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Is Artificial Intelligence Better than Manpower? The Effects of Different Types of Online Customer Services on Customer Purchase Intentions

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Abstract: Artificial intelligence has been widely applied to e-commerce and the online business service field. However, few studies have focused on studying the differences in the effects of types of customer service on customer purchase intentions. Based on service encounter theory and superposition theory, we designed two shopping experiments to capture customers' thoughts and feelings, in order to explore the differences in the effects of three different types of online customer service (AI customer service, manual customer service, and human–machine collaboration customer service) on customer purchase intention, and analyses the superposition effect of human–machine collaboration customer service. The results show that the consumer's perceived service quality positively influences the customer's purchase intention, and plays a mediating role in the effect of different types of online customer service on customer purchase intention; the product type plays a moderating role in the relationship between online customer service and customer purchase intention, and human–machine collaboration customer service has a superposition effect. This study helped to deepen the understanding of AI developers and e-commerce platforms regarding the application of AI in online business service, and provides reference suggestions for the formulation of more perfect business service strategies.

Keywords: artificial intelligence; service encounter theory; perceived service quality; superposition effect; customer purchase intention; e-commerce

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1. Introduction

According to the World Robotics Report 2020, worldwide sales of service-oriented artificial intelligence (AI) have increased by approximately 85% in five years [1]. Tractica predicts that the growth rate of the global AI customer service (AICS) market will be seven times faster than that of the traditional manual customer service (MCS) market, reaching $126 billion in market revenue by 2025 [2]. The number of AI customer services on Facebook Messenger soared from 11,000 to 300,000 between 2016 and 2019 [3]. Studies estimate that intelligent customer service can help humans handle 80% of routine problems. The current global business cost of $1.3 trillion generated by 265 billion customer service inquiries per year would be reduced by 30% with the help of intelligent customer service. With the advancement of AI technology, AI application scenarios have been extended from industrial production to customer service [4]. Chatbots are used to provide medical advice to users of the British National Health and Medical System [5], and online businesses such as Taobao, Tencent and JD have also adopted AICS on a large scale, which brings obvious benefits to businesses. Service-oriented artificial intelligence can effectively reduce service costs, respond to a large number of repetitive problems around the clock, and make communication between enterprises and users faster and easier [6–8].

However, Davenport [9] found limited acceptance of current service-based AI by some users, especially in more complex services where users prefer to be served by a real person. Gray [10] argued that AI cannot replace MCS because current AI lacks the ability to "feel", and users have an increased lack of trust in AICS.

In recent years, new human–machine collaboration customer service (HMCCS) modes have been used in online business services, and scholars have found that AI is good at handling repetitive mechanical problems, while manual work is more suitable for personalized problems in the human–machine collaboration process [6]. Some scholars have proposed that human–AI collaboration in marketing services will be the mainstream service method in the future [11]. As such, who can bring better service experience to users with AICS, MCS, and HMCCS? Do different types of online customer service have different effects on consumers' purchase intention?

Through a literature survey, we found that there are many studies on the impact of online customer service on customer satisfaction [3,5,6]. There are also some studies focusing on the impact of factors of AICS on customer purchase intention [7] and on the comparison of AICS and MCS [8,12]. There are also fewer studies comparing MCS, AICS, and HMCCS in online business service contexts, and fewer studies focusing on the superposition effects of online HMCCS [6,11].

Based on the above, this paper examines different online customer service types (AICS vs. MCS vs. HMCCS) based on service encounter theory and superposition theory perspectives. This study explores whether consumers differ in their purchase intention with different online customer service types, and verifies whether the superposition effect of HMCCS exists, whilst exploring and verifying the mediating role of perceived service quality and the moderating role of the product type.

2. Literature Review

2.1. Types of Online Customer Service

The most important aspect of online customer service types is to determine the classification. Earlier studies have simply classified customer service according to industry [13]. In recent years, service marketing scholars have carried out extensive exploratory research on online customer service classification from a management perspective, and have proposed numerous new classification methods. Liu [14] proposed that online customer service types can be classified into text-based customer service, voice-based customer service, and video-based customer service according to the different modes of online customer service communication. Gao [15] found that online customer service types can be classified into pre-sales customer service, in-sales customer service, and after-sales customer service according to the items of customer service. Thoms [16] believed that customer service may be classified into human-provided and device-provided services according to the classification dimension of whether the service is provided by a human or equipment. Existing online customer service research is mostly MCS or AICS [4], and this article explores the impact of different online customer service types on customer purchase intentions, which is consistent with the classification of customer service based on the classification dimension being provided by people or equipment. Therefore, based on Thoms' classification and the synthesis of existing research, this paper classifies online customer service types into MCS, AICS, and HMCCS according to the different subjects of online customer service in a service encounter.

MCS has become a bridge between enterprises and users. Its applications cover multiple industries—such as communications, finance, and e-commerce—and touch all aspects of people's daily lives. Nowadays, people are accustomed to the "one-on-one" service provided by MCS, which can provide personalized and customized services with more empathy, especially when customers have special needs [9]. The excellent service attitude of MCS can increase users' recognition of enterprises and platforms [17]. However, some scholars have found that, due to the substantial increase in user inquiries within a certain period of time, insufficient resources and the low efficiency of MCS staff will cause frequent errors in business processing [18], especially in the communications industry, where MCS has problems such as poor experience perception and long waiting times [19].

In recent years, such problems have been solved by the emergence of AICS. AICS is a machine dialogue system that interacts with human users through natural language [20]; it can automatically participate in user conversations [21], serving users from multiple aspects, such as information seeking, query searching [22], and social media [23,24]. AICS has been used widely in online services. Existing studies show that AICS has the advantage of all-weather service [6]; on the one hand, AICS provides a new way of satisfying user needs and can be used to provide uninterrupted service, shorten response times, and improve customer purchase intentions [25]. Various expressions—including verbal, visual, and auditory expressions—will cause users to produce completely different responses [26]. On the other hand, users may be reluctant to interact with AICS because of its lack of empathy and performance instability [27], leading some companies to take a relatively conservative approach to the use of AICS, such that they try to find a more efficient and rational customer service model [25].

