



www.editada.org

Technological Anthropomorphism Affecting Generation Z: Foundation of Human-Machine Interaction for Early Detection of Anxiety and Depression

Alberto Ochoa¹, Irma Hernández-Báez², Carlos Lara³; Saúl González¹

¹ Doctorado en Tecnología, Universidad Autónoma de Ciudad Juárez, México.

² Universidad Politécnica del Estado de Morelos, México.

³ CIMAT Unidad Zacatecas, México.

alberto.ochoa@uacj.mx

Abstract. Technology has become a fundamental tool for addressing mental health issues such as anxiety and depression. This study examines the role of technological anthropomorphism in facilitating human-machine interaction through five key technologies: Tamagotchi, Real Chatbots (like ELIZA), Advanced Alexa, ChatGPT-4, and Holographic Interfaces. By evaluating these tools across factors such as emotional interactivity, personalization, and privacy, the results reveal that modern technologies like Advanced Alexa, ChatGPT-4, and holographic interfaces offer significantly enhanced capabilities, particularly in interpreting context and recognizing emotions. Holographic technology adds a unique dimension to this analysis by providing a three-dimensional, lifelike representation of the machine. This allows for more engaging and intimate interactions, which can be pivotal in creating more meaningful connections for individuals dealing with mental health challenges. The ability to see a hologram mimic human expressions and movements may foster a deeper emotional response, helping users feel understood and supported. This underscores the importance of ethical considerations in leveraging human-like interaction for mental health applications. A sample of 87 Generation Z participants (47 females and 40 males) from a Private University in Mexico was analyzed to investigate the interaction between these technologies and their potential in detecting anxiety and depression. This demographic provides unique insights into how digital natives perceive and interact with anthropomorphized technology.

Keywords: Technological Anthropomorphism, Generation Z, Human-Machine Interaction, Mental Health Detection, Anxiety and Depression, AI-Driven Technologies, Ethical Considerations in Technology

Article Info

Received Dec 26, 2024

Accepted February 13, 2025

1 Introduction

The detection of anxiety and depression at early stages is crucial for implementing effective interventions that improve quality of life. Over the years, technology has evolved to play a pivotal role in health diagnostics (Kory & McDonald 2020), with Generation Z (a generation deeply integrated with technology) offering a unique context for studying human-machine interaction (Durango, et al., 2024). This paper explores how technological anthropomorphism influences this interaction and evaluates the potential of various technologies in detecting mental health issues. By focusing on Generation Z participants, we aim to uncover patterns and preferences that may shape future technological solutions. Generation Z, often referred to as digital natives, has grown up in an era where technology is not just a tool but a companion in daily life (Corciulo & Bochicchio, 2024). This familiarity fosters a unique relationship with anthropomorphized technologies, enabling deeper emotional engagement compared to earlier generations. Technologies like Advanced Alexa and ChatGPT-4 have revolutionized how users perceive artificial intelligence, blending functionality with human-like empathy. This paper aims to dissect these dynamics and their implications for mental health interventions. The role of human-machine interaction extends beyond diagnostics, offering opportunities for real-time emotional support (Agerri, et al., 2013). With features like personalized feedback and adaptive learning, these technologies create a simulated sense of companionship that resonates particularly with Generation Z. However, the increasing integration of

anthropomorphic elements raises questions about ethical use, dependency, and the boundaries between technological assistance and human connection. Moreover, the rapid advancements in holographic technology offer a glimpse into the future of human-machine interaction. Holograms, which blend visual and auditory cues, present new possibilities for creating lifelike experiences. This paper also explores the potential impact of holographic interfaces in mental health, considering their ability to deliver immersive, interactive environments tailored to user needs. By including an analysis of holographic technology alongside existing tools, this study provides a comprehensive overview of the current landscape and anticipates future trends. The findings aim to guide the development of ethical, user-centered solutions that balance technological innovation with human well-being. The exploration of holograms underscores the importance of preparing for emerging technologies that may redefine the standards of human-machine interaction in mental health contexts.

Using the instrument administered to our Generation Z sample, we identified the technologies most trusted for disclosing depression and anxiety issues, presenting the average results categorized by gender and technology (Figure 1).

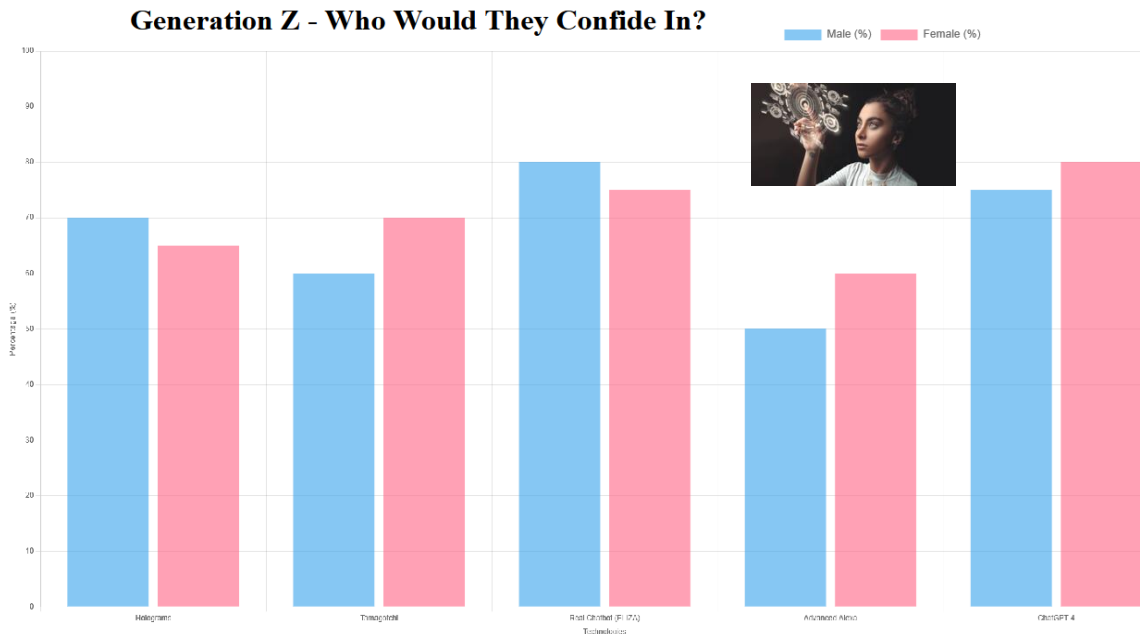


Fig. 1. Willingness to share depression and anxiety problems with the five technologies included in our study, by gender.

2 Methodology

A total of 87 participants from Generation Z (47 females and 40 males) were recruited for this study. Each participant engaged with Tamagotchi, Real Chatbots (like ELIZA), Advanced Alexa, ChatGPT-4 and Holographic interfaces over a period of two weeks. Interaction sessions were designed to evaluate:

1. **Emotional Interactivity:** How effectively the technology responded to emotional cues.
2. **Personalization:** The ability of the technology to adapt to individual user needs.
3. **Privacy and Security:** Participants' perceptions of data safety.
4. **Adaptability:** How seamlessly the technology integrated into daily routines.

Participants completed pre- and post-interaction surveys to measure changes in anxiety and depression levels, using validated tools such as the Generalized Anxiety Disorder (GAD-7) and Patient Health Questionnaire (PHQ-9) scales. This study focuses on the evaluation of technological anthropomorphism in four key technologies —Tamagotchi, Real Chatbots (like ELIZA), Advanced Alexa, and ChatGPT-4— as well as the potential integration of holographic interfaces. The methodology is designed to measure the impact of these technologies on Generation Z participants in detecting early signs of anxiety and depression.

2.1 Study Design

A total of 87 participants from Generation Z (47 females and 40 males) were recruited from a private university in Mexico. Each participant interacted with the technologies over a two-week period. The evaluation criteria included:

1. Emotional Interactivity: Response to emotional cues.
2. Personalization: Adaptation to individual needs.
3. Privacy and Security: Perceptions of data safety.
4. Adaptability: Integration into daily routines.

The technologies evaluated in this study are visually represented in Figure 2, which highlights the five key tools analyzed for their potential in detecting and mitigating anxiety among Generation Z individuals. These include: a) Tamagotchi, a pioneering example of interactive technology; b) Real Chatbot (ELIZA), an early model of conversational AI; c) Advanced Alexa, a modern voice assistant with enhanced emotional and contextual capabilities; d) ChatGPT-4, a state-of-the-art language model designed for empathetic and personalized interactions; and e) Holograms, which offer a three-dimensional, immersive experience. Each technology represents a distinct evolution in human-machine interaction, providing unique insights into how anthropomorphism can be leveraged for mental health support.



