The Role of Perceived Emotional Support in AI Mental Health Chatbots among Generation Z

Mardiana[1], Ossi Ferli[2], Henderi[3], Evelyn Anderson[4*], Alni Cahyani[5]
[1, 5]Faculty of Economics and Business, University of Raharja, Indonesia
[2]Faculty of Economics, STIE Indonesia Banking School, Indonesia
[3]Faculty of Sciences and Technology, University of Raharja, Indonesia
[4]REY Group, United States
[1]mardiana@raharja.info, [2]ossi.ferli@ibs.ac.id, [3]henderi@raharja.info, [4]evelyn77@rey.zone, [5]alni.cahyani@raharja.info
***Corresponding Author**

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ABSTRACT

Artificial Intelligence (AI) mental health chatbots are increasingly used by Generation Z as a source of emotional support and digital companionship. The growing interaction between users and AI systems has raised questions regarding the ability of AI chatbots to provide empathetic communication and contribute to users' emotional well-being. This study aims to examine the role of perceived emotional support and perceived empathy in AI mental health chatbots on AI companionship and emotional well-being among Generation Z users. This study employed a quantitative approach using survey data collected from 160 Generation Z respondents who had experience using AI mental health chatbots. Data were analyzed using Structural Equation Modeling Partial Least Squares (SEM-PLS) to evaluate the relationships among variables. The findings indicate that perceived emotional support and perceived empathy positively influence AI companionship. Furthermore, AI companionship significantly contributes to emotional well-being. The results also show that perceived emotional support and perceived empathy have direct positive effects on emotional well-being among Generation Z users. AI mental health chatbots have the potential to provide emotionally supportive and empathetic interactions that enhance users' emotional well-being. The study highlights the importance of integrating human-centered and empathetic features into AI systems to support psychological well-being in digital healthcare environments.

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1. INTRODUCTION

The rapid development of Artificial Intelligence (AI) has significantly transformed the healthcare sector [1], including the area of mental health support. This transformation is increasingly relevant to the global agenda of sustainable development, particularly the United Nations Sustainable Development Goals (SDGs), specifically SDG 3 (Good Health and Well-Being), which emphasizes the importance of promoting mental health and improving well-being across all age groups. In addition, SDG 9 (Industry, Innovation and Infrastructure) highlights the role of technological innovation in expanding access to digital services and supporting quality of life through innovative solutions. In recent years, AI-powered chatbots have become increasingly popular as accessible tools for emotional communication and psychological assistance, particularly among

Generation Z [2, 3]. As a digitally native generation, Generation Z tends to rely heavily on digital platforms for communication, self-expression, and emotional interaction. The emergence of AI mental health chatbots provides users with immediate access to emotional support through interactive conversations that are available anytime and anywhere. Compared to traditional mental health services, AI chatbots offer convenience, anonymity, accessibility, and non-judgmental interactions, making them appealing for users who may feel uncomfortable sharing personal emotions with others [4]. The increasing use of AI chatbots for emotional communication has raised important discussions regarding the ability of AI systems to simulate empathy and provide emotional support similar to human interaction. Several AI chatbot platforms, such as ChatGPT, Replika, and Character.AI, are frequently used not only for information retrieval but also for emotional conversations, stress relief, and companionship. This phenomenon reflects the growing role of AI as a social actor capable of engaging users in emotionally meaningful interactions. As users spend more time communicating with AI systems, perceptions regarding emotional support and empathy become increasingly important in shaping their psychological experiences and emotional well-being [5].

Previous studies have examined AI applications in healthcare and digital services, focusing primarily on system performance [6], user satisfaction, service quality, and technology acceptance. However, limited studies have specifically explored the psychological and emotional dimensions of AI mental health chatbots, particularly regarding how perceived emotional support and perceived empathy influence users' emotional well-being. Existing research also tends to emphasize functional effectiveness rather than the emotional relationship formed between users and AI systems [7, 8]. Furthermore, studies investigating AI companionship as a mediating factor between emotional support, empathy, and emotional well-being remain relatively scarce, especially among Generation Z users. This gap indicates the need for further investigation into the social and emotional mechanisms underlying human-AI interaction in mental health contexts.

This study is grounded in Computers Are Social Actors (CASA Theory), which explains that individuals tend to apply social norms and emotional expectations when interacting with computers or AI systems [9]. Through this perspective, users may perceive AI chatbots as socially responsive entities capable of understanding emotions, offering support, and creating companionship. In addition, Social Support Theory supports the argument that emotional support can positively influence an individual's psychological condition and emotional well-being. Therefore, interactions with AI mental health chatbots may contribute to emotional comfort and psychological support similarly to human social interaction [10].