HMCCS refers to the simultaneous execution of tasks by artificial and intelligent robots in a shared workspace; that is, artificial and AI robots jointly participate in work at the same time [28]. Research scholars have gradually focused their research on the field of human–computer collaboration, and Epstein [29] proposed the concept of collaboration intelligence, which means that humans assign tasks to computers or share tasks with computers; the purpose of collaboration intelligence is not to replace human beings, but to engage in work with them. Successful collaboration intelligence can establish synergy between humans and computers in order to achieve goals. This means that the focus of the human–AI relationship is transferred to collaboration. By reviewing the development process of AI and human–computer interaction, Fan et al. [30] found that their relationship gradually changed from being alternate to being mutually driven, and that it will be synergistic in the future. Meanwhile, scholars have found that human–AI collaboration could improve work efficiency in various industries. Some regular tasks of teaching in the field of online education are being replaced by AI, which greatly improves the efficiency of teaching work [31]. Research scholars in the field of online healthcare have found that human–AI collaboration is most productive in psychotherapy [32]. A collaboration human–machine approach to task assignment in industrial assembly can achieve cost reductions and productivity improvements [33]. However, fewer studies in online business services have focused on the impact of HMCCS on customer purchase intentions.

In summary, the existing studies have analyzed a large number of different customer service types in various industries, but there are fewer comparative studies of online customer service types in business services. In addition, scholars are continuing to explore the impact of the type of online customer service on customer consumption in the current moment; according to existing research, service staff are one of the key factors affecting customer purchase intentions [13]. Accordingly, this study will build on existing theory in order to further explore whether there are differences in the effects of various customer service types on customer purchase intentions in online business service contexts.

2.2. Perceived Service Quality

Perceived service quality originated from research on customer satisfaction. It is believed that the perceived service quality is the difference degree between the customer's expectations of the service and the actual perceived performance [34]. Subsequent scholars have conducted in-depth studies on perceived service quality, and proposed that perceived service quality is a kind of comprehensive judgment and perception of the quality of service made subjectively by customers when they use a product or service [35].

In online business activities, the service quality depends on the subjective evaluation made by consumers regarding online customer service output and service interaction processes. Cha et al. [36] argued that consumers' perceived service quality of shopping websites positively affects customer purchase intentions. Wang et al. [37] proposed that user service quality in B2C social e-commerce platforms affects customers' evaluations of the effectiveness of the experience. Users play an important role in improving the quality of online customer service; as such, their perception of service quality is particularly valuable, and the evaluation of online customer service quality by users' "perceived service quality" has become the main core of service quality research. Studies have concluded that online customer service is important for the improvement of perceived service quality; as such, it is particularly vital to improve the service quality of customer service agents, and thus influence customer purchase intentions.

In summary, perceived service quality refers to the user's evaluation of service quality, reflecting the user's subjective perception of online customer service. Currently, it is generally accepted that the consumer's perceived service quality is the main factor influencing purchase intentions in the study of customer purchase intentions. Therefore, this study introduces perceived service quality as a mediating variable, and discusses the role that it plays in the influence of different customer service types on customer purchase intentions.

2.3. Service Encounter Theory

Shostack proposed the service encounter theory in his study of service quality management in companies, arguing that the contact between the customer and the service system is a key factor affecting the customer's perceived service quality [38]. Some scholars have defined service contact, in a narrow sense, as the face-to-face interaction between customers and service personnel [39], and in a broad sense based on a wide range of elements included in the service process, such as service personnel, service facilities, and the service environment, etc. [40]. All of the touch-points of customers in the process of receiving services belong to the scope of service contact [41]. The contact between consumers and customer service staff in this paper is a broad service contact.

Service encounter theory has been gradually improved after years of development, and the academic community has widely used service encounter theory in offline interpersonal service contact in the retail, restaurant, and hotel industries to explain customer satisfaction with electronic services, customer purchase intentions, and other issues [42]. With the development of IT giving rise to a series of information products and services, human–machine interaction is gradually replacing traditional MCS offline service contact as the mainstream form of service contact.

Meanwhile, service encounter theory's application transferred from offline to online; for example, Froehle et al. [43] proposed a service contact based on human–technology interaction. Massad et al. [44] outlined the meaning of technology-involved service contact as an interactive process that uses the Web as a medium, and the use of advanced IT technologies to achieve service contact. In addition, many scholars have begun to study the impact of various service touch joints on e-service customer purchase intentions in the context of information technology. Inbar et al. [45] argue that increasing interaction between consumer and screen in the service process can improve information sharing and the consumer's sense of control over the system bringing customer purchase intentions. Beatson [46] investigated customers' stay in hotels and found that the use of self-service technology contact had an impact on customer purchase intentions.

Consumers' direct feelings and judgments about the quality of online customer service come from all the "contact joint" in the process of communication between consumers and customer service, and all the touch-points belong to the service contact when consumers receive the service. Service contact is an important part of consumers' experience of service quality and is a direct source of service quality perception, and the process of service contact is the core factor for consumers to measure service quality [37]. This paper introduces service encounter theory, from the perspective of broad service contact, in order to find the main factors that affect the quality of the touch-points of online customer service, so as to improve customer purchase intentions with customer service, and to help companies and platforms to improve service quality and successfully accomplish their goals.

2.4. Superposition Theory

Superposition theory originated in the field of physics, where Dirac first proposed in 'Principles of Quantum Mechanics' that two or more states can be superimposed and then produce a superposition effect, which is an amplification of the superposition effect in the same direction [47]. Superposition theory refers to the effect produced by the combination of several different factors in mathematical physics, which is equal to the cumulative effect of these factors individually, producing a cumulative effect greater than a single effect [48].