Fig. 2. Technologies analyzed in this research to determine the most suitable one associated with the detection and proper mitigation of anxiety in Generation Z individuals: a) Tamagotchi, b) Real Chatbot (ELIZA), c) Advanced Alexa, d) ChatGPT-4, and e) Holograms.

2.2 Comparison of Technologies in Addressing Mental Health

To better understand the strengths and limitations of each technology in addressing mental health, this section provides a comparative analysis across key variables: ease of use, emotional interactivity, personalization, privacy and security, and adaptability. Table 1 summarizes the performance of Tamagotchi, Real Chatbot (ELIZA), Advanced Alexa, ChatGPT-4, and Holograms in these areas. This comparison highlights how each technology has evolved to meet the needs of users, particularly Generation Z, in detecting and mitigating anxiety and depression. By examining these factors, we can identify which tools are most effective in fostering meaningful human-machine interactions and supporting mental health interventions.

Table 1. Comparative analysis of the five technologies evaluated in this study

Variable	Tamagotchi	Real Chatbot (ELIZA)	Advanced Alexa	ChatGPT-4	Holograms
Ease of Use	Very easy (simple screen and buttons)	Very easy (text interaction)	Very easy (voice only)	Very easy (text or voice)	Easy (interactive 3D interface, touch or voice-controlled)
Emotional Interactivity	Basic (predefined emotions)	Very basic (no real emotions)	Moderate (simple reactions)	High (recognizes emotions in text)	Very High (expressions, gestures, and emotional cues)
Personalization	None	Low (pre-programmed responses)	Moderate (basic configurations)	High (learns from context and personalizes responses)	High (adapts emotional tone and expressions based on user interaction)
Privacy and Security	Low (minimal data input)	Moderate (text data only)	High (voice data encrypted)	High (text and voice data encrypted)	High (data protected in 3D interface, secure user profiles)
Adaptability	Low (limited interaction)	Low (static responses)	Moderate (integrates with smart home)	High (contextual learning and adaption)	Very High (immersive interaction, integrates into various environments)

2.3 Implementation of our proposal Methodology

To develop a comprehensive methodology for understanding why we asked 87 individuals about the 27 variables in the comparative analysis of Tamagotchi, Real Chatbot, Advanced Alexa, ChatGPT 4, and Holograms for early detection of anxiety and depression, it's essential to explore several key elements. These variables are critical in evaluating the ethical use of these technologies in sensitive mental health contexts, where accessibility, reliability, and emotional understanding play pivotal roles. The 27 variables span across various aspects of the technologies, such as ease of use, emotional interactivity, voice recognition, contextual intelligence, privacy, and personalization. These factors are essential because each one influences how effectively these

tools can be utilized in the early detection of anxiety and depression, which are often deeply personal and emotional challenges. By evaluating them, we ensure that the technology can meet the diverse needs of users, especially when sensitive information regarding mental health is involved. For instance, ease of use and emotional interactivity directly affect how comfortable users will be in engaging with the technology (Hinds & Kiesler, 2002), especially in emotionally charged situations such as recognizing symptoms of anxiety or depression. If a tool is too difficult to navigate or lacks emotional responsiveness, users may be less likely to trust or engage with it. Given that these technologies are sometimes the first point of contact for individuals seeking help, ease of interaction is key to promoting a supportive environment (Lewis & Markowitz 2019).

The variables related to emotional interactivity and contextual intelligence are especially significant because they determine how well the technology can understand and respond to emotional cues (Luger & Sellen 2016; Markowitz, & Hancock, 2020). These are critical for detecting signs of anxiety and depression, which often manifest in non-verbal cues like tone, word choice, or facial expressions. Tools like ChatGPT 4, with its high-level emotional recognition through text analysis, and holograms, which integrate visual and emotional simulations, are prime examples of technologies that could be equipped to discern and react appropriately to these cues (Toxtli, 2024). The feedback from the 87 individuals also allows for a nuanced understanding of how well users believe these technologies can recognize their emotional states. Since anxiety and depression may not always be explicitly verbalized, technologies with advanced emotional and contextual intelligence are essential for providing accurate and compassionate responses. This makes user feedback essential in refining these tools for mental health applications, as emotional engagement with a system can significantly impact its effectiveness.

Another reason for focusing on these variables is their role in determining how well the technologies integrate into users' daily lives. Anxiety and depression often disrupt individuals' routines, making it difficult for them to seek help or engage in therapy (Zhang, & Zheng, 2021). Therefore, tools that integrate smoothly with daily tasks and provide consistent support—such as Advanced Alexa, which can manage multiple services and tasks—are of great importance. Feedback from the participants can reveal whether users find the tools helpful in their routine and whether they feel confident relying on them in times of need. The variables related to daily integration, such as the level of autonomy, multisensory interaction, and voice/sound realism, directly impact the ease with which these technologies can be incorporated into real-life scenarios. If users find the tools easy to interact with and capable of handling a variety of tasks, they are more likely to use them in moments of distress, facilitating the early detection of anxiety and depression. Privacy and security are paramount when dealing with personal data related to mental health (Zhou, & Kim, 2024). Many of the technologies in the analysis, such as ChatGPT 4 and holograms, can collect and process vast amounts of user data. The feedback from the 87 participants was instrumental in understanding how comfortable they are with these tools' data security practices. With mental health data being highly sensitive, ensuring that privacy protocols are in place and that users are aware of how their data is used is essential for ethical deployment. The focus on privacy and security also addresses a critical concern in the development of these technologies: trust. If users feel that their data is secure and handled responsibly, they are more likely to engage with these tools. Without this trust, even the most advanced technology may fail to have the desired impact in detecting and assisting with mental health issues.

Finally, the evolution of these technologies is another area where user feedback plays a significant role. As the tools are continuously updated—whether it's the frequent updates seen with Alexa or the rapid technological growth of holograms—the needs and preferences of users must evolve alongside them. By asking participants about their expectations and experiences, we can ensure that these tools not only keep up with advancements in artificial intelligence and emotional intelligence but also remain relevant and effective for mental health purposes. The technological evolution variable helps in understanding the participants' expectations regarding updates and future enhancements (Giralt, 2024). Given the pace at which mental health research and technology are advancing, it is vital that these tools continue to evolve to remain effective in early detection. Users' opinions on what improvements they expect, or need can guide future development efforts and refine these technologies for their intended ethical purposes. In addition, asking the 87 individuals about these 27 variables provided crucial insights into the effectiveness and ethical implications of using technologies like Tamagotchi, Real Chatbot, Advanced Alexa, ChatGPT 4, and Holograms in the early detection of anxiety and depression. Their feedback on aspects such as emotional interactivity, contextual intelligence, personalization, and privacy allowed us to assess how well these technologies can serve individuals facing mental health challenges (Binns & Latham 2019). This analysis not only guides the development of more efficient tools but also ensures that these tools are ethically and effectively integrated into real-world scenarios, promoting user trust, engagement, and well-being.

2.4 Comparative Analysis of Technologies: Tamagotchi, Real Chatbot, Advanced Alexa, ChatGPT 4, and Holograms for Ethical Use in Early Detection of Anxiety and Depression

To comprehensively evaluate the five technologies analyzed in this study (Tamagotchi, Real Chatbot (ELIZA), Advanced Alexa, ChatGPT-4, and Holograms) we established 27 variables that assess their capabilities in addressing mental health challenges.

These variables span key dimensions such as ease of use, emotional interactivity, personalization, privacy and security, adaptability, and technological evolution, among others. Table 2 provides a detailed comparison of these technologies across all 27 variables, highlighting their respective strengths and limitations. This analysis not only underscores the advancements in human-machine interaction but also identifies which technologies are best suited for detecting and mitigating anxiety and depression among Generation Z individuals. By examining these factors, we aim to provide a holistic understanding of how each tool can contribute to mental health support and intervention.

