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AI as your ally: The effects of AI-assisted venting on negative affect and perceived social support

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AI as Your Ally: The Effects of AI-Assisted Venting on Negative Affect and Perceived Social Support

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Abstract

In recent years, artificial intelligence (AI) chatbots have made significant strides in generating human-like conversations. With AI's expanding capabilities in mimicking human interactions, its affordability and accessibility underscore the potential of AI chatbots to facilitate negative emotional disclosure or venting. The study's primary objective is to highlight the potential benefits of AI-assisted venting by comparing its effectiveness to venting through a traditional journaling platform in reducing negative affect and increasing perceived social support. We conducted a pre-registered within-subject experiment involving 150 participants who completed both traditional venting and AI-assisted venting conditions with counterbalancing and a wash-out period of 1-week between the conditions. Results from the frequentist and Bayesian dependent samples *t*-test revealed that AI-assisted venting effectively reduced high and medium arousal negative affect such as anger, frustration, and fear. However, participants in the AI-assisted venting condition did not experience a significant increase in perceived social support and perceived loneliness, suggesting that participants did not perceive the effective assistance from AI as social support. This study demonstrates the promising role of AI in improving individuals' emotional well-being, serving as a catalyst for a broader discussion on the evolving role of AI and its potential psychological implications.

Keywords: AI-assisted Venting; Traditional Venting; Negative Affect; Perceived Social Support; Perceived loneliness

AI as Your Ally: The Effects of AI-Assisted Venting on Emotional Well-Being and Perceived Social Support

In recent years, there has been a noteworthy rise in reported stress levels (Gagné et al., 2021; Regehr et al., 2013; Tan et al., 2023), coupled with a surge in feelings of loneliness across various age groups (Surkalim et al., 2022; Twenge et al., 2021; Wang et al., 2021). This feeling of loneliness often correlates with a lack of social support (Chalise et al., 2010; Pinquart & Sorensen, 2001; Wang et al., 2018), characterised by individuals struggling to find someone to have meaningful conversations with (Bell, 1985; Konno et al., 2021). This absence of supportive relationships is of significant concern as it has been associated with exacerbated stress, mental distress, and suicidal ideation (Kim & Fredriksen-Goldsen, 2016; Klein et al., 2021; Li et al., 2023; Macrynikola et al., 2018).

Concurrently, the technological landscape has been revolutionised by rapid advancements in artificial intelligence (AI) (Peyravi et al., 2020). Particularly, AI has achieved remarkable breakthroughs in language recognition (Roser, 2022), sentiment analysis (Taherdoost & Madanchian, 2023) and natural language generation (Meera & Geerthik, 2022), enabling it to simulate human-like conversations. Indeed, this aligns with existing research on human-robot interactions (HRI) that investigates how such interactions may mitigate loneliness, highlighting an overall improvement in well-being (Laban et al., 2023a, 2023b). However, recognising the limited accessibility of social robots to individuals, it is crucial to explore other alternatives such as AI chatbots. Significantly, certain AI-driven chatbots, such as ChatGPT, have developed capabilities akin to "theory of mind"—a cornerstone of human communication—enabling them to complete theory-of-mind tasks on par with nine-year-old children (Kosinski, 2023). This suggests that AI chatbots possess the ability to analyse and understand certain aspects of human desires and needs through our inputs (Nah et al., 2023; Krueger, 2023).

Furthermore, with the advancements of large language models (LLMs), unlike traditional rule-based chatbots, LLM-powered chatbots can engage in context-sensitive conversations and adopt conversational personas, allowing for more natural and human-like interactions (Ferrario et al., 2024; Laban et al., 2024; Wester et al., 2024). In fact, recent studies have shown that LLMs are increasingly being used in mental health and therapeutic settings, such as powering chatbots for cognitive behavioural therapy and mental health counselling (Lai et al., 2024; Obradovich et al., 2024), demonstrating their potential to offer emotional and well-being support. Despite these advancements, the effectiveness of LLM-powered AI chatbots as viable substitutes for human conversation partners, particularly in fostering perceived social support and reducing loneliness, remains an area of exploration.

As we explore the expanding capabilities of AI chatbots in mimicking human interactions, one standout application is its potential to facilitate negative emotional disclosure or *venting*, a process where individuals channel their frustrations and dissatisfaction (Carver et al., 1989). This form of disclosure offers potential therapeutic value, aligning with the human tendency to verbalise concerns (Lieberman et al., 2007; Lumley et al., 2012; Riddle et al., 2016). In an era marked by pervasive loneliness (McPherson et al., 2006; Twenge et al., 2021; Wang et al., 2021), the challenge of finding a non-judgmental listener becomes even more pronounced (Bell, 1985; Konno et al., 2021) and without a reliable confidant, individuals may avoid self-disclosure (Laban et al., 2023b).

