

# A Study of Older Adults' Satisfaction with Chat Assistant

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**Abstract:** With the rapid development of artificial intelligence technology, intelligent question and answer systems such as Chat Assistant are increasingly used in daily life. However, as a special category of user group, the cognitive fitness and satisfaction assessment of elderly people to such intelligent systems have not been sufficiently studied yet. The purpose of this study is to explore the cognitive fitness and satisfaction of older adults with Chat Assistant Q&A results, in order to provide a basis for improving the design of these systems and enhancing the user experience of older adults. To this end, this paper provides an in-depth study of older adults' use of technology by designing and distributing a questionnaire. Analytical methods such as the ACSI indicator model and Structural Equation Modeling (SEM) were used to explore the relationship between satisfaction and various factors, thereby providing valuable guidance to help improve and optimize the Chat Assistant system.

## 1 Introduction

With the rapid development of science and technology, artificial intelligence technology has made significant progress in various fields [1,2]. Among them, natural language processing technology has become a highlight. Chat Assistant, as a representative of natural language processing, has shown great potential in various fields with its ability to simulate human conversations. However, there are cognitive and technical differences in the elderly population when dealing with this technology, posing challenges to how they can effectively apply Chat Assistant [3,4].

The global population is aging [5]. The percentage of the elderly population is climbing day by day, and by 2021, there will be more than 750 million people aged 65 and older worldwide, accounting for approximately 10% of the global population [6]. It is predicted that by 2050, the number of people aged 65 and older will increase to nearly 1.6 billion [7]. Although older adults are gradually becoming more and more engaged with technology, when it comes to the use of new technologies and digital tools, they require more of a learning curve and adaptation time, reinforcing the problematic digital capacity integration of older adults [8].

Additionally, according to a March survey by the Pew Research Center, 58 percent of adults in the U.S. know about or have used Chat Assistant, with knowledge positively correlating with educational attainment. However, the percentage of those who are aware of Chat Assistant declines with age, with only 8% of the 65+ age group being aware of Chat Assistant. This suggests that older people's knowledge and use of Chat

Assistant is relatively low, and more education and popularization efforts are needed [9].

## 2 Research methodology and data sources

### 2.1 ACSI Satisfaction Indicators

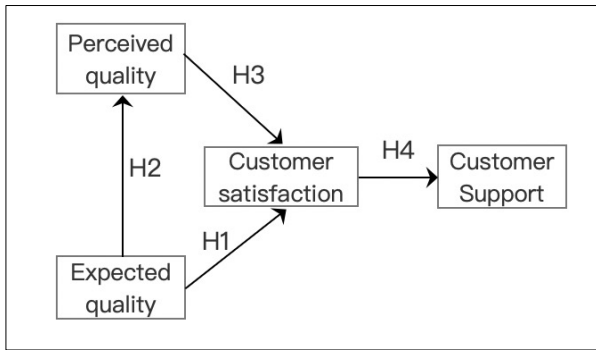
The ACSI (American Customer Satisfaction Index) is the main indicator widely used for satisfaction analysis. Data are collected through questionnaires and statistical analysis methods, and key indicators such as expected quality, perceived quality, perceived value, customer satisfaction, customer complaints, and customer loyalty are considered in an integrated way [10]. Expected quality reflects consumers' high expectations of a product or service, whereas perceived quality reveals evaluations after actual experience. Perceived value integrates quality and price, while customer satisfaction is one of the core indicators of ACSI, reflecting the overall level of satisfaction. In addition, customer complaints and customer loyalty are also important measurement factors. The overall structure of the ACSI consists of an Expectation Index, a Value Index, a Satisfaction Index, and a Willingness Index, which provide companies with comprehensive user feedback for improving and optimizing the user experience.

### 2.2 Research hypothesis

In the topics explored in this paper, the author will depict the bonds, intertwining and interactions between the various elements of the theoretical framework, presenting the depth, vein and strength of their

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connections. The figure below shows the structure and direction of this connection in detail:



**Fig. 1.** Modelling older people's satisfaction with Chat Assistant quiz results.

Based on the research summarized above, this paper proposes the following hypotheses:

H1: The quality of older adults' expectations of Chat Assistant question and answer results has a positive effect on older adults' satisfaction;

H2: The quality of older adults' expectations of Chat Assistant quiz results has a positive effect on older adults' perceived quality of Chat Assistant question results;

H3: There is a positive effect of perceived quality of Chat Assistant question outcomes on older adults' satisfaction;

H4: Older adults' satisfaction has a positive effect on older adults' support;

### 2.3 SEM structural equation modeling

SEM (Structural Equation Modeling) is a statistical analysis method that is commonly used to assess the association between observed variables and underlying constructs, while structural modeling describes the relationship between underlying constructs. [4] Through data collection, parameter estimation, and model fitting, structural equation modeling is able to validate the accuracy and fit of a theoretical model, thus providing insight into the object of study. Given that the structural variables in the ACSI model are difficult to measure directly, this paper establishes multiple observable variables corresponding to these four variables for observation.