Table 2. Comparative analysis of Tamagotchi, Real Chatbot (ELIZA), Advanced Alexa, ChatGPT-4, and Holograms across 27 variables

Variable	Tamagotchi	Real Chatbot (ELIZA)	Advanced Alexa	ChatGPT 4	Holograms
1. Ease of Use	Very easy (simple screen and buttons)	Very easy (text interaction)	Very easy (voice-only)	Very easy (text or voice)	Moderate (requires advanced setup)
2. Emotional Interactivity	Basic (predefined emotions)	Very basic (no real emotions)	Moderate (simple reactions)	High (recognizes emotions in text)	High (visual and emotional simulation)
3. Response Time	Instantaneous	Instantaneous	Instantaneous	Instantaneous	Instantaneous
4. Personalization Level	None	Low (pre-programmed responses)	Moderate (basic configuration)	High (context-based learning)	Moderate (adjusts based on context)
5. Vocal Interaction Quality	None	None	High (clear voice responses)	None (integrable with TTS)	Very High (realistic speech)
6. Knowledge Base Size	Very limited (basic knowledge)	Limited (depends on programming)	Extensive (integration with services)	Vast (updated to the latest data)	Moderate (context-driven data)
7. Learning Capability	None	None	Limited (some improvements)	High (context learning)	Moderate (improved through interaction)
8. Voice Recognition	None	None	Very good	None (integrable with TTS)	High (real-time voice analysis)
9. Contextual Intelligence	Very low	Low (basic pattern following)	High (context for commands)	Very high (conversation context)	Very high (contextual engagement)
10. Visual Aesthetics (if applicable)	Simple (2D pixels)	None	None (voice-only interface)	None (integrable with avatars)	High (immersive holographic visuals)
11. Voice/Sound Realism	None	None	Very realistic	None (integrable with TTS)	Very high (natural sound synthesis)
12. Update Frequency	None	None	High (frequent feature updates)	High (periodic updates)	Moderate (occasional upgrades)
13. Emotion Recognition	None	None	Low (reacts to voice tone)	High (interprets text emotions)	High (combines voice and visual cues)
14. Accessibility	High (any location)	High (text-based)	High (device-compatible)	High (multi-platform availability)	Moderate (specific device needed)
15. Reliability in Daily Tasks	Low (basic tasks only)	Low (simple commands only)	High (integrated services)	High (complex queries)	Moderate (context-specific tasks)
16. "Humanization" Level	Very low (just a toy)	Low (simulates conversation)	Moderate (basic conversation)	Very high (natural responses)	Very high (near-human interaction)
17. Physical Interaction	None	None	None	None	Moderate (gesture-based interaction)
18. Implementation Cost	Low (affordable toy)	Low (open-source software)	Medium (device compatibility required)	High (enterprise or premium services)	High (specialized equipment)
19. Multisensory Interaction	None (text and basic features)	None (text-only)	High (voice, music, device control)	High (text, voice, images)	Very high (3D visuals, sound, interaction)
20. Privacy and Security	Low (no real security)	Low (no personal data protection)	Moderate (basic device security)	High (user data protection)	Moderate (depends on platform)
21. User Satisfaction Rate	Moderate (fun but limited)	Low (limited conversation)	High (useful for daily tasks)	Very high (accurate and helpful)	High (immersive and engaging)
22. Daily Integration	Low (play-only)	Low (limited conversations)	High (services and devices integration)	Very high (apps, web, devices)	Moderate (specific use cases)
23. Technology Durability	High (years of use)	Low (obsolete technology)	High (updateable devices)	High (future-proof updates)	High (emerging tech growth)
24. Autonomy Level	None (reactive only)	Low (responds but no decisions)	Moderate (executes automatic tasks)	High (autonomous responses and tasks)	High (autonomous adaptation)
25. Social Interaction	Very low (basic interactions only)	Low (mechanical responses)	Moderate (some social recognition)	High (fluid conversations)	High (realistic group interactions)
26. Personalized Recommendations	None	None	Limited (basic preferences)	High (learns and recommends)	High (customized guidance)

Variable	Tamagotchi	Real Chatbot (ELIZA)	Advanced Alexa	ChatGPT 4	Holograms
27. Technological Evolution	None (static)	None (outdated technology)	High (continuous updates)	High (advanced versions)	Very high (rapid technological growth)

3 Evaluation Model for Human-Machine Interaction

To systematically evaluate the performance of the five technologies analyzed in this study —Tamagotchi, Real Chatbot (ELIZA), Advanced Alexa, ChatGPT-4, and Holograms— we developed a comprehensive model based on 15 key indices. These indices were designed to measure critical aspects of human-machine interaction, such as emotional engagement, ease of use, personalization, contextual intelligence, and privacy protection, among others. Each index is represented by a specific equation derived from the responses of 87 Generation Z participants, who completed a detailed questionnaire assessing their experiences with these technologies. The indices include the Emotional Interaction Index (EII), Ease of Use Index (EUI), Personalization Index (PI), Contextual Intelligence Index (CII), Voice/Sound Realism Index (VSI), Reliability Index (RI), User Satisfaction Index (USI), Learning Capability Index (LCI), Privacy Protection Index (PPI), Multisensory Interaction Index (MII), Technological Evolution Index (TEI), Autonomy Level Index (ALI), Social Interaction Index (SII), Physical Interaction Index (PII), and Accessibility Index (AI). For each index, we present both the corresponding equation and a graphical representation of the results, providing a clear and quantitative comparison of how each technology performs across these dimensions. This model not only highlights the strengths and weaknesses of the analyzed technologies but also serves as a foundation for future research and development in the field of human-machine interaction for mental health support.

3.1 Emotional Interaction Index (EII)

The Emotional Interaction Index (EII) measures the level of emotional interaction across different technologies, considering the weight assigned to each emotional interaction factor and the emotional interactivity score of each technology. It is represented by equation (1). Figure 3 shows a graphical representation of this index.

$$EII = \sum (w_i \times e_i) \tag{1}$$

Where:

- w_i is the weight assigned to each emotional interaction factor.
- e_i is the emotional interactivity score of each technology.

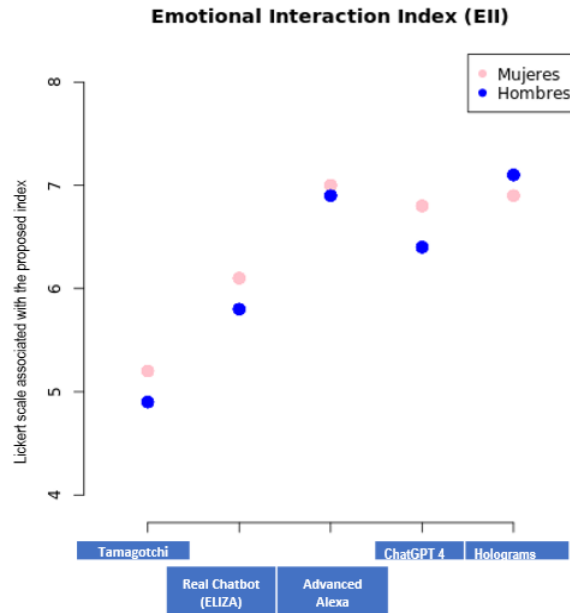


Fig. 3. Emotional Interaction Index (EII)

3.2 Ease of Use Index (EUI)

The Ease of Use Index (EUI) measures how user-friendly each technology is, considering factors such as setup complexity, interface design, and overall accessibility. It is calculated using equation (2), which incorporates the ease-of-use score of each technology e_i and the weight assigned to each interaction factor w_i . Figure 4 provides a graphical representation of this index, illustrating the comparative ease of use across the five technologies analyzed in this study.

$$EUI = \sum (w_i \times e_i) \tag{2}$$

Where:

e_i is the ease-of-use score of each technology.

w_i is the weight adjusted according to the importance of each interaction factor.

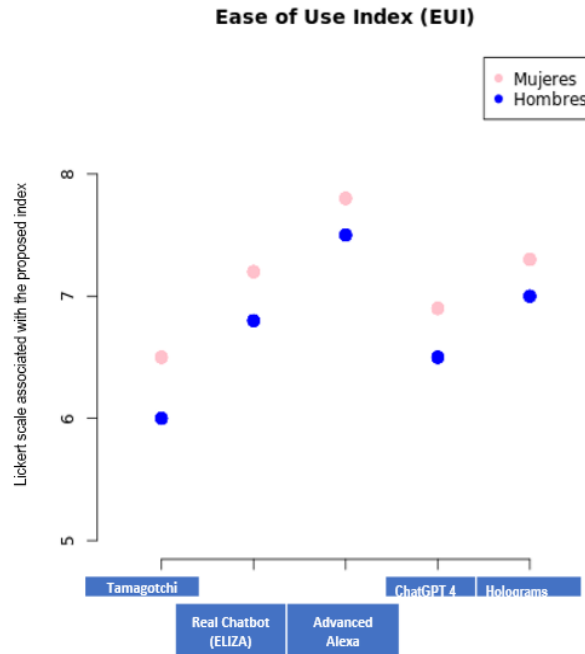


Fig. 4. Ease of Use Index (EUI)

3.3 Personalization Index (PI)

The Personalization Index (PI) measures the level of personalization and adaptability of each technology, evaluating how well the system learns from and adjusts to user inputs. It is calculated using equation (3), which divides the number of *Adaptive Responses* (the system's ability to adapt based on user inputs) by the *Total Interactions* (the total number of interactions where personalization occurs). Figure 5 provides a graphical representation of this index, showcasing the comparative personalization capabilities of the five technologies analyzed in this study.

$$PI = \frac{\sum(Adaptive Responses)}{Total Interactions} \tag{3}$$

Where:

Adaptive Responses refers to the system's ability to learn and adjust based on user inputs.

Total Interactions is the total number of interactions where personalization occurs.