While the act of disclosure is therapeutic, the feedback or alternative viewpoints one receives post-venting may play a role in amplifying well-being (Behfar et al., 2019; Parlamis, 2010; Parlamis, 2012). Herein lies AI chatbot's dual advantage. First, it provides a safe haven for those wary of judgement or overburdening their loved ones, offering them an alternative outlet (Brandtzaeg et al., 2021). Second, it equips those devoid of social support with a platform to unpack their stressors. Thus, given its adeptness at personalised and empathetic responses (Ayers et al., 2023; Inkster et al., 2018), AI chatbots could be positioned as a promising avenue for individuals seeking open and supportive conversations.

Despite the considerable potential exhibited by AI chatbots as an effective conversation partner in addressing the prevalent issue of loneliness in society, it is notable that there is limited research in this particular domain (Hohenstein et al., 2023). There is also a dearth of studies examining the role of AI chatbots in facilitating the venting process (Sabour et al., 2023). Generally, venting has been studied in the context of journaling whereby participants are typically tasked to write about an emotional issue, exploring their deepest feelings and thoughts about the event for 15 to 30 minutes a day (Kloss & Lisaman, 2022; Pennebaker, 1997; Ullrich & Lutgendorf, 2002). However, the results of such studies indicate that traditional venting is not effective in reducing negative affect (Demerouti & Cropanzano, 2016; Francis & Pennebaker, 1992).

In fact, previous research has revealed that the act of venting alone does not help to regulate emotions effectively (Parlamis, 2012; Zhao et al., 2024). One promising way to enhance the effectiveness of the venting process would be to receive responses afterwards (Behfar et al., 2019; Parlamis, 2010). However, due to the widespread prevalence of loneliness, responsive human feedback may not always be readily accessible and available for individuals seeking emotional outlets (Surkalim et al., 2022; Wang et al., 2021). Thus, given the ability of AI chatbots to provide nuanced responses (Ayers et al., 2023; Inkster et al., 2018), coupled with its widespread accessibility (Lee, 2020; Poola, 2017), it is imperative to study how AI chatbots can effectively augment the traditionally less effective venting process, with potential implications for one’s well-being and social connectedness.

Therefore, the primary objective of the current pre-registered study is to shed light on the potential benefits of AI-assisted venting by comparing the effectiveness of venting to an AI chatbot to a traditional journaling platform in reducing negative affect and perceived stress levels. A high-powered within-subject experimental design (N = 150) was employed to further enhance statistical power and reduce error rates due to individual differences (Charness et al., 2012; Hartanto et al., 2020). Additionally, counterbalancing was implemented with a one-week interval to minimise potential carryover effects (Reese, 1997). We hypothesised that individuals who engage in venting to an AI chatbot will experience lower levels of negative affect, reduced perceived stress, increased perceived social support, and decreased perceived loneliness than those who engage in venting through a traditional journaling platform.

Methods

Transparency and Openness

The current study's design and its analysis plan were pre-registered (AsPredicted #140875, #144294). The relevant pre-registration document, materials, data, and code required to reproduce our analyses have been made publicly available on ResearchBox #1950 (https://researchbox.org/1950). Data cleaning and visualisation were done in R version 4.1.2 (R Core Team, 2023). Single-level reliabilities were calculated using *psych* version 2.4.6.26 (Revelle, 2024). Violin plots were created using *ggplot2* version 3.5.1 (Wickham, 2016). All analyses were conducted in JASP version 0.17.3 (JASP Team, 2023).

Participants and Design

The study adopted a high-powered within-subject experimental design (N = 150), in which all participants experienced both the AI-assisted venting and traditional venting conditions. Utilising a within-subject experimental design allowed us to minimise the influence of individual differences, enhance statistical power and reduce error rates due to individual differences (Charness et al., 2012; Hartanto et al., 2023). For the first session, the conditions were counterbalanced such that half the participants were randomly assigned to the AI-assisted venting condition while the other half were assigned to the traditional venting condition. After a one-week washout period to reduce potential carryover effects (Reese, 1997), those that had been previously assigned to the AI-assisted venting condition were assigned to the traditional venting condition, and vice versa. Hence, by the end of the study, all participants would have experienced both conditions.

All participants were recruited from a local university in Singapore, in exchange for one course credit. To maximize statistical power, we pre-registered and aimed to recruit a sample size of 150 to achieve at least 80% power to detect an effect size of $|d| = 0.23$ (two-tailed), 90% power to detect an effect size of $|d| = 0.27$ (two-tailed), and 95% power to detect an effect size of $|d| = 0.30$ (two-tailed). A total of 182 young adults participated in the current study, all of whom were required to complete a writing task followed by a survey in both the AI-assisted and traditional venting conditions, with a wash-out period of 1 week between the two sessions. Twenty-eight participants were excluded following the pre-registered exclusion criteria—that is, due to either failing one of the two attention checks in the study or because they rated themselves as being low in English proficiency (refer to Measures section below). One participant was excluded as the participant did not attend both sessions. The last three participants' data were then removed to meet the pre-registered sample size. This resulted in a final sample of 150 participants (Table 1). All participants gave informed consent and data collection was approved by the local institutional review board [IRB-23-108-A081(823)].

