Journal of Contemporary Economics and Management

jcem.pol-aca.com


Article

# Usage Intention and Influencing Factors of AI-Powered Intelligent Customer Service in E-Commerce Enterprises: An Investigative Study

LI Rong[1*], LIU Siyi[1], DING Yinzhi[1], ZHANG Guoyin[2]

[1]School of Economics and Management, Shanxi University, Taiyuan, 030006, Shanxi, China
[2]School of Economics and Management, Taiyuan University of Technology, Taiyuan, 030002, Shanxi, China

**Correspondence:** LI Rong, School of Economics and Management, Shanxi University, Taiyuan, 030006, Shanxi, China

**Email:** lizirong@sxu.edu.cn

**Citation:**

**Copyright:** © 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

**Abstract:** With the development of the Internet economy, the transformation of traditional customer service into AI-powered intelligent customer service has become an inevitable trend for the growth of e-commerce enterprises. However, current AI-powered intelligent customer service still faces significant constraints in meeting consumers' personalized needs. This study employed a comprehensive approach combining the literature research method, interview method, and questionnaire survey method to systematically explore the influencing factors affecting college student users' adoption of AI-powered intelligent customer service and strategies for improving service quality. Through the application of the factor analysis method, twelve variables were reduced to four principal factors: technical characteristics, service quality, personal perception, and social influence. The structural equation model (SEM) was then employed to conduct a path analysis of the influencing factors. The study found that social influence, service quality, technical characteristics, and personal perception all had a significant positive effect on college student users' willingness to use e-commerce enterprises' AI-powered intelligent customer service.Among them, technical characteristics have the greatest impact, followed by service quality, personal perception, and social influence. This study provided a particular reference value for e-commerce enterprises to refine the design and application of AI-powered intelligent customer service.It offered policy implications for promoting the healthy development of the AI-powered intelligent customer service industry.

**Keywords:** AI-powered intelligent customer service, University students, Factor analysis, Structural equation model

# 1. INTRODUCTION

With the deep integration of China's Internet economy and artificial intelligence (AI) technology, an increasing number of e-commerce enterprises are gradually adopting AI-powered intelligent customer service to replace human customer service. Thereby fulfilling their goal of reducing costs and improving efficiency. As an automated service system integrated with AI technology, AI-powered intelligent customer service simulates human communication patterns to provide online consumers with instant consultation response and problem-solving strategies (Shao, 2017). AI intelligent customer service demonstrates significant potential in areas such as 24/7 service availability, personalized interactive experience, operational efficiency improvement, and data-driven decision support. However, AI intelligent customer service still has many shortcomings, such as insufficient accuracy of the dialogue system, suboptimal user experience design, and weak data security and privacy protection, which lead most users to prefer human customer service when faced with complex needs.Therefore, relevant researchers must continuously optimize the AI-powered intelligent customer service system to enhance user experience, while also ensuring that user data security and privacy are fully protected.

According to the CNNIC (2024) report, the 20-24 age group exhibits the highest mobile online shopping penetration rate (91.6%) and the most frequent annual order placement among all demographic segments in China. University students form the core constituency of this cohort, with their exposure to and usage frequency of AI-powered customer service significantly exceeding the societal average. Consequently, this paper focuses on university students as its research subjects to investigate the factors influencing their use of AI-powered customer service systems. First, earlier work was sorted by a literature review and then refined through short interviews that clarified the research frame. Next, a questionnaire supplied real data on how these students currently deal with AI bots when shopping online. Finally, factor analysis and structural equation modelling (SEM) were combined to spot the key antecedents of usage intention, map their links and weigh their strength, so that online retailers can turn the findings into concrete steps for better service and stronger student appeal.

# 2. RESEARCH ON E-COMMERCE ENTERPRISES AI-powered INTELLIGENT CUSTOMER SERVICE

### *2.1 Concept of E-commerce Enterprises: AI-Powered Intelligent Customer Service*

By December 2023, China’s online retail sales had reached 15.4 trillion yuan, marking the eleventh consecutive year that it ranked first globally (CNNIC, 2024). This growth has drawn attention to consumers’ use of AI-powered customer service during online shopping. These systems are intelligent software platforms that rely on technologies such as human–computer interaction and natural language processing. Delivered through instant messaging tools on mobile devices or web pages, they provide real-time support to customers (Shao, 2017). Outside China, researchers sorted AI into four types—mechanical, analytical, intuitive and empathetic (Hollebeek,Sprott,&Brady, 2021) — while Pitardi and Wirtz (2021) define robotic service as an autonomous, adaptive interface that can interact, communicate and serve customers; they further classify service robots by function, socio-emotional capacity and relational ability.

Domestic research stresses the gap between early question-answering engines and today’s AI bots. Liu Mengxiao (2018) noted that modern systems add multi-turn dialogue, sentiment detection, topic clustering and self-learning to plain Q&A, and she describes AI customer service as an (NLP)-based, human-like agent that solves problems by phone, text or web in real time.

AI intelligent customer service is most widely used in the e-commerce sector. Li (2021) believes that the current application of AI-powered intelligent customer service in the e-commerce field mainly leverages deep learning technologies, computer vision recognition technologies, the establishment of AI-powered intelligent customer service robot systems, as well as sentiment analysis and intent recognition technologies to enhance the use of AI-powered intelligent customer service in e-commerce. Savants conducted an in-depth study on the applications and risks of generative artificial intelligence in the e-commerce sector. He believes that its main application areas include data collection and analysis, AI-powered intelligent customer service and shopping guidance, copywriting and code generation, and AI digital human live streaming (Bao,&Hong, 2024). Based on this, this paper defines AI-powered intelligent customer service applied in E-commerce enterprises as: a tool based on Natural language processing, artificial intelligence, and human-computer interaction technologies, which communicates and interacts with users of E-commerce enterprises in real time in the form of Anthropomorphization, to handle and resolve issues related to transaction processes and products.