Based on these considerations, this study aims to examine the role of perceived emotional support and perceived empathy in AI mental health chatbots on AI companionship and emotional well-being among Generation Z users. This study is expected to contribute theoretically by extending the application of CASA Theory and Social Support Theory in the context of AI mental health chatbots. Practically, the findings may provide insights for AI developers and digital healthcare practitioners to design more empathetic and emotionally supportive AI systems that promote positive psychological experiences for users [11].

2. LITERATURE REVIEW

2.1. Computers Are Social Actors Theory

This study is grounded in Computers Are Social Actors (CASA Theory), which explains that individuals tend to unconsciously apply social rules and interpersonal behaviors when interacting with computers or artificial intelligence systems. According to this theory, users may perceive AI systems as social entities capable of providing emotional responses, empathy, and companionship [12, 13]. As AI technology becomes increasingly conversational and human-like, users are more likely to establish emotional connections with AI chatbots. In the context of mental health chatbots, the perception of empathy and emotional support may influence users' psychological experiences similarly to interactions with humans. Therefore, CASA Theory provides a relevant theoretical foundation for understanding how AI mental health chatbots affect emotional well-being among Generation Z users [14].

In addition, this study is also supported by Social Support Theory, which emphasizes the importance of emotional support in improving psychological conditions and emotional stability [15]. Emotional support can help individuals reduce stress, feel understood, and improve emotional comfort. Through AI mental health chatbots, users may perceive emotional assistance that contributes positively to their emotional well-being [16].

2.2. Perceived Emotional Support

Perceived emotional support refers to the extent to which individuals feel emotionally supported, comforted, and understood during interactions with AI mental health chatbots. Emotional support is considered an important factor in digital mental health services because users tend to seek reassurance, understanding, and psychological comfort during emotional conversations [17]. AI chatbots that provide supportive and comforting responses may help users feel emotionally connected and psychologically assisted. Previous studies have indicated that emotional support in digital communication environments can positively influence users' emotional experiences and psychological outcomes.

2.3. Perceived Empathy

Perceived empathy refers to users' perceptions regarding the ability of AI chatbots to understand emotions, demonstrate care, and respond appropriately to emotional situations. In AI-mediated communication, empathy becomes a critical factor because users expect emotionally sensitive interactions rather than merely informational responses. AI systems capable of simulating empathetic communication may create more engaging and emotionally satisfying interactions [18]. As AI conversational capabilities continue to evolve, empathetic responses are increasingly recognized as an essential component in improving user trust, comfort, and emotional engagement.

2.4. AI Companionship

AI companionship refers to the emotional attachment and sense of companionship users experience while interacting with AI chatbots. The concept reflects how users may perceive AI systems as companions capable of providing social presence and emotional interaction [19, 20]. Frequent interactions with AI chatbots may reduce feelings of loneliness and create emotional closeness, especially among individuals who actively seek emotional communication through digital platforms. AI companionship is particularly relevant among Generation Z users, who are highly familiar with technology-based communication and digital social interaction.

2.5. Emotional Well Being

Emotional well-being refers to an individual's positive emotional condition, including feelings of calmness, comfort, emotional stability, and reduced psychological distress. Emotional well-being is an important aspect of mental health because it reflects how individuals manage emotions and maintain positive psychological experiences. Interactions with emotionally supportive and empathetic AI chatbots may contribute positively to emotional well-being by providing comfort, reassurance, and emotional companionship [21].

2.6. Previous Studies

Recent studies have increasingly explored the role of artificial intelligence in healthcare and emotional support systems, particularly in relation to user experience, empathy, and psychological well-being. The growing adoption of AI mental health chatbots has encouraged researchers to examine how AI-driven interactions influence emotional comfort, companionship, and mental health outcomes. Previous findings indicate that empathetic communication and emotional support provided by AI systems may positively affect users' emotional experiences and satisfaction. Several studies related to AI empathy, emotional support, companionship, and emotional well-being are presented in Table 1.