Table 1

Demographics of the Current Study

Characteristic	*M (SD)* or %	Range	Skewness	Kurtosis
Sex (% Female)	78.67%	-		
Ethnicity (% Chinese)	74.67%	-		

Nationality (% Singaporean)	92.67%	-		
Age (Years)	21.00 (1.72)	18–29	0.71	2.12
Education Attainment (Mother)[1]	7.55 (3.62)	0–12	-0.83	-0.86
Education Attainment (Father)[2]	7.75 (3.38)	1–12	-0.89	-0.70
Objective Socioeconomic Status	3.33 (1.61)	1–6	0.34	-0.99
Subjective Socioeconomic Status	6.21 (1.41)	2–9	-0.37	-0.07

Note. *N* = 150, Education attainment was rated on a scale of 0 (*No schooling*); 1 (*Primary school*); 2 (*N Level*); 3 (*O Level*); 4 (*A Level*); 5 (*International Baccalaureate*); 6 (*Nitec*); 7 (*Higher Nitec*); 8 (*Polytechnic Diploma*); 9 (*Other Diploma*); 10 (*Bachelor's Degree*); 11(*Master's Degree*); 12 (*PhD, EdD, JD, or professional degree*). Subjective socioeconomic status was measured using a 10-point ladder scale adapted from Adler et al. (Adler et al., 2000). Objective socioeconomic status was rated through monthly household income, on a scale of 1 *(< $2000);* 2 *($2000 - $5999);* 3 *($6000 - $9999);* 4 *($10,000 - $14,999);* 5 *($15,000 - $19,999);* 6 *(> $20,000).*

[1] 11 Participants did not provide data on maternal education attainment.

[2] 16 Participants did not provide data on paternal education attainment.

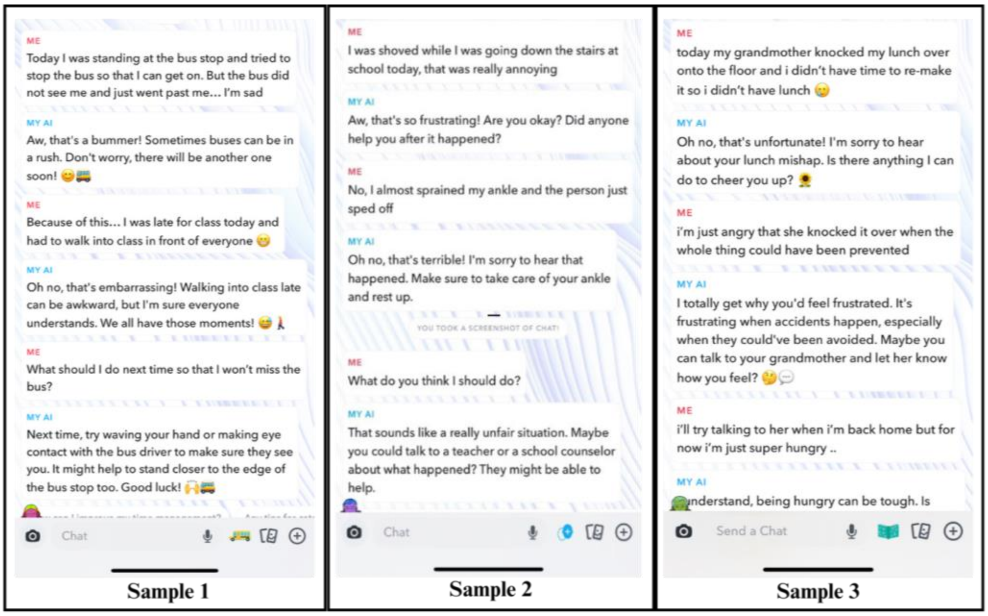
Procedure

Data was collected over a period of three weeks, during which participants attended two sessions with a washout period of 1 week. Prior to each session, participants were briefed thoroughly on the procedure of the experiment and the importance of compliance with the instructions. To minimise demand characteristics, participants were given a cover story in which they were told that the aim of the experiment was to test their focus through a writing task. They were then given the freedom to drop out of the experiment without penalty should they feel that they were unable to comply. If they consented to participate, participants were then asked to complete a writing task followed by a survey.

AI-assisted venting and traditional venting conditions had slightly different instructions. Venting has generally been studied in the context of journaling whereby participants are typically tasked to write about an emotional issue for 15 to 30 minutes a day (Kloss & Lisaman, 2022; Pennebaker, 1997; Ullrich & Lutgendorf, 2002). This was adapted in our traditional venting condition by instructing participants to recall and elaborate on the most significant irritation or inconvenience that they had experienced this week by writing about it in a Word document for 10 minutes. In contrast, in the AI-assisted venting condition, participants were instructed to recall and elaborate on the most significant irritation or inconvenience that they had experienced this week to MyAI. MyAI is an AI chatbot developed by Snapchat, powered by LLMs such as OpenAI's ChatGPT technology (Heath, 2023). It is positioned as a persona that is able to provide dynamic and personalised replies to users (Heath, 2023). Figure 1 provides examples of how conversations with MyAI are facilitated. Additionally, participants were told to use the replies provided by MyAI to further facilitate the conversation. They were also instructed not to write about their experience all within a single message, but to write about their event as if they were texting someone for 10 minutes (see Appendix for the full set of instructions for both conditions).