### *2.2 Research Orientation of E-commerce Enterprises: AI-Powered Intelligent Customer Service*

AI-powered intelligent customer service primarily consists of two components: the intelligent knowledge base and the intelligent analysis engine. The intelligent knowledge base involves building a high-quality corpus by gathering relevant knowledge from multiple sources. This corpus serves as the foundation for the AI-powered intelligent customer service knowledge base to retrieve answers. The more extensive the corpus, the more questions the system can effectively address (Zheng & Gong, 2020). The intelligent analysis engine addresses the challenge that user queries are typically unstandardized and can be phrased in many different ways. Therefore, it is essential to normalize these varied expressions to match them with standardized queries within the same knowledge base (Shi, , Cai, , Chen, , Chen, & Li, 2017). The main research areas of AI-powered intelligent customer service include the following:

#### *2.2.1 Research at the Background Level*

Chen (2021) proposed that it is necessary to continue utilizing big data technology in the development of AI, thereby gradually improving the operational efficiency of the AI-powered intelligent customer service system. This is especially important for institutions such as banks, which process large volumes of data regularly. The integration of AI-powered intelligent customer service is crucial for meeting the banking needs of billions of people nationwide and alleviating staffing pressures on banks. Chen, Peng, &Duan (2022) focused on exploring how to enhance the service quality of mobile banking AI-powered intelligent customer service through AI technology, promoting the high-quality development of mobile banking services.

#### *2.2.2 Research at the Technical Level*

At the domestic level, the Shanghai Research Institute of China Telecom Corporation Limited explored the application of new technologies in the customer service systems of telecom operators and illustrated the effectiveness of these technologies in practical applications through case studies (Wang & Lu, 2018). At the international level, Soltani studied the framework and process of a knowledge-based AI intelligent service system for e-commerce customers. The resulting model is capable of responding to customer needs quickly and efficiently, providing high-quality customer service (Soltani, 2021).

#### *2.2.3 Research on the Application Level*

Savants proposed that Artificial intelligence technology has broad application prospects in multiple areas such as identity authentication, online customer service, and information retrieval.

They suggested that efforts should be made in several aspects, including intensifying research and development, improving management and service levels, strengthening data security protection, and establishing an ethical and legal framework, to create a favorable environment for AI development (Chen, Ran & Ming, 2018).

2.2.4 Research at the Customer Level

At home, Yang and Zhai (2022) demonstrated that when an AI shares its knowledge with people, users are more likely to participate. Trust lies in the middle and carries the effect, and giving the AI a human face strengthens or weakens that path. Abroad, Chung and co-workers utilized smart service logs to predict what buyers would do next; accurate predictions keep them coming back and increase profits (Chung, Ko & Joung, 2020).

Work to date follows four lines. First, map where the tool came from and where it is going. Second, keep upgrading chips and sensors so the bot can feel mood and tailor replies. Third, note that shops, city halls, bus apps and street cameras all run the same talk engine. Fourth, test how speed, tone and errors shape user trust, then feed the scores back into the knowledge base.

*2.3 Research on the Influencing Factors of Usage Intention of AI-powered Intelligent Customer Service in E-Commerce Enterprises*

College students sit at the heart of online retail. Watching how they take up AI chat support tells us how young buyers judge new tech. Fast answers and tailor-made fixes make shopping smoother and quietly turn student users into repeat fans. Field notes show that when a routine problem appears—course login, parcel track, coupon rule—their first move is often the store bot; it costs less time than a human queue (Li, Zhang & He, 2017). Cai et al. spelt out the point: intuitive and concise design can maintain users' willingness to use more than complex functions; Once the interface becomes complex (for example, the menu level is too deep or the guidance is unclear), users are likely to lose after a frustrated experience, and the possibility of return is very low (Cai, Gao & Yan, 2024). Kshetri (2019) adds that big-data engines can scan click trails across campus networks and feed the bot a sharper picture of each user’s taste; sharper hints lift both satisfaction and cross-sell yield.

Yet the same studies record limits. Wang and Zhang find that accuracy slips when questions stretch beyond a single turn. Chung shows that stalled replies erode trust; a wrong course-code answer can push a student back to the phone and colour later ratings (Ketron, 2019). Future appearances must therefore keep two goals in view: raising multi-turn precision and holding the simple, friendly surface. Only then will students stay, and the service will improve.

Based on the above analysis, it is evident that university students, as the primary consumer group for e-commerce enterprises, play a crucial role in enhancing the service quality of AI-powered customer support systems. With the rise of generative artificial intelligence, the intelligence level of AI customer service has significantly increased, markedly boosting user engagement frequency. However, this also implies that the factors influencing user adoption of AI customer service are becoming more complex. Therefore, it is necessary to explore and validate the relationships between newly introduced variables (such as intelligence level and interactivity) and other influencing factors, while also comparing the relative weights of these factors across different levels.

### *2.4 Theoretical Foundations*

#### *2.4.1 TAM Model*

The Technology Acceptance Model (TAM) was proposed by Fred Davis (1986) based on the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB). It aims to elucidate individuals' willingness to accept and adopt new technologies, whilst analysing factors influencing users' acceptance and utilisation of technology. Within the TAM framework, the emphasis is placed on the perceived usefulness and perceived ease of use of an information technology system as prerequisites influencing an individual's propensity to adopt technology, ultimately determining their behavioural intentions and patterns. The Technology Acceptance Model identifies two primary determinants: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which an individual believes using the new technology will enhance their work performance, while perceived ease of use denotes the perceived effort required to learn and use the new technology. Originally applied to research on employee acceptance of new information technologies, the TAM model remains pertinent to this study as AI-powered customer service within e-commerce platforms inherently incorporates technological elements.

#### *2.4.2 UTAUT Model*

The UTAUT model was proposed by Venkatesh V. et al (Venkatesh, Morris, Davis, & Davis, 2003). by integrating eight theoretical frameworks: the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivation Model (MM), Theory of Planned Behaviour (TPB), Combined TAM and TPB model, Computer Perceived Usefulness Model (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). The four key influencing factors of the UTAUT model are performance expectancy, effort expectancy, social influence, and facilitation conditions, which directly impact users' behavioural intentions and usage behaviour. Furthermore, four moderating variables—gender, age, experience, and voluntariness—exert significant influence on behavioural intention and usage behaviour. The UTAUT model finds applicability in information systems, e-commerce, and emerging technology domains. Consequently, this paper extends the UTAUT framework, employing factor analysis to investigate the factors influencing university students' willingness to use AI-powered customer service systems.

## 3. RESEARCH DESIGN

### *3.1 Research Method*

The study was divided into two steps. First, exploratory factor analysis pooled overlapping survey items and minimised information loss. Four latent factors were kept. Second, a SEM was employed to examine the relationships among these factors and usage intention. SEM reads the covariance matrix simultaneously, handles multiple outcomes, and converts abstract ideas into measurable scores, yielding cleaner estimates than separate regressions. With this tool, the study examined whether and to what extent each driver influenced students' willingness to use AI chat support and determined if the four hypotheses hold.

