot interaction and their reported trust in AI chatbot systems. Each point represents and individual respondent, with the horizontal axis indicating their agreement level with the statement "I am concerned about how my data is used during chatbot interaction", and the vertical axis showing their aggregated trust score. Visually, the data points are widely dispersed across the trust scale for each level of privacy concern, with no clear clustering pattern (Field, 2018; Hayes, 2017). The fitted trendline exhibits a slight positive slop, suggesting a marginal increase in trust scores as privacy concern increases. However, the slope is almost flat, indicating that the association between the two variables is extremely weak.

Figure 2: Scatterplot Illustrating Trust- Data Privacy Concern Correlation



5.3.2 Hierarchical Regression for Trust

A hierarchical regression was conducted to predict Trust based on the next constructs: demographic, usage, and perception- based predictors, this will help to address and support Q1/H1 and verify results from Section 5.3.1. Three models were tested, progressively, Model 1 included only demographic variable (Age, Gender) and explained 4.3% of the variance in Trust ($R^2 = 0.043$, F=0.805, $p > 0.045$), indicating no significant predictive power. In Model 2 (adding shopping frequency) did not improve the model significantly report 4.3% ($R^2 = 0.043$, F=0.529, $p > .0666$), suggesting that frequency of use alone does not explain variance in Trust. And model 3 (adding fairness, empathy, frustration, and data concern) alone side the previous predictors, substantially increased the explained variance to 43.2% ($R^2 = 0.432$, $\Delta R^2 = 0.389$, F= 3.364, $p < 0.009$), while empathy, frustration, and data concern are non-significant, perceived fairness emerged as the only significant predictor ($\beta = 0.560$, $t = 4.083$, $p < 0.001$), indicating that perceptions of fairness in chatbot responses strongly enhance trust. The ANOVA for Trust, Model 3 was also significant as it happen in satisfaction ANOVA ($F(7,31) = 3.364$, $p = 0.009$)(See Appendix 3), again highlighting the importance of these perception- based predictors. Port-hoc comparisons revealed that the strongest mean differences in both Trust and Satisfaction were linked to fairness perceptions (Field, 2018). These results indicate that H1 is not supported, as concern over data privacy did not significantly predict Trust, instead fairness emerged as the dominant determinant of Trust, suggesting that procedural and distributive justice perceptions may outweigh privacy concerns in shaping trust in AI chatbots.

Table 10: Model Summary Trust

	Model 1					Model 2					Model 3				
Variables	**B**	**SE**	**β**	**t**	**Sig.**	**B**	**SE**	**β**	**t**	**Sig.**	**B**	**SE**	**β**	**t**	**Sig.**
Constant	19.888	5.792		3.434	0.002	19.328	7.151		2.703	0.011	15.911	6.893		2.308	0.028
Age	-0.08	0.13	-0.107	-0.619	0.54	-0.08	0.132	-0.107	-0.611	0.545	-0.093	0.109	-0.125	-0.86	0.396
Gender	-2.608	2.082	-0.217	-1.253	0.218	-2.642	2.125	-0.22	-1.243	0.222	-2.639	1.849	-0.22	-1.428	0.163
Frequency						0.171	1.248	0.023	0.137	0.892	-0.001	1.034	0	-0.001	0.999
Fairness											2.385	0.584	0.56	4.083	<.001
Empathy											-1.414	0.906	-0.224	-1.559	0.129
Frustration											-0.694	1.059	-0.093	-0.656	0.517
Data Concern											0.572	0.635	0.135	0.9	0.375
R^2	0.043					0.043					0.432				
Sig.(ANOVA)	0.455					0.666					0.009				
F	0.805					0.529					3.364				
ΔR^2						0					0.389				

5.3.3. RQ2/ H2- Customer satisfaction with chatbot agent interactions significantly differs depending on the nature of the service query.

This hypothesis aimed to assess whether customer satisfaction with Amazon Marketplace Ireland's chatbot interactions varies according to the nature of the service query. The underlying assumption, based on prior literature (McLean and Osei-Frimpong, 2019; Følstad and Brandtzæg, 2020), is that different query types such as simple information question, order issues, complaints/returns, or other request may get varying levels of satisfaction depending on the chatbot's ability to resolve the matter efficiently, communicate understanding, and maintain a pleasant interaction.

Variables and Measurement

Two key variables were used, the first, issue type, was a single categorical variable asking "What type of issue did you contact the chatbot for?" with four responses categories, general question, order issue, complaint/return, and other. Then, satisfaction Total (SatT), and aggregate score derived from eight Likert-scale items (1=strongly disagree to 5=strongly agree) measuring overall satisfaction, perceived resolution, ease of use, and emotional response to the chatbot. Higher scores indicate greater satisfaction. Both variables were measure using self-reported responses from the online questionnaire. Given the combination of a multi-categorical independent variable and a continuous dependent variable, a one-way ANOVA was selected to test for mean differences in satisfaction across the four query types.