Figure 1

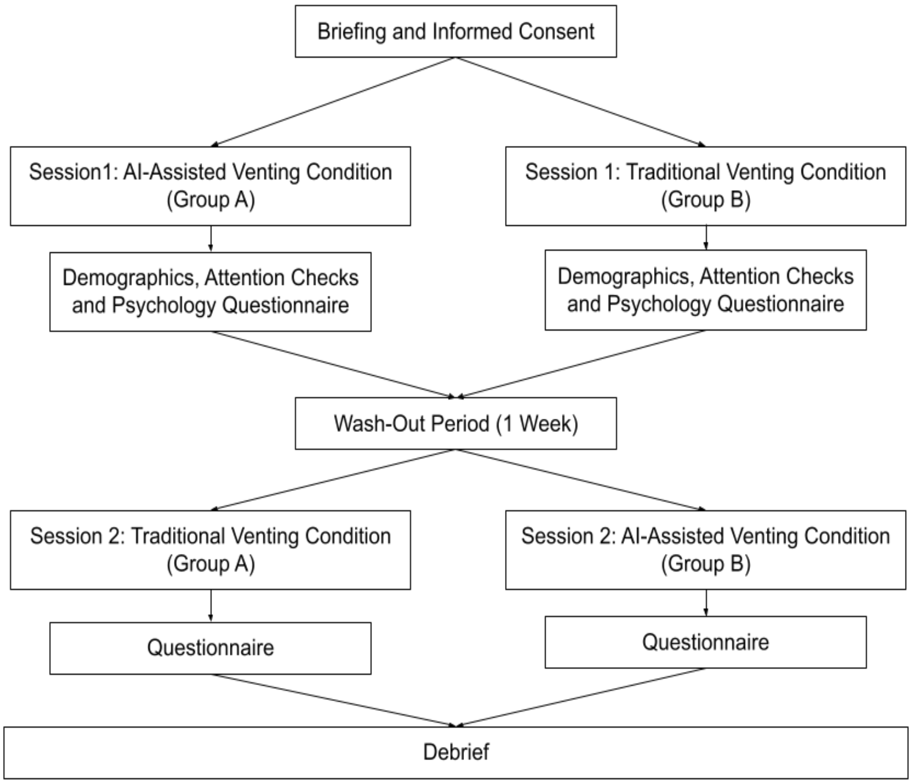
Examples of a Conversation with MyAI



After completing the writing tasks, participants were presented with the following set of questionnaires in a randomised sequence: deception questions regarding focus and attention, perceived loneliness scale (Russell et al., 1980), perceived social support scale (Kuczynski et al., 2021), negative affect scale (Russell, 1980), and perceived stress question. The first attention check was randomly embedded within the deception questionnaire, and the second attention check was randomly embedded within the perceived social support questionnaire. Participants also answered a set of demographic questions at the end of the first session. Figure 2 summarises the experimental flow of the current study.

Figure 2

Experimental Flow



Measures

Exclusion Criteria

English Proficiency. English proficiency was assessed using an adapted version of the Language Experience and Proficiency Questionnaire (Marian et.al., 2007). This measure was adapted to only include items measuring the proficiency in speaking, understanding, and reading of the English language. Participants were instructed to rate their proficiency levels on an 11-point scale (0 = *None*, 10 = *Perfect*) in response to the following question: "On a scale from zero to ten, please select your level of proficiency in speaking/understanding/reading of the English language". Participants who rated themselves with an average score of less than 3 were excluded from the study. This exclusion criterion was set in place to ensure that participants could effectively express their recalled event while journaling. Furthermore, to standardise the effects of venting across all participants, they were required to conduct the writing task in English.

Attention Check. Participants' focus was assessed during our study through a total of two attention check questions at various points of our survey. The attention check was conducted for both sessions of the study. These questions required participants to provide a fixed answer to demonstrate their attentiveness throughout the study (*"Overall, I feel that- please disregard the statement and choose disagree for this statement."* and *"I feel good - please disregard the statement and choose a moderate amount for this statement"*). Participants who failed at least one of the two attention checks were excluded from the study.

Key Outcomes

Negative Affect. Participants' negative affect was assessed in each session using the negative affect subscale of the Circumplex Model of Affect (Russell, 1980). The adjectives used to describe the negative affect are grouped into three different levels of arousal: high, medium, and low. Participants were asked to rate their current emotional state with regard to negative affect adjectives such as angry, hostile, and irritable on a five-point scale (1 = *Not at all*, 5 = *Extremely*). The order of items assessing participants' negative affect was randomised. A mean score for all nine items was calculated for each participant for each session (Cronbach's α: AI-assisted venting condition = .89, traditional venting condition = .88). Additionally, a mean score was also calculated for each of the levels of arousal of negative affect, that is, low arousal negative affect (Cronbach's α: AI-assisted venting condition = .92, traditional venting condition = .90), medium arousal negative affect (Cronbach's α: AI-assisted venting condition = .90, traditional venting condition = .89), and high arousal negative affect (Cronbach's α: AI-assisted venting condition = .76, traditional venting condition = .76).