### *3.2 Questionnaire Design*

The questionnaire comprises both scaled and non-scaled measurement items. Non-scaled items include personal background information and an investigation into respondents' willingness to use AI-powered customer service during online shopping. For the scaled measurement items, the author conducted preliminary surveys and reviewed existing literature, drawing upon scales from prior research to ultimately identify twelve factors potentially influencing willingness to use AI customer service. Each measurement item employs a five-point Likert scale, ranging from 1 (not at all important) to 5 (extremely important).

The survey covers aspects such as the response speed of AI Intelligent Customer Service and its problem-solving capability (Kumar & Benbasat,2006). Besides, the ability to provide uninterrupted service (Song,Wang,Chen,Li,&Zhang, 2020), the comfort level in communicating with AI-powered intelligent customer service (Illescas-Manzano, Martínez-Puertas,& Segovia-López, 2025) and the level of trust in AI-powered intelligent customer service (McKnight, Choudhury,&Kacmar,2002). Moreover, the sense of security regarding information safety (Gefen, Karahanna, & Straub, 2003), ease of use (Zhang & Zhou, 2019), personalized services (Zhou, 2021), multi-channel access to services (Su, 2023), progress and innovation (Yang, Wei, Zhang &Li, 2021), evaluations of AI-powered intelligent customer service by friends or classmates, and the brand image of AI-powered intelligent customer service (Chevalier & Mayzlin, 2006). It should be noted that in many cases, AI-powered intelligent customer service is used passively rather than being actively chosen. For example, after a conversation on a mobile phone, Taobao may directly switch to AI-powered intelligent customer service for a response. In the questionnaire design scale of this study, it referred to the situation where respondents, after passively using AI-powered intelligent customer service in e-commerce enterprises, actively chose to continue using it.

**Table 1.** Scale Design

| Number | Item | Source |
|---|---|---|
| 1 | Response speed of AI intelligent customer service | Kumar et al, 2006[23] |
| 2 | AI Intelligent Customer Service problem-solving capability | Song Shuang Yong et al, 2020[24] |
| 3 | AI Intelligent Customer Service ability to provide 24/7 uninterrupted service | |
| 4 | Comfort level when communicating with AI Intelligent Customer Service | Liu et al 2015[25] |
| 5 | Level of trust in AI Intelligent Customer Service | McKnight et al, 2006[26] |
| 6 | Sense of security when using AI Intelligent Customer Service (e.g., confidence in personal information protection) | Gefen et al,2003[27] |
| 7 | Ease of use of AI Intelligent Customer Service (e.g., navigation, command comprehension) | |
| 8 | Personalized services of AI Intelligent Customer Service (e.g., remembering your preferences, providing customized suggestions) | Zhang Chen et al,2019[28]<br>Pucihar et al,2017[29] |
| 9 | Multi-channel access provided by AI Intelligent Customer Service (e.g., web, mobile apps, social media, etc.) | Yinhua Su,2023[30]<br>Yang et al, 2021[31] |
| 10 | Continuous improvement and innovation of AI Intelligent Customer Service through Artificial intelligence technology | |
| 11 | Friends' or classmates' evaluations of AI Intelligent Customer Service | Chevalier et al, 2006[32] |
| 12 | Brand image of AI Intelligent Customer Service (e.g., brand awareness, professionalism) | Keller et al,1993[33] |

## 4. E-commerce Enterprises AI-Powered Intelligent Customer Service Usage Intention influencing factors: Factor Analysis

The Factor Analysis of e-commerce enterprises' AI-powered intelligent customer service usage intention influencing factors includes group characteristic analysis, data collection and processing, reliability and validity testing, and factor analysis.

### *4.1 Group Characteristic Analysis*

The survey sample mainly consists of sophomore and junior students, accounting for 71.8%, with a nearly equal gender ratio among respondents. Based on the organization of the questionnaires and the summary of relevant data, the current characteristics of such users in using AI-powered intelligent customer service on e-commerce platforms are as follows:

First, in terms of online shopping software usage, the preference ranking of university student users for online shopping software is as follows: Mobile phone Taobao, Pinduoduo, JD.com, Tik Tok, and others. This ranking is also relatively consistent with the current market development status of e-commerce software.Second, in terms of the use of online shopping AI-powered intelligent customer service, nearly 90% of respondents reported using AI-powered intelligent customer services, indicating a high penetration rate of AI-powered intelligent customer service among young consumer groups.

### *4.2 Data Collection and Processing*

Between 2 March and 5 April 2024, I handed out the survey through Questionnaire star, Rednote, Tik Tok, Micro-blog, and mutual-help chat groups. To keep the numbers sound, I dropped any form that showed a single repeated answer or was finished in an impossibly short time. I also ran an outlier check and removed a handful of replies that were clearly keyed in by mistake or by misreading the questions. After this cleaning, the raw set of 1,100 shrunk to 980 valid cases. Because only online shoppers who had actually spoken to an AI service were of interest, I then set aside 103 cases from the "never used" group, leaving 877 questionnaires for the final analysis.

### *4.3 Reliability and Validity Test*

Reliability was assessed with Cronbach's alpha; the obtained value is 0.788, above the 0.70 threshold, indicating satisfactory internal consistency.

**Table 2.** Questionnaire Reliability Test

| **Cronbach's alpha** | **Number of terms** |
|---|---|
| 0.788 | 12 |

To check validity I ran Bartlett's test of sphericity. The survey data gave a KMO value of 0.786, above the 0.5 cut-off, and the significance level was below 0.05, so the variables are judged to be sufficiently inter-correlated for factor analysis.

**Table 3.** Validity Test of Questionnaire

| **KMO Measure of Sampling Adequacy** | | **0.786** |
|---|---|---|
| Bartlett's Test of Sphericity | Approximate Chi-Square | 3512.227 |
| | Degrees of Freedom | 66 |
| | Significance | 0.000 |

*4.4 Analysis of AI-Powered Intelligent Customer Service Usage Intention influencing factors: Based on Factor Analysis*

Based on the questionnaire survey results, this study identified 12 specific Observed Variables that may influence university student users in choosing AI Intelligent Customer Service services. Through Factor Analysis, multiple related Observed Variables were grouped into a few unobservable factors, thereby analyzing the factors that influence the usage of AI Intelligent Customer Service by this user group.

*4.4.1 Factor Analysis Test*

Validity checks returned a KMO of 0.786 and a Bartlett $\chi^2$ of 3,512.227 ($p < 0.05$). These numbers point to sizeable overlap among the variables and justify moving on to factor analysis.

