“Thank God I’m Fly!”: A Gyaru Persona Chatbot for Adopting a Positive Mindset to Prevent and Mitigate Negative Emotions

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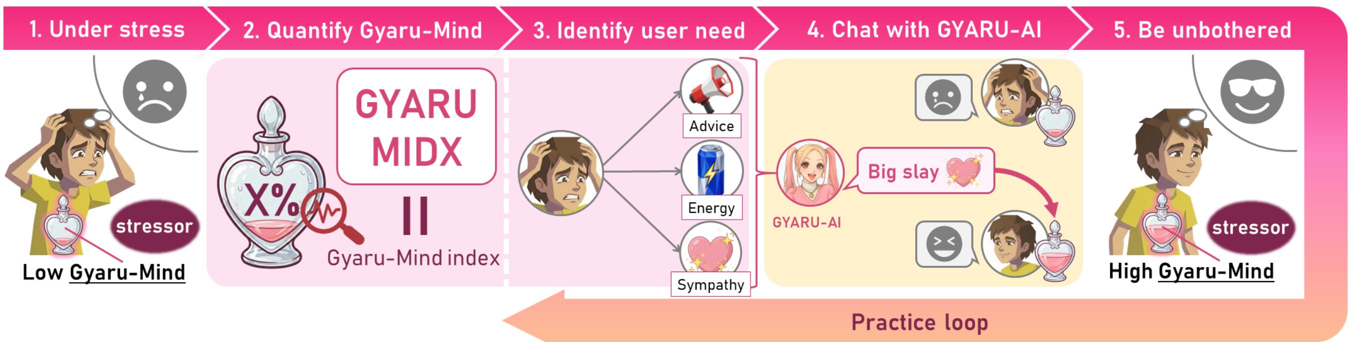

Figure 1: Users Can Be Resilient to Negative Emotions By Adopting Gyaru-mind Through Chatting with an Agent Assigned with a Gyaru Persona. GYARU-AI is a text-based conversational system that responds using Gyaru-style language to encourage users, while estimating and providing feedback on users’ positive mindset (Gyaru-mind) through the Gyaru-mind index (*GYARU-MIDX*). This feedback supports users in adopting Gyaru-mind and may help prevent or mitigate negative emotions in the short and long term.

Abstract

Conversational agents have been explored to support emotion regulation and reduce users’ distress, and their personas are often designed to be empathetic and approachable. However, much prior work focuses on coping after stress has occurred, and overly empathic personas can suggest harmful thinking for users. To address these limitations, we explore a new mindset, “Gyaru-mind”: a Japanese cultural mindset that emphasizes positivity, self-respect, and frankness. We therefore built a text-based chatbot, “GYARU-CHAT”, to help users adopt Gyaru-mind. In this system, an AI agent “GYARU-AI” acts as a role model of Gyaru-mind and selects a response mode from the user’s input to balance empathetic and frank stances. In addition, GYARU-AI estimates a prototype Gyaru-mind index, “GYARU-MIDX”, to make the user’s Gyaru-mind level visible. Our study revealed that chatting with a Gyaru-minded persona increases users’ positive emotions.

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CCS Concepts

• **Human-centered computing** → **Natural language interfaces**; *Interactive systems and tools.*

Keywords

conversational agent, Gyaru, culturally grounded persona, large language model

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1 Introduction

Constant experience of negative emotions can harm a person’s mental health and lead to mental illness. To mitigate negative emotions, emotion regulation is known to be effective, as it influences both the emotions individuals experience and how they perceive negative consequences [14]. Also, adopting a positive mindset can develop resilience to negative emotions [10], supporting longer-term emotional well-being.