Subsequent research expanded into other subject areas. On the one hand, superposition theory is used in news communication research, especially the communication of public events which make headlines. The superposition effect is the amplification of the superposition's impact in the same direction, which refers to "the multiplicative effect of several related components superimposed on each other" [47]. Li et al. referred to the superposition effect as the amplification effect, and believed that the positive and multiplicative effects of superposition can be achieved through the synergistic development of multiple components [49]. Zhao argued that there is a superposition effect of public events, and the information multiplication effect is highlighted when hot events are superimposed through WeChat communication [50]. On the other hand, superposition theory is used in economic development research, and Wang believed that the social value and cultural value of a brand become its market value after superposition, which has a superposition effect, and both can jointly promote the market value [51]. Cheng believes that the superposition effect of institutional dividend and demographic dividend can have an effect on the improvement of the quality of economic development [52]. This paper focuses on the application of the superposition theory to explore whether the customer purchase intentions of the human-plus-machine collaboration service model are greater than the customer purchase intentions of a single human or machine service in the online business service domain.

3. Research Hypothesis and Research Model

With the emergence and application of more intelligent services in online business services, AICS has achieved timeliness and accuracy; in some cases, the service process does not even require human involvement, and the ever-maturing AICS has weakened the role of the human in the service process [26]. Davenport et al. [9] found three advantages of AICS over MCS in marketing campaigns: first, the former is available at all times; second, it has a lower error rate; and third, the deployment of the former can be flexibly adjusted according to fluctuations in demand. Chung et al. [22], in their study of AICS and customer purchase intentions in the context of luxury brands, found that the use of AICS for e-services increased customer purchase intentions for the brand. Holzwarth et al. [53] found that AICS in online shopping increases consumers' positive attitudes and purchase intentions towards products when studying the impact of AICS on consumers' purchase intentions in the context of e-commerce. In addition, some studies have shown that the adoption of service-oriented AI by enterprises can effectively reduce costs, and that AICS can greatly improve efficiency [54]. In terms of "human vs. AI" efficiency, AI outperforms humans in all of the ways [55]. According to the service encounter theory, the difference of service subjects in the service process can be one of the key factors affecting customer purchase intentions [39]. Accordingly, the following hypothesis is proposed:

Hypothesis 1a. *Consumers have higher purchase intentions with AICS (vs. MCS).*

Furthermore, scholars have found that when AI and humans are connected in the right way, they can acquire greater intelligence and make better decisions, and human–AI collaboration significantly improves the efficiency and quality of tasks [56]. The combined effect of human–machine collaboration enables a two-way enhancement of the intelligence of both parties, amplifying the capabilities of both parties in their respective areas of expertise, creating new value and allowing for more possibilities for the future of work [57]. The combination of AI and humans enhances service efficiency and provides more experience;

AI in HMCCS can increase responsiveness and accuracy. Artificial parts can improve the efficiency of the handling of personalized problems, and can make the service more enthusiastic; the combination of the two subjects will have a superposition effect on the impact of customer purchase intentions, thus making the impact of HMCCS on customer purchase intentions greater than that of a single form of service. Accordingly, we propose the following hypotheses:

Hypothesis 1b. *The impact of HMCCS on customer purchase intentions has a superposition effect.*

Hypothesis 1c. *Consumers have greater purchase intentions with HMCCS (vs. MCS or AICS).*

Perceived service quality is the consumer's subjective evaluation of the quality of online customer service during the shopping process. While academic circles are dedicated to service quality evaluation research, they are also examining the relationship between service quality and behavioral variables such as customer purchase intentions. Parasuraman [34] argued that service quality is a key factor influencing customer satisfaction with services [58]; since then, the results of other studies have supported this view. Oliver [36] distinguished between the concepts of service quality and satisfaction, and showed that service quality directly and positively influences customer purchase intentions. Cronin et al. [59] argued that service quality is a prerequisite for customer purchase intentions in a study of the relationship between service quality, customer satisfaction, and purchase intentions. Anderson et al. [60] concluded that service quality positively and significantly affects customer purchase intentions, and that quality improvement should be based on customer needs in order to improve customer purchase intentions. In conclusion, the existing studies generally agree that consumers' perceived service quality is a key factor influencing customer purchase intentions.

Moreover, it has been confirmed that antecedent variables in the service industry could enhance customer purchase intentions by improving perceived service quality. For example, Chen [61] found that perceived service quality mediated the relationship between the activities of customer engagement and customer purchase intentions. Yong [62] found that the perceived service quality in the courier service industry mediated the effect between the antecedent variables and customer purchase intentions. Accordingly, we propose the following research hypothesis:

Hypothesis 2. *Perceived service quality has a positive effect on customer purchase intentions, and mediates the relationship between online customer service type and customer purchase intentions.*

In the field of marketing, scholars often divide products into search-type products and experience-type products according to whether they can judge the attributes of the products before purchase [63]. Search-type products mean that product attributes are available before purchase, whereas experience-type products mean that the product's attributes are not directly available before purchase, and must be obtained through post-purchase use experience; as such, consumers need to evaluate the product quality with the experience of purchase [64].

Some scholars have proposed paradigms in studies of online review usefulness voting in which cell phones and digital cameras are search-type products and cosmetics are experience-type products, and have verified the moderating role of the product type in the relationship between review polarity and usefulness voting [65]. In an experimental study of the effect of the product type on different review styles, electronic products such as cell phones were search-type products, and clothes were experience-type products [66]. The moderating role of the product type in the relationship between word-of-mouth consistency and purchase intention has also been explored, with flight services as experience-type products and cell phones as search-type products [67].