Table 1. Previous Studies

No	Author	Title	Findings
1	[22]	AI Empathy and User Satisfaction in Digital Healthcare	AI empathy positively influenced user satisfaction and emotional trust.
2	[23]	Emotional Support in AI Chatbots and Psychological Comfort	Emotional support significantly improved users' psychological comfort.
3	[24]	AI Companionship and Loneliness Reduction among Young Adults	AI companionship reduced loneliness and improved emotional experiences.

4	[25]	Human Like Interaction in AI Mental Health Chatbots	Human-like communication increased emotional engagement with AI systems.
5	[26]	Empathetic AI Communication and Emotional Well Being	Empathetic AI interaction positively affected emotional well-being.

Based on the previous studies presented in Table 1, most researchers have focused on AI empathy, emotional support, user satisfaction, and psychological outcomes in digital healthcare contexts. The findings consistently indicate that emotionally responsive AI systems can positively influence users' emotional experiences and well-being. However, limited studies have simultaneously examined perceived emotional support, perceived empathy, AI companionship, and emotional well-being within a single integrated model [27], particularly among Generation Z users of AI mental health chatbots [28]. Therefore, this study attempts to address this gap by investigating the relationships among these variables using the perspectives of CASA Theory and Social Support Theory.

2.7. Hypothesis Development

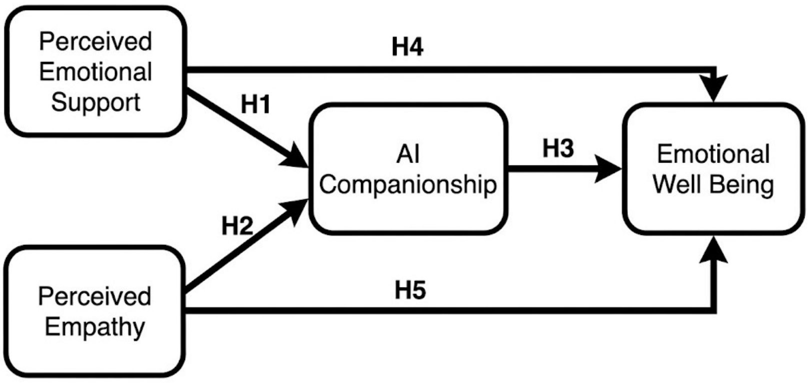

Figure 1. Conceptual Framework

Based on Figure 1, the following hypothesis is proposed:

- **H1 Perceived emotional support positively influences AI companionship**

  Perceived emotional support provided by AI mental health chatbots may encourage users to develop emotional attachment and companionship with AI systems. Supportive interactions can create feelings of comfort and emotional closeness, increasing the perception of AI companionship [29].

- **H2 Perceived empathy positively influences AI companionship**

  Perceived empathy may strengthen users' emotional connection with AI chatbots because empathetic responses can create feelings of understanding and care. When users perceive AI systems as empathetic, they may develop stronger companionship toward AI interactions [30].

- **H3 AI companionship positively influences emotional well-being**

  AI companionship may positively contribute to emotional well-being because users who perceive AI as emotionally supportive companions may experience greater emotional comfort and reduced psychological distress [31].

- **H4 Perceived emotional support positively influences emotional well-being**

  Perceived emotional support may directly improve emotional well-being by helping users feel psychologically supported, emotionally understood, and emotionally comforted during interactions with AI chatbots [32].

- **H5 Perceived empathy positively influences emotional well-being**

  Perceived empathy may also directly influence emotional well-being because empathetic interactions can create positive emotional experiences and emotional reassurance for users [33].

3. METHODOLOGY

This study employed a quantitative research approach to examine the relationships among perceived emotional support, perceived empathy, AI companionship, and emotional well-being among Generation Z users of AI mental health chatbots. A quantitative method was considered appropriate because this study aimed to test the proposed hypotheses and analyze the causal relationships between variables using statistical procedures [28, 34].

The population of this study consisted of Generation Z individuals who had experience using AI mental health chatbots for emotional communication, psychological support, stress relief, or personal conversations. The respondents were selected using a purposive sampling technique because the study required participants with specific characteristics relevant to the research objectives [35]. The criteria for respondents included individuals aged between 17 and 27 years who had used AI chatbot platforms such as ChatGPT, Character.AI, or Replika for emotional interaction or mental health-related communication at least two times within the last month. A total of 160 respondents participated in this study.