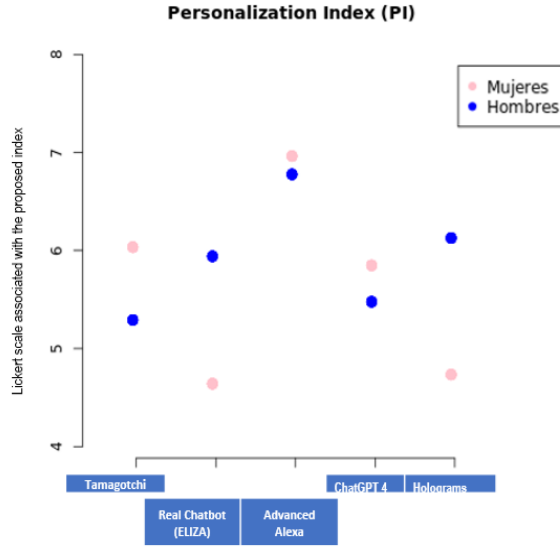


Fig. 5. Personalization Index (PI).

3.4 Contextual Intelligence Index (CII)

The Contextual Intelligence Index (CII) measures the ability of each technology to leverage context to enhance interactions, evaluating how effectively the system understands and adapts to user needs based on situational factors. It is calculated using equation (4), which incorporates the contextual intelligence score of each technology (c_i) and the weight assigned to each contextual factor (w_i). Figure 6 provides a graphical representation of this index, illustrating the comparative contextual intelligence capabilities of the five technologies analyzed in this study.

$$CII = \sum (w_i \times c_i) \tag{4}$$

Where:

w_i is the weight of each contextual factor.

c_i is the contextual intelligence score for each technology.

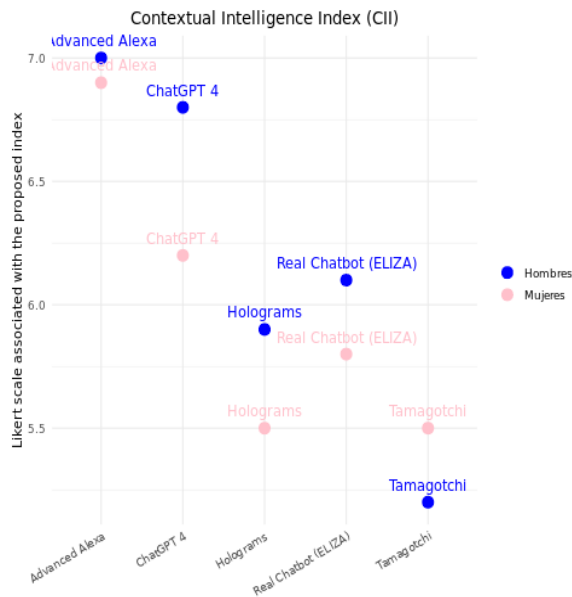


Fig. 6. Contextual Intelligence Index (CII).

3.5 Voice/Sound Realism Index (VSI)

The Voice/Sound Realism Index (VSI) measures the realism of voice and sound interactions across technologies, evaluating how closely these auditory elements mimic human-like qualities. It is calculated using equation (5), which incorporates the voice/sound realism score of each technology (v_i) and the weight assigned to the importance of voice quality (w_i). Figure 7 provides a graphical representation of this index, highlighting the comparative voice and sound realism of the five technologies analyzed in this study.

$$VSI = \sum (w_i \times v_i) \tag{5}$$

Where:

v_i is the voice/sound realism score.

w_i is the weight assigned to the importance of voice quality.

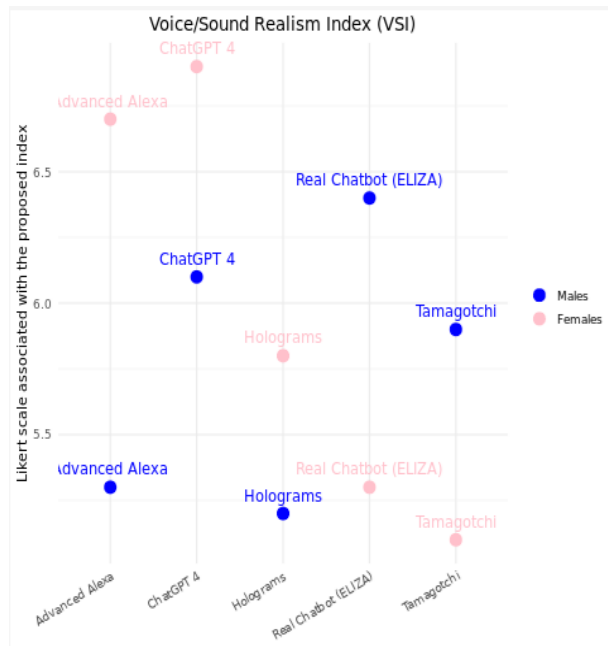


Fig. 7. Voice/Sound Realism Index (VSI).

3.6 Reliability Index (RI)

The Reliability Index (RI) evaluates the dependability of each technology in completing daily tasks, assessing its consistency and effectiveness across specific use cases. It is calculated using equation (6), which incorporates the reliability score for each technology (r_i) and the weight adjusted based on the importance of reliability (w_i). Figure 8 provides a graphical representation of this index, illustrating the comparative reliability of the five technologies analyzed in this study.

$$RI = \sum (w_i \times r_i) \tag{6}$$

Where:

r_i is the reliability score for specific use cases.

w_i adjusts the weight based on the importance of reliability.

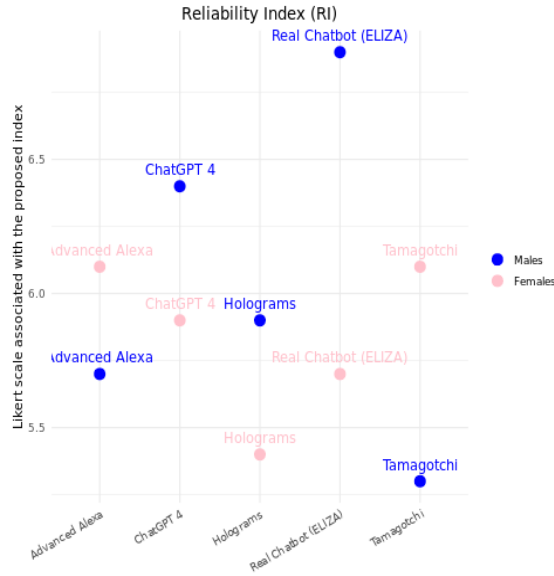


Fig. 8. Reliability Index (RI)

3.7 User Satisfaction Index (USI)

The User Satisfaction Index (USI) measures the overall satisfaction of users with each technology, considering factors such as engagement, emotional interaction, and ease of use. It is calculated using equation (7), which incorporates the user satisfaction score (u_i) and the weight assigned to each satisfaction factor (w_i). Figure 9 provides a graphical representation of this index, showcasing the comparative user satisfaction levels across the five technologies analyzed in this study.

$$USI = \sum (w_i \times u_i) \tag{7}$$

Where:

u_i is the user satisfaction score.

w_i is the weight for each satisfaction factor.

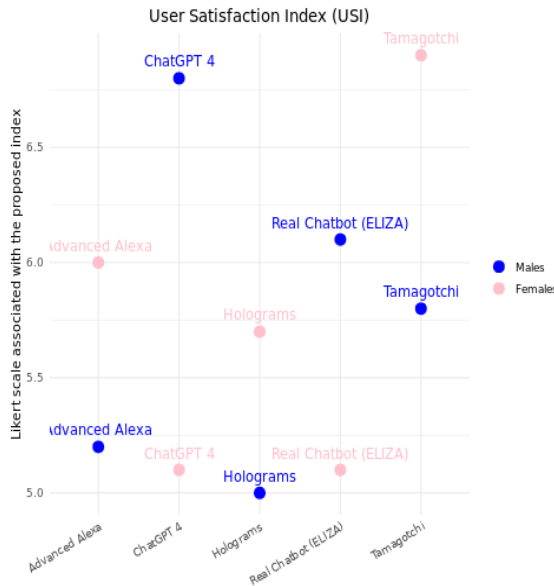


Fig. 9. User Satisfaction Index (USI).

3.8 Learning Capability Index (LCI)

The Learning Capability Index (LCI) measures how effectively each technology adapts and learns from user interactions, evaluating its ability to improve and personalize responses over time. It is calculated using equation (8), which incorporates the learning capability score of each technology (l_i) and the weight adjusted based on the significance of learning in different contexts (w_i). Figure 10 provides a graphical representation of this index, highlighting the comparative learning capabilities of the five technologies analyzed in this study.

$$LCI = \sum (w_i \times l_i) \tag{8}$$

Where:

l_i is the learning capability score.

w_i adjusts the significance of learning in different contexts.