Statistical Test Applied and Results

Prior to running the ANOVA, test of normality (Kolmogorov–Smirnov and Shapiro–Wilk) (See Appendix 4) were conducted for each group. Results indicated that for General Question, Order Issues, and Complaint/Return categories, the p-values exceeded 0.05, suggesting no violation of normality, the "other category had few cases (n=2) for a reliable normality assessment. Homogeneity of variances was assessed implicitly through ANOVA robustness to mild violations, given balanced group sizes except for "Other". The ANOVA was deemed appropriate as assumptions were broadly met, and the dependent variable was measured at an interval level. Descriptive statistics show relatively close mean satisfaction scores across the four categories (See Table 7).

Table 7: H2 Descriptive Statistics

Category	Mean (M)	Standard Deviation (SD)	Sample Size (n)
General Questions	25.05	10.14	22
Order Issues	24.36	5.33	14
Complaint/Return	23.4	4.78	5
Other	22	11.31	2

The one-way ANOVA found no statistically significant differences in satisfaction between groups: $F(3,39)= 0.120$, $p=0.948$(See Appendix 5). Effect size estimates were negligible ($\eta^2 = 0.009$) (See Appendix 6), suggesting that issues type explains less than 1% of the variance in satisfaction. The lack of significant differences suggest that, in this sample, customer satisfaction with chatbot interactions is relatively consistent across different service contexts. This findings does not support H2, which predicted variation based on query type.

5.3.4. Hierarchical Regression for Satisfaction

A hierarchical multiple regression analysis was performed to examine the predictors of customer Satisfaction with Amazon Marketplace Ireland's chatbot interactions, addressing and confirming RQ2/H2 results from Section 5.3. It was addressed based on the next constructs: demographic, usage, and perception. Model 1 which included demographic variables (age and gender), explaining only 4.6% of the variance in satisfaction ($R^2 = .046$, $p > .05$), indicating no significant predictive power. In Model 2 it was additionally added, shopping frequency, significantly improved model fit, accounting for 28.0% of the variance ($R^2 = .28$, $p < .07$), shopping frequency emerger as a significant negative predictors ($\beta = -0.49$, $t = -3.418$, $p = .002$), suggesting that customers who shop more frequently on Amazon tend to report lower satisfaction with chatbot interaction.

Model 3 which included fairness, empathy, frustration, and data concern, raising the explained variance to 40.2% ($R^2 = .402$, $p < .014$). In the final model, perceived fairness emerged as a statistically significant positive predictor ($\beta = .336$, $t = 2.417$, $p = .022$), indicating that customers who view chatbot responses as fair tend to report higher satisfaction, the effects of empathy, frustration, and data concern remained non-significant. The ANOVA for Model 3 confirms that the set of predictors was statistically significant $F(7, 32)$(See Appendix 2) $= 3.069$, $p = .014$. This highlights the importance of procedural fairness in shaping positive customer evaluation, even more so than emotional or privacy related consideration. These findings partially support H2 by showing that variation in satisfaction is inked to certain interaction features particularly fairness and usage frequency although not direct to the query type as initially hypothesised.

Table 9: Model Summary Satisfaction

	Model 1					Model 2					Model 3				
Variables	**B**	**SE**	**β**	**t**	**Sig.**	**B**	**SE**	**β**	**t**	**Sig.**	**B**	**SE**	**β**	**t**	**Sig.**
Constant	34.845	9.102		3.828	<.001	53.631	9.721		5.517	<.001	49.4	11.33		4.359	<.001
Age	-0.146	0.206	-0.12	-0.709	0.483	-0.132	0.181	-0.11	-0.728	0.471	-0.14	0.177	-0.12	-0.8	0.432
Gender	-4.355	3.335	-0.221	-1.306	0.2	-2.998	2.964	-0.15	-1.011	0.319	-2.09	3.027	-0.11	-0.69	0.495
Frequency						-5.974	1.748	-0.49	-3.418	0.002	-5.94	1.709	-0.49	-3.47	0.001
Fairness											2.327	0.963	0.336	2.417	0.022
Empathy											-0.6	1.507	-0.06	-0.4	0.694
Frustration											-0.86	1.76	-0.07	-0.49	0.63
Data Concern											-0.27	1.036	-0.04	-0.26	0.799
R^2	0.046					0.28					0.402				
Sig.(ANOVA)	0.416					0.07					0.014				
F	0.899					4.667					3.069				
ΔR^2						0.234					0.122				

5.3.5. RQ3/ H3- Trust mediates the relationship between perceived empathy and overall satisfaction with AI chatbots interactions.

This hypotheses aimed to examined whether trust serves as a mediating variable in the relationship between perceived empathy and overall satisfaction with AI chatbot interactions on Amazon Marketplace Ireland. The underlying rationale, as outlined in Sub-question 3, was to assess if the absence of human interaction diminished perceptions of empathy, and if such perceptions influences satisfaction indirectly through trust.