*4.4.2 Factor Extraction*

**Table 4.** Common Factor Variance

| common factor variance | | |
|---|---|---|
| | **Initial** | **Extraction** |
| Ease of use of AI Intelligent Customer Service (e.g., navigation, command comprehension) | 1.000 | 0.701 |
| Continuous improvement and innovation of AI Intelligent Customer Service through Artificial intelligence technology | 1.000 | 0.687 |
| AI Intelligent Customer Service problem-solving capability | 1.000 | 0.700 |
| Friends' or classmates' evaluations of AI Intelligent Customer Service | 1.000 | 0.771 |
| Brand image of AI Intelligent Customer Service (e.g., brand awareness, professionalism) | 1.000 | 0.792 |
| AI Intelligent Customer Service ability to provide 24/7 uninterrupted service | 1.000 | 0.732 |
| Response speed of AI intelligent customer service | 1.000 | 0.704 |
| Multi-channel access provided by AI Intelligent Customer Service (e.g., web, mobile apps, social media, etc.) | 1.000 | 0.694 |
| Personalized services of AI Intelligent Customer Service (e.g., remembering your preferences, providing customized suggestions) | 1.000 | 0.655 |
| Level of trust in AI Intelligent Customer Service | 1.000 | 0.686 |
| Sense of security when using AI Intelligent Customer Service (e.g., confidence in personal information protection) | 1.000 | 0.709 |
| Comfort level when communicating with AI Intelligent Customer Service | 1.000 | 0.713 |
| Extraction method: Principal Component Analysis. | | |

Table 4. shows the communalities after factor extraction: all twelve original variables exceed 0.5, indicating that the extracted factors account for a satisfactory share of each variable's variance.

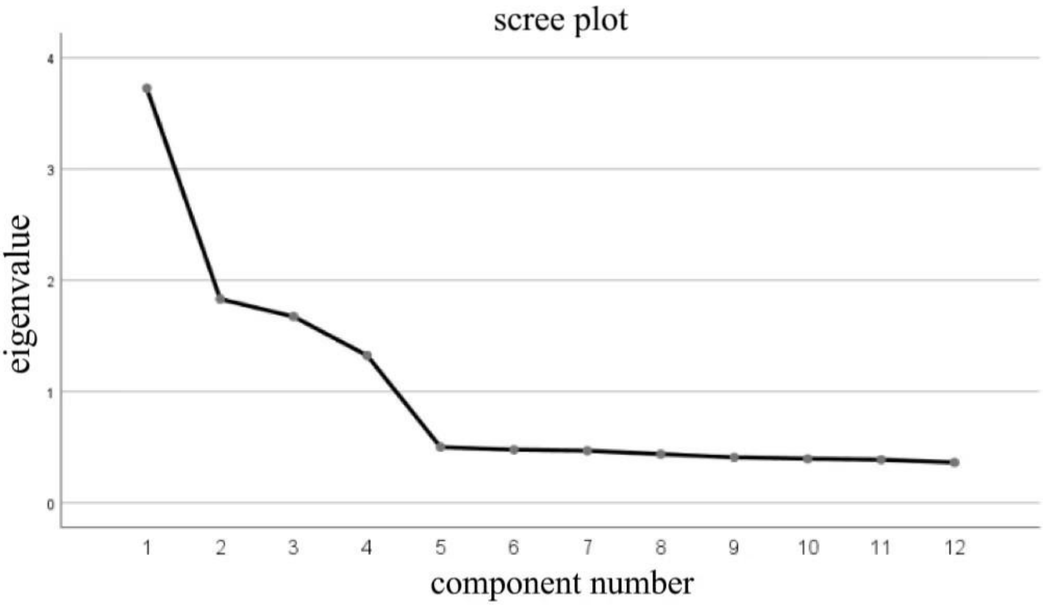


**Fig 1.** Gravel Plot of Cumulative Contribution Rates of Each Component in the Model

Figure 1. plots the eigenvalues in descending order. The first four factors stand well above the rest, accounting for most of the variance; beyond the fourth point the curve slopes gently and flattens, indicating negligible additional information. Components 1–4 are therefore retained.

**Table 5.** Total Variance Table Explained by Common Factors in the Model

| **Total Variance Explained** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
| | Total | Percentage of Variance | Cumulative Percentage | Total | Percentage of Variance | Cumulative Percentage | Total | Percentage of Variance | Cumulative Percentage |
| 1 | 3.669 | 30.573 | 30.573 | 3.669 | 30.573 | 30.573 | 2.729 | 22.738 | 22.738 |
| 2 | 1.863 | 15.552 | 46.095 | 1.863 | 15.552 | 46.095 | 2.139 | 17.828 | 40.566 |
| 3 | 1.657 | 13.811 | 59.906 | 1.657 | 13.811 | 59.906 | 2.112 | 17.603 | 58.169 |
| 4 | 1.356 | 11.301 | 71.207 | 1.356 | 11.301 | 71.207 | 1.565 | 13.038 | 71.207 |
| 5 | 0.504 | 4.202 | 75.409 | | | | | | |
| 6 | 0.481 | 4.005 | 79.415 | | | | | | |
| 7 | 0.471 | 3.927 | 86.96 | | | | | | |
| 8 | 0.434 | 3.618 | 80.890 | | | | | | |
| 9 | 0.412 | 3.434 | 90.394 | | | | | | |
| 10 | 0.401 | 3.342 | 93.736 | | | | | | |
| 11 | 0.393 | 3.272 | 97.008 | | | | | | |
| 12 | 0.359 | 2.992 | 100.00 | | | | | | |

Extraction method: Principal Component Analysis.

Table 5. shows the total variance explained by the common factors in the influencing factors analysis model used in this study. As indicated in the table, four factors have eigenvalues greater than 1, with a cumulative variance contribution rate of 71.207%. Based on the overall expectations, four common factors were extracted, accounting for the majority of the information represented by each indicator.

When the factor count is set to four, the extracted dimensions line up with the constructs proposed in this study, so four factors are retained.