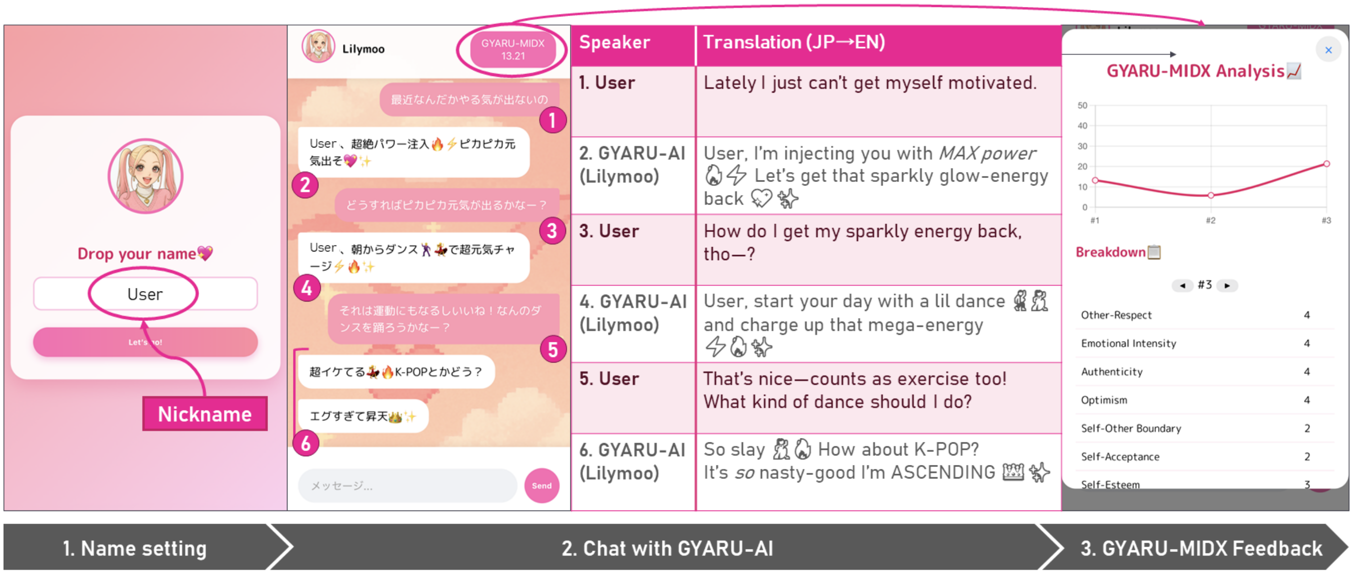

Figure 2: GYARU-CHAT Interface. (1) Users enter a nickname before starting the session. (2) Users chat with GYARU-AI (Lilymoo); the right-hand table shows an English translation of the Japanese dialogue. GYARU-MIDX is updated based on the user’s response per 50 Japanese characters and displayed in the upper-right badge. (3) Tapping the upper-right badge opens the GYARU-MIDX feedback view, which displays the trajectory of the score and a breakdown of the eight factor scores, each ranging from 0 to 5.

Therefore, researchers have developed emotion regulation systems with conversation agents [7, 8, 27, 33]. For example, Mishra *et al.* developed a dialog-based therapy system for mental health patients that employs a chatbot with an empathetic persona [22]. However, these studies primarily focus on addressing mental health difficulties after they have already emerged. Not only the post-onset intervention, but also *preventing* or *mitigating* negative emotions from happening is important for well-being. As current chatbot personas are primarily designed for post-onset intervention, they are designed to act empathetically [30]. As a result, prior chatbots neither prevent nor mitigate negative emotions.

Therefore, as a persona of emotion regulation assistance systems, we propose *“Gyaru,”* a Japanese cultural persona associated with glamorous self-expression and slang-rich speech[17, 21]. This persona could be effective for helping users develop resilience to negative emotions, as the mindset inspired by Gyaru, which is *“Gyaru-mind,”* is known to have high positivity and respect for both oneself and others [1]. This mindset encourages oneself and others to approach challenges with lighthearted confidence rather than anxiety [1], which aligns with resilience to negative emotions. Therefore, we hypothesize that by interacting with a Gyaru persona agent, users can not only experience short-term increases in positivity but also adopt Gyaru-mind, thereby building long-term resilience to negative emotions.

We propose *GYARU-CHAT*, a text-based conversational system for adopting Gyaru-mind, powered by a Gyaru persona AI agent, *GYARU-AI*. When users input text for conversation, GYARU-AI determines context-appropriate responses, such as providing advice, energizing the user, or expressing empathy, and then generate response with Gyaru-style language (Fig. 1). To encourage users to adopt Gyaru-mind, GYARU-CHAT provides feedback indicating how closely users’ behavior aligns with Gyaru, through the Gyaru-mind index *GYARU-MIDX*, a score that estimates the user’s Gyaru-mind level throughout the conversation. By reflecting on this feedback, users may be able to practice and internalize aspects of Gyaru-mind over time, which could support short-term emotion regulation and potentially sustained use.

In our study with 24 participants, we observed increased positivity and decreased negativity among users who interacted with GYARU-AI compared to those who interacted with a chatbot with a default persona. Furthermore, through a two-week study with two participants, we identified design implications, such as the need to balance an authentically Gyaru-like persona with clear recognition of the agent as an AI.