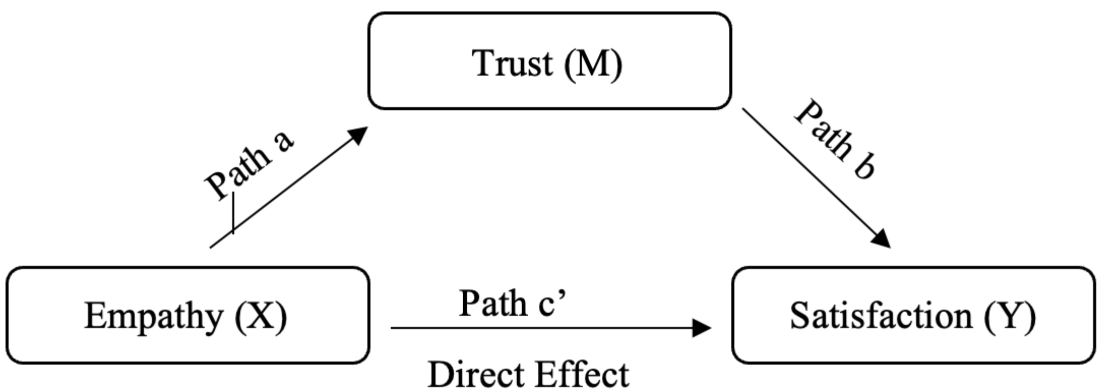
Variables and Measurement

Three constructs were included in the analysis, empathy, measured through a single Likert-scale item ("compared to human agents, I feel that chatbot responses are less empathetic"), reverse-coded so that higher scores indicated greater perceived empathy. Trust, measured as a composite score of five Likert-scale items capturing perceived reliability, honesty, and credibility of the chatbot system. And Satisfaction, measured through a compound score of eight Likert-scale items reflecting perceived service quality, effectiveness in resolving issues, and overall pleasantness of interaction. All items were measured on a 5-point Likert-scale (1=strongly disagree, 5=strongly agree). Compound scores for trust and satisfaction demonstrated strong internal consistency (Cronbach's alpha > 0.85), indicating reliability for further inferential testing.

Statistical Test Applied and Results

To test the mediation hypothesis, a simple mediation analysis (Model 4) was conducted using Andrew F. Hayes (2017, 2022) PROCESS macro for IBM SPSS Statistics- version 29.0.2.0, this approach was selected because it allows for the estimation of direct, indirect, and total effects of perceived on satisfaction, while accounting for trust as a mediator (Hayes, 2022). The mediation analysis was performed to investigate whether there was significant direct effect of Empathy(X) on Satisfaction(Y), having mediated for Trust(M) (See Figure 2). The method applies bootstrapping (5, 000 resamples) (See Appendix 7) which generates bias-corrected 95% to estimate the bias-corrected confidence intervals (CIs) for the indirect effect, which is recommended when the sampling distribution is unknown or when normality assumptions are not met.

Figure 2: Illustrative graph of mediation pathways.



The mediation analysis did not support H3. As shown in table 8, the effect of empathy on trust (path a) was negative and not statistically significant (β= -0.622, SE=0.9847, p= 0.531, 95% CI [−2.6122, 1.3683]), indicating that empathy perceptions did not reliably predict trust levels. Conversely, the path from Trust significantly predicted satisfaction (path b: β= 0.562, SE= 0.2318, p= 0.020, 95% CI [0.0935, 1.0314]), indicating that higher trust was associated with higher satisfaction. Neither the total effect (path c: β = 0.2195, p = 0.8866) nor the direct effect (path c': β = 0.5693, p = 0.6969) of the empathy on satisfaction were significant. The indirect effect (a x b= -0.350, SE=0.6162, 95% CI [-1.677, 0.9336]) included zero, indicating that trust did not mediate the Empathy- Satisfaction relationship in this dataset. These results suggests that, empathy does not exert a measurable influence on satisfaction either directly or indirectly through trust. Full PROCESS Model 4 Matrix can be found in Appendix 7.

Table 8: Summary Table Mediation Model 4 Results

Summary Table Mediation Model 4 Results						
Path	β	SE	p-value	95% CI Lower	95% CI Upper	Significance
a (Empathy→ Trust)	-0.622	0.9847	0.5312	-2.6122	1. 3683	Not Significant
b (Trust→ Satisfaction)	0.5624	0.2318	0.02	0.0935	1.0314	Not Significant
c (Total effect Empathy→ Satisfaction)	0.2195	1.5295	0.8866	-2.8718	3.3109	Not Significant
c' (Direct effect Empathy→ Satisfaction controlling for Trust)	0.5693	1.4511	0.6969	-2.3658	3.5044	Not significant
Indirect effect (a x b)	-0.3498	0.6162	0.5702	-1.6771	0.9355	Not Significant

5.4. Overall Summary

This section synthesises the statistical results represented in Section 5.3 and 5.4. .The Interpretation is structured according to the study three hypotheses (H1-H3), highlighting key statistical findings and the general patterns that emerged. The purpose is to integrate the findings into a coherent understanding of how AI chatbots interactions on Amazon Marketplace Ireland influence customer trust and satisfaction. The purpose of the current research was to investigate the relationship between customer perceptions of AI chatbot interactions and two central outcomes trust and satisfaction, while considering the potential influence of empathy, fairness, privacy concerns, and query type.