According to the service encounter theory, a wide range of elements included in the service process, such as the customer service type and the merchandise type, are part of the service encounter, which is a key factor influencing consumers' perceived service quality [40], and the difference in merchandise type has received extensive attention. On the basis of previous studies, the moderating role of the product type cannot be ignored when seeking to understand the differences affecting customer purchase intentions and customer service. On the one hand, the parameters of search-type products are fixed, AICS makes information responses more timely and accurate, and AICS is excellent at performing repetitive activities based on data so that tasks can be completed efficiently and accurately [68]; as such, in most scenarios, AI is used for repetitive and mechanical primary tasks with weak intelligence and creativity, and the impact of the use of AICS for search-type products on the perceived service quality of consumer service and customer purchase intentions will be greater than that of MCS. On the other hand, the attributes and usage effects of experience-type products cannot be obtained directly before purchase, and more comprehensive information can be obtained only after one's own experience; MCS is required to give relatively professional and accurate answers to customers' questions according to unexperienced experience, such that the impact of using MCS for experience-type products on consumers' service perception service quality and customer purchase intentions will be greater than that of AICS. Accordingly, the following research hypotheses were proposed:

Hypothesis 3. *The product type moderates the relationship between the online customer service type and customer purchase intentions, and the mediating effect of perceived service quality is also moderated by the product type.*

Hypothesis 3a. *For search-type products, the impact of AICS on customer purchase intentions is greater than that of MCS, and consumers' perceived service quality for AICS is greater.*

Hypothesis 3b. *For search-type products, the impact of HMCCS on customer purchase intentions is greater than that of AICS, and consumers' perceived service quality of HMCCS is greater.*

Hypothesis 3c. *For experience-type products, the impact of MCS on customer purchase intentions is greater than that of AICS, and the perceived service quality of MCS is greater.*

Hypothesis 3d. *For experience-type products, the impact of HMCCS on customer purchase intentions is greater than that of HMCCS, and consumers' perceived service quality is greater for human–machine collaboration.*

In summary, the theoretical framework model shown in Figure 1 is constructed in this paper.

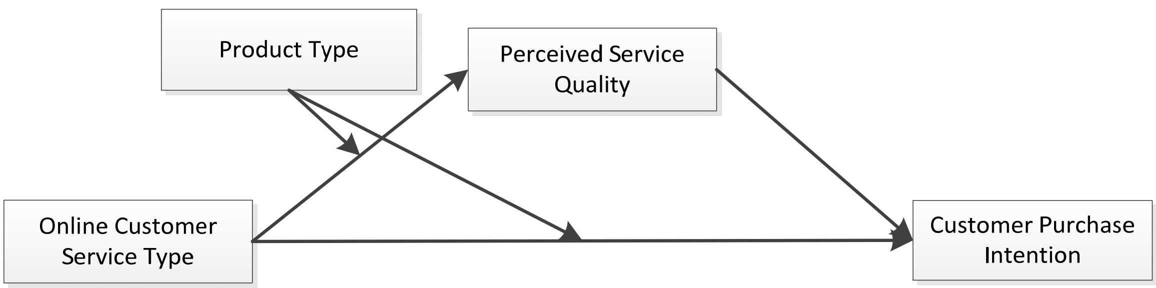

Figure 1. Theoretical model.

4. Research Method

In order to test our research hypotheses, we designed two laboratory experiment studies. The main purpose of Experiment 1 was to test Hypothesis 1, in order to test the difference in the effect of the online customer service type (AICS vs. MCS vs. HMCCS) on customer purchase intentions and the superposition effect of HMCCS. The purpose of

Experiment 2 was to test Hypothesis 2 (the mediating role of perceived service quality) and Hypothesis 3 (the moderating role of the product type).

4.1. Laboratory Experiment 1

4.1.1. Experimental Design

The experiment selected undergraduates from a university in China as the experimental subjects. According to the CNNIC report, people aged 18–25 account for 56% of the online consumers in China, and they are the main group of online consumers; as such, the results of the survey on university students can reflect the behavioral and psychological characteristics of the general consumer population [39]. Three common daily necessities—such as T-shirts, chocolate and mugs—were selected as the online products.

Experiment 1 used the scenario experiment method to verify Hypothesis 1. We adopted a 3 (online customer service type: AI vs. artificial vs. human–machine collaboration) $\times$ 3 (online products: T-shirt, chocolate, mug) mixed model design, in which the online customer service type was an inter-group design, and the product type was an intra-group design. A 3 (online customer service type: AI vs. human vs. human–machine collaboration) $\times$ 3 (online product: T-shirt, chocolate, mug) mixed-model design was used, where the online customer service type was a between-group design and the product type was a within-group design.

According to a Taobao store's pre-sales chat data analysis of T-shirts, chocolates and mugs for the past three months, we initially obtained 20 high-frequency keywords used by customers; we invited 30 college students to participate in the pre-test experiment of the keyword decision survey, and we finally determined 3 keywords. The t-shirt's keywords were shrinkage, fabric, and color. The chocolate's keywords were "ingredients", "taste", and "storage time". The mug's keywords were "odor", "high temperature resistance", and "sealing".

The experiment was designed to be close to a realistic online shopping situation, and a real Taobao store was selected. In order to avoid the interference of brand preferences, the experiment was blurred and circumvented for brands and names. The formal experiment was conducted in a quiet environment; each participant completed the experiment independently, and the duration of each experiment was about 10 min.

The AICS uses a Taobao official robot named "Dianxiaomi". The MCS is provided by three project team members, and the system randomly assigns manual customer in the experiment. HMCCS is offered by "Dianxiaomi" in cooperation with manual customer.

There were 210 participants who were invited to participate in the experiment, including 101 males and 109 females, with an average age of 20 years. The subjects were randomly assigned to three groups of situations: AICS, MCS, and HMCCS.