Perceived Stress. Participants' perceived stress was assessed in each session using a single item ("How stressed do you feel right now?") rated on an 11-point scale (0 = *No stress,* 10 = *Extremely stressed).*

Perceived Social Support. Participants' perceived social support was assessed using an adapted 3-item version of the Social Interaction Quantity and Quality scale (Kuczynski et al., 2021). The original item "I felt understood/cared by others today" was revised to become two items on our scale "I feel understood by others right now" and "I feel cared by others right now". The original item "I expressed my true feelings to others today" was revised to state "I feel like I recently expressed my true feelings to others". These changes were made to accurately measure participants' perceived social support after undergoing each condition. Participants were asked to report their current feelings of perceived social support on an 11-point scale (0 = *Not at all,* 10 = *Extremely*). The order of items assessing participants' perceived social support was randomised. A mean score for all three items was calculated. Cronbach's α was .85 in the AI-assisted venting condition and .79 in the traditional venting condition.

Exploratory Outcome

Perceived Loneliness. Participants' level of perceived loneliness was assessed as an exploratory outcome using a modified version of the Revised UCLA Loneliness Scale (Russell et.al., 1980). In order to accurately measure participants' current perceived loneliness after undergoing each condition, the phrasing of the items in this scale were all revised to state "Right now" (e.g., "Right now, I feel left out" instead of "How often do you feel left out"). This scale encompassed six items, and participants were asked to indicate their current feelings of perceived loneliness on a five-point scale (1 = *Not at all,* 5 = *Extremely*). The order of items assessing participants' perceived loneliness was randomised. A mean score for all six items was calculated. Cronbach's α was .93 in the AI-assisted venting condition and .92 in the traditional venting condition.

Results

Negative Affect

Following our pre-registered analytic plan, we tested whether there was a difference in negative affect between the AI-assisted venting and traditional venting condition using both frequentist and Bayesian two-tailed dependent-samples *t*-test (see Table 2). Participants experienced lower negative affect in the AI-assisted venting condition (M = 1.57, SD = 0.63) as compared to when they were in the traditional venting condition (M = 1.69, SD = 0.61). The frequentist analysis revealed that the difference between the two conditions was significant (d = -0.18, 95% CI = [-0.34, -0.02], $t(149) = -2.17$, p = .031). However, the Bayesian *t*-test revealed anecdotal support for the null hypothesis, BF_{10} = 0.89.

Table 2

Summary of the Current Study's Findings

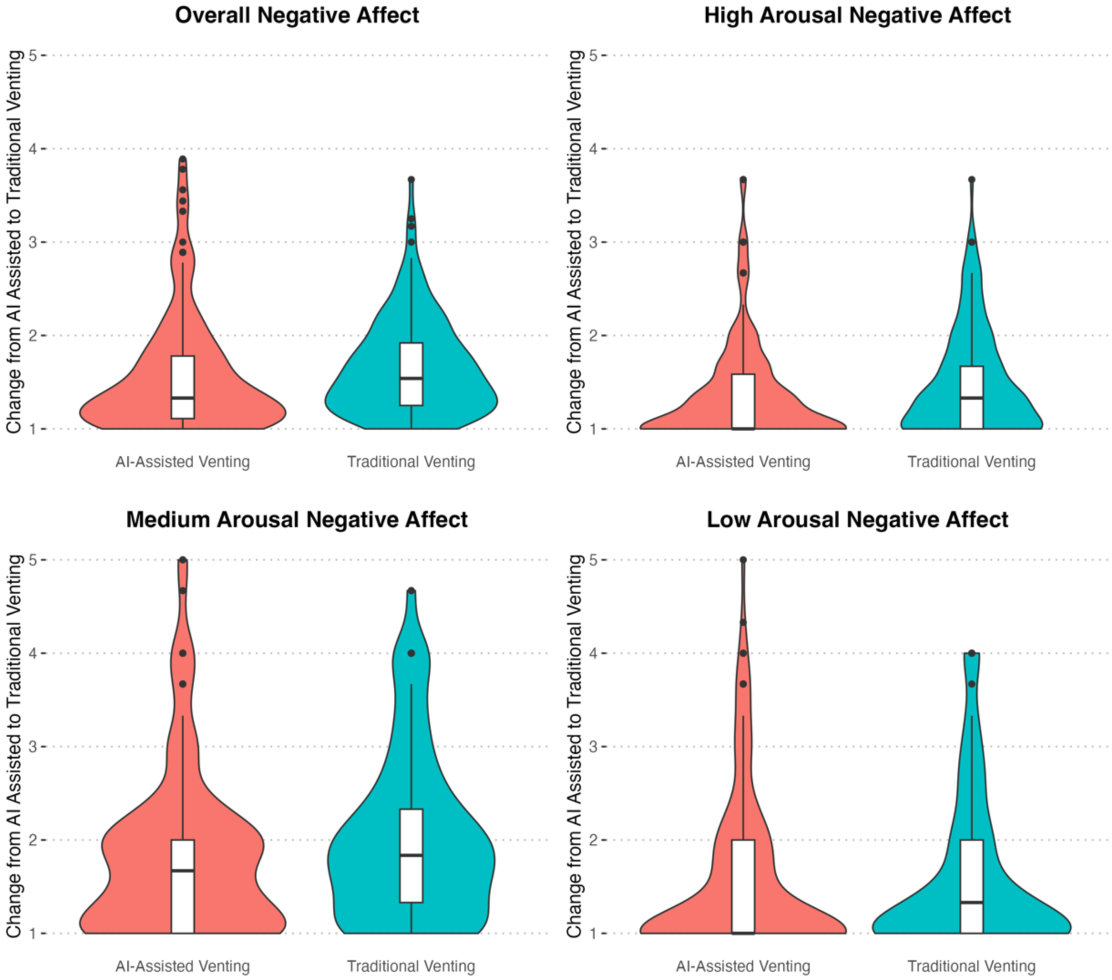
	AI-Assisted Venting	Traditional Venting				
Outcome	*M (SD)*	*M (SD)*	*d*	*95%* CI	*p*	BF_{10}
Negative Affect	1.57 (0.63)	1.69 (0.61)	-0.18	[-0.34, -0.02]	.031	0.89
High Arousal Negative Affect	1.35 (0.53)	1.49 (0.56)	-0.20	[-0.36, -0.04]	.016	1.56
Medium Arousal	1.81 (0.88)	2.01 (0.89)	-0.20	[-0.36, -0.04]	.014	1.76