### *4.4.3 Factor Rotation*

**Table 6.** Rotation Component Matrix

| Rotated Component Matrix a | | | | |
|---|---|---|---|---|
| | Component | | | |
| | 1 | 2 | 3 | 4 |
| Ease of use of AI Intelligent Customer Service (e.g., navigation, command comprehension) | 0.820 | 0.09 | 0.114 | 0.091 |
| Continuous improvement and innovation of AI Intelligent Customer Service through Artificial intelligence technology | 0.805 | 0.125 | 0.094 | 0.122 |
| Multi-channel access provided by AI Intelligent Customer Service (e.g., web, mobile apps, social media, etc.) | 0.824 | 0.169 | 0.076 | 0.060 |
| Personalized services of AI Intelligent Customer Service (e.g., remembering your preferences, providing customized suggestions) | 0.804 | 0.066 | 0.052 | 0.023 |
| AI Intelligent Customer Service problem-solving capability | 0.128 | 0.819 | 0.046 | 0.105 |
| AI Intelligent Customer Service ability to provide 24/7 uninterrupted service | 0.102 | 0.841 | 0.089 | 0.075 |
| Response speed of AI intelligent customer service | 0.076 | 0.826 | 0.123 | 0.018 |
| Level of trust in AI Intelligent Customer Service | 0.103 | 0.062 | 0.819 | 0.026 |
| Sense of security when using AI Intelligent Customer Service (e.g., confidence in personal information protection) | 0.058 | 0.118 | 0.829 | 0.075 |
| Comfort level when communicating with AI Intelligent Customer Service | 0.118 | 0.075 | 0.830 | 0.063 |
| Friends' or classmates' evaluations of AI Intelligent Customer Service | 0.101 | 0.137 | 0.081 | 0.858 |
| Brand image of AI Intelligent Customer Service (e.g., brand awareness, professionalism) | 0.112 | 0.034 | 0.061 | 0.880 |
| Extraction method: Principal Component Analysis. | | | | |
| a. Rotation converged after 5 iterations. | | | | |

The first common factor primarily explains the four influencing factors: “Ease of use of AI-powered intelligent customer service (e.g., navigation, command comprehension),” “Personalized services of AI-powered intelligent customer service (e.g., remembering your preferences, providing customized suggestions),” “Multi-channel access provided by AI-powered intelligent customer service (e.g., web, mobile apps, social media, etc.),” and “Continuous improvement and innovation of AI Intelligent Customer Service through AI technology.”The second common factor primarily explained the three influencing factors: “Response speed of AI-powered intelligent customer service,” “Problem-solving capability of AI-powered intelligent customer service,” and “Ability of AI Intelligent Customer Service to provide 24/7 uninterrupted service."The third common factor primarily explains the three influencing factors: "Comfort level during interaction with AI-powered intelligent customer service," "Level of trust in AI-powered intelligent customer service," and "Sense of security when using AI-powered intelligent customer service (e.g., confidence in personal information protection)."The fourth common factor primarily explains the two influencing factors: "Friends' or classmates' evaluations of AI-powered intelligent customer service," and "Brand image of AI-powered intelligent customer service (e.g., reputation, professionalism)."

*4.4.4 Principal Factor Naming*

According to the theory of Factor Analysis, the common characteristics of variables with high loadings in each Principal Factor are summarized, thereby categorizing the 12 influencing factors into four Principal Factor. As a result, the influencing factors of E-commerce enterprises' AI-powered intelligent customer service Usage Intention are identified, as shown in the chart.

The first principal factor was related to the technical characteristics of AI-powered intelligent customer service, and was therefore named the Technical Characteristics Factor. The second principal factor was closely associated with the service quality of AI-powered intelligent customer service, and was named the service quality factor. The third principal factor was strongly related to the personal perception of online shopping customers, and was named the personal perception factor. The fourth principal factor was determined by the social influence of AI Intelligent Customer Service, and was thus named the Social Influencing Factors.

**Table 7.** Naming of Main Factors

| Factors | influencing factors for choosing online shopping AI Intelligent Customer Service | Naming |
|---|---|---|
| Factor One | Ease of use of AI Intelligent Customer Service (e.g., navigation, command comprehension)<br>Personalized services of AI Intelligent Customer Service (e.g., remembering your preferences, providing customized suggestions)<br>Multi-channel access provided by AI Intelligent Customer Service (e.g., web, mobile apps, social media, etc.)<br>Continuous improvement and innovation of AI Intelligent Customer Service through Artificial intelligence technology | technical characteristics factors |
| Factor Two | Response speed of AI intelligent customer service<br>AI Intelligent Customer Service problem-solving capability<br>AI Intelligent Customer Service ability to provide 24/7 uninterrupted service | Service quality factors |
| Factor Three | Comfort level when communicating with AI Intelligent Customer Service<br>Level of trust in AI Intelligent Customer Service<br>Sense of security when using AI Intelligent Customer Service (e.g., confidence in personal information protection) | personal perception factors |
| Factor Four | Friends' or classmates' evaluations of AI Intelligent Customer Service<br>Brand image of AI Intelligent Customer Service (e.g., brand awareness, professionalism) | Social influencing factors |

## 5. E-commerce Enterprises' AI-Powered Intelligent Customer Service Usage Intention Influencing Factors: SEM Analysis

Next, the researcher ran SEM on the student data to explain why they choose AI chat support when shopping online. Drawing on the factor results, the researcher set up a model with four latent blocks—tech features, service quality, personal feelings, and social cues—and tested how each block drives usage intention.

### *5.1 Hypothesized Impact Pathways*

#### *5.1.1 Service Quality of AI-Powered Intelligent Customer Service*

Among the various factors influencing consumer experience, the service quality of e-commerce customer service is the most critical. For university student users, response speed is particularly important. These users expect prompt replies to their inquiries to meet their needs. Therefore, faster response times can better align with user expectations and also increase their usage frequency and popularity (Kumar,N. & Benbasat,I, 2006). Secondly, the problem-solving capability of AI-powered intelligent customer service is also especially important to users. AI-powered intelligent customer service, equipped with efficient problem-solving abilities can not only better meet the specific needs of users but also effectively enhance their Usage Intention and loyalty (Song et al. 2020).The 24/7 uninterrupted service provided by E-commerce enterprises AI Intelligent Customer Service is also highly favored by users. Since these users tend to have more flexible lifestyles, the round-the-clock online service of AI-powered intelligent customer service allows them to receive timely assistance and responses at any time, thereby further enhancing their trust in and reliance on AI-powered intelligent customer service. Based on the above, Hypothesis 1 can be proposed:

H1 Service Quality has a significant positive impact on university student users' usage intention of AI-powered intelligent customer service.