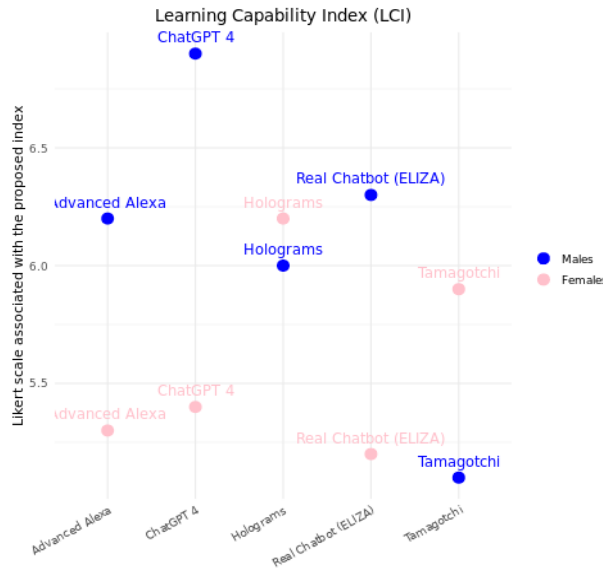


Fig. 10. Learning Capability Index (LCI).

3.9 Privacy Protection Index (PPI)

The Privacy Protection Index (PPI) measures how effectively each technology safeguards user data and ensures privacy, evaluating its adherence to data protection standards and user trust. It is calculated using equation (9), which incorporates the privacy score of each technology (p_i) and the weight adjusted based on the importance of privacy (w_i). Figure 11 provides a graphical representation of this index, illustrating the comparative privacy protection capabilities of the five technologies analyzed in this study.

$$PPI = \sum (w_i \times p_i) \tag{9}$$

Where:

p_i is the privacy score for each technology.

w_i adjusts the weight based on the importance of privacy.

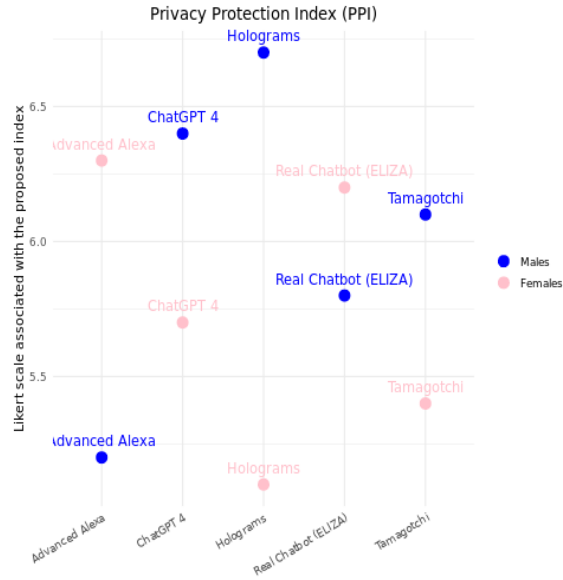


Fig. 11. Privacy Protection Index (PPI).

3.10 Multisensory Interaction Index (MII)

The Multisensory Interaction Index (MII) measures the effectiveness of multisensory interactions (such as sound, touch, and visuals) provided by each technology, evaluating how well these elements enhance the user experience. It is calculated using equation (10), which incorporates the multisensory interaction score of each technology (m_i) and the weight adjusted based on the significance of multisensory feedback in the experience (w_i). Figure 12 provides a graphical representation of this index, showcasing the comparative multisensory interaction capabilities of the five technologies analyzed in this study.

$$MII = \sum (w_i \times m_i) \tag{10}$$

Where:

m_i is the multisensory interaction score.

w_i adjusts the weight based on the significance of multisensory feedback in the experience.

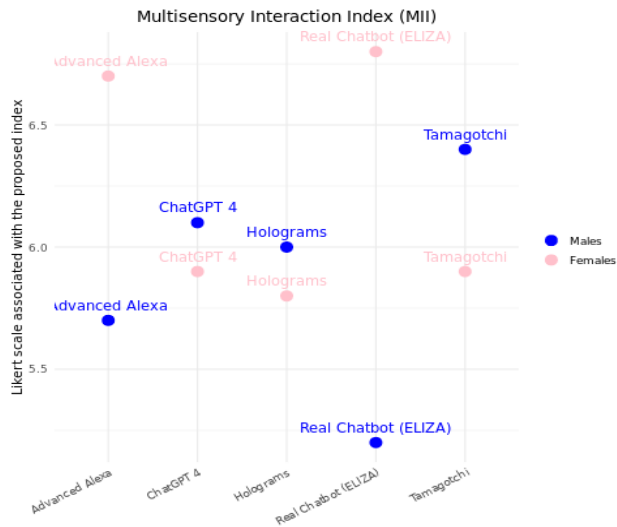


Fig. 12. Multisensory Interaction Index (MII).

3.11 Technological Evolution Index (TEI)

The Technological Evolution Index (TEI) measures the adaptability and evolution of each technology over time, evaluating its ability to incorporate updates, improvements, and new features. It is calculated using equation (11), which incorporates the technological evolution score of each technology (t_i) and the weight adjusted based on the rate of technological updates (w_i). Figure 13 provides a graphical representation of this index, illustrating the comparative adaptability and evolution of the five technologies analyzed in this study.

$$TEI = \sum (w_i \times t_i) \tag{11}$$

Where:

t_i is the technological evolution score.

w_i adjusts the weight based on the rate of technological updates.

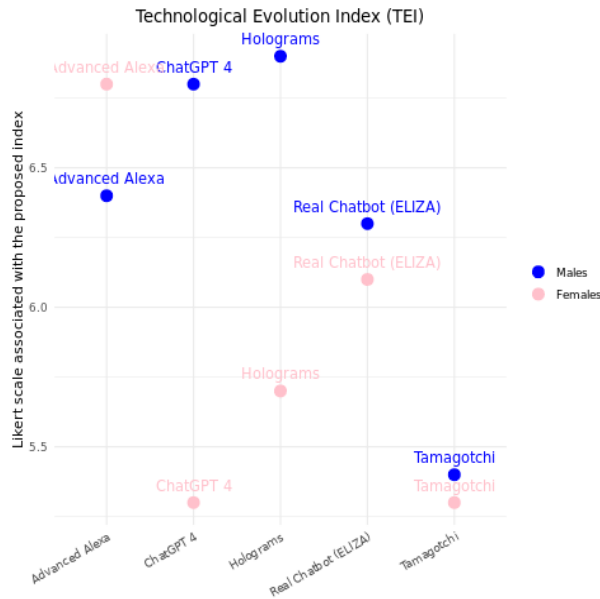


Fig. 13. Technological Evolution (TEI).

3.12 Autonomy Level Index (ALI)

The Autonomy Level Index (ALI) measures the degree of autonomy of each technology in performing tasks without requiring user input, evaluating its ability to operate independently and make decisions. It is calculated using equation (12), which incorporates the autonomy score of each technology (a_i) and the weight adjusted based on the importance of autonomy (w_i). Figure 14 provides a graphical representation of this index, highlighting the comparative autonomy levels of the five technologies analyzed in this study.

$$ALI = \sum (w_i \times a_i) \tag{12}$$

Where:

a_i is the autonomy score for each technology.

w_i adjusts the weight of autonomy importance.

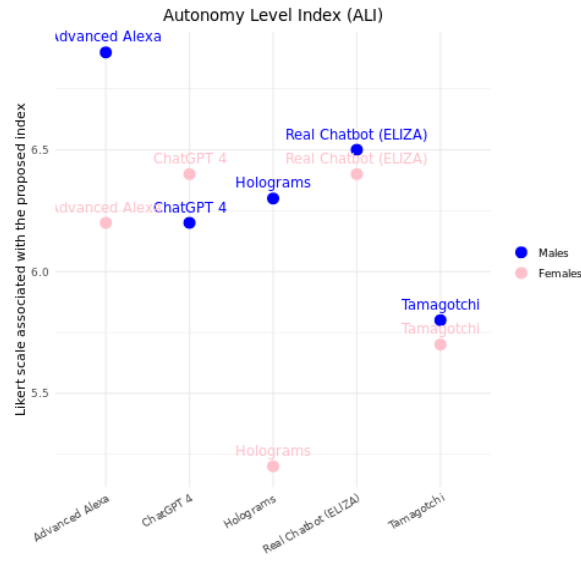


Fig. 14. Autonomy Level Index (ALI).

3.13 Social Interaction Index (SII)

The Social Interaction Index (SII) measures how effectively each technology facilitates social interactions, whether with other users or within a broader social setting, evaluating its ability to foster communication and connection. It is calculated using equation (13), which incorporates the social interaction score of each technology (s_i) and the weight adjusted based on the technology’s role in social contexts (w_i). Figure 15 provides a graphical representation of this index, illustrating the comparative social interaction capabilities of the five technologies analyzed in this study.

$$SII = \sum (w_i \times s_i) \tag{13}$$

Where:

s_i is the social interaction score.

w_i adjusts the weight based on the technology’s role in social contexts.