Table 2. Demographic Characteristics of Respondents

Characteristics	**Category**	**Frequency**	**Percentage**
Gender	Male	68	42.5%
	Female	92	57.5%
Age	17–20 Years	49	30.6%
	21–24 Years	81	50.6%
	25–27 Years	30	18.8%
AI Chatbot Usage Frequency	2–5 Times per Month	58	36.3%
	6–10 Times per Month	64	40.0%
	More than 10 Times per Month	38	23.7%
Most Frequently Used Platform	ChatGPT	89	55.6%
	Character.AI	41	25.6%
	Replika	30	18.8%

Based on Table 2 data were collected through an online questionnaire distributed using Google Forms. The questionnaire consisted of statements measuring perceived emotional support, perceived empathy, AI companionship, and emotional well-being. All measurement items were adapted from previous studies and modified to fit the context of AI mental health chatbots. The measurement scale used in this study was a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Perceived emotional support was measured based on users' perceptions regarding the emotional comfort and psychological support provided by AI chatbots. Perceived empathy referred to users' perceptions of the chatbot's ability to understand emotions and provide empathetic responses [26, 36]. AI companionship measured the extent to which users perceived AI chatbots as companions capable of providing emotional closeness and social interaction. Emotional well-being referred to users' positive emotional conditions after interacting with AI mental health chatbots.

The data analysis technique used in this study was Structural Equation Modeling Partial Least Squares (SEM-PLS) using SmartPLS. SEM-PLS was selected because it is suitable for predictive research models and capable of analyzing complex relationships among latent variables. The analysis process included measurement model evaluation through validity and reliability testing, followed by structural model evaluation to test the proposed hypotheses. Convergent validity was assessed using factor loadings and Average Variance Extracted (AVE), while reliability was evaluated using Cronbach's Alpha and Composite Reliability values. Hypothesis testing was conducted by examining path coefficients, t-statistics, and p-values obtained through the bootstrapping procedure.

4. RESULTS AND DISCUSSION

This section presents the results of data analysis using Structural Equation Modeling Partial Least Squares (SEM-PLS). The analysis includes respondent characteristics, measurement model evaluation, structural model evaluation, and hypothesis testing. The findings are discussed to explain the relationships among perceived emotional support, perceived empathy, AI companionship, and emotional well-being among Generation Z users of AI mental health chatbots.

4.1. Measurement Model Evaluation

The measurement model evaluation was conducted to assess the validity and reliability of the constructs used in this study. Convergent validity was evaluated using factor loadings and Average Variance Extracted (AVE), while reliability was assessed using Cronbach's Alpha and Composite Reliability values. The recommended threshold values include factor loadings above 0.70, AVE above 0.50, and reliability values above 0.70. The results of convergent validity and reliability testing are presented in Table 3.

Table 3. Validity and Reliability Analysis Results

Variable	Indicator	Loading Factor	AVE	Composite Reliability	Cronbach's Alpha
Perceived Emotional Support	PES1	0.812	0.683	0.896	0.845
	PES2	0.841			
	PES3	0.829			
	PES4	0.817			
Perceived Empathy	PE1	0.824	0.691	0.899	0.851
	PE2	0.836			
	PE3	0.847			
	PE4	0.821			
AI Companionship	AIC1	0.838	0.702	0.904	0.858
	AIC2	0.852			
	AIC3	0.831			
	AIC4	0.840			
Emotional Well Being	EWB1	0.826	0.688	0.898	0.849
	EWB2	0.841			
	EWB3	0.819			
	EWB4	0.835			

Based on Table 3, all indicators demonstrated factor loading values above 0.70, indicating satisfactory convergent validity. Furthermore, all AVE values exceeded the recommended threshold of 0.50, confirming that each construct adequately explained the variance of its indicators. The Composite Reliability and Cronbach's Alpha values for all variables were also above 0.70, indicating that the measurement instruments used in this study were reliable and internally consistent.

4.2. Structural Model Evaluation

The structural model evaluation was conducted to examine the explanatory power of the proposed research model. The coefficient of determination (R^2) was used to measure the predictive accuracy of endogenous variables in the model. The results of the structural model evaluation are presented in Table 4.

Table 4. R-Square (R^2) Value Results

Endogenous Variable	R^2 Value	Interpretation
AI Companionship	0.648	Moderate
Emotional Well Being	0.712	Strong

Based on Table 4, the R^2 value for AI companionship was 0.648, indicating that perceived emotional support and perceived empathy explained 64.8% of the variance in AI companionship. Meanwhile, the R^2 value for emotional well-being was 0.712, meaning that perceived emotional support, perceived empathy, and AI companionship collectively explained 71.2% of the variance in emotional well-being. These findings indicate that the proposed research model has strong explanatory capability.