2 Related Work

2.1 Conversational Agent and Personal Informatics Systems for Emotion Regulation

Researchers have explored various conversational agents [7] for supporting users after they experience negative emotions. Prior work has proposed counseling systems that are personalized for individual cases [20, 22]. Multimodal agents can also support individuals’ emotion regulation by generating content (*e.g.* images) that helps users take a more objective view of their emotions [35]. Yet many interventions still emphasize episodic relief, leaving sustained skill or mindset formation under-supported [8, 27, 33]. This motivates our focus on designing systems that foster a positive mindset (Gyaru-mind) in users to build resilience to negative emotions.

Table 1: Eight Gyaru-mind Factors and PLS Weights for Aggregating Factor Scores into GYARU-MIDX. We derived eight factors from a Japanese book describing Gyaru-mind [1]. We compute GYARU-MIDX by scoring each factor on a 0–5 scale and aggregating the eight factor scores using a PLS regression model.

Factor	One-line description	PLS weight
Emotional Intensity[26]	Strength of affect display (e.g., intensifiers, exclamations).	1.535
Self-acceptance[32]	Accepting oneself as-is, strengths and weaknesses included.	1.371
Linguistic Creativity[4]	Playful use of slang, neologisms, metaphors, etc.	1.133
Self-esteem[25]	How positively one evaluates their own worth.	1.106
Optimism[28]	A general expectation that things will work out.	0.875
Authenticity[11]	Choosing in line with one's values rather than external pressure.	0.477
Other-Respect[15]	Respect for others' value, individuality, and dignity.	0.133
Self–Other Boundary[23]	Keeping one's stance without fusing with or blocking others' emotions.	-0.043

2.2 Personas for Conversational Agents

The persona of conversational agents often focuses on sympathizing and being friendly [18, 29], as these personas can mitigate the anxiety and loneliness of users [16]. To provide tailored emotional support, prior work has explored both manual persona customization [37] and automatic persona adaptation during interaction [5, 6, 22]. However, sympathetic responses alone may not be sufficient to foster a positive mindset and may also pose risks by reinforcing harmful thinking [30]. We therefore propose a Gyaru-style persona that is not only sympathetic and friendly, but also youth-oriented and self-affirming, which we hypothesize to be effective in assisting users in gaining resilience by adopting Gyaru-mind.

3 GYARU-CHAT: Chat System for Users to Adopt Gyaru-mind

GYARU-CHAT (Fig. 2) is a text-based dialogue system designed to help users adopt "Gyaru-mind" through interaction with the system. In GYARU-CHAT, GYARU-AI generates responses using Gyaru-style language. To provide context-aware responses, GYARU-AI first classifies users' context into one of three labels (advice, sympathy, or energy) before generating a response. In addition, to provide explicit feedback on users' adoption of Gyaru-mind, the system estimates the user's *GYARU-MIDX*, which represents the degree of Gyaru-mind alignment as a numerical score out of 50. GYARU-MIDX is computed by scoring eight factors extracted from users' utterances on a scale of 0–5 and aggregating them into a total score ranging from 0 to 50.

3.1 GYARU-CHAT UI

We implemented GYARU-CHAT as a smartphone application. In the initial screen, users enter their nickname, which GYARU-AI will call the user during the conversation. Then it transitions to the chat screen, and the conversation with GYARU-AI, which is named Lilymoo, starts. GYARU-AI estimates users' GYARU-MIDX, which ranges from 0 to 50 (the higher the more Gyaru-style the user is speaking), every 50 characters and displays it in the pink box in the upper right of the interface. When users tap the pink box, they can view the temporal progression of GYARU-MIDX as well as the breakdown of the eight factor scores used to compute the overall GYARU-MIDX, which are described in Sec. 3.3.

3.2 Controlling Persona and Responses of GYARU-AI

We use a large language model (LLM), GPT-4.1-mini, to generate responses to users, approximately in 50 Japanese characters. To provide context-aware responses, GYARU-AI first classifies the user's context into one of three labels, "Advice," "Sympathy," or "Energy," before generating a response. In "Advice" mode, the agent provides candid advice (*e.g., "Nah babe, don't"*); in "Sympathy" mode, it offers positive empathy (*e.g., "You slayed!"*); and in "Energy" mode, it produces brief affirmative responses (*e.g., "Yesss!"*). GYARU-AI generates these replies using a small set of mode-specific few-shot examples [3, 19]. The examples and prompts were authored by one of our authors, based on the actual Gyaru-style language from Gyaru-person that was seen on social media[9].