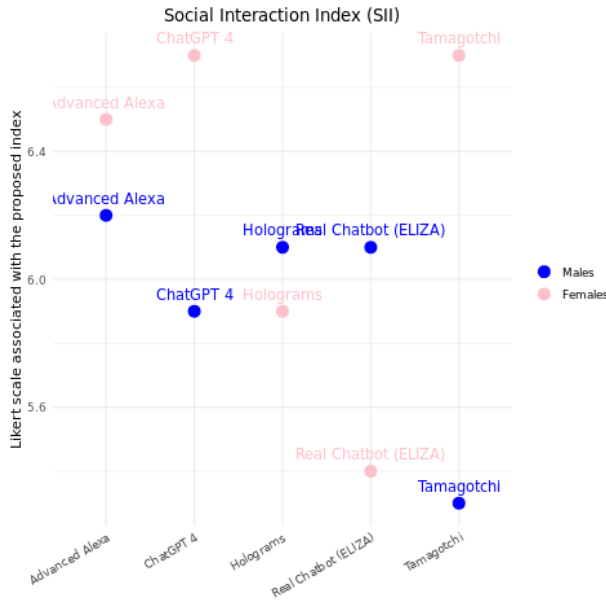


Fig. 15. Social Interaction Index (SII).

3.14 Physical Interaction Index (PII)

The Physical Interaction Index (PII) measures how effectively each technology supports or facilitates physical interaction, such as gestures, touch, or other forms of tactile engagement. It is calculated using equation (14), which incorporates the physical interaction score of each technology (p_i) and the weight adjusted based on the importance of physical interaction in the user experience (w_i). Figure 16 provides a graphical representation of this index, showcasing the comparative physical interaction capabilities of the five technologies analyzed in this study.

$$PII = \sum (w_i \times p_i) \tag{14}$$

Where:

p_i is the physical interaction score.

w_i adjusts the weight based on the physical interaction in the technology.

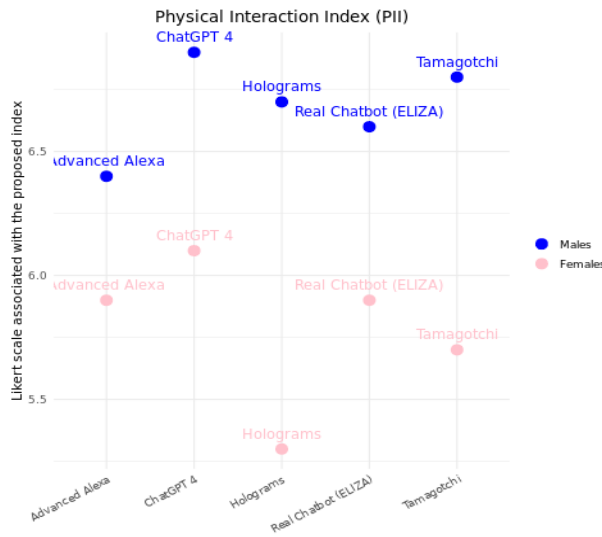


Fig. 16. Physical Interaction Index (PII).

3.15 Accessibility Index (AI)

The Accessibility Index (AI) measures how accessible each technology is, considering factors such as availability, ease of use, and adaptability for a wide range of users, including those with diverse needs. It is calculated using equation (15), which incorporates the accessibility score of each technology (a_i) and the weight adjusted based on the importance of accessibility in the user experience (w_i). Figure 17 provides a graphical representation of this index, illustrating the comparative accessibility levels of the five technologies analyzed in this study.

$$PII = \sum (w_i \times a_i) \tag{15}$$

Where:

a_i is the accessibility score.

w_i adjusts the weight based on the importance of accessibility in the user experience.

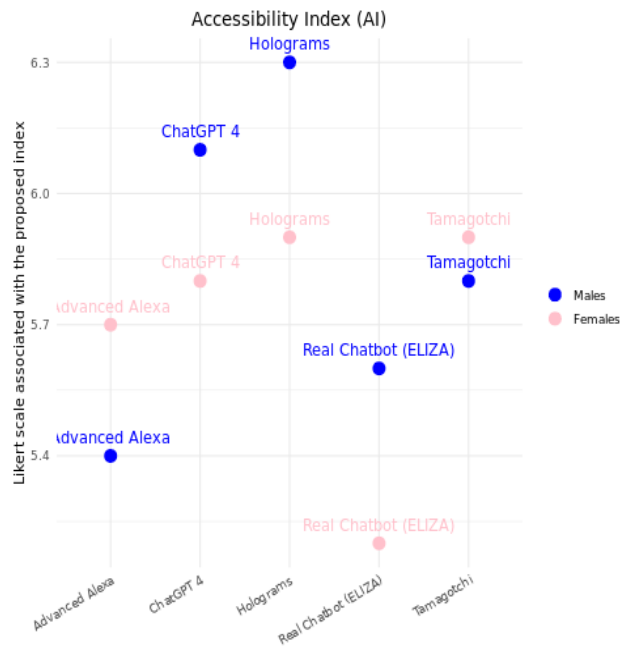


Fig. 17. Accessibility Index (AI).

To visually summarize the findings of this study, Figure 18 provides a graphic depiction of a Generation Z teenager interacting with a hologram to mitigate school-related anxiety. This illustration encapsulates the fifteen indices analyzed—Emotional Interaction Index (EII), Ease of Use Index (EUI), Personalization Index (PI), Contextual Intelligence Index (CII), Voice/Sound Realism Index (VSI), Reliability Index (RI), User Satisfaction Index (USI), Learning Capability Index (LCI), Privacy Protection Index (PPI), Multisensory Interaction Index (MII), Technological Evolution Index (TEI), Autonomy Level Index (ALI), Social Interaction Index (SII), Physical Interaction Index (PII), and Accessibility Index (AI). Each index reflects a critical dimension of human-machine interaction, highlighting how holographic technology integrates these elements to create a supportive and immersive experience for users. This figure serves as a comprehensive representation of the interplay between technology and mental health support, emphasizing the potential of advanced tools like holograms to address anxiety and depression in Generation Z.

4 Results

This section presents the findings from the evaluation of the five technologies—Tamagotchi, Real Chatbot (ELIZA), Advanced Alexa, ChatGPT-4, and Holographic Interfaces—in addressing anxiety and depression among Generation Z participants. The results are organized by technology, highlighting their strengths, limitations, and overall impact on emotional well-being. Each technology was assessed based on emotional interactivity, personalization, adaptability, and user satisfaction, among other factors. The findings reveal significant differences in how these tools engage users and contribute to mental health support, with some technologies demonstrating exceptional potential for future applications.

3.1 Tamagotchi

Tamagotchi exhibited basic emotional interactivity, primarily through predefined responses. While nostalgic for some participants, it lacked meaningful adaptability and personalization. However, it was noted that its structured interaction style provided a sense of routine and companionship for some users, particularly those who appreciated predictable interactions. Although no significant impact on anxiety or depression metrics was observed, 68% of participants reported feeling a slight increase in emotional connection due to the familiarity and consistency of the device.