To provide a clearer visualization of the relationships among variables, the structural model generated from the SEM-PLS analysis is presented in Figure 2. The figure illustrates the relationships between perceived emotional support, perceived empathy, AI companionship, and emotional well-being, including the path coefficients and explanatory power of the endogenous variables.

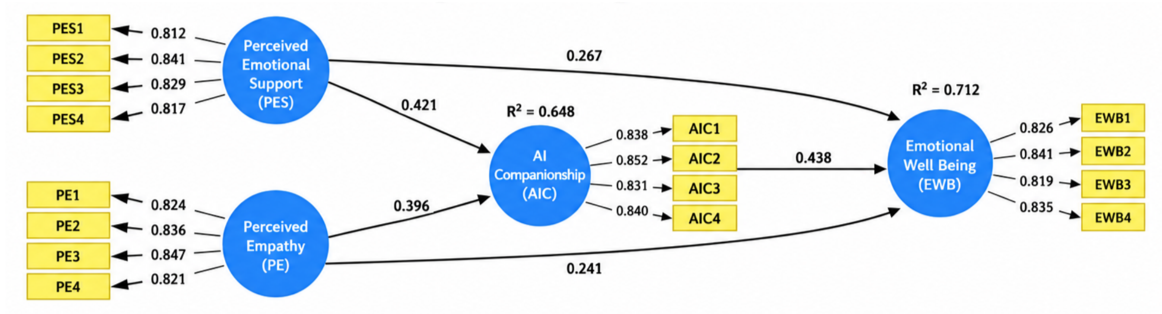

Figure 2. SEM-PLS Algorithm Model

Figure 2 demonstrates that all structural relationships in the proposed model have positive path coefficients. Perceived emotional support and perceived empathy both showed substantial contributions to AI companionship, while AI companionship significantly influenced emotional well-being. The figure also indicates strong explanatory power for emotional well-being, suggesting that emotionally supportive and empathetic AI interactions play an important role in shaping positive emotional experiences among Generation Z users.

4.3. Hypothesis Testing

Hypothesis testing was conducted using the bootstrapping procedure in SEM-PLS. The significance of the relationships among variables was evaluated based on path coefficients, t-statistics, and p-values. A relationship was considered significant if the t-statistic exceeded 1.96 and the p-value was below 0.05. The results of hypothesis testing are presented in Table 5.

Table 5. Hypothesis Testing Results

Hypothesis	Relationship	Path Coefficient	T-Statistic	P-Value	Result
H1	Perceived Emotional Support → AI Companionship	0.421	5.873	0.000	Supported
H2	Perceived Empathy → AI Companionship	0.396	5.214	0.000	Supported
H3	AI Companionship → Emotional Well Being	0.438	6.028	0.000	Supported
H4	Perceived Emotional Support → Emotional Well Being	0.267	3.482	0.001	Supported
H5	Perceived Empathy → Emotional Well Being	0.241	3.105	0.002	Supported

Based on Table 5, all proposed hypotheses were supported. Perceived emotional support significantly influenced AI companionship, indicating that emotionally supportive AI interactions increased users' feelings of companionship toward AI chatbots. Similarly, perceived empathy significantly influenced AI companionship, suggesting that empathetic communication strengthened emotional attachment between users and AI systems.

Figure 3 confirms that all proposed relationships are statistically significant, as indicated by the high t-statistics values and significant path coefficients. The strongest relationship was identified between AI companionship and emotional well-being, indicating that emotional attachment and companionship toward AI chatbots play a crucial role in improving users' emotional conditions. The bootstrapping results further validate the robustness of the proposed research model and support all hypotheses developed in this study.