Before the experiment, the subject members checked whether the computer hardware and software were running normally, and also informed the subjects of the experimental precautions and steps. The subjects were told that they needed to purchase online products (T-shirts, chocolates, mugs), and that they had sufficient payment capacity. After the subjects understood the basic information of the store products, they then consulted the online customer service on their own regarding the products (including keywords), and were required to a complete customer purchase intentions questionnaire after the consultation. The measurement of the purchase intention drew on the findings of Liu et al. [69] (see Table 1); on the basis of this scale survey, this paper adjusted the scale items and used three scale items ("based on the current service, I would like to buy this product"; "based on the current service, I am likely to buy this product"; and "based on the current service, I would recommend the product to a friend"), using a 5-point Likert scale for measurement. Finally, the subjects were asked to fill in statistical information such as their gender, age, and education level. The results of the experiment were collected and the experiment was concluded by thanking the participants.

Table 1. Questionnaire items.

Constructs	Items	Statistics
Customer purchase intentions	Based on the current service, I would like to buy this product. Based on the current service, I am likely to buy this product. Based on the current service, I would recommend the product to a friend.	Liu et al. (2021)
Perceived service quality	Customer service personnel use friendly web expressions when communicating with me. Customer service personnel always provide reliable and accurate service. Customer service personnel can respond to my problems very quickly. Customer service personnel can provide professional service. Customer service personnel can always solve my personalized problems effectively.	Bernardo et al. (2012)

4.1.2. Analysis and Results

In order to observe the difference in the overall effect of the online customer service type on customer purchase intentions, we integrated and analyzed the data of the three products. The data were first analyzed and processed using SPSS22.0 software, and the Cronbach's alpha coefficient was used to test the reliability of the customer purchase intention scale. The results showed that the Cronbach's α of this experimental customer purchase intentions scale was 0.926, indicating that the scale had a high level of reliability.

The study used an independent sample *t*-test to verify Hypothesis 1, and the results showed that consumers were less satisfied with AICS (M_{AI} = 3.086, SD = 0.705, t = −9.133, $p < 0.05$) compared to MCS (M_{manual} = 3.952, SD = 0.669); Hypothesis 1a was not confirmed. HMCCS ($M_{human\text{–}machine\ collaboration}$ = 4.340, SD = 0.535, t = −4.633, $p < 0.05$) has significantly higher customer purchase intentions than humans or AICS, and the effect of HMCCS on customer purchase intentions has a superposition effect; Hypothesis 1b and Hypothesis 1c were supported.

In order to further show the results, we analyzed the differences of the customer purchase intentions for different online customer services for each of the three products. The specific results are shown in Figure 2. From Figure 2, we can see that for the T-shirts, the AICS group (M_{AI} = 3.057, SD = 0.625) had significantly higher customer purchase intentions than the MCS group (M_{manual} = 3.8476, SD = 0.742, t = −4.823, $p < 0.05$) and the HMCCS group ($M_{human\text{–}machine\ collaboration}$ = 4.362, SD = 0.568, t = −3.255, $p < 0.05$). For the chocolate, the AICS group (M_{AI} = 2.819, SD = 0.742) had significantly higher customer purchase intentions than the MCS (M_{manual} = 3.962, SD = 0.541, t = −7.36, $p < 0.05$) and HMCCS groups ($M_{human\text{–}machine\ collaboration}$ = 4.285, SD = 0.543, t = −2.499, $p < 0.05$). For mugs, the AICS group (M_{AI} = 3.381, SD = 0.647) had significantly higher customer purchase intentions than the MCS (M_{manual} = 4.047, SD = 0.710, t = −4.104, $p < 0.05$) and HMCCS groups ($M_{human\text{–}machine\ collaboration}$ = 4.371, SD = 0.503, t = −2.201, $p < 0.05$).

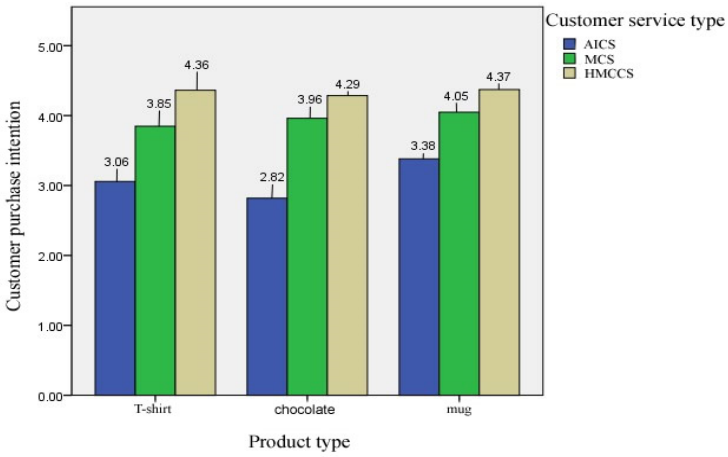

Figure 2. Customer purchase intentions of different online customer services for three products.

Experiment 1 verified the differences in the effects of three different online customer services on customer purchase intentions, and verified the existence of the superposition effect of human–machine collaboration. However, Experiment 1 failed to reflect the mechanism of the impact of different online customer services on customer purchase intentions. According to the service encounter theory, the product types in the service process all belong to the category of service contact, and consumers' perceived service quality of online customer service is the key factor of subjective evaluation. Therefore, we further investigated the moderating role of the product type within the influence of different online customer services and customer purchase intentions in the subsequent experiments, and introduced the perceived service quality in order to further explain the influence of different online customer services on the customer purchase intentions, as well as the reasons for the differences.

4.2. Laboratory Experiment 2

4.2.1. Experimental Design

Study 2 used a scenario-based experimental approach to test Hypotheses 2 and 3. A 2 (product type: search-type products vs. experience-type products) $\times$ 3 (online customer service type: AICS vs. MCS vs. HMCCS) between-group experimental design was used. A total of 204 participants were invited to take part in Experiment II, including 82 males and 122 females. The subjects were randomly assigned to six groups of situations: search-type/AICS, search-type/MCS, search-type/HMCCS, experience-type/AICS, experience-type/MCS, and experience-type/HMCCS.

