

# Generative AI in Healthcare

CONSUMER BEHAVIOR INSIGHTS

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# 1. Introduction

In recent years, Generative Artificial Intelligence (GenAI) has developed rapidly in many industries. GenAI had a significant impact on the healthcare industry, greatly helping us to handle administrative tasks, enhance patient care and improve efficiency. In addition, hospital employees can concentrate on high-value work and give patients personalized treatment thanks to this technology.

However, the use of GenAI in healthcare poses both opportunities and challenges. While it can manage administrative tasks, improve patient engagement, and enhance decision-making, it also raises concerns about user satisfaction, privacy concerns, and diagnostic accuracy. In this case, it is essential to develop strategies to integrate GenAI effectively and ethically in healthcare.

This report aims to explore consumer behavior and their attitude towards GenAI in the healthcare industry. The research employs a mixed-methods approach, combining quantitative and qualitative analysis. Data collection was conducted by using online surveys, and all data was analyzed and processed in SPSS. In the analysis, we explore the main effect of independent variable(IV) on dependent variables(DVs:trust and safety). Besides, the study also examines the roles of mediators and moderators. The analysis and results mentioned will be shown in the Finding part. Based on the results of the data collected, we gain insights about the consumer perception of GenAI in healthcare, which provides idea and inspiration for future optimization of AI in healthcare.

# 2. Trend Background

Generative AI in healthcare reveals several important insights. ChatGPT has shown promise in enhancing patient communication and providing diagnostic support, as well as automating routine tasks. However, there are significant concerns about data privacy and the accuracy of the information generated. To gain insight into AI in healthcare, we searched for paper on the field and we will show our findings in this part.

| Student's name | Paper  | Journal's name         | Main findings  | How is it relevant to your research?   |
|----------------|--|------------------------|--|--|
| Tong Zhao      | Casella, M., Montomoli, J., & Bimonte, S. (2023). Surviving ChatGPT in | Frontiers in Radiology | The paper investigates the implications of using ChatGPT in healthcare, focusing on its potential benefits and challenges. Key findings include improved patient communication, enhanced diagnostic support, and the potential for | Provide both the advantages and risks associated with deploying generative AI in |

|                 |   |                                      |   |   |
|-----------------|---|--------------------------------------|---|---|
|                 | healthcare.<br><i>Frontiers in Radiology</i> , 3, 1224682.  |                                      | automating routine tasks. However, it also highlights concerns regarding data privacy, the accuracy of generated information, and the need for rigorous oversight to prevent misuse.  | healthcare settings.  |
| Duarte Ferreira | Yim, D., Khuntia, J., Parameswaran, V., & Meyers, A. (2024). Preliminary evidence of the use of generative AI in health care clinical services: Systematic narrative review. <i>JMIR Medical Informatics</i> , 12(1), e52073. | JMIR Medical Informatics             | GenAI is being increasingly used in health care. Physicians, specialists, and other providers have started primarily using GenAI as an aid or tool to gather knowledge, provide information, train, or generate suggestive dialogue between physicians and patients or between physicians and patients' families or friends.  | GenAI informs rather than assists or automates clinical service functions in health care. This paper helps us to Better understand the role of GenAI in healthcare.   |
| António Cadaixa | Chen, Y., & Esmailzadeh, P. (2024). Generative AI in medical practice: In-depth exploration of privacy and security challenges. <i>Journal of Medical Internet Research</i> , 26, e53008.                                     | Journal of Medical Internet Research | The paper examines the potential applications and associated security and privacy risks of generative AI in healthcare. It focuses on various categories such as medical diagnostics, drug discovery, virtual health assistants, medical research, and clinical decision support. The paper identifies threats at different stages of the AI life cycle—data collection, model development, and implementation—highlighting the necessity for robust security and privacy measures. | The study on "GenAI in administrative and paperwork" can ensure that the implementation of generative AI in administrative tasks is secure, compliant, efficient, and ethically sound which can be helpful for our study. |