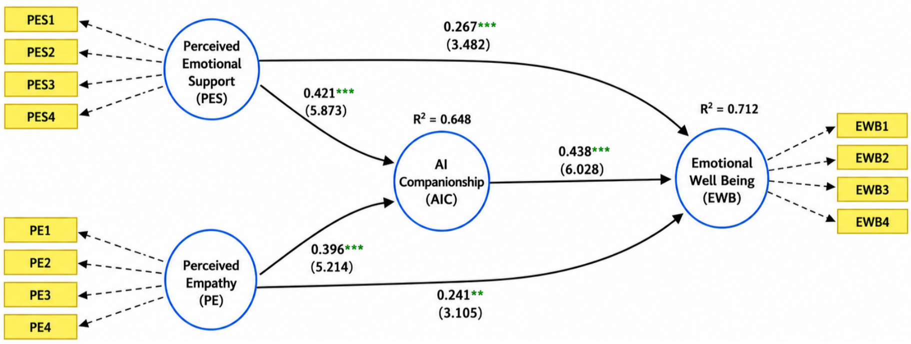

Figure 3. Bootstrapping Result

The findings also revealed that AI companionship significantly influenced emotional well-being. This result indicates that users who perceived AI chatbots as companions experienced higher emotional comfort and positive psychological conditions. In addition, perceived emotional support and perceived empathy were found to directly influence emotional well-being, suggesting that emotionally supportive and empathetic interactions contributed positively to users' emotional experiences. These findings support Computers Are Social Actors (CASA Theory), which explains that users may treat AI systems as social actors capable of emotional interaction. The results indicate that AI mental health chatbots are not only perceived as technological tools but also as emotionally responsive companions capable of providing psychological comfort. Furthermore, the findings are consistent with Social Support Theory, which emphasizes the importance of emotional support in improving emotional well-being.

The results of this study also align with previous studies that highlighted the role of empathetic AI interactions in improving psychological comfort, emotional satisfaction, and emotional engagement. However, this study extends prior research by integrating perceived emotional support, perceived empathy, AI companionship, and emotional well-being into a single research model focused specifically on Generation Z users of AI mental health chatbots.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide important managerial implications for AI developers and digital healthcare providers. The significant influence of perceived emotional support and perceived empathy on AI companionship indicates that AI mental health chatbots should be designed not only to deliver accurate information but also to provide emotionally supportive and empathetic interactions. Developers should prioritize human-centered communication features, such as emotionally adaptive responses, supportive language, and personalized interaction styles, to improve users' emotional engagement and psychological comfort during conversations with AI systems.

In addition, the significant effect of AI companionship on emotional well-being suggests that creating a sense of companionship is essential in AI mental health services. AI chatbot platforms should enhance social presence and emotional interaction quality to encourage users to feel emotionally connected and supported. Features such as conversational continuity, emotional recognition, and context-aware responses may strengthen users' emotional attachment and improve their overall emotional well-being. These findings also highlight the potential of AI chatbots as accessible digital emotional support tools for Generation Z users in technology-driven environments.

6. CONCLUSION

This study examined the role of perceived emotional support and perceived empathy in AI mental health chatbots on AI companionship and emotional well-being among Generation Z users. The findings revealed that perceived emotional support and perceived empathy significantly influenced AI companionship, indicating that emotionally supportive and empathetic AI interactions can strengthen users' emotional attachment toward AI chatbots. Furthermore, AI companionship was found to positively influence emotional well-being, suggesting that users who perceive AI chatbots as companions tend to experience more positive emotional conditions.

The study also demonstrated that perceived emotional support and perceived empathy directly contributed to emotional well-being. These findings confirm that AI mental health chatbots are capable of providing emotionally meaningful interactions that may improve users' psychological comfort and emotional experiences. The results support Computers Are Social Actors (CASA Theory), which explains that users may treat AI systems as social actors capable of emotional interaction and companionship.

This study contributes to the growing literature on empathetic artificial intelligence and digital mental health by integrating perceived emotional support, perceived empathy, AI companionship, and emotional well-being into a single research model. However, this study has several limitations, including the focus on Generation Z respondents and the use of self-reported questionnaire data. Future studies are encouraged to explore other demographic groups, include longitudinal approaches, and investigate additional variables related to AI-human emotional interaction and psychological outcomes.

7. DECLARATIONS

7.1. About Authors

Mardiana (MM) https://orcid.org/0000-0003-4367-9562

Ossi Ferli (OF) https://orcid.org/0009-0003-1180-344X

Henderi (HH) https://orcid.org/0000-0002-9354-4992

Evelyn Anderson (EA) https://orcid.org/0000-0002-8431-6795

Alni Cahyani (AC) https://orcid.org/0009-0006-1468-9197

7.2. Author Contributions

Conceptualization: MM; Methodology: AC; Software: EA; Validation: HH and OF; Formal Analysis: MM and AC; Investigation: EA; Resources: OF; Data Curation: HH; Writing Original Draft Preparation: MM and AC; Writing Review & Editing: EA and HH; Visualization: MM; All authors, MM, OF, HH, EA, and AC, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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