5.4.1. Key Findings

The H1 proposed that higher privacy concerns would be associated with lower levels of trust in chatbot systems. This hypothesis was not supported. Both correlation and regression analyses showed no statistically significant relationship between concern over data use and trust levels. These suggest that privacy concerns are not meaningful determinant of trust in this context, possibly indicating that users feel sufficiently protected by Amazon's compliance with privacy regulations such as GDPR. H2 proposed that satisfaction with chatbot interactions would vary depending on the nature of the service query. This hypothesis was not supported, as one-way ANOVA results indicated no significant differences in satisfaction across the four query types: general question, order issues, complaints/returns, or other requests. Satisfaction scores were relatively consistent across these categories, suggesting that the chatbot's performance is perceived similarly regardless of the interaction's context. Although small sample sizes in certain categories (especially "Other") may have limited the statistical power to detect differences.

H3 tested whether trust mediates the relationship between perceived empathy and overall satisfaction. Mediation analysis (PROCESS Model 4) found no evidence of mediation, as empathy did not significantly predict trust, and the indirect effect was not statistically significant (Hayes, 2017). While trust did significantly predict satisfaction, the indirect effect (Empathy- Satisfaction) mentioned before did not predict satisfaction either. The results indicate that, empathy's lack of predictive power and it does not play a substantial role in shaping trust or satisfaction in this dataset. Across all analyses, perceived fairness emerged as the most consistent and robust predictor, significantly influencing both trust and satisfaction. In the hierarchical regression models, fairness was the only variable to significantly and positively predict both outcomes, underscoring its importance in customer evaluations of chatbot interactions.

In contrast, empathy and privacy concerns did not have significant effects in any tested model, and shopping frequency was negatively associated with satisfaction, suggesting that mores limitations in chatbot service. Overall, the evidence indicates that customer perceptions of fairness encompassing transparency is central to positive evaluations of AI chatbot interactions on Amazon Marketplace Ireland. Other relation attributes, such as empathy, appear less influential in this context, and privacy concerns do not significantly shape trust levels.

Chapter 6: Discussion

This chapter provides a reflective and critical evaluation of the current study's findings on how AI chatbot interactions on Amazon Marketplace Ireland influence customer trust and satisfaction, focusing on the roles of privacy concern, query type, empathy, and fairness. Drawing on the statistical analyses from Chapter 5, it explores in the Section 6.1, Result interpretation, Section 6.2 implications of the findings for theory and practice, with explicit reference to study's hypotheses. In Section 6. 3 study's strengths, and how they support the evidential value of the results. In Section 6.4 opportunities for future research that logically follow from the data and acknowledges in Section 6.5 the limitations transparently. The discussion aims to integrate empirical evidences with broader theoretical and practical considerations.

6.1. Results interpretation

This section explains what the statistical findings mean for the study's core question of How AI chatbot interactions on Amazon Marketplace Ireland shape trust and satisfaction and links the results to the study's conceptual lenses (Human-Computer trust, institution based trust, and service quality justice perspectives). It then situates the evidence against prior research, offering critical explanations for convergence and divergence, and proposes plausible social, contextual and methodological cause.

6.1. 1. Interpreting the findings against theory and hypotheses

Taken together, the result point to a service justice pathway rather than purely relational (empathy driven) pathway. Across models, perceived fairness was a core element of procedural and distributive justice consistently predicted both trust and satisfaction, whereas empathy and privacy concern did not show significant effects. This pattern aligns with trust frameworks that distinguish what the systems does (competence, consistency, rule application) from how it feel (warmth, social presence). In the human- computer trust tradition and institution based trust, the current evidence suggest that competence and integrity cues in a transactional marketplace context (Kohn, 2021; McKnight et al., 2011). Accordingly, H1 (higher privacy =concern lower trust) was not supported, H2 (satisfaction differs by query type) was not supported, and H3 (trust mediates empathy and satisfaction) was not supported. The absence of mediation further indicates that, in this setting, empathy does not create satisfaction via trust; instead, users appear to form trust and satisfaction judgements primarily from cues about equity, clarity, and consistency.