$$X = \Lambda_x \xi + \delta \quad (1)$$

$$Y = \Lambda_y \eta + \varepsilon \quad (2)$$

$$\eta = B_\eta + r\xi + \zeta \quad (3)$$

where  $\xi$  denotes the exogenous latent variable,  $\eta$  denotes the endogenous latent variable,  $x$  and  $y$  denote the observed variables affecting  $\xi$  and  $\eta$ , respectively,  $X$  denotes the matrix of factor loading coefficients of  $x$  with  $\xi$ ,  $Y$  denotes the matrix of factor loading coefficients of  $y$  with  $\eta$ ,  $\delta$  and  $\varepsilon$  denote the error terms that are unexplained by  $\xi$  and  $\eta$ ,  $\eta$  is the matrix of endogenous latent variables,  $\xi$  denotes the matrix of exogenous latent variables,  $B$  denotes the matrix of path coefficients between the endogenous latent values,  $r$  denotes the matrix of path coefficients between the exogenous latent variable values, and  $\zeta$  denotes the

matrix of interference terms that are not explained by the endogenous latent variables.

## 3 Statistical data and analysis of results

### 3.1 Data sources

Given the inconvenience of carrying a laptop computer for testing, the author decided to evaluate the Q&A effect through the Chat Assistant application installed on the cell phone. The author relayed the questions of the elderly to Chat Assistant, and the answers given by Chat Assistant were fed back to the elderly, followed by a satisfaction questionnaire. The main target of this questionnaire survey was the elderly, and a survey walk-through method was used to distribute the questionnaires. After explaining the purpose and significance of the survey to the interviewees, the author dictated the questions in the questionnaire one by one, assisted them in filling out the questionnaire, and distributed and retrieved the questionnaires on the spot. In the end, a total of 230 questionnaires were distributed and 215 valid questionnaires were successfully retrieved.

Among them, in terms of gender, 51.2% were male and 48.8% were female. The age distribution was mainly concentrated in 50-60 years old (57.1%), 61-70 years old (30.2%), and 71 years old and above (12.7%). In terms of education, the proportion of respondents in primary and secondary schools and below/secondary schools and junior colleges is 57.6%, that of junior colleges is 26.8%, and that of undergraduates and above is 15.6%. The frequency of smart product usage showed that the highest percentage of daily usage was 77.9%, 14.5% for several times a week, 7.3% for several times a month, and 1.9% for no usage. In the experience of using smart products, cell phone/tablet users accounted for the most, accounting for 80.5%, smart voice assistant users accounted for 14.6%, and smart home device users accounted for 6.1%.

From this data, it can be seen that the gender distribution of this questionnaire group is relatively balanced, with slightly more men. In terms of age level, it is mainly concentrated in 50-70 years old, while the sample above 70 years old is relatively small. In terms of education level, it is mainly elementary school and below, showing a trend of relatively low education. In response to the frequency of use of digital products, most people use them daily, indicating that respondents generally have a high frequency of exposure to digital products. However, in terms of experience in using smart products, the frequency of exposure to the use of products like smart voice assistants and smart home devices is still at a low level. Such a trend may reflect the fact that digital smart products have not yet been popularized among middle-aged and low-educated people, while senior and highly educated people have relatively more experience with smart products.

### 3.2 Reliability and validity analysis

In this study, SPSS AU online statistical software was used to validate the reasonableness of the latent variables by applying Cronbach's alpha reliability coefficient method and KMO validity test, and the demographic characteristics of the sample were analysed through descriptive statistics. Second, the satisfaction model of the elderly was tested through structural equation modelling (SEM), assuming that there was a causal relationship between the variables and that the latent variables could be measured by the explicit variables. The relationship between the variables was tested by covariance, and linear regression coefficients were estimated to test the model fit and the effect of variable paths. The statistical indicators of the variables are shown in the table below.

**Table 1.** Table of statistical indicators for variables.

Variant	Number of indicators	Cronbach's $\alpha$	Bartlett's test of sphericity significance sig	KMO value
Expected quality	2	0.754	0.000	0.762
Perceived quality	8	0.869	0.000	0.893
Satisfaction	2	0.857	0.000	0.844
Degree of support	2	0.738	0.000	0.712

The data in the above table contains four variables: quality of expectation, perceived quality, satisfaction and support. The analysis of the professional statistical indicators revealed good internal consistency of the variables, indicating high reliability of the measurement tool. The Bartlett's test of sphericity with a significance value of 0.000 indicated the existence of correlation among the variables, which further supported the rationality of conducting factor analysis. The high KMO value indicates that the data is suitable for factor analysis and helps to explain the underlying structural relationships. These professional statistical results fully support the reliability and validity of the data.