According to the existing studies, cell phones and cosmetics are respectively classified as search-type products and experience-type products [30]. In this paper, cell phones and facial cleanser are used as examples for the experimental operations. The product descriptions contain product information such as the name, origin, and basic parameters, but do not involve leading terms in order to avoid the interference of merchant propaganda in the test judgment.

Based on the analysis of the pre-sales chat data of a Taobao store of cell phones and a store of facial cleanser for nearly three months, we initially obtained 20 high-frequency keywords used by customers, and invited 30 college students to participate in the pre-test experiment of the keyword decision survey; we finally determined five keywords. The cell phone keywords were "genuine", "delivery time", "accessories", "freebie", and "returns"; the facial cleanser keywords were "cleaning effect", "usage", "available length", "irritation", and "recommend one".

Consistent with Experiment 1, a real Taobao store was used, and each subject completed the experiment independently; the duration of each experiment was about 10 min. Before the experiment, the subject members checked whether the computer hardware and software could operate normally, and informed the subjects of the experimental precautions and steps at the same time. The subjects were told that they needed to purchase a cell phone or facial cleanser online, and that they had sufficient payment capacity to exclude the influence of price factors. After the subjects understood the basic information of the store products, they then consulted the online customer service about the products (including keywords) on their own, and had to complete the questionnaire of perceived service quality and customer purchase intentions after the consultation.

The measurement of the perceived service quality was based on the content of the SERVQUAL scale and the research scale of Bernardo et al. [70] (see Table 1); on the basis of the survey of this scale, the scale items were adjusted, and five scale items were used ("customer service personnel use friendly web expressions when communicating with me"; "customer service personnel always provide reliable and accurate service"; "customer service personnel can respond to my problems very quickly"; "customer service personnel can provide professional service"; "customer service personnel can always solve my personalized problems effectively"). The three formal items for purchase intention measurement were the same as in Experiment 1, and were measured on a 5-point Likert scale. Finally, the subjects were asked to fill in statistical information such as their gender, age, education level, and so on. The results of the experiment were collected, and the experiment was concluded by thanking the participants.

4.2.2. Analysis and Results

The Cronbach's α for the customer purchase intentions scale of Experiment 2 was 0.933, and the Cronbach's α for the perceived service quality scale was 0.813, indicating that the scale has a high level of reliability. To test the relationship between perceived service quality and purchase intention in Hypothesis 2, firstly, regression analysis was carried out between the perceived service quality and customer purchase intentions, and the results showed that perceived service quality positively affects customer purchase intentions ($\beta = 0.882$, $t = 27.052$, $p < 0.01$).

Secondly, the PROCESS Macro, developed by Hayes [71], was used in SPSS for the testing of the hypothesized framework, for two reasons: first, it is evident that the PROCESS Macro algorithm produces similar results with structural equation modelling [72]; second, it requires limited skills to perform complex analysis, even with mediators and two moderators at the same time, as is the case in the present study [71]. Regardless of the number of equations in the model, PROCESS estimates each equation separately, and "the estimation of the regression parameters in one of the equations has no effect on the estimation of the parameters in any other equations defining the model" [71].

The PROCESS Model 4 mediation model in SPSS macro prepared by Hayes was selected for the regression analysis. The results are shown in Table 2; the effect of the online customer service type on purchase intentions was significant ($\beta = 0.594$, $t = 10{,}658$, $p < 0.01$), and the direct effect of the online customer service type on purchase intentions remained significant when the mediating variable was put in ($\beta = 0.088$, $t = 2.148$, $p < 0.05$); as such, Hypothesis 2 is confirmed.

Table 2. Mediating model test of the perceived quality of service.

	Customer Purchase Intentions		**Customer Purchase Intentions**		**Perceived Service Quality**	
	B	**t**	**B**	**t**	**B**	**t**
Online Customer Service Type	0.088	2.148 **	0.594	10.658 ***	0.611	11.137 ***
Perceived Service Quality	0.829	20.284 ***				
R-Square	0.784		0.353		0.374	
F	374.583		113.588		124.024	

Notes: *** $p < 0.001$; ** $p < 0.05$.

In addition, the bootstrap 95% confidence interval for the direct effect of service quality on purchase intention and the mediating effect of perceived service quality can be found that the upper and lower limits are non-zero (see Table 3), and it can be concluded that service quality not only affects purchase intention directly but also through the mediating effect of perceived service quality. The direct effect (0.099) and the mediating effect (0.572) account for 85% and 15% of the total effect (0.671).

Table 3. Decomposition table of the total effect, direct effect and mediating effect.

	Effect	**BootSE**	**BootLLCI**	**BootULCI**	**Effect Ratio**
Mediating Effects of Perceived Service Quality	0.572	0.063	0.449	0.696	85%
Direct Effect	0.099	0.048	0.006	0.193	15%
Total Effect	0.671	0.066	0.542	0.799	

Secondly, PROCESS Model 8 of the SPSS macro prepared by Hayes [72], which is consistent with the theoretical model of this study, was selected in order to test the mediated model with moderation. The results are shown in Tables 4 and 5. After putting the product type into the model, the product terms of the online customer service type and product type had significant effects on the purchase intentions and perceived service quality (purchase intention: t = 2.089, $p < 0.05$; perceived service quality: t = 2.123, $p < 0.05$), indicating that the product type can play a moderating role not only in the direct effect of the customer service type on purchase intention but also in the effect of the perceived service quality; it can moderate the effect of the online customer service type on perceived service quality, and Hypothesis 3 is confirmed.

Table 4. Moderated mediation model test.

	Perceived Service Quality			Customer Purchase Intentions		
	coeff	**se**	**t**	**coeff**	**se**	**t**
Constant	3.743	0.041	90.925 ***	0.086	0.189	0.454
Online Customer Service Type	0.573	0.052	11.393 ***	0.113	0.046	2.444 **
Product Type	−0.202	0.082	−2.452 **	−0.067	0.060	−1.111
Online Customer Service Type × Product Type	0.214	0.101	2.123 **	0.153	0.073	2.089 **
Perceived Service Quality				0.975	0.050	19.469 ***
R-Square	0.404			0.789		
F	46.547			191.815		

Notes: *** $p < 0.001$; ** $p < 0.05$.