|              |  |  |  |  |
|--------------|--|--|--|--|
| Ran Zhou     | <p>Nova, K. (2023). Generative AI in healthcare: Advancements in electronic health records, facilitating medical languages, and personalized patient care. <i>Journal of Advanced Analytics in Healthcare Management</i>, 7(1), 115-131.</p> | Journal of Advanced Analytics in Healthcare Management | <p>This research explores the application of generative AI techniques in healthcare to address three significant areas: enhancing electronic health records (EHRs) through automated conversation summarization, simplifying complex medical language into patient-friendly summaries, and providing personalized care recommendations using data from smartwatches and wearables.</p> | <p>Simplifying complex medical language into patient-friendly summaries can be one of the most indispensable parts of our topic.</p>                                 |
| Xiner Ye     | <p>Johnson, P., &amp; Williams, H. (2024). Revolutionizing personalized medicine with generative AI: A systematic review. <i>Journal of Personalized Medicine</i>, 13(2), 123-139.</p>   | Journal of Personalized Medicine                       | <p>The paper reviews the role of deep generative models (DGMs) in personalized medicine. Generative AI accelerates drug candidate discovery and predicts new drug efficacy and safety.</p>   | <p>This paper provides insights into how generative AI improves efficiency and accuracy in personalized medicine, aiding AI integration into healthcare systems.</p> |
| Tausif Ahmad | <p>Pediaditis, M., Zhang, P., &amp; Boulos, M. N. K. (2023, August 24). Generative AI in medicine and healthcare: Promises, opportunities</p>  | The Future of Internet of Medical Things II            | <p>Challenges include ethical considerations, accuracy, reliability, data privacy, security concerns, and minimizing bias. The article reviews these potential applications and challenges comprehensively.</p>  | <p>Define the challenges of GenAI in healthcare.</p>   |

|             |   |           |   |   |
|-------------|---|-----------|---|---|
|             | and challenges.   |           |   |   |
| Mengmeng Li | <p>Takita, H., Kabata, D., Walston, S. L., Tatekawa, H., Saito, K., Tsujimoto, Y., ... &amp; Ueda, D. (2024). Diagnostic performance comparison between generative AI and physicians: A systematic review and meta-analysis. <i>medRxiv</i>, 2024-01.</p> | medRxiv   | <p>This systematic review and meta-analysis examine the diagnostic performance of generative AI models compared to physicians across various medical specialties. The study underscores the potential of generative AI in healthcare, while also highlighting the need for rigorous research and larger sample sizes to minimize bias.</p>                      | <p>This paper is relevant because it provides a comprehensive analysis of how generative AI models perform in real-world diagnostic tasks compared to human physicians.</p> |
| Ran Tian    | <p>Gallazzi, E., La Maida, G. A., &amp; Cabitza, F. (2023). Editorial: Clinical integration of artificial intelligence in spine surgery: Stepping in a new frontier. <i>Frontiers in Surgery</i>, 10, 1351643.</p>  | Frontiers | <p>AI can categorise patients into distinct groups based on preoperative characteristics, aiding in personalized surgical planning. In addition, AI models show high predictive performance in making surgical decisions and optimizing treatment strategies. Furthermore, AI algorithms effectively classify endplate lesions, reducing doctors' workload.</p> | <p>Through this paper, we can gain detailed and specific insights into the practical applications of AI in the medical field.</p>   |

### 3. Methodological Notes

For this study, data was collected using an online survey created on the Qualtrics website with several questions which were structured as follows:

At the beginning of the survey, participants were required to give their consent to ensure everyone agreed to take part. The research then introduced a scenario set in a hospital where a doctor treats a patient. Three different scenarios were presented:

1. In the first scenario, Generative AI handles all the administrative and paperwork tasks without any human oversight.
2. In the second scenario, Generative AI manages these tasks, but with human supervision.
3. In the third scenario, medical staff handle all the administrative and paperwork tasks themselves.