#### *5.1.2 Personal Perception*

Personal experience sits at the centre of AI chat use. When the bot can mimic real human chat, students feel more at ease and are ready to stay in the session (Chung,et al. 2020). Trust followed the same line: the more reliable the bot, the more it is relied upon (Song,et al.2020). This trust is built on brand name, peer recommendations, and first-hand proof that answers are fast and accurate. A bot that is both accurate and always there gives strong backup at the exact moment it is needed. Strict data rules add the final layer; once users see their details are locked away, comfort and intention rise again. These gains in ease and trust push students to keep using the service and lay ground for later upgrades. Hence:

H2 Personal Perception has a significant positive impact on the usage intention of university student users toward AI-powered intelligent customer service

#### *5.1.3 Technical Characteristics of AI-Powered Intelligent Customer Service*

Reviews of technical features point to four staples: ease of use, personal fit, multi-channel reach and continuous learning. A sound system keeps screens short and paths few so that a new user can open the box and leave with the answer in seconds (McKnight,et al. 2002). Next, it must turn data into tailor-made replies that match one person's exact question, lifting both usefulness and satisfaction (Gefen,et al. 2003). Channel freedom is just as basic; students swap from text to voice to mini-program without losing thread, which raises reach and flexibility (Zhang,et al. 2019). Under the surface, deep nets, NLP loops and live analytics continually train the weights, enabling the bot grasp more questions and returns better answers over time (Zhou, 2021). These tech cues shape usage intention. Hence:

H3 Technical Characteristics have a significant positive impact on the Usage Intention of university student users toward AI-powered intelligent customer service.

*5.1.4 Social Influence*

Feedback from friends or classmates plays a significant role in influencing this group of users when deciding whether to use AI-powered intelligent customer service. For this core consumer segment, word-of-mouth and social influence are primary sources of information. Positive recommendations from peers often spark greater interest and willingness among users to try and adopt AI Intelligent Customer Service (Su, 2023). At the same time, the widespread use of social networks allows the strengths and weaknesses of these platforms to spread rapidly, further affecting the acceptance and usage intentions of more users. In this process, image and word of mouth play a vital role in the promotion and user adoption of AI-powered intelligent customer service. Therefore, when promoting e-commerce AI Intelligent Customer Service, it is important to focus on building a positive reputation and shaping a strong brand image to attract specific groups of e-commerce users (Yang,et al. 2021). Based on the above, hypothesis 4 can be proposed:

H4 Social Influence has a significant positive impact on he AI-powered intelligent customer service usage intention of university student users.

Based on the aforementioned assumptions and incorporating UTAUT theory, this paper proposes a conceptual model of university students' willingness to use AI-powered customer service systems:

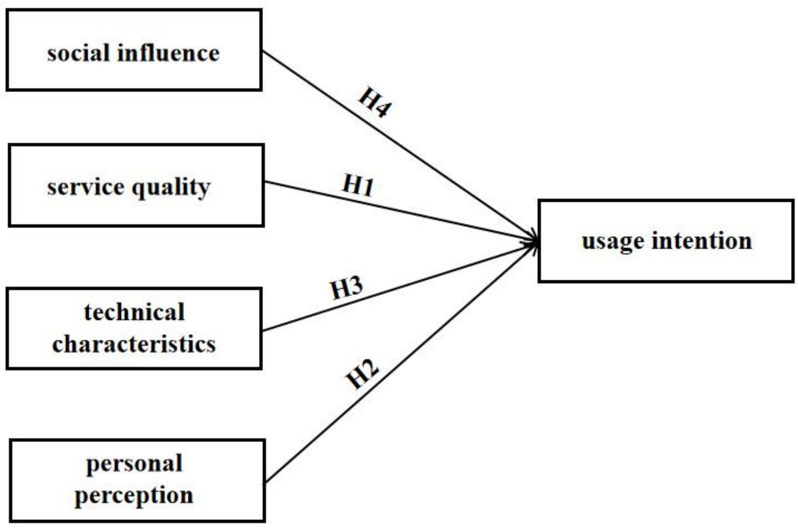


**Fig 2.** Conceptual Model of Factors Influencing University Students' Willingness to Use AI Intelligent Customer Service in E-commerce Enterprises

*5.2 Analysis of the Influence Path Model*

Based on the preceding analysis and hypotheses, the causal path model shown in Figure 3. was drawn with AMOS.

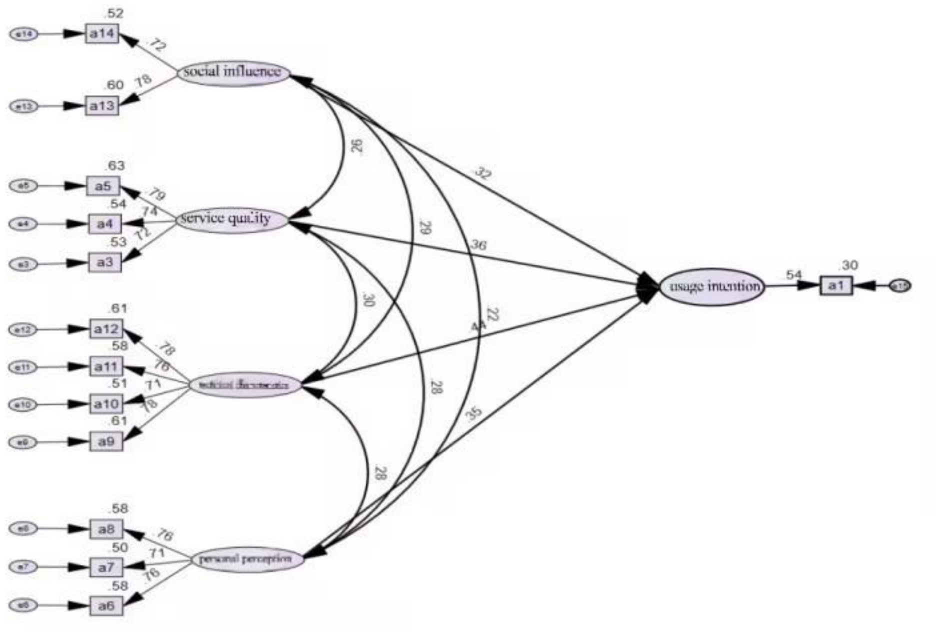

**Fig 3.** Path Diagram of Structural Equation Modeling of Factors Influencing the Willingness of College Students to Use AI Intelligent Customer Service on E-Commerce Platforms

### *5.3 Model Results*

To test the proposed model and hypotheses, the study estimated the structural equation model with AMOS. Table 8. reports the results: $\chi^2/df = 1.133$ (< 3.0), GFI, AGFI, CFI, RFI, NFI, IFI and TFI are all above 0.95, and RMSEA = 0.012 (< 0.08).A smaller SRMR value indicates a better model fit. Typically, an SRMR value below 0.08 is considered acceptable for model fit. The SRMR value in this study is 0.027. These values indicate that the model fits the data well and the hypothesised relationships are empirically supported.