Table 5. Mediating effect on different levels of perceived service quality.

	Index	Effect	BootSE	BootLLCI	BootULCI
Moderated Mediating Effects	effect1 (M − 1SD)	0.454	0.065	0.333	0.583
	effect2 (M + 1SD)	0.663	0.087	0.499	0.830
Proportion of Moderated Mediation Effects	effect2 − effect1	0.209	0.102	0.015	0.415

Finally, a simple slope analysis shows (see Figures 3 and 4) that, as can be seen from Figure 3, the effect of the online customer service type on the perceived service quality tends to increase gradually as the product type increases. From Figure 4, it can be seen that as the product type increases, the effect of the online customer service type on purchase intention tends to gradually increase. In addition, the mediating effect of the product type on the perceived service quality in the relationship between the online customer service type and purchase intentions also tended to increase (see Table 5), i.e., as the subject's product type increased, the online customer service type was more likely to improve consumers' purchase intentions by increasing their perceived service quality.

The difference in the effect of the online customer service type on customer purchase intentions in the condition of product type moderation was tested using an independent sample *t*-test, and the results are shown in Figure 5. For search-type products, the difference in customer purchase intentions between AICS and MCS is significant (Δmean = 0.476, t = −3.346, $p < 0.01$); that is, the customer purchase intentions of MCS are greater than those of AICS. The difference in the perceived service quality between AICS and MCS is significant (Δmean = 0.640, t = −4.716, $p < 0.01$), i.e., consumers' perceived service quality of MCS is greater than that of AICS, and Hypothesis 3a is not confirmed. In addition, the customer purchase intentions of HMCCS are significantly greater than those of MCS (Δmean = 0.505, t = −3.817, $p < 0.01$), which indicates that the addition of AICS to MCS in a collaboration mode has a superposition effect on customer purchase intentions. The difference in perceived service quality between HMCCS and MCS is significant (Δmean = 0.291, t = −2.435, $p < 0.01$), which means that consumers' perceived service quality of HMCCS is greater than that of MCS, and Hypothesis 3b is confirmed.

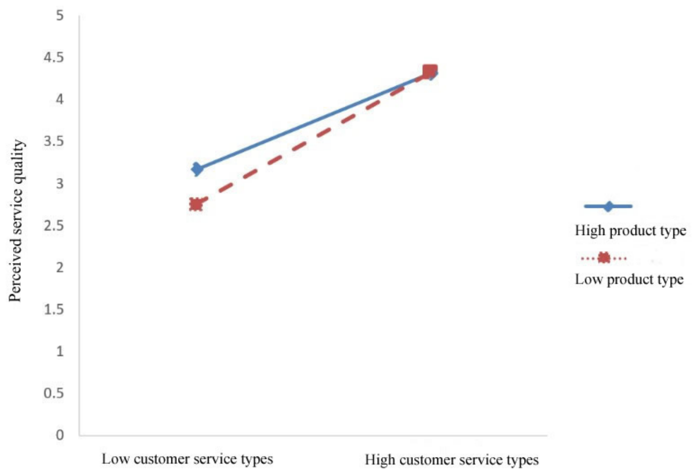

Figure 3. Moderating effect of product types with regard to online customer service types and perceived service quality.

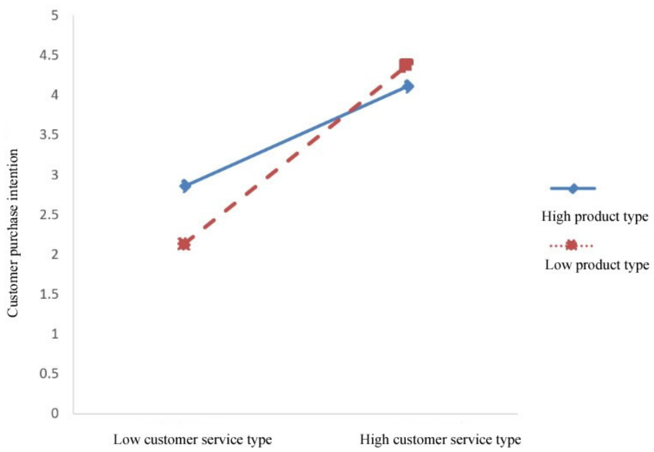

Figure 4. Moderating effect of product types with regard to online customer service types and purchase intentions.

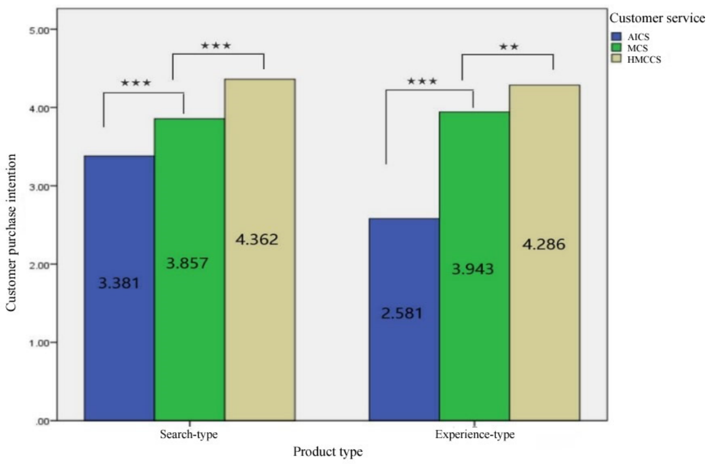

Figure 5. Results of the effect of the online customer service type on purchase intentions for different product types. Notes: ★★★ $p < 0.001$; ★★ $p < 0.05$.