To maintain consistency and avoid influencing the results, the questions that followed were designed to match the context of these scenarios. Each participant was randomly assigned to one of the scenarios, ensuring an even distribution among the different conditions.

The survey began with questions focused on observing the dependent variables, mediators, and moderators, including Behavioural Intention, Privacy, Safety, Trustworthiness, Expertise, Trust, Enjoyment, and Competence. An attention check was placed on the 5th question, requiring respondents to choose a specific answer. After these initial questions, a manipulation check was included, asking participants whether they thought the administrative tasks and paperwork were handled by Generative AI alone, Generative AI with human supervision, or by human employees. The final section of the survey included demographic questions.

The participants ranged in age from 21 to 45 years old, with the majority being female. Many reported having a bachelor's degree as their highest level of education. The most common employment status among the participants was either unemployed or full-time students.

For our analysis, we started with 73 responses. During the filtering process, we aimed to exclude participants who failed the attention check, failed the manipulation check, or did not complete the full survey.

## 4. Hypothesis

**H1:** The involvement of AI The involvement of GenAI in performing paperwork services in a hospital will have a positive impact on customers' level of trust.

**H2:** The involvement of AI The involvement of GenAI in performing paperwork services in a hospital will have a positive impact on customers' level of safety.

**H3:** The relationship between the involvement of GenAI and trust is mediated by the level of enjoyment.

**H4:** The relationship between the involvement of GenAI and safety is mediated by the level of enjoyment

## 5. Findings

First, we would like to clarify the roles of variables in our research.

Dependent variables (DV): Safety, Trust; Independent variables (IV): GenAI, GenAI & Human, Only Human; Moderator: AI Knowledge; Mediator: Enjoyment

At the beginning of the survey, the manipulation check was conducted to examine whether our experiment was successful. Overall, manipulation checks help ensure the reliability and validity of our experiment's findings. For this part, we performed Chi-square to explore if there was significant difference among the 3 scenarios. For the results, the p-value of Pearson Chi-square is less than 0.001, which is obviously less than 0.05. The outcome indicates that there is a significant difference among our different scenarios. In this case, the experiment is effective and successful.

In the next step, we explored the main effect between DV and IV. As there are 3 scenarios in IV, we adopted the ANOVA to perform this test. The result shows that there is a significant effect of the involvement of GenAI on Safety at the  $p < 0.05$  level for the three conditions. [ $F(2,195) = 3.28, p = 0.04$ ]. Post hoc comparison using the Tukey HSD test demonstrates that the mean score for the GenAI & Human condition ( $M = 6.15, SD = 1.44$ ) is significantly different than the only human condition ( $M = 5.47, SD = 1.76$ ). However, the GenAI condition ( $M = 6.00, SD = 1.57$ ) doesn't significantly differ from the other two conditions. We conducted the same test for the other DV, but both ANOVA and Post Hoc test shows that there is not significant difference among the variables. In conclusion, the involvement of GenAI impacts people's sense of safety but does not influence their level of trust.

Moderator is a variable that influences the strength or direction of the relationship between IV and DV. In our research, we selected the level of AI knowledge as the moderator and tested the relationship between the moderator and each of the two dependent variables separately. The results are as follows. The level of AI knowledge and its interaction with the independent variable do not have a significant impact on the sense of safety and trust, which means the level of AI knowledge doesn't moderate our experiment.

### DV: Trust

|                   | F     | Sig.  |
|-------------------|-------|-------|
| IV * AI_Knowledge | 1.475 | 0.169 |

## DV: Safety

|                   | F     | Sig.  |
|-------------------|-------|-------|
| IV * AI_Knowledge | 0.424 | 0.906 |

Differentiating from moderator, mediator is a variable that clarifies the mechanism behind the relationship between DV and IV. Through Model 4 in Process, we selected 5000 Bootstrap samples for the mediation analysis. The outcome indicates that enjoyment mediates the relationship between the independent variable and each of the dependent variables.