Negative Affect						
Low Arousal Negative Affect	1.55 (0.84)	1.57 (0.81)	-0.02	[-0.18, 0.14]	.770	0.10
Perceived Stress	4.59 (2.39)	4.99 (2.48)	-0.16	[-0.32, 0.01]	.060	0.52
Perceived Social Support	6.04 (2.05)	5.93 (2.06)	0.05	[-0.11, 0.21]	.512	0.11
Perceived Loneliness	1.83 (0.91)	1.80 (0.84)	0.05	[-0.12, 0.21]	.580	0.11

As per our pre-registered analytic plan, we also investigated the effects of AI-assisted venting on high, medium, and low arousal negative affect (Table 2, Figure 3). We found that the AI-assisted venting condition resulted in significantly lower levels of both high arousal (d = -0.20, 95% CI = [-0.36, -0.04], p = .016, BF_{10} = 1.56) and medium arousal (d = -0.20, 95% CI = [-0.36, -0.04], p = .014, BF_{10} =1.76) negative affect as compared to the traditional venting condition. However, no significant differences in the levels of low arousal negative affect (d = -0.02, 95% CI = [-0.18, 0.14], p = .770, BF_{10} = 0.10) were found.

Figure 3

Violin Plots for Negative Affect



Note. N = 150. The width of each violin indicates the density of the data, with wider section reflecting a higher concentration of values. Embedded within the violins are boxplots. The horizontal line within the box represents the median. The width of the box represents the interquartile range. The dots beyond the whiskers represents outliers.

Perceived Stress

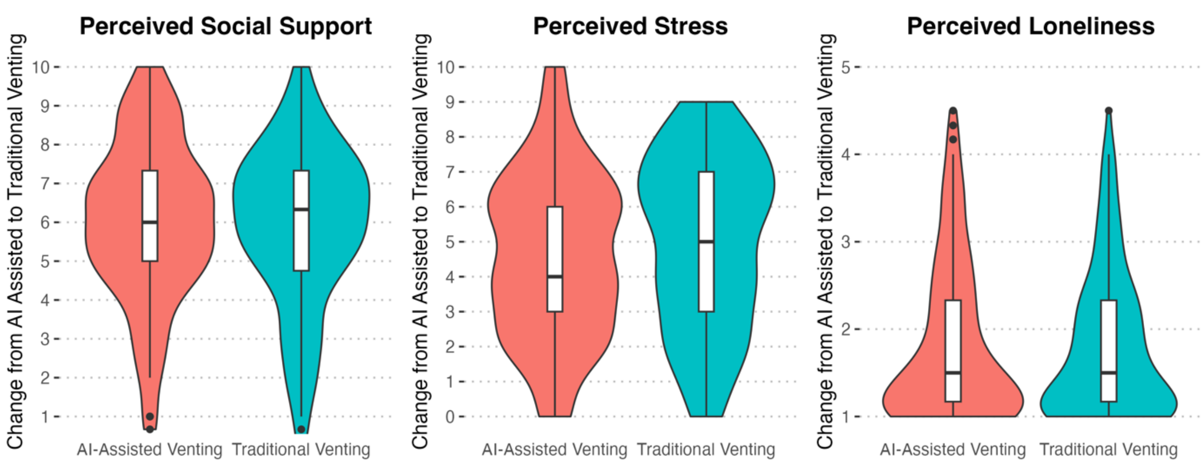
As per our pre-registered analytic plan, we analysed whether there was a difference in perceived stress between the AI-assisted venting and traditional venting condition using both frequentist and Bayesian two-tailed dependent-samples *t*-test (Table 2, Figure 4). There was no significant difference between participants' perceived stress in the AI-assisted venting condition (*M* = 4.59, *SD* = 2.39) and in the traditional venting condition (*M* = 4.99, *SD* = 2.48), *d* = -0.16, 95% CI = [-0.32, 0.01], $t(149) = -1.90$, $p = .060$. Likewise, the Bayesian *t*-test also provided anecdotal support for the null hypothesis, $BF_{10} = 0.52$.