Similarly, for experience-type products, the difference in customer purchase intentions between AICS and MCS is significant (Δmean = 1.362, t = −6.268, $p < 0.01$), which means that the customer purchase intentions of MCS are greater than those of AICS. The difference in perceived service quality between HMCCS and MCS is significant (Δmean = 1.029, t = −6.142, $p < 0.01$); that is, consumers' perceived service quality of HMCCS is greater than that of MCS, and Hypothesis 3c is confirmed. In addition, customer purchase intentions of HMCCS is greater than that of MCS (Δmean = 0.343, t = −2.230, $p < 0.05$), indicating that the effect of adding AICS to MCS in the mode of joint collaboration had a superposition effect on customer purchase intentions; the difference in perceived service quality between HMCCS and MCS was significant (Δmean = 0.331, t = −2.612, $p < 0.01$), that is, the perceived service quality of HMCCS is greater than that of MCS by consumers, and Hypothesis 3d is confirmed.

Experiment 2 explores the mediating role of perceived service quality in the relationship between different types of online customer service on customer purchase intentions, which contributes to our knowledge of customer purchase intentions and further explains the reasons for the differences in the impact of different online customer service on customer purchase intentions. The results support the view of previous studies that service quality is a key factor affecting customer purchase intentions, and it is particularly important to improve the service quality of customer service staff and thus influence customer purchase intentions. Then, the moderating role of the product type in the influence of different online customer service and customer purchase intentions was examined, and the results found that the product type can play a moderating role in the relationship between the perceived service quality and customer purchase intentions for different types of online customer service.

5. Discussion and Implications

5.1. Conclusions

In recent years, AI online customer service has received increasing attention [3,5,8,11], and the consumer's shopping experience is considered a key factor for the long-term survival and growth of merchants [6,12,17]; however, few scholars have noticed the relationship between the impact of different online customer services and users' purchase intentions [7]; thus, based on service encounter theory, this paper analyzed the differences in the impact of AICS, MCS, and HMCCS on customer purchase intentions by simulating the shopping environment with different types of customer service, and explored the superposition effect under the joint AI and manual service, drawing the following conclusions.

First, AI is not always better than manual service. The experimental results show that different types of online customer service have a significant impact on the differences of customer purchase intentions. The customer purchase intentions of MCS are significantly higher than those of AICS; the customer purchase intentions of HMCCS are higher than those of AICS or MCS, and the impact of HMCCS on customer purchase intentions has a superposition effect.

Second, perceived service quality positively affects customer purchase intentions and mediates the effect of the online customer service type on customer purchase intentions. This paper identified the relationship between the consumer's perceived service quality and purchase intentions, and verified that the consumer's perceived service quality is a key factor influencing customer purchase intentions with the service under different types of online customer service models.

Third, product types have a moderating effect in the process of online customer service type's influence on perceived service quality and customer purchase intentions. There are differences in the effects of the three types of customer service on customer purchase intentions for different product types, and there is a superposition effect of HMCCS on the effects of customer purchase intentions. In search- and experience-type products, the impact of MCS on customer purchase intentions is significantly greater than that of AICS, and the perceived service quality is higher; HMCCS provides consumers with more adequate and comprehensive services, and HMCCS customer purchase intentions are higher than those of a single AICS or MCS.

5.2. Theoretical Contributions

This paper makes several theoretical contributions to the literature.

First, this study expanded the application of service encounter theory in the field of service marketing and service design. Most of the previous studies were based on expectation confirmation theory and the technology acceptance model in order to analyze the factors that affect customer purchase intentions when AICS is provided [6,11,12]. In this paper, we regarded customer-centered online customer service as the contact point, and studied the differences in the customer's perceived service quality and purchase intentions for different types of customer service, expanding the service encounter theory from the service marketing field to the service design field and providing a new idea for business platforms to reflect customer needs from the perspective of contact points.

Second, this paper introduced superposition theory to the study of customer purchase intentions in the field of service marketing. Superposition theory originated from the field of physics, and was used in natural science research such as mathematics [49]; it was subsequently used widely in journalism, communication and economic development research [52], but it has rarely been applied in the service marketing field. In this paper, based on the analysis of the differences in the impact of a single form of human or AICS, the superposition effect of HMCCS was explored, and the role of different product types in the superposition effect of HMCCS was examined in order to enrich the application context of superposition theory in the marketing field.

Thirdly, there is a different, innovative classifying method of online customer service. Previous studies mostly classified online customer service according to industry dimensions [13], different communication methods [14], and the different job content of customer service [15]. This paper classified online customer service types from the perspective of service contact points, and divides online customer service into three types—namely AICS, MCS, and HMCCS—according to the different service providers. From the perspective of consumer perception, we analyzed the inner mechanism of the influence of the product type and online customer service type on customer purchase intentions, and to a certain extent promoted the development of research on the influence of online customer purchase intentions. This provides a new theoretical perspective for future research on online customer service.

5.3. Managerial Implications

The research findings provide several significant managerial implications for online product community managers. First, this research confirms that both experience-type products and search-type products can achieve the best service effects in the HMCCS model. Therefore, marketers should adopt appropriate service models for the design of online customer service in order to improve product marketing performance in the Internet environment. Second, for both search-type and experience-type products, the HMCCS model is the optimal strategy for sales. This requires marketers to take measures not only to improve the efficiency of AICS but also to encourage the enhancement of MCS to address customization and other special query information in customer service, thus improving the quality of customer service.

5.4. Limitations and Future Research

Similarly, this paper has some limitations that call for further research. First, this research explored the differences in the effects of three types of customer service on customer purchase intentions in the context of different types of products from the Taobao platform; however, whether other customer service platforms have similar effects should be subject to further examination. Secondly, this paper explored the moderating effect of the product type on the impact effect of online customer service forms based on service encounter theory, while other variables such as customer service disclosure on the impact effect of MCS and AICS may also have a moderating effect; further research may explore the interaction between customer service disclosure and the product type. Finally, HMCCS has an important marketing value, and whether more AICS time in the human–machine collaboration model is better deserves further exploration in the future.

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