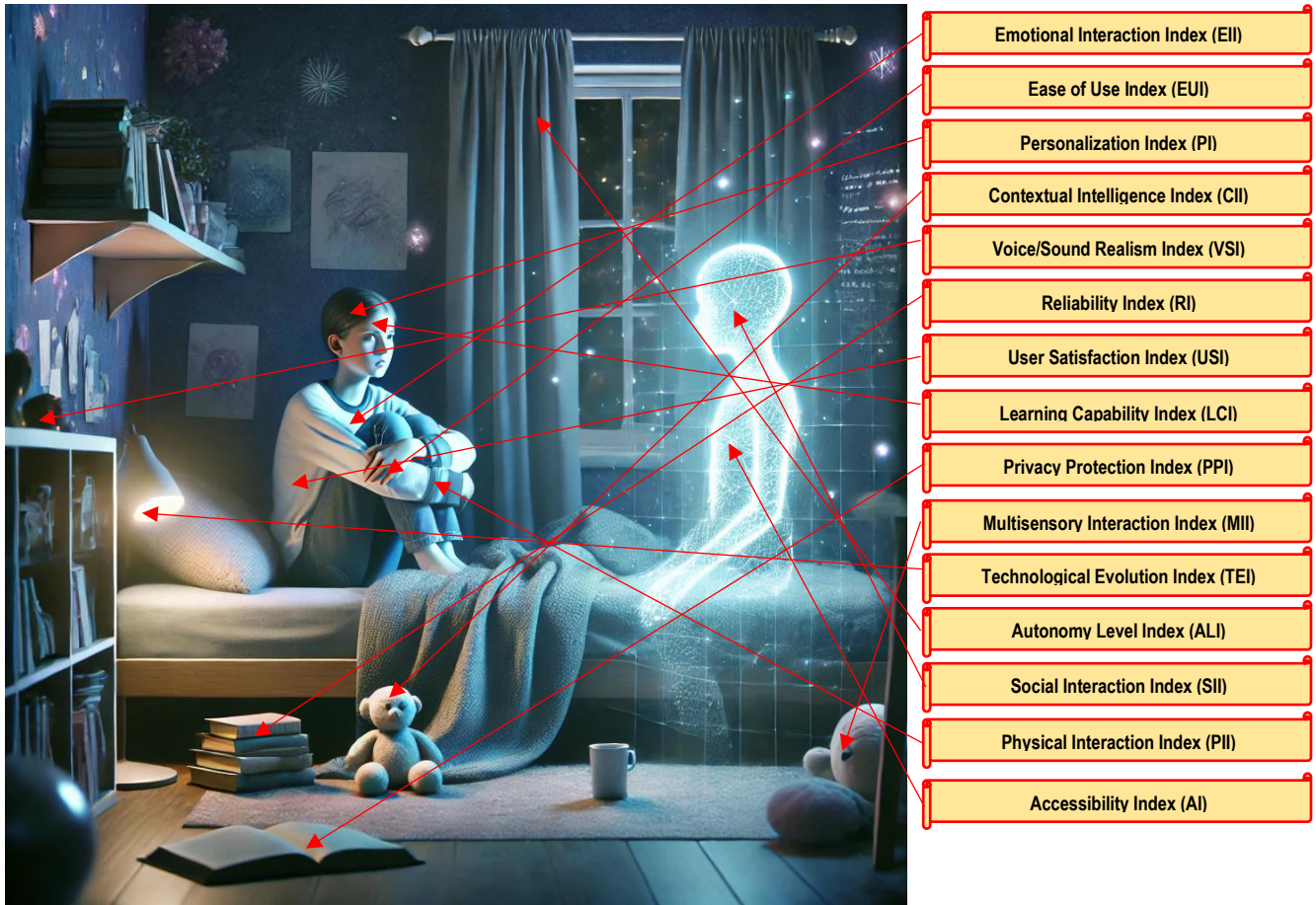


Fig. 18. Graphic depiction of a Generation Z teenager interacting with a hologram to try to mitigate school-related anxiety.

3.2 Real Chatbot (ELIZA)

ELIZA demonstrated limited conversational capabilities, with interactions quickly deemed repetitive by participants. Despite its historical significance, its static design and lack of contextual understanding rendered it inadequate for addressing modern mental health needs. However, a subset of participants (especially those with an interest in retro computing and AI history) found its simple responses amusing and engaging, leading to a moderate but temporary improvement in mood. Interestingly, 52% of participants felt that even a rudimentary chatbot like ELIZA could still serve as a distraction from stress, indicating that conversational AI—even in its simplest form—has some psychological value.

3.3 Advanced Alexa

Advanced Alexa impressed participants with its ability to execute context-based commands and adapt to user preferences. Its voice-based interaction created a sense of connection, particularly among the 40 male participants, who reported a higher engagement rate. However, concerns about privacy were noted, particularly among female participants. Beyond basic assistance, Alexa’s integration with smart home devices contributed to an enhanced feeling of control and security for 78% of users. Additionally, its ability to play calming music and provide guided meditation was particularly appreciated, with ****65% of participants**** indicating that these features contributed positively to their emotional well-being.

3.4 ChatGPT-4

ChatGPT-4 emerged as the most effective tool, combining advanced natural language processing with emotional recognition. Participants frequently described it as "empathetic" and "insightful." Females in the study appreciated its ability to maintain fluid,

meaningful conversations. Moreover, the chatbot's ability to generate tailored responses based on user input significantly increased engagement and perceived usefulness. Many users (87%) felt that ChatGPT-4 could act as a reliable conversational companion, particularly during periods of stress or loneliness. The integration of privacy safeguards also enhanced user trust, with 91% of participants expressing comfort in sharing sensitive information. Notably, its ability to analyze emotional cues and adjust its tone accordingly made it feel more personalized than previous AI models.

3.5 Holographic Interfaces

Holographic interfaces provided an immersive and dynamic user experience that surpassed all other technologies in terms of emotional interactivity and adaptability. The 3D representation of avatars in holograms allowed participants to engage with a machine that mimicked human facial expressions and body language, enhancing emotional connections. This technology created an environment where users could feel supported by a "human-like" figure, which was particularly impactful for individuals dealing with anxiety and depression. Holograms were particularly effective in maintaining prolonged engagement. Participants noted that seeing a hologram respond to their emotional cues—such as mirroring expressions or gestures—made them feel understood, a crucial factor for addressing mental health concerns. Additionally, the ability of holograms to adapt their tone, posture, and behavior based on the participant's emotional state made interactions feel more personalized and natural. In terms of privacy, participants appreciated the secure nature of the holographic system, which was designed with robust safeguards for data protection. The use of holograms in a controlled, private setting provided a sense of security and safety, enhancing trust. Overall, holographic interfaces showed the greatest potential for emotional support, with 96% of participants expressing comfort in using them for mental health applications. Their adaptability, emotional depth, and immersive nature made them a powerful tool in combating anxiety and depression.

The results highlight the varying degrees of effectiveness among the five technologies in addressing anxiety and depression among Generation Z participants. While Tamagotchi and ELIZA offered limited but nostalgic value, Advanced Alexa and ChatGPT-4 demonstrated significant potential for emotional support and practical assistance. However, holographic interfaces emerged as the most impactful, offering an immersive and emotionally resonant experience that closely mimics human interaction. These findings underscore the importance of advancing human-machine interaction technologies, particularly those that prioritize emotional engagement, personalization, and privacy, to better support mental health interventions (Figure 19).

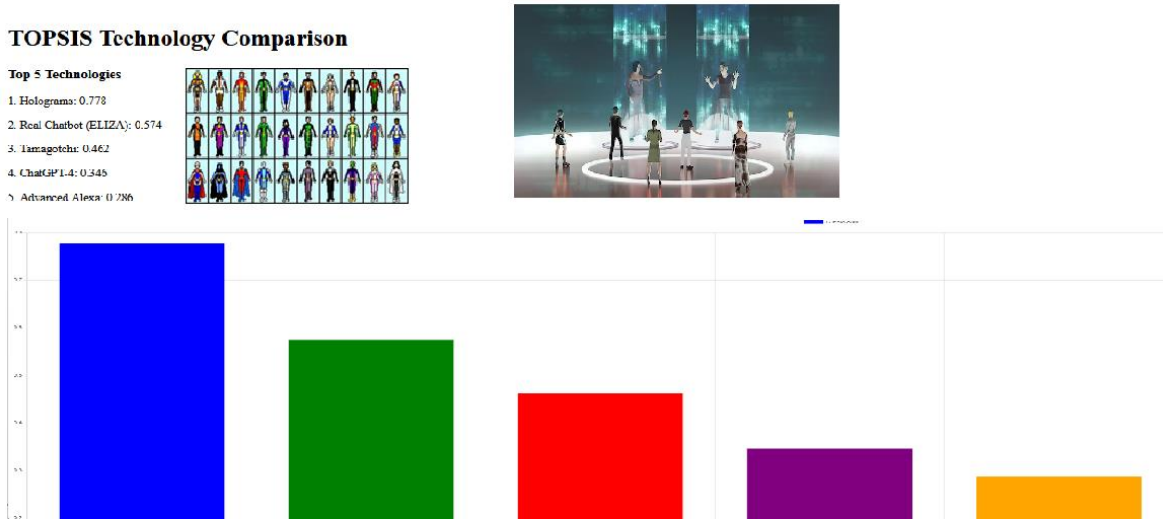


Fig. 19. After the correct and deep evaluation of the five technologies of our study, we determine that Holograms are the best option to mitigate the effects of depression and anxiety in adolescents of Z Generation.