6.1.2. Comparison with prior studies

Two contrasts stand out. First, prior E-commerce work often reports that privacy risk depresses trust (Beldad et al., 2010; Eastlick et al., 2006). Here, privacy concern showed no association with trust. A defensible explanation is contextual, in Ireland GDPR governed environment and on a platform with strong brand assurance, privacy may be treated as table stakes rather that a differentiator; user weigh process transparency and fairness more heavily than additional privacy rhetoric (Glikson and Woolley, 2020; Wang and Siau, 2019). Second, studies of chatbot experience often find lower satisfaction for complex or emotionally charge issues, where bots struggle to display empathy or flexibility (Følstad and Brandtzæg, 2020; Chaves and Gerosa, 2021). In our data, satisfaction did not differ by query type. Two readings are admitted, first Amazon patterns, response templates and predictable escalation afford a uniform service and second, statistical power was limited due to smaller cells muting detectable differences. By contrast, our finding that fairness reliability predicts trust and satisfaction is consistent with research showing that procedural justice and explainability foster reliance on automated agents, particularly when users must accept policy bound outcomes (McLean and Osei-Frimpong, 2019; Glikson and Woolley, 2020).

6.1.3. What this means for the research Question

For Amazon Marketplace Ireland, the data indicate that customer appraise chatbot interactions through a justice and competence lens more than a relational warmth lens. Trust and satisfaction are shaped chiefly by whether processes feel fair, consistent, and well explained; neither general privacy worry nor perceived empathy meaning fully shifts these outcomes in this sample. This answers the research question by specifying which attributes of chatbots communication matter most locally and how they influence outcomes, improving procedural fairness and transparency is the most credible route to stronger trust and higher satisfaction.

6.2. Implications

Revisiting Privacy-Trust Assumptions (H1)

The findings offer several implications for both academic research and practice in AI mediated customer service. From a theoretical perspective, this study challenges some long held assumptions regarding the determinants of trust in digital environments. For instance, H1 showed that privacy concern was not significantly related to trust contradicting earlier findings by Beldad et al (2010) and Eastlick et al (2006) , who identified privacy risk as a key inhibitor of trust in online systems. The current study found no significant relationship between data privacy concerns and trust in chatbots, participants did not appear to translate their concerns over data use into lower trust in AI chatbots. A explanation may be contextual: Irish Amazon users may view Amazon's data handling as trustworthy due to stringent EU data protection laws (GDPR), reducing the salience of privacy as a determinant of trust. This interpretation aligns with the argument of Glikson and Woolley (2020) who argue that trust in AI can be shaped by institutional safeguards rather than solely by user perceptions. In this context, alternatively, trust may be shaped more strongly by functional and service related factors, such as fairness and responsiveness, which other parts of the present study found to be significant predictors in Section 5.

Toward a Service-Quality view of satisfaction (H2)

The second hypotheses proposed that Satisfaction would differ by query type (general questions, order issues, complaints/returns, other). The one-way ANOVA found no significant differences, indicating a relatively uniform satisfaction profile across service context. The absence of significant variation in satisfaction across different query types (H2) also diverges from earlier studies Følstad and Brandtzæg (2020) and Chaves and Gerosa (2021), they suggest that more complex or emotionally charged issues tend to yield poorer chatbot experiences partly due to empathy and flexibility limitations. Two interpretations are credible. First, Amazon's ability to deliver a consistent service standard across interaction types, or cultural and platform specific factors that attenuate such differences. Second, user expectation management through consistent patterns, clear escalation cues, and predictable response formats may equalise satisfaction even when the underlying task complexity varies. Put differently, satisfaction in this context appears less about the category of the problem and more about how fairly and efficiently the interaction is handle (See Chapter 5). Additionally, the small sample size for certain categories (particularly "Other" and "Complaint/Return") may have limited statistical power to detect meaningful differences and suggesting caution in generalising this finding.

Trust as a Pathway from relational to outcome variables? (H3)

The third hypothesis tested whether trust mediates the link between perceived empathy and satisfaction. The mediation analysis (H3) further revealed that while trust significantly predicts satisfaction, empathy did not exert a meaningful direct or indirect effect. This contrasts with studies such as Cai et al., (2024), who reports that relational empathic cues can influence satisfaction, sometimes via trust, in chatbot or service recovery settings. The results in the current study suggests that in this case, relational cues like empathy are less influential than fairness related perceptions. This could indicate that for task oriented platforms like Amazon Marketplace, functional justice and transparency outweigh interpersonal qualities in shaping user evaluations. Overall, these findings contribute to the literature emphasising fairness as a dominant driver to trust and satisfaction in E-commerce chatbot interactions, while questioning the generalisability of empathy and privacy concern effects observed in prior research.