## 6. Trend Insights

### 6.1 Key Takeaways – Conclusions

In conclusion, while the involvement of GenAI in hospital paperwork services has shown some significant impacts, there are several important findings and considerations.

#### Impact on Safety and Trust

Based on the findings, the involvement of GenAI positively impacts customers' sense of safety but does not significantly influence their level of trust. The ANOVA results indicate that customers feel safer when GenAI is involved, either alone or in combination with human efforts. However, trust levels remain unaffected across different scenarios, suggesting that other factors might play a role in shaping trust in AI technologies.

#### Role of Enjoyment

The analysis highlights that enjoyment mediates the relationship between GenAI involvement and both safety and trust. This suggests that how enjoyable customers find the interaction with GenAI significantly influences their perceptions of safety and trust. Ensuring that GenAI systems are engaging and enjoyable to use could be a key strategy for enhancing customer experience.

#### Moderator Analysis

The level of AI knowledge does not moderate the relationship between GenAI involvement and the dependent variables of safety and trust. This indicates that



whether customers are knowledgeable about AI does not significantly alter their perceptions of safety and trust when interacting with GenAI systems.

### **Successful Manipulation Check**

The manipulation check confirms the reliability and validity of the experimental setup. The significant differences among the three scenarios validate the effectiveness of the conditions tested. This ensures that the experimental findings are robust and dependable.

Overall, this study provides valuable insights into how GenAI impacts customer perceptions in hospital settings. The positive effect on safety highlights a key benefit of integrating AI into healthcare services. Ensuring enjoyable user experiences and addressing other potential trust factors could further enhance the acceptance and effectiveness of AI in healthcare. Further research is necessary to explore these aspects in more detail and across different contexts.

## **6.2 Limitations**

During our research process, we identified several potential limitations that may affect the interpretation and application of our results. The primary limitations of this study are as follows:

### **Lack of Sample Diversity**

Despite employing various scenarios and variables, the diversity of our sample may still be insufficient. The majority of respondents were young individuals with experience and some knowledge of AI, which may not represent all demographics, particularly older adults who utilize healthcare services more frequently.

### **Operationalization of Independent Variables**

The operationalization of the independent variables—generative artificial intelligence (GenAI) and human-only—may not fully capture the complexity of real-world applications. In practice, AI implementations can be more intricate, involving more interactions and use cases than those set up in our experiments.

### **Short-term Experimental Design**

Our experimental design was short-term, focusing on immediate reactions and changes in attitudes. In the long run, the impact of AI applications on trust and sense of security might differ, especially as users become more familiar and accustomed to these technologies.

## References

1. Cascella, M., Montomoli, J., & Bimonte, S. (2023). Surviving ChatGPT in healthcare. *Frontiers in Radiology*, 3, 1224682.
2. Chen, Y., & Esmailzadeh, P. (2024). Generative AI in medical practice: In-depth exploration of privacy and security challenges. *Journal of Medical Internet Research*, 26, e53008.
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4. Johnson, P., & Williams, H. (2024). Revolutionizing personalized medicine with generative AI: A systematic review. *Journal of Personalized Medicine*, 13(2), 123-139.
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8. Yim, D., Khuntia, J., Parameswaran, V., & Meyers, A. (2024). Preliminary evidence of the use of generative AI in health care clinical services: Systematic narrative review. *JMIR Medical Informatics*, 12(1), e52073.

## Appendix

### Manipulation Check

#### Chi-Square Tests

|                                 | Value               | df | Asymptotic<br>Significance<br>(2-sided) |
|---------------------------------|---------------------|----|---|
| Pearson Chi-Square              | 21.570 <sup>a</sup> | 4  | <.001                                   |
| Likelihood Ratio                | 21.293              | 4  | <.001                                   |
| Linear-by-Linear<br>Association | 6.382               | 1  | .012                                    |
| N of Valid Cases                | 198                 |    |   |

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.39.