3.3 GYARU-MIDX: Index of Measuring Users Gyaru-mind

To measure how Gyaru-minded users are, we referred to a Japanese book describing Gyaru-mind [1]. Following discussions among the authors, we decomposed the Gyaru mindset into eight factors, as shown in Table 1. Based on the user input, we measure these eight factors and aim to compute GYARU-MIDX. Specifically, for each of the eight Gyaru-mind factors $j \in \{1, \dots, 8\}$, we assign a score $x_j \in [0, 5]$ on a 5-point scale using an LLM (GPT-4.1). We then estimate *GYARU-MIDX* using a linear function trained via partial least squares (PLS) regression. The model computes a GYARU-MIDX, $\tilde{y} \in [0, 50]$, as a weighted linear combination of the eight factor scores, $\tilde{y} = \beta_0 + \sum_{j=1}^{8} \beta_j x_j$, where β_0 denotes the intercept and β_j represents the regression coefficient corresponding to factor j. Below, we describe the dataset and the training method of the function.

3.3.1 How to Collect the Training Data. For training the GYARU-MIDX predictor, we collected 29 Japanese online interview articles covering 69 speakers, including Gyaru celebrities and non-celebrity individuals. To ensure diversity in speaker backgrounds, we sampled articles from a range of publishers, including fashion magazines, newspapers, and business magazines. We treated each speaker as one training instance. The first author assigned a ground-truth *GYARU-MIDX* score $y \in [0, 50]$ to each speaker using a 50-point Likert scale, which serves as the target variable for PLS

Table 2: Study 1 outcomes before and after the chat (descriptive statistics). The table reports PANAS (Positive Affect; Negative Affect) and trait self-efficacy scores for each condition, presented as mean, standard deviation (SD), and ranges [min–max].

Outcome	Stat.	Pre-Task		Post-Task	
		Gyaru	Default	Gyaru	Default
Positive Affect	Mean	23.92	23.67	25.50	18.75
	SD	7.89	6.29	10.00	8.49
	min–max	[15–37]	[15–34]	[12–41]	[8–36]
Negative Affect	Mean	13.92	18.08	11.58	16.83
	SD	4.91	8.55	3.45	5.31
	min–max	[8–21]	[8–31]	[8–17]	[10–25]
Self-Efficacy	Mean	69.00	63.50	67.83	63.42
	SD	15.97	12.33	16.84	12.80
	min–max	[46–92]	[48–88]	[42–95]	[49–84]

Table 3: ANCOVA results for Study 1. β_{group} denotes the adjusted between-condition difference in post-task outcomes (Gyaru − Default), controlling for the corresponding pre-task score. 95% confidence intervals (CIs) are reported. * indicates $p < .05$.

Outcome	β_{group}	95% CI	p
Positive Affect	6.51	[1.08, 11.94]	0.021*
Negative Affect	-3.28	[-6.04, -0.53]	0.022*
Self-Efficacy	-0.62	[-7.07, 5.83]	0.843

regression. Because Gyaru-mind does not yet have a strict scoring rubric, this annotation was based on the first author's holistic understanding of Gyaru-mind based on the book describing what Gyaru-mind is [1]. In addition, we used an LLM to assign scores to the eight Gyaru-mind factors, forming an input feature vector $\mathbf{x} = (x_1, \dots, x_8)$, where each component $x_j \in [0, 5]$.

3.3.2 PLS Training. As the GYARU-MIDX predictor, we selected a PLS regression model because the factors may be correlated, and PLS enables the estimation of a linear model while minimizing the influence of these potentially correlating factors [13, 36]. The data annotated and collected were used to train the PLS model. We selected the number of latent components K by leave-one-out cross-validation (LOO-CV)[12, 34], evaluating $K \in \{1, \dots, 8\}$ and choosing the value with the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

4 User Study

We conducted two studies to investigate (1) whether a Gyaru-minded persona positively affects users' emotions and (2) whether GYARU-AI has the potential to support users in adopting Gyaru-mind, as described in the following sections. All participants were Japanese, and this study was approved by Komazawa University's ethics committee.

4.1 Study 1: Short-Term Effects of GYARU-AI

We recruited 24 participants (10 males, 14 females; age: $M = 21.79$, $SD = 1.53$) and asked them to interact with a chatbot for 15 minutes about a personal challenge they wished to overcome. Half of the participants interacted with GYARU-AI, while the other half interacted with a chatbot using the same LLM using a default persona (*i.e.,* without a persona specification). Both conditions used an identical minimal text-only chat interface and the same LLM (GPT-4.1-mini).