Fairness as a Cross-Cutting Construct

From practical standpoint, the results highlights perceived fairness as the most powerful driver of both trust and satisfaction (See Chapter 5). This implies that organisations should prioritise procedural and distributive justice in chatbot interactions. Transparency in decision making, consistent application of policies, and equitable treatment of customers appear to carry more weight that affective cues such as empathy. While relational warmth may still play a role in certain high stakes service contexts, the findings suggest that in fast-paced transactional settings like Amazon Marketplace, efficiency and fairness dominate customer evaluations. Furthermore, the lack of mediation between empathy and satisfaction via trust suggest that investments in simulating human like emotional responses may yield limited returns in such environments. Instead, resources may be better directed toward optimising accuracy, response time, and procedural clarity.

6.3. Strengths

The current research offers several methodological and conceptual strengths, including the simultaneous examination of multiple hypotheses relationship (H1-H3) within a unified analytical framework, offering a comprehensive view of the factors influencing trust and satisfaction. The integration of diverse analytical techniques such as descriptive statistics, regression analysis, ANOVA, and mediation modelling (PROCESS Model 4), they enabled robust triangulation of results and deeper insights into the data structure. This strength claim that fairness not empathy or privacy concern was the most reliable predictors, because the signal recurred across distinct models with different assumptions. Each hypothesis was transparently operationalised with measurable constructs, privacy concern (H1), query type (H2), and empathy, trust, and satisfaction (H3), allowing direct tests of theory. By focusing on Amazon Marketplace Ireland adds contextual relevance by addressing the under-researched intersection of AI chatbot interactions, E-commerce, and European regulatory environments. Moreover, the study's identification of fairness as a core driver of both trust and satisfaction provides a valuable contribution to academic discourse while offering practical guidance for managerial decision- making.

Equally, the current study's emphasis on justice related variables proved well judged, fairness emerged as a robust predictor across specifications, indicating the instrument captures a meaningful dimension of user evaluation. Methodological clarity and replicability using well documented procedures (PROCESS with bootstrap CIs) and reporting diagnostics in chapter 5 enhance the cumulative value of the findings. Notably, the discussion accepts non-support for H1-H3 where appropriate and advances theory consistent explanation rather than stretching the data, evidencing scholarly reflexivity. Because the models were coherently specified and controlled, the null results are informative rather than inconclusive, and the consistent positive pattern of fairness as a determinant of trust and satisfaction will merit integration into theory and managerial practice.

6.4. Future Directions

While this study provide valuable insights into the factors influencing trust and satisfaction in AI chatbot interaction, several avenues remain open for future research. Future work should strengthen power, balance, and design precision. Expanding the sample size and ensuring greater diversity among respondents would enhance generalisability and improve statistical power, particularly for underrepresented query categories such as “Complaint/ Return” and “Oher”. Longitudinal research could further explore how repeated interactions with chatbots shape trust and satisfaction over time, capturing potential shifts in customer attitudes as familiarity increases. Additionally, comparative analyses across different E-commerce platforms (eBay, Shopify, Alibaba) and service sectors, such as banking or health, could determine whether fairness remains the dominant driver of perceptions in varied contexts. Employing mixed-methods approaches, such as qualitative interviews, would provide richer insights into how customers interpret fairness, empathy, and privacy in AI mediated service. Finally, integrating behavioural metrics such as resolution rates, repeat usage, or escalation patterns alongside self-reported measures would offer a more objective and comprehensive assessment of chatbot effectiveness. Additionally, research should examine heterogeneity of effects and operational mechanisms. Moderation analyses can assess whether usage intensity, digital literacy, or age alter the impact of fairness and trust on satisfaction, helping identify segments that experiment scripted interactions and rigid or opaque.

6.5. Limitations

The study offers useful insights but several limitations temper the inferences that can be drawn. First, the final analytic sample of 42(after excluding non-users of Amazon’ chatbot) is modest; small cell size in some issue type categories (Complaint/ Return, Other) reduce statistical power and the precision of estimates, particularly for H2, and warrant cation when generalising effect size (Field, 2018; Saunder et al., 2019). The relatively short fieldwork window also restricted recruitment, further limiting coverage of rarer query types. Second, the cross-section design captures associations at a single point in time, so causality cannot be inferred for example, higher trust might elevate perceived fairness rather than the reverse, or both could reflect unmeasured factors (brand attitudes, prior satisfaction with Amazon). Third, the current study relies on self-reported perceptions, which are susceptible to common method variance, social desirability, and recall bias. Although Chapter 5 reported acceptable internal consistency for multi-item composites (trust and satisfaction), some constructs most notably privacy concern, measured with a single item are inherently less reliable, which may attenuate observe relationship. In addition, construct operationalisation may not have captures sufficient breadth or granularity for relational attributes (empathy), where separating cognitive from affective component could yield greater sensitivity.