Perceived Social Support

Based on the pre-registered analytic plan, we used frequentist and Bayesian two-tailed dependent *t*-test to analyse whether there was a difference in perceived social support between AI-assisted venting and traditional venting condition (Table 2, Figure 4). There was no significant difference between participants' perceived social support in the AI-assisted venting condition (*M* = 6.04, *SD* = 2.05) and in the traditional venting condition (*M* = 5.93, *SD* = 2.06), *d* = 0.05, 95% CI = [-0.11, 0.21], $t(149) = 0.66$, $p = .512$. Consistent with the frequentist analysis, the Bayesian *t*-test provided moderate support for the null hypothesis, $BF_{10} = 0.11$.

Figure 4

Violin Plots for Perceived Social Support, Perceived Stress and Perceived Loneliness



Note. N = 150. The width of each violin indicates the density of the data, with wider section reflecting a higher concentration of values. Embedded within the violins are boxplots. The horizontal line within the box represents the median. The width of the box represents the interquartile range. The dots beyond the whiskers are outliers.

Exploratory Analysis on Perceived Loneliness

For exploratory purposes, we tested the effect of AI-assisted venting on perceived loneliness (Table 2, Figure 4). Using frequentist two-tailed dependent samples *t*-test, we found that there was no significant difference in perceived loneliness between participants in the AI-assisted venting condition (M = 1.83, SD = 0.91) and in the traditional venting condition (M = 1.80, SD = 0.84), d = 0.05, 95% CI = [-0.12, 0.21], $t(149) = 0.55$, p = .580. Similarly, the Bayesian *t*-test provided moderate support for the null hypothesis, $BF_{10} = 0.11$.

Discussion

Amidst the rising prevalence of stress and loneliness (Surkalim et al., 2022; Tan et al, 2023), AI chatbots hold the potential to provide a promising solution to mitigate the detrimental outcomes of these issues due to its human-like capabilities (Korteling et al., 2021). Hence, in this study, we aimed to examine the potential benefits of AI-assisted venting in reducing negative affect, perceived stress, loneliness while enhancing perceived social support, in comparison to traditional venting. A high-powered within-subject experiment (N = 150) was conducted to determine the effectiveness of AI-assisted venting in decreasing individuals' negative affect, perceived stress, perceived loneliness, and increasing perceived social support, with the traditional venting condition as the control.

Firstly, consistent with our hypothesis, the experimental group utilising AI-assisted venting exhibited a significant decrease in negative affect compared to the control group employing the traditional venting method. This reduction in negative affect was specific to high arousal negative affect and medium arousal negative affect. The results suggest that the personalised responses received by the AI chatbot could have played a pivotal role in reducing high arousal negative affect such as frustration (Russell, 1980), and medium arousal negative affect such as fear (Russell, 1980) that the participants were experiencing. The effectiveness of the AI-assisted venting could be attributed to the validation, tailored advice and coping strategies that were provided by the AI chatbot in real-time. This personalised interaction likely made the participants feel heard and understood, encouraging them to express their emotions more openly (Gelbrich et al., 2020; Meng & Dai, 2021).

However, the differences in negative affect could also be due to the fact that AI-assisted venting may have been less likely than traditional venting to induce negative affect (Bushman et al., 2002; Parlamis et al., 2010), resulting in a lower level of negative affect in AI-assisted venting, given the brief 10-minute session. Interestingly, we did not observe any significant differences in low arousal negative affect as well as perceived stress. The lack of significant findings could be attributed to the possibility that in the context of venting, participants are more likely to recall events that are high or medium arousal. This aligns with previous findings, which suggest that venting may be more effective in improving high arousal affect than low arousal affect (Audet et al., 2023).

On the other hand, our study did not yield significant results for perceived social support and perceived loneliness. This finding raises an interesting perspective on the role of AI chatbots in managing one's well-being. While AI-assisted venting effectively reduces negative affect and provides immediate emotional relief, individuals do not perceive the effective support provided by the AI chatbot to be social support (Mou, 2017), possibly given their awareness that the AI chatbot remains fundamentally a machine. This is supported by prior research conducted by Croes & Antheunis (2021) investigating interactions between the participants and chatbot Mitsuku, whereby the results revealed that feelings of friendship were low. Croes & Antheunis (2021) attributes this finding to the absence of shared experiences and the chatbot's inability to reference past conversations. These limitations leads to the interactions between individuals and the chatbot feeling robotic. Consequently, participants may be acutely aware of the artificial nature of AI chatbots, possibly explaining why participants did not perceive the additional social support and companionship received from the AI chatbot as authentic as human connection, resulting in the lack of effect on perceived social support and perceived loneliness.