**Table 8.** Results of Model Adaptability Test

| Model | $\chi^2$/df | RMSEA | SRMR | NFI | RFI | IFI | TLI | CFI | GFI | AGFI |
|---|---|---|---|---|---|---|---|---|---|---|
| Default model | 1.133 | 0.012 | 0.027 | 0.983 | 0.977 | 0.998 | 0.997 | 0.998 | 0.989 | 0.982 |
| Criteria for determination | <3.00 | <0.08 | <0.05 | >0.90 | >0.90 | >0.90 | >0.90 | >0.90 | >0.90 | >0.90 |

The results show that the model error variance values are all positive, with no negative values observed; regarding the overall model fit test, the displayed values of indicators such as GFI, AGFI, NFI, RFI, IFI, TLI, and CFI are all greater than 0.95, meeting the requirements.

**Table 9.** Hypothesis Verification Results of Structural Equation Modeling

| Research Hypotheses | Structural Model Paths | Standardized Path Coefficients (β) | P-values | Hypothesis Test Results |
|---|---|---|---|---|
| H1 | social influence → Usage Intention | 0.214 | *** | Assumption holds |
| H2 | service quality → Usage Intention | 0.266 | *** | Assumption holds |

| Research Hypotheses | Structural Model Paths | Standardized Path Coefficients (β) | P-values | Hypothesis Test Results |
|---|---|---|---|---|
| H3 | technical characteristics → Usage Intention | 0.282 | *** | Assumption holds |
| H4 | personal perception → Usage Intention | 0.244 | *** | Assumption holds |

Note:*P < 0.05； **P < 0.01； ***P < 0.001

Table 9. shows that social influence, service quality, technical features and personal feelings all raise the intention to use AI chat support; H1, H2, H3 and H4 were therefore supported. With p-values significant, the standardized path coefficients give the order of strength: technical features (0.282) exert the largest effect, followed by service quality (0.266), personal feelings (0.244) and social influence (0.214).

For these student shoppers, the core appeal lies in the technology itself: speed, accuracy and the chance to receive a tailor-made reply. Service quality comes next; fast, correct and reliable answers remain the baseline against which any new tool is judged. Personal feelings matter because the chat event is judged not only by the outcome but also by how smooth, friendly and safe it feels. Social influence plays a smaller, yet still visible, role: peers' stories and online reviews nudge the decision to try or stay.

Taken together, the four forces shape usage intention. Providers who want to keep young buyers on the bot must continually upgrade the engine, tighten service standards, safeguard privacy, and build positive word of mouth simultaneously.

## 6. Research Conclusions and Implications

### *6.1 Research Conclusions*

A survey was designed to map the factors that shape students' willingness to use AI chat support when they shop online. Factor analysis cut the items into four blocks: service quality, personal feelings, technical features and social influence. SEM tests revealed that all four lift usage intention variables—technical features carried the most substantial weight, followed by service quality, personal feelings and social impact.

### *6.2 Research Limitations and Future Prospects*

Firstly, this study exclusively surveyed university students, with the sample concentrated within the 18-24 age bracket. It did not account for factors such as income, geographical location, or the willingness to use AI customer service among other demographic groups.

Secondly, the research context was confined to e-commerce customer service scenarios involving 'continued voluntary use after passive triggering,' excluding situations where customers proactively seek assistance, such as during procurement or post-sales dispute resolution. The static cross-sectional data employed in this study cannot reveal the intrinsic logic between variables from a dynamic perspective.

Therefore, future research could further explore the mechanisms influencing willingness to use AI-powered customer service. This could involve stratified sampling to include diverse groups with significant differences in age, occupation, income, urban/rural residence, and digital literacy. Concurrently, longitudinal research methods could be employed to investigate users' willingness to utilise AI-powered customer service provided by e-commerce enterprises.

*6.3 Policy Implications*

Based on the data analysis results, in order to enhance the Usage Intention of this user group toward E-commerce enterprises AI Intelligent Customer Service, this paper offers the following recommendations as potential references for relevant stakeholders:

First, on the issue of service quality, builders and regulators must set a higher standard for AI chat support. Clear standards, regular audits and a public scorecard can keep maintain high response speed and accuracy. Firms that fall below the line should be given notice and required to fix the gaps.

Second, to address to personal needs, developers should analyse anonymous logs for common student questions and tune replies so each user hears the answer that best fits their needs. At the same time, privacy code must be hardened—stronger encryption, less data kept, and plain-language consent—so trust rises with every turn of the chat.

Third, for the engine itself, firms and government can fund joint labs that link new algorithms to real campus shopping pain-points. Targeted grants, cloud credits and open data sets will let teams test faster models, safer speech classifiers and channel-hopping interfaces, thereby improving the overall service level without incurring additional costs to students.

Consumers live in a social web, so builders and officials should run media stories, host public talks and open online forums that let shoppers see what AI chat support can do. A built-in feedback loop—quick forms and monthly reports—will keep the tool aligned with real needs and speed up word-of-mouth.

Policymakers should therefore write rules that cover all four bars: service quality, personal feelings, technical edge and social cues. Targeted action on these points will increase uptake, cut contact-centre costs, and make trade on e-platforms faster and cheaper for both parties.

## AUTHOR CONTRIBUTIONS

LI Rong: Conceptualization; methodology; research design; supervision; writing – review and editing. LIU Siyi: Investigation; data collection; questionnaire administration; writing – original draft. DING Yinzhi: Data curation; statistical analysis; factor analysis and SEM modelling; visualization. ZHANG Guoyin: Validation; technical guidance; critical revision of the manuscript; project administration.

## ACKNOWLEDGEMENTS

The authors would like to thank the participants and interviewees for their valuable contributions to this study. The authors also appreciate the constructive comments provided by anonymous reviewers and the editorial team.

## CONFLICT OF INTEREST STATEMENT

The authors declare that there are no commercial or financial relationships that could be construed as a potential conflict of interest.

## DATA AVAILABILITY STATEMENT

The data generated and analyzed in this study are available from the corresponding author upon reasonable request. All data will be provided without undue restriction.