Forth, category imbalance likely reduced the statistical power of the ANOVA used to test H2, given the non-significant differences in satisfaction by issue type, subsequent mediation analyses did not include issue category as a covariate (Field, 2018). Nonetheless, the descriptive patterns remain informative and could guide qualitative follow-ups. Fifth, the platforms and regulation specific context Amazon Marketplace Ireland operating under GDPR means external validity is bounded; results may not transfer for less regulated markets, smaller platforms, or sectors with intrinsically higher data sensitivity (health, banking). Finally, mediation tests are power hungry, particularly when path coefficients are modest, the non-significant indirect effect in H3 may reflect a genuine absence of mediation and/or limited power (Hayes, 2017). Future research should address these constraints through larger, stratified samples to balance cells, longitudinal designs linked to behavioural endpoint (resolution rate, re-contacts) and multi-methos measurements (combining surveys with interaction logs) alongside refined, multi-item scales for constructs such as empathy and privacy concern.

Chapter 7: Main Conclusions

This thesis set out examine how AI driven chatbot interactions on Amazon Marketplace Ireland shape two foundational outcomes of service experience customer trust and customer satisfaction and to identify which attributes of the interaction are most consequential in highly regulated, platform setting. Motivated by mixed evidence in prior research and a clear gap in Irish, marketplace specific studies, the project tested three hypotheses concerning the effects of privacy concern, query type, and perceived empathy (with trust modelled as a mediator) on satisfaction. The empirical strategy combined descriptive analysis with hierarchical regression, a one-way ANOVA, and a mediation tests (PROCESS Model 4). After filtering for respondent who had actually engaged with Amazon's chatbot, the analytic sample compromised 42 participants. Across analyses, a coherent pattern emerged. First, perceived fairness capturing whether the chatbot seemed to apply rules consistently and explain decisions clearly was the most reliable predictor of both trust and satisfaction. This signal repeated across different model specifications and analytic lenses, indicating that justice appraisals (clarity, consistency) comminated how users evaluated chatbot encounters. Second, privacy concern showed no significant association with trust, leading to non- support H1.

In a GDPR context and on platform with strong brand assurances, privacy appears to function as "table stakes"; it is necessary but not differentiating for users' trust judgements. Third, satisfaction did not differ significantly by query type, so H2 was not supported. This could reflect either a genuinely uniform service standard across issues or limited statistical power for smaller categories. Forth, the mediation hypothesis (H3) was not supported, perceived empathy did not significantly predict trust, the indirect effect of empathy on satisfaction via trust was not significant, and the direct effect of empathy on satisfaction was also not significant, confirming its central role even though empathy did not feed into one of the models, suggesting that users maybe more sensitive to friction.

Across models, a single pattern was robust, perceived fairness which emerged as the strongest, most consistent predictor of both trust and satisfaction. Customers who felt that the chatbot handle queries even handedly, explained decision and applied policies consistently reported higher trust and greater satisfaction, even when empathy and privacy concern did not move the needle. Methodologically, the current study contributes an integrated analytic view of chatbot evaluations in an specific European marketplace (Amazon Marketplace Ireland), descriptive profiles, hierarchical regressions for trust and satisfaction, and ANOVA for issues-type differences, and a mediation test for empathy trust satisfaction pathway. Substantively the work qualifies general claims form broader E-commerce literatures by showing that in high assurance, platform governed environment, customers appear to weight fairness and process clarity more heavily than privacy concern.

In sum, the current research advances understanding of AI mediated customer service in a real world European marketplace. It shows that, Amazon Marketplace Ireland, trust and satisfaction are anchored less in privacy salience or simulated warmth than in perceived fairness, process transparency, and consistent escalation. It also add Irish evidence to a literature still dominated by larger markets, the study offers a practical blueprint, if platforms want automated agents to earn customer confidence, they should design for fairness and make decisions explainable, handovers predictable, and outcomes consistent. Under such conditions, chatbots can meet and sometimes exceed the standards customers bring to digital service, not by imitating human, but by being clear, fair, and reliable machines.

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Appendix

Appendix 1: Questionnaire Instrument

Question Number	Variable Name	Variable Description
	Age	Open-ended (respondent states age)
	Gender	○ Female ○ Male ○ Prefer not to say
1	How often do you shop on Amazon Marketplace Ireland?	○ Daily ○ Weekly ○ Monthly ○ Rarely ○ Never
2	Have you ever interacted with an AI-powered chatbot on Amazon Marketplace Ireland? If "Not Sure," please proceed to end of the survey	○ Yes ○ No ○ Not Sure
3	What type of issue did you contact the chatbot for?	○ General question (e.g., delivery times, product availability) ○ Order issue (e.g., tracking, delay) ○ Complaint or return ○ Other (please specify): ________
4	Overall satisfaction with the AI chatbot interaction	○ Strongly Agree ○ Agree ○ Neutral

		○ Disagree ○ Strongly Disagree
5	Provided responses that were helpful and met my needs	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
6	The chatbot's responses were timely	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
7	The chatbot understood my queries effectively	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
8	The language used was clear and easy to understand	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
9	I felt that the chatbot was empathetic to my concerns	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
10	It was able to handle my issue without escalation to human support	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree

		○ Strongly Disagree
11	The chatbot personalized the conversation based on my issue or previous interactions	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
12	I felt frustrated or anxious when communicating with the chatbot?	○ Yes ○ No ○ Unsure
13	Compared to human agents, I feel that chatbot responses are less empathetic?	○ Yes ○ No ○ Unsure
14	I trust the information provided by the chatbot	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
15	I feel confident in the chatbot's ability to assist me	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
16	The chatbot enhances my shopping experience on Amazon	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
17	I prefer using the chatbot over contacting human customer service for basic inquiries	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree

		○ Strongly Disagree
18	I would use the chatbot again for future inquires	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
19	I was clearly informed that I was interacting with an AI chatbot and not a human.	○ Yes ○ No ○ Not Sure
20	I am concerned about how my data us used during chatbot interactions	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree
21	I believe the chatbot is fair and unbiased in how it responds to customer queries	○ Strongly Agree ○ Agree ○ Neutral ○ Disagree ○ Strongly Disagree

Appendix 2: ANOVA Test for Satisfaction

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	125.108	2	62.554	0.899	.416[b]
	Residual	2573.67	37	69.559		
	Total	2698.78	39			
2	Regression	755.662	3	251.887	4.667	.007[c]
	Residual	1943.11	36	53.975		
	Total	2698.78	39			

3	Regression	1083.97	7	154.853	3.069	.014[d]
	Residual	1614.8	32	50.463		
	Total	2698.78	39			

Appendix 3: ANOVA Test for Trust

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	42.652	2	21.326	0.805	.455[b]
	Residual	953.348	36	26.482		
	Total	996	38			
2	Regression	43.166	3	14.389	0.529	.666[c]
	Residual	952.834	35	27.224		
	Total	996	38			
3	Regression	429.981	7	61.426	3.364	.009[d]
	Residual	566.019	31	18.259		
	Total	996	38			

Appendix 4: Normality Test H2

Tests of Normality

	What type of issue did you contact the chatbot for?	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
SatT	General question	0.144	22	.200*	0.958	22	0.447
	Order Issue	0.101	14	.200*	0.967	14	0.835
	Complint or Return	0.185	5	.200*	0.925	5	0.56
	Other	0.26	2	.			

Appendix 5: One-way ANOVA Analysis for H2

ANOVA

SatT

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	25.375	3	8.458	0.12	0.948
Within Groups	2749.369	39	70.497		
Total	2774.744	42			

Appendix 6: ANOVA Effect Size for H2

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
SatT	Eta-squared	0.009	0	0.036
	Epsilon-squared	-0.067	-0.077	-0.038
	Omega-squared Fixed-effect	-0.065	-0.075	-0.038
	Omega-squared Random-effect	-0.021	-0.024	-0.012

Appendix 7: PROCESS Model 4 Matrix (Completed)

Run MATRIX procedure: Mediation Model 4

```
**************** PROCESS Procedure for SPSS Version 4.3.1 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
```

Model : 4
Y : SatT
X : Emp
M : TrustT

Sample
Size: 42

Custom
Seed: 31216

****
OUTCOME VARIABLE:
TrustT

Model Summary

R	R-sq	MSE	F	df1	df2	p
.0994	.0099	26.5053	.3989	1.0000	40.0000	.5312

Model

	coeff	se	t	p	LLCI	ULCI
constant	15.1080	1.8234	8.2857	.0000	11.4228	18.7932
Emp	-.6220	.9847	-.6316	.5312	-2.6122	1.3683

****
OUTCOME VARIABLE:
SatT

Model Summary

R	R-sq	MSE	F	df1	df2	p
.3627	.1316	56.9857	2.9543	2.0000	39.0000	.0639

Model

	coeff	se	t	p	LLCI	ULCI
constant	15.2797	4.4064	3.4676	.0013	6.3668	24.1926
Emp	.5693	1.4511	.3923	.6969	-2.3658	3.5044
TrustT	.5624	.2318	2.4260	.0200	.0935	1.0314

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:

SatT

Model Summary

R	R-sq	MSE	F	df1	df2	p
.0227	.0005	63.9456	.0206	1.0000	40.0000	.8866

Model

	coeff	se	t	p	LLCI	ULCI
constant	23.7770	2.8321	8.3954	.0000	18.0529	29.5011
Emp	.2195	1.5295	.1435	.8866	-2.8718	3.3109

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
.2195	1.5295	.1435	.8866	-2.8718	3.3109

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.5693	1.4511	.3923	.6969	-2.3658	3.5044

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TrustT	-.3498	.6395	-1.6771	.9355

Normal theory test for indirect effect(s):

	Effect	se	Z	p
TrustT	-.3498	.6162	-.5677	.5702

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

------ END MATRIX -----