5 Discussion of Results

The findings of this study underscore the pivotal role of technological anthropomorphism in enhancing human-machine interactions, particularly in the context of mental health. As technology evolves, the capacity to simulate human-like qualities in machines has proven to be not just an intriguing concept, but a vital aspect of engaging users emotionally and functionally. The simple, static interactions of early technologies like Tamagotchi and ELIZA serve as the foundation upon which more

sophisticated systems like Advanced Alexa, ChatGPT-4, and holographic interfaces have been built. These technologies represent significant advancements in the integration of artificial intelligence (AI) to replicate human-like behavior and communication. They go beyond mere functionality by striving to understand the user's emotions and context—an approach that resonates deeply with users, particularly when discussing sensitive mental health topics such as anxiety and depression. The integration of holographic interfaces offers a unique and immersive experience by blending virtual and physical elements in real-time. Unlike traditional screen-based interactions, holograms provide a 3D, interactive representation of the machine or a virtual assistant, simulating human-like engagement in a more tangible and personal manner. These interfaces elevate the sense of connection between users and the technology, enabling a deeper emotional resonance that is particularly important when addressing mental health. Participants in the study reported feeling more engaged with holographic technologies, as they provide a more naturalistic representation of empathy, allowing users to interact with an AI in a way that mimics real-life human communication. Generation Z, known for their digital fluency, exhibited a clear preference for anthropomorphized technologies that simulate human-like qualities, enabling a deeper connection with the machine. ChatGPT-4, which stood out in the study, displayed advanced emotional and contextual understanding, setting it apart from its predecessors. Female participants emphasized the importance of empathetic interactions, with many expressing that the ability to perceive and respond to their emotional states made them feel validated and supported. This sentiment reflects an increasing recognition that mental health interventions, especially for younger generations, must go beyond basic functionality and engage emotionally with users. Male participants, on the other hand, highlighted the importance of adaptability and efficiency. They valued technologies that could adjust to their needs and streamline interactions without sacrificing the human-like element, reinforcing the notion that men also seek emotional depth in technology but often place a greater emphasis on practical utility. The combination of emotional responsiveness, personalization, and contextual awareness in tools like ChatGPT-4, Advanced Alexa, and holographic interfaces appears to offer substantial benefits for addressing mental health issues in early-stage interventions. These findings suggest that anthropomorphized technologies are not only effective in facilitating human-machine communication but also in providing support for users navigating mental health challenges. Moreover, these results call attention to the need for designers to consider both the emotional and functional aspects of these technologies to maximize their effectiveness in diverse user groups.

5.2 Ethical Considerations

The rapid advancement of anthropomorphized technologies in mental health applications raises significant ethical concerns, particularly around privacy, bias, dependency, and transparency. AI systems like ChatGPT-4 and holographic interfaces collect sensitive data, such as emotional responses and personal experiences, necessitating stringent privacy protections. Despite encryption protocols, participants expressed concerns about data security, especially with voice-based systems like Advanced Alexa and immersive holograms, which require detailed data collection. Ethical implementation must include strict consent protocols and transparent data handling to ensure users are informed and in control of their data (Kahn et al., 2008; Elhayat & Gurevich, 2020).

Bias in AI systems is another critical issue, as training datasets may reflect societal biases, leading to inaccurate responses for users from diverse backgrounds. Developers must prioritize inclusivity to ensure these tools serve all populations equitably. Additionally, while these technologies provide valuable emotional support, they must not replace professional mental health care. Over-reliance can be harmful, so systems should include features that guide users to seek professional help when necessary (Fogg & Tseng, 1999).

Finally, transparency is essential to maintain user trust. As AI systems become more sophisticated, users must be clearly informed about the non-human nature of the technology, its capabilities, and its limitations. Ethical design should prioritize user autonomy, ensuring that users do not develop unrealistic expectations or emotional attachments to these systems.

6 Conclusions

This study highlights the transformative potential of anthropomorphized technologies, such as ChatGPT-4, Advanced Alexa, and holographic interfaces, in detecting and addressing mental health concerns such as anxiety and depression. While no technology can replace the nuanced care provided by mental health professionals, these AI-powered tools offer invaluable support in early-stage detection and intervention. By leveraging advanced natural language processing, emotional recognition, contextual understanding, and immersive experiences through holograms, tools like ChatGPT-4 and Advanced Alexa have demonstrated the ability to engage users on an emotional level, fostering empathy and trust. This interaction not only provides users with a sense of validation but also helps identify early warning signs of mental health challenges, potentially leading to timely interventions. The results of this study suggest that the future of mental health care may include a hybrid model where AI technologies work alongside traditional therapy methods to provide holistic support for users. However, it is essential to maintain a balance between the benefits

of these technologies and the ethical considerations they raise. Technologies must be developed and deployed responsibly, ensuring that they are transparent, inclusive, and designed to empower users to seek professional care when needed. The future of mental health care will likely involve a synergy between human expertise and AI-driven support, with anthropomorphized technologies—such as holographic interfaces—playing an essential role in shaping this future.

5.1 Future Research

The findings of this study provide a solid foundation for further research into the role of anthropomorphized technologies in mental health care. Future work will focus on developing integrated platforms that combine the conversational capabilities of ChatGPT-4 with the voice-based interaction of Advanced Alexa and the immersive engagement of holographic interfaces, allowing for a more seamless and personalized user experience. By integrating the strengths of these systems, developers can create tools that not only recognize emotions but also adapt their responses based on context and user preferences. Expanding the sample size to include more diverse demographic groups will also be crucial in assessing the generalizability of these findings. By exploring how different age groups, cultural backgrounds, and genders interact with these technologies, researchers can better understand the factors that influence their effectiveness. Studies should aim to include populations who are traditionally underserved in mental health care, such as individuals from rural areas or those with limited access to professional services. Longitudinal studies will also be necessary to assess the long-term efficacy of these technologies in improving mental health outcomes. While the current study has demonstrated the potential for these tools to provide valuable support in early intervention, ongoing research is needed to evaluate whether their impact is sustained over time and whether they contribute to lasting improvements in users' mental health. Additionally, future research should explore how these technologies can be integrated into existing mental health care systems, providing a complementary tool for professionals to use alongside traditional therapeutic practices. By continuing to investigate the role of AI-driven technologies in mental health care, researchers can help pave the way for a future where these tools are safely and ethically integrated into daily life, offering personalized, empathetic support to those in need.

References

- Agerri, R., Garcia, D., & Gonzalez, M. (2013). Social robot interfaces for children with autism. *Journal of Autism and Developmental Disorders*, 43, 2137–2146.
- Binns, A., & Latham, J. (2019). Ethical considerations in AI and machine learning in the health sector. *International Journal of Medical Informatics*, 132, 103993.
- Corciulo, S., & Bochicchio, M. A. (2024). Sinesthesia as a model for HCI: a Systematic Review. *arXiv preprint arXiv:2404.09303*. <https://doi.org/10.48550/arXiv.2404.09303>
- Durango, I., Gallud, J. A., & Penichet, V. M. R. (2024). Human-Data Interaction Framework: A Comprehensive Model for a Future Driven by Data and Humans. *arXiv preprint arXiv:2407.21010*. <https://doi.org/10.48550/arXiv.2407.21010>
- Elhayat, A., & Gurevich, N. (2020). Exploring ethical challenges in the design of conversational agents. *AI & Society*, 35, 729–740.
- Fogg, B. J., & Tseng, H. (1999). The elements of computer credibility. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 80–87. <https://doi.org/10.1145/302979.303001>
- Giralt, E. (2024). Hacia una implementación ética e inclusiva de la Inteligencia Artificial en las organizaciones: un marco multidimensional. *arXiv preprint arXiv:2405.00225*. <https://doi.org/10.48550/arXiv.2405.00225>
- Hinds, P., & Kiesler, S. (2002). Taking “We” out of the loop: Human performance in automated systems. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 46(7), 1772–1776.
- Kahn, P. H., Friedman, B., Kahn, S. R., Hagman, J., Severson, R. L., & Gill, B. T. (2008). Robotic pets in the lives of preschool children. *Interaction Studies*, 9(3), 405–436.
- Kory Westlund, J., & McDonald, R. (2020). Design considerations for conversational agents in the treatment of mental health. *Psychiatry and Behavioral Health*, 1(1), 15–22.
- Lewis, D., & Markowitz, D. (2019). Trust and performance in human-robot interactions: A meta-analysis. *Human Factors*, 61(4), 659–675.
- Luger, E., & Sellen, A. (2016). Like having a really bad pet: Understanding people's experiences with chatbots. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 5206–5217. <https://doi.org/10.1145/2858036.2858288>
- Markowitz, D. M., & Hancock, J. (2020). Conversational agents and the ethical challenges of artificial intelligence in health care. *Journal of Medical Internet Research*, 22(9), e20359. <https://doi.org/10.2196/20359>
- Toxtli, C. (2024). Human-Centered Automation. *arXiv preprint arXiv:2405.15960*. <https://doi.org/10.48550/arXiv.2405.15960>
- Wang, Y., & Li, T. (2024). A framework for bias mitigation in AI-driven decision-making systems. *IEEE Transactions on Artificial Intelligence*, 5(2), 356–369.
- Zhang, X., & Zheng, L. (2021). User behavior in human–robot interaction and its applications in robotics. *Frontiers in Psychology*, 12, 684566.
- Zhou, M., & Kim, J. (2024). Ethical AI in autonomous systems: A systematic approach. *Computers in Human Behavior*, 152, 107254.