### 3.3 Model checking

Table 2 shows the parameters of the model fit indicators, for the structural equation modelling (SEM) fit indicators, it is observed that the CMIN/DF value is 2.523, which is within the acceptable range, indicating a good model fit. The CFI, TLI and IFI are all above 0.9, indicating a good model fit. The SRMR is 0.072, which is lower than 0.08, and meets the criterion of a good model fit. RMSEA was 0.60, slightly above 0.50, but still within the acceptable range. PNFI was 0.765, exceeding 0.5, indicating that the simplicity of the model was maintained. Combining these fit metrics, we conclude that the structural equation model exhibits a good fit on these data.

**Table 2.** Table of parameters for model adaptation indicators.

Indicators	Standard value	Resulting value
CMIN/DF	<3	2.523
CFI	>0.9	0.931
TLI	>0.9	0.923
IFI	>0.9	0.926
SRMR	<0.8	0.072
RMSEA	<0.8	0.6
PNFI	>0.5	0.765

### 3.4 Hypothesis testing

The regression analysis of the standardized regression coefficients in Table 3 and the data in the test allows the following conclusions to be drawn:

The regression coefficients in the research hypotheses present a clear relationship. There is a significant positive relationship between quality of expectation and satisfaction, quality of expectation has a positive effect on perceived quality, there is a significant positive relationship between perceived quality and satisfaction, and finally satisfaction shows a significant positive relationship on support. All these relationships passed in statistical tests with p-values less than 0.001, indicating that they are statistically significant. In terms of overall model fit, the indicators used (CMIN/DF, CFI, TLI, IFI, SRMR, RMSEA, PNFI) performed well and met the standard values. This further strengthens the credibility of the study results. Therefore, the findings strongly support the research hypotheses, reveal the complex and close relationship between expected quality, perceived quality, satisfaction and support, and provide strong data support for further understanding and optimisation of the operations involved.

**Table 3.** Table of indicators for hypothesis testing

Research hypothesis	Regression coefficient	p value	pass or fail
H1: Expected quality → Satisfaction	0.843	***	pass
H2: Perceived quality → Expected	0.916	***	pass
H3: Perceived quality → Satisfaction	1.035	***	pass
H4: Satisfaction → Degree of support	0.954	***	pass

### 3.5 Customer satisfaction analysis

Combined with the data in Table 4, a comprehensive analysis of the Chat Assistant elderly user satisfaction questionnaire data reveals a series of key insights. Multi-scenario Q&A support and dialogue efficiency in desired quality have a significant impact on user satisfaction, with standardized regression coefficients of 0.076 and 0.084, respectively. Multi-scenario Q&A support, dialogue efficiency, knowledge richness, and

dialogue fluency in perceived quality are the key drivers, with standardized regression coefficients of 0.086, 0.088, 0.091, and 0.089, respectively. However, misleadingness and information security had relatively little impact on the ratings, with standardised regression coefficients of 0.073 and 0.083, respectively. Elderly users' expectations were mainly focused on dialogue efficiency and dialogue fluency. It is recommended to optimise these two aspects to better meet the needs of elderly users and enhance their satisfaction with Chat Assistant.

**Table 4.** Satisfaction Score Table

Secondary variable	Trivially variable	Regression coefficient	Satisfaction score
Expected quality	Multi-scenario Q&A support	0.076	3.52
	Dialogue efficiency	0.084	3.89
Perceived quality	Multi-scenario Q&A support	0.086	4.13
	Dialogue efficiency	0.088	4.21
	Accuracy of answers	0.074	3.34
	Contextual coherence	0.075	3.72
	Knowledge enrichment	0.091	4.27
	Dialogue fluency	0.089	4.11
	Information security	0.083	3.11
	Misleading	0.073	3.43

An in-depth study of the questionnaire data provides a comprehensive guide to the optimisation of Chat Assistant. The optimisation of expectation quality and perception quality is the key path to improve user satisfaction. In addition, combining the results of the survey conducted by Zhejiang Senior Citizen Newspaper, 84.58% of the elderly people chose "simplify the operation process", 57.94% chose "more comfortable and convenient", 66.82% chose "popularise", and the others chose "make Chat Assistant more popular". The elderly who chose "more comfortable and convenient" accounted for 57.94 per cent, those who chose "to make it more popular" accounted for 66.82 per cent, and the others accounted for 6.54 per cent. It can be seen that although there are differences in the level of understanding of Chat Assistant among the elderly, many of them do not know about it. The survey also found that the attitude of the elderly towards smart products is polarised, with some elderly holding curiosity and inquisitiveness about the new technology and willing to take the initiative to contact and learn about it, while others have cognitive and acceptance barriers to its use and hold resistance to the new technology. The majority of older people want smart products with simplified operating procedures and user-friendly interfaces that can solve daily life challenges and provide more convenient services.