## Reference

1.Bao, J. X., & Hong, H. (2024). Research on the current application status and risks of generative artificial intelligence in the e-commerce industry. Time-honored Brand Marketing, (7), 55–57. https://qikan.cqvip.com/Qikan/Article/Detail?id=7111827455

2.Cai, N., Gao, S., & Yan, J. (2024). How the communication style of chatbots influences consumers' satisfaction, trust, and engagement in the context of service failure. Humanities and Social Sciences Communications, 11(1). https://doi.org/10.1057/s41599-024-03212-0

3.Chen, T., Ran, L. Y., & Ming, C. G. (2018). Research on the application of artificial intelligence in government services. E-Government, (3), 22–30. https://doi.org/10.16582/j.cnki.dzzw.2018.03.003

4.Chen, W. B., Peng, H. Z., Duan, B., Li, J., & Wang, Y. (2022). Research on the application of intelligent customer service in commercial banks. Financial Technology Times, 30(7), 53–55. https://qikan.cqvip.com/Qikan/Article/Detail?id=7107593968

5.Chen, Z. F. (2021). Research on artificial intelligence customer service systems under the background of big data. Information and Computer (Theoretical Edition), 33(8), 180–182. https://qikan.cqvip.com/Qikan/Article/Detail?id=7104986681

6.Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of Marketing Research, 43(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

7.China Internet Network Information Center. (2024). The 53rd statistical report on China's internet development. https://www.cnnic.com.cn/IDR/ReportDownloads/202405/P020240509518443205347.pdf

8.Chung, M., Ko, E., & Joung, H. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. Journal of Business Research, 117, 587-595. https://doi.org/10.1016/j.jbusres.2018.10.004

9.Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: Theory and results. [Doctoral dissertation, Massachusetts Institute of Technology. https://dspace.mit.edu/bitstream/handle/1721.1/15192/14927137-MIT.pdf

10.Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

11.Hollebeek, L., Sprott, D. E., & Brady, M. K. (2021). Engaged to a robot? The role of AI in service. Journal of Service Research, 24(1), 30-41. https://doi.org/10.1177/10946705209022

12.Illescas-Manzano, M. D., Martínez-Puertas, S., Cardoso, A., & Segovia-López, C. (2025). Use of online shop chatbots: How trust in seller moderates brand preference and purchase intention. https://doi.org/10.1007/978-3-031-70488-8_10

13.Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. Journal of Marketing, 57(1), 1–22. https://doi.org/10.1177/002224299305700101

14.Ketron, S. K. (2019). Naletelich, Victim or beggar? Anthropomorphic messengers and the savior effect in consumer sustainability behavior. Journal of Business Research, 96, 73–84. https://doi.org/10.1016/j.jbusres.2018.11.004

15.Kshetri, N., & Voas, J.M. (2019). Online Advertising Fraud. Computer, 52, 58-61. https://doi.org/10.1109/MC.2018.2887322

16.Kumar, N., & Benbasat, I. (2006). The influence of recommendations and consumer reviews on evaluations of websites. Information Systems Research, 17(4), 425–439. https://doi.org/10.1287/isre.1060.0107

17.Li, L., Zhang, X., & He, N. (2017). Human-computer interaction, network platform service quality, and new service development performance from the perspective of content providers: A theoretical model and research propositions. Science and Technology Management Research, 37(1), 207–214. https://doi.org/10.3969/j.issn.1000-7695.2017.01.037

18.Li, X. (2021). Development, application and research prospects of artificial intelligence in the field of e-commerce. New Economy, (12), 71–74. https://qikan.cqvip.com/Qikan/Article/Detail?id=7106387426

19.Liu, M. X. (2018). Research on influencing factors of E-commerce consumers' adoption intention of intelligent customer service [Master's thesis, Nanjing University]. https://doi.org/10.27235/d.cnki.gnjiu.2018.000415

20.McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. The Journal of Strategic Information Systems, 11(3–4), 297–323. https://doi.org/10.1016/S0963-8687(02)00020-3

21.Pitardi, V., & Wirtz, J. (2021). Service robots, agency and embarrassing service encounters. Journal of Service Management, 33(2), 389-414. https://doi.org/10.1108/JOSM-12-2020-0435

22.Shao, D. (2017). An analysis of the application of intelligent customer service in call volume diversion. Communications World, (9), 135. https://qikan.cqvip.com/Qikan/Article/Detail?id=672173290

23.Shi, J. S., Cai, H. Y., Chen, Y. X., Chen, Q., & Li, W. (2017). Research on the application of intelligent robots in customer service centers of the electric power industry. Electronic Test, 28(07), 133. https://doi.org/10.16520/j.cnki.1000-8519.2017.13.068

24.Soltani, Z. K. (2021). The applications of artificial intelligence in logistics and supply chain. Turkish Journal of Computer and Mathematics Education, 12(13), 4488–4499. https://www.kiphub.com/paper/691d203bf8357c9bd7c845b8

25.Song, S. Y., Wang, C., Chen, C. L., Li, Y., & Zhang, H. (2020). Sentiment analysis techniques for intelligent customer service systems. Journal of Chinese Information Processing, 34(2), 80–95. https://qikan.cqvip.com/Qikan/Article/Detail?id=7101919672

26.Su, Y. (2023). Visualization design of health detection products based on human-computer interaction experience in intelligent decision support systems. Mathematical Biosciences and Engineering, 20(9), 16725–16743. https://doi.org/10.3934/mbe.2023745

27.Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

28.Wang, Z., Ren, H., & Lu, X. H. (2018). Application and key technologies of artificial intelligence in customer service systems. Telecommunication Science, 34(12), 84–91.https://doi.org/10.11959/J.ISSN.1000-0801.2018302

29.Yang, L., Wei, Y., Zhang, K., & Li, X. (2021). Deep learning-based natural language processing in ophthalmology: Applications, challenges and future directions. Current Opinion in Ophthalmology, 32(5), 397–405. https://doi.org/10.1097/ICU.0000000000000789

30.Yang, Z. Y., & Zhai, S. L. (2022). A study on the relationship between information transparency of artificial intelligence and customer fit in service consumption—An analysis based on customer trust and anthropomorphization. Price Theory and Practice, (4), 193–196. https://doi.org/10.19851/j.cnki.CN11-1010/F.2022.04.110

31.Zhang, C., & Zhou, G. (2019). Innovative advantages of e-commerce platforms and competition be tween online and offline vendors. Economic and Management Research, 40(3), 45–57. https://doi.org/10.13502/j.cnki.issn1000-7636.2019.03.004
32.Zheng, R. R., & Gong, X. F. (2020). Innovative research and practice on customer service data a nalysis based on AI technology. Science and Informatization, (34), 37. https://d.wanfangdata.com.cn/periodical/kxyxxh202034032
33.Zhou, Q. (2021). Research on the influence mechanism of AI customer service on consumers' cust omization attitude.[Doctoral dissertation, Huazhong University of Science and Technology]. https://doi.org/10.27157/d.cnki.ghzku.2021.001919

**Disclaimer/Publisher's Note:** The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of *Journal of Contemporary Economics and Management* (JCEM) and/or its editor(s). JCEM and/or the editor(s) disclaim any responsibility for harm to persons or property resulting from any ideas, methods, instructions, or products referred to in the content.