Furthermore, building a sense of connection and companionship requires time (Hall, 2019) but in our study, participants conversed with the AI chatbot for 10 minutes, which may not have been sufficient to foster meaningful connections. To gain deeper insights on the potential of AI in replicating human connection, future research could employ qualitative methodologies such as focus group discussions or thematic analyses of participants' responses to better understand participants' subjective experiences with AI-assisted venting. Future studies could also explore the possibility of adopting a virtual avatar chatbot, instead of a traditional text-based chatbot, which is capable of utilising non-verbal cues (e.g. facial expressions, voice) to enhance the sense of authenticity.

Despite these findings, the current study does have several limitations. Firstly, although our study provides valuable insights into the short-term benefits of AI-assisted venting in reducing negative affect, the long-term effects of AI-assisted venting remain unexplored due to the short time frame of our experimental design. Future research endeavours should delve into longitudinal studies to determine whether these positive effects endure over time. A possible approach could involve replicating our study, with participants engaging in AI-assisted venting over an extended period (e.g. several months). Assessments of negative affect, perceived stress, perceived social support and perceived loneliness should be conducted at multiple, regular intervals. Secondly, given the absence of pre-venting data, we were only able to assess the relative effectiveness of AI-assisted venting against traditional venting in reducing negative affect. Hence, future studies should include pre-venting measurements to better assess the absolute change in negative affect across conditions. Thirdly, the interaction with AI chatbots in our current study is limited to the venting process. Future research should be done to explore the potential of AI chatbots in various types of conversations beyond venting such as practising gratitude (Hartanto, et al., 2023) and self-compassion (Ferrari et al., 2019). This could potentially open up new avenues for enhancing overall well-being through interactions with AI chatbots.

Furthermore, the present study does not have a venting-to-human control, which would have allowed for a more direct comparison between AI-assisted venting and human responses. Future research should expand on our findings by including a venting-to-human control, gaining additional insights into the differences in well-being outcomes when receiving a response from an AI chatbot versus a human. Lastly, given that the study is predominantly composed of female university students from Singapore, the generalisability of our findings are limited. This is because the age and education level of participants may influence the effectiveness of AI-assisted venting differently across different populations. For example, younger and more educated individuals may be more tech-savvy and familiar with AI technology, potentially making them more comfortable interacting with AI chatbots and using them for venting purposes (Chan & Lee, 2023; Prensky, 2001). Additionally, given that majority of our participants are females, this may limit the generalisability of our findings to males. Hence, future research should replicate our findings with a more diverse sample to gain a more comprehensive understanding of the impact of AI-assisted venting across various populations.

In conclusion, the current study establishes the promising benefits of AI-assisted venting in reducing high and medium arousal negative affect, affirming the potential of AI chatbots in improving one's emotional well-being. Recognising the unique advantages of AI chatbots, such as affordability, 24/7 availability, unbiased responses, and the ability to provide personalised support, our study demonstrates the promising role of AI chatbots in extending support to individuals who may not otherwise have access to human support. The current study may serve as a catalyst for broader discussions on the evolving role of AI in improving individuals' well-being and the opportunities and challenges that lie ahead in this field.

Appendix

Instructions for AI-assisted venting condition (experimental) and traditional venting condition (control)

Instructions for AI-assisted venting condition: "*Recall the <u>most significant inconvenience/irritation you experienced this week</u> and express it to MyAI. You should express your thoughts as if you are writing a journal, elaborating on what you felt during the event and why you felt this way. As MyAI will provide replies to your messages, please use the replies to further facilitate the conversation. Please note that this portion should be conducted for <u>10 minutes</u>, so do ensure that you spend time to further elaborate on the event to prevent ending this portion prematurely. Avoid writing about your experience all within one message. A structure you could follow is: 1) What happened in this event? Respond to any relevant replies, 2) What did you feel as this event occurred? Respond to any relevant replies, 3) Why did you feel this way? Respond to any relevant replies, 4) Why do you think this event happened? Respond to any relevant replies, 5) What if this event happens again? Respond to any relevant replies. Focus on the details of the event that caused you inconvenience or irritation. Elaborating on such aspects should make up the majority of your conversation with MyAI."* (emphasis as shown).

Instructions for traditional venting condition: *"Recall the <u>most significant inconvenience/irritation you experienced this week</u> and express it through Microsoft Word. You should express your thoughts as if you are writing a journal, elaborating on what you felt during the event and why you felt this way. Please note that this portion should be conducted for <u>10 minutes</u>, so do ensure that you spend time to further elaborate on the event to prevent ending this portion prematurely. Avoid writing about your experience all within one paragraph. A structure you could follow is: 1) What happened in this event? 2) What did* *you feel as this event occurred? 3) Why did you feel this way? 4) Why do you think this event happened? 5) What if this event happens again? Focus on the details of the event that caused you inconvenience or irritation. Elaborating on such aspects should make up the majority of your journaling session."* (emphasis as shown).

Data Availability Statement

The relevant pre-registration document, materials, data, and code required to reproduce our analyses have been made publicly available on ResearchBox #1950 (https://researchbox.org/1950).

Declaration of Interest

The authors declare no conflict of interest.

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