### Oneway(DV: Safety)

#### ANOVA

SafetyM

|                | Sum of<br>Squares | df  | Mean Square | F     | Sig. |
|----------------|-------------------|-----|-------------|-------|------|
| Between Groups | 16.539            | 2   | 8.269       | 3.280 | .040 |
| Within Groups  | 491.654           | 195 | 2.521       |       |      |
| Total          | 508.193           | 197 |             |       |      |

### Oneway(DV: Trust)

#### ANOVA

Trust\_M

|                | Sum of<br>Squares | df  | Mean Square | F     | Sig. |
|----------------|-------------------|-----|-------------|-------|------|
| Between Groups | 11.123            | 2   | 5.562       | 2.592 | .077 |
| Within Groups  | 418.332           | 195 | 2.145       |       |      |
| Total          | 429.455           | 197 |             |       |      |

### Mediator: enjoyment, DV: Trust

Indirect effect(s) of X on Y:

|         | Effect | BootSE | BootLLCI | BootULCI |
|---------|--------|--------|----------|----------|
| Enjoy_M | -.1054 | .0488  | -.2112   | -.0210   |

### Mediator: enjoyment, DV: Safety

Indirect effect(s) of X on Y:

|         | Effect | BootSE | BootLLCI | BootULCI |
|---------|--------|--------|----------|----------|
| Enjoy_M | -.1027 | .0485  | -.2077   | -.0219   |

### Moderator: AI Knowledge, DV: Trust

#### Tests of Between-Subjects Effects

Dependent Variable: Trust\_M

| Source            | Type III Sum of Squares | df  | Mean Square | F       | Sig.  | Partial Eta Squared |
|-------------------|-------------------------|-----|-------------|---------|-------|---------------------|
| Corrected Model   | 44.432 <sup>a</sup>     | 15  | 2.962       | 1.400   | .151  | .103                |
| Intercept         | 2000.148                | 1   | 2000.148    | 945.470 | <.001 | .839                |
| IV                | 9.170                   | 2   | 4.585       | 2.167   | .117  | .023                |
| AI_Knowledge      | 7.754                   | 5   | 1.551       | .733    | .599  | .020                |
| IV * AI_Knowledge | 24.971                  | 8   | 3.121       | 1.475   | .169  | .061                |
| Error             | 385.022                 | 182 | 2.116       |         |       |                     |
| Total             | 7922.000                | 198 |             |         |       |                     |
| Corrected Total   | 429.455                 | 197 |             |         |       |                     |

a. R Squared = .103 (Adjusted R Squared = .030)

### Moderator: AI Knowledge, DV: Safety

#### Tests of Between-Subjects Effects

Dependent Variable: SafetyM

| Source            | Type III Sum of Squares | df  | Mean Square | F       | Sig.  | Partial Eta Squared |
|-------------------|-------------------------|-----|-------------|---------|-------|---------------------|
| Corrected Model   | 45.728 <sup>a</sup>     | 15  | 3.049       | 1.200   | .275  | .090                |
| Intercept         | 1900.343                | 1   | 1900.343    | 747.867 | <.001 | .804                |
| IV                | 14.177                  | 2   | 7.088       | 2.790   | .064  | .030                |
| AI_Knowledge      | 21.891                  | 5   | 4.378       | 1.723   | .131  | .045                |
| IV * AI_Knowledge | 8.610                   | 8   | 1.076       | .424    | .906  | .018                |
| Error             | 462.465                 | 182 | 2.541       |         |       |                     |
| Total             | 7368.750                | 198 |             |         |       |                     |
| Corrected Total   | 508.193                 | 197 |             |         |       |                     |

a. R Squared = .090 (Adjusted R Squared = .015)