We measured Positive and Negative Affect Schedule (PANAS [31]; positive affect [PA] and negative affect [NA]) and trait self-efficacy [24] before and after the conversation. PA and NA were computed as summed scores (range: 8–48), and trait self-efficacy was computed as a summed score (range: 23–115). We conducted a one-way analysis of covariance (ANCOVA) to compare the changes in these metrics from pre- to post-task score for each condition. We adopted ANCOVA because pre-task scores could influence post-task scores and thus act as a confounding factor; *e.g.,* participants with higher baseline positivity may show smaller increases after the intervention.

Table 2 summarizes pre- and post-task outcomes by condition, and Table 3 reports the ANCOVA statistics. The ANCOVA indicated higher post-intervention PA and lower post-intervention NA in the Gyaru-mind persona than in the default persona, whereas self-efficacy did not differ significantly. Specifically, after controlling for baseline scores, the adjusted post-outcome difference was $\beta_{\text{group}} = 6.51$ for PA and $\beta_{\text{group}} = -3.28$ for NA (Gyaru−default), suggesting increased positivity and reduced negativity in the Gyaru-mind persona condition. These results provide initial evidence that the Gyaru-mind persona can promote short-term positivity.

4.2 Study 2: Two-Week Pilot Deployment and Design Feedback

To investigate if Gyaru-mind has potential in developing long-term resilience to negative emotions, we conducted two week study with two participants (P1 and P2). They used GYARU-CHAT for 5–10 minutes every evening for two weeks. After two weeks, we conducted semi-structured interviews and collected System Usability Scale (SUS)[2].

In the interviews, while several participants reported that GYARU-AI helped them become more resilient to negative emotions, the perceived duration of this effect varied. For example, P1 noted that the effect was short-term, stating that it *"lasted a few hours"* but was *"reset"* by the next day. In contrast, P2 reported *"waking up feeling refreshed"* the following morning, suggesting a potentially longer-lasting positive effect associated with gaining an intuitive understanding of Gyaru-mind and adopting it. Participants also mentioned that GYARU-MIDX captured their temporary mental-well and illness: *"I was surprised when my GYARU-MIDX scored only seven, but it matched how I felt. I was so stressed that day, and I sent Lilymoo depressed words."* (P1) Also, the SUS scores were 87.5 (P1) and 82.5 (P2).

Participants indicated that GYARU-AI’s cheerful responses were beneficial but also left room for improvement. P2 noted that the relatively short responses (approximately 50 characters) helped them avoid overthinking and facilitated an effective emotional shift from negative emotion. In contrast, P1 reported that the brevity of the responses made it harder to continue the conversation, as the length was insufficient for deep discussion. P1 therefore, suggested making the response length context-dependent. P1 preferred not to include overly specific persona details in the chat agent, such as personal preferences or a birthday, as this made the agent feel overly human-like and induced a sense of discomfort. P1 expressed that maintaining a clear boundary in which the agent is recognized as an AI was more desirable.

Taken together, the results of this study may suggest the potential of Gyaru-mind to support users’ positivity beyond the short term, while also highlighting the need for more context-aware conversational modes for interactions that require longer responses (*e.g.,* discussions), as well as a careful balance between making the agent authentically Gyaru-like and clearly recognizable as an AI to ensure user acceptance.

5 Conclusion and Future Work

We presented GYARU-CHAT, a system that helps users adopt Gyaru-mind. Our study revealed that the Gyaru persona has a short-term positive effect on users’ emotions and a potential long-term effect. We envision to further design our system so that GYARU-AI serves as a role model of Gyaru-mind, leading to long term resilience to negative emotions.

Our work has several limitations. First, only one author was involved in the data annotation process. This is because, as the Gyaru persona has received limited attention in academic literature, it is not yet rigorously defined, making standardized annotation challenging. Second, the articles used for dataset construction require further careful large-scale collection to ensure sufficient coverage for capturing Gyaru-mind. Third, our long-term deployment was a small pilot with a limited number of participants; thus, findings about sustained use should be interpreted cautiously. Future work should recruit a larger and more diverse sample to examine whether users can continue using the system as a habit and whether the experience differs across personas and user backgrounds. In addition, GYARU-AI is currently designed for Japanese-only conversations, as Gyaru is a culturally specific concept and has not yet been systematically translated into other languages.

To strengthen the validity of our approach, we plan to further formalize the definition of the Gyaru persona. Once a more rigorous definition is established, we aim to adapt Gyaru-style language to other languages and cultural contexts. We also plan to leverage opt-in private chat data from users who do and do not exhibit Gyaru-mind, and to re-annotate ground-truth scores using multiple raters familiar with Gyaru-mind.

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