## 4 Conclusions and recommendations

Combining the questionnaire data and the results of the survey conducted by Zhejiang Senior Citizen Newspaper, this study concludes that personalized service and simplification of the operation process should be an important direction for Chat Assistant to improve, in order to better satisfy the needs of the elderly users and to enhance their acceptance and experience of using digital technology.

To meet the specific needs and usage scenarios of the elderly, this study proposes the following insightful recommendations and provides detailed explanations for each of them: firstly, in order to improve the contextual clarity and reduce ambiguity of Chat Assistant-generated text, it is recommended to optimise the natural language generation model and introduce a more interpretable language generation model, such as recurrent neural network (RNN) or long-short term memory network (LSTM). Second, as older users may be less familiar with domain-specific terminology, it is suggested that a domain adaptive mechanism be introduced to ensure that Chat Assistant is better adapted to older users in multi-scenario Q&A and is friendly to users who are less familiar with the technical requirements. Third, in order to meet the needs of elderly users for extensive knowledge, it is recommended to deepen the integration of knowledge graphs and present information intuitively and vividly through graphical interfaces or charts and other forms. Fourth, in view of the sensitivity of the elderly to privacy, it is recommended to introduce privacy enhancement techniques, such as differential privacy and zero-knowledge proof, to ensure that Chat Assistant better protects the personal information of elderly users. Fifth, to enhance the experience of older users, it is recommended to personalise the interface design of Chat Assistant and optimise the interaction methods, including voice interaction and simple and clear graphical interfaces, to adapt to the cognitive characteristics of older people. Sixth, to meet the possible auditory or visual differences of the elderly, it is recommended to integrate multimodal learning to make Chat Assistant more comprehensively understand and respond to the needs of the elderly users by recognising and adapting to different information input methods.

Finally, to ensure that Chat Assistant can adapt to the changing needs and contexts of older adults, it is recommended that mechanisms for continuous learning and updating be provided to make it easier for older users to keep up with the technology through personalised learning paths. These recommendations aim to ensure that Chat Assistant can be more relevant to the needs of the older population and provide a more friendly and intelligent interaction experience when serving them.

## References

1. Domshlak, C.; Hüllermeier, E.; Kaci, S.; Prade, H. Preferences in AI: An Overview. *Artif. Intell.* 2011, 175 (7), 1037–1052.

2. Yonghao Cui; Cong Shang; Strongqi Chen; Jianye Hao. Artificial intelligence overview: the development of AI. *Radio Communication Technology* 2019, 45 (3), 225-231.
3. Gu, D. N.; Chou, L.. Analysis of cognitive function characteristics and influencing factors of the elderly in China. *Journal of Nanjing Institute of Population Management Cadre* 2003, No. 2, 3-9+13.
4. Yi, Weining; Kang, Xiaoping. A multilevel analysis of factors influencing cognitive functioning in the elderly in China. *Chinese Journal of Mental Health* 2008, No. 7, 538-542.
5. Kulik, C. T.; Ryan, S.; Harper, S.; George, G. Aging Populations and Management. *Acad. Manage. J.* **2014**, 57 (4), 929–935.
6. Kinklaze, R.; Metreveli, S. Statistical Analysis of Demographic Aging of the Population. *Procedia - Soc. Behav. Sci.* **2014**, 156, 174–177.
7. Richard-Eaglin, A.; Campbell, J. G.; Utley-Smith, Q. The Aging Veteran Population: Promoting Awareness to Influence Best Practices. *Geriatr. Nur. (Lond.)* **2020**, 41 (4), 505–507.
8. Deary, I. J.; Corley, J.; Gow, A. J.; Harris, S. E.; Houlihan, L. M.; Marioni, R. E.; Penke, L.; Rafnsson, S. B.; Starr, J. M. Age-Associated Cognitive Decline. *Br. Med. Bull.* **2009**, 92 (1), 135–152.
9. Yuliang L.; Hongliang L.; Xiang B.; Lianwen J.; School of Artificial Intelligence and Automation, Huazhong University of Science and Technology, Wuhan 430074, China. A brief analysis of ChatGPT: historical evolution, current applications, and future prospects. *J. Image Graph.* **2023**, 28 (4), 893–902.
10. Angelova, B.; Full Professor at Ss Cyril and Methodius University, Economic Institute, Prolet nr 1, Skopje-Macedonia; Zekiri, J.; Assistant Professor at South East European University, Business and Economics Faculty, Ilindenska nn, Tetovo-Macedonia. Measuring Customer Satisfaction with Service Quality Using American Customer Satisfaction Model (ACSI Model). *Int. J. Acad. Res. Bus. Soc. Sci.* **2011**, 1 (3), 27.