Human-centered Design and Evaluation of a Knowledge-based Conversational Agent for Student Well-being

Jieyu Wang [1], Li Zhang [2], Abdullah Abuhussein [1], Dingfang Kang [1], and Katherina G. Pattit [3,*]

[1] Information Systems, Herberger Business School, St. Cloud State University, St. Cloud, USA
[2] Finance, Herberger Business School, St. Cloud State University, St. Cloud, USA
[3] Office of the Provost, St. Cloud State University, St. Cloud, USA
Email: {jwang2 (J.W.); lzhang (L.Z.); aabuhussein (A.A.); dingfang.kang (D.K.); katherina.pattit (K.G.P.)}@stcloudstate.edu
*Corresponding author

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***Abstract*—This study extends prior exploratory research on student acceptance and expectations of well-being conversational agents by developing and evaluating a high-fidelity conversational agent using a human-centered AI design approach. The prototype incorporates evidence-based mental health screening instruments, including the Patient Health Questionnaire-9 (PHQ-9) and assessments for anxiety, sleep, and panic symptoms, alongside a structured knowledge base from verified resources from the Anxiety and Depression Association of America (ADAA), the Mayo Clinic, and the American Academy of Sleep Medicine (AASM). An empirical usability study was conducted with twenty university students engaged in task-oriented usability testing and post-interaction interviews to assess system usability, user satisfaction, and perceived conversational intelligence. Findings indicate that participants perceived the conversational agent as credible, easy to use, and emotionally supportive, while expressing persistent concerns regarding privacy and data security. The results substantiate the user-centered design framework articulated in earlier work and demonstrate its evolution into a functional and deployable model for student well-being support. This research provides empirically grounded recommendations for the design of credible, trustworthy, and knowledge-based AI-driven wellness interventions in higher education.**

***Keywords*—human-centered Artificial Intelligence (AI), user-centered design, empirical usability study, student well-being, knowledge-based conversational agent, user trust, credibility**

I. INTRODUCTION

Student well-being has become a central concern in higher education, as increasing academic, social, and financial pressures contribute to rising levels of stress, anxiety, sleep disturbances, and burnout among university students [1–3]. Although many institutions recognize the seriousness of these challenges, access to mental health and well-being support remains limited due to resource shortages, stigma surrounding help-seeking, and long wait times for counseling services [4]. As a result, universities are exploring scalable and cost-effective technological solutions such as Artificial Intelligence (AI) driven Conversational Agents (CAs) to extend wellness support through immediate, private, and nonjudgmental interactions [5, 6].

Prior research has shown that CAs can assist users by promoting emotional reflection, offering informational guidance, and supporting behavioral regulation [7, 8]. However, most existing work with student populations has focused on perceptions, expectations, and conceptual designs rather than on evaluating fully functional systems in real interaction settings [9, 10]. A critical gap therefore remains in understanding how high-fidelity, user-centered well-being conversational agents perform in authentic contexts, and whether they can effectively address key factors such as usability, trust, and privacy.

This work advances earlier exploratory research on student acceptance and expectations of well-being conversational agents [1]. While the prior research identified user needs and proposed foundational design guidelines, the present work moves beyond conceptualization by implementing a high-fidelity prototype and conducting a systematic usability evaluation. Such evaluation is essential because survey data alone cannot reveal how users experience dialog dynamics, emotional responsiveness, or concerns regarding credibility and data privacy during real-time interaction.

To ensure responsible and clinically informed functionality, the prototype integrates evidence-based screening modules including Patient Health Questionnaire-9 (PHQ-9) items, anxiety-related indicators, circadian rhythm sleep assessments, and panic symptom checks. Through structured interaction tasks and subsequent qualitative and quantitative assessments involving twenty university students, the current work examines ease of use, perceived emotional support, credibility of information, and user concerns related to authenticity and privacy.

By empirically validating a user-centered framework for a well-being conversational agent, this research provides both theoretical and practical contributions to the design of ethical, knowledge-based, and accessible AI systems in higher education. The findings offer guidance for future implementations of conversational agents in university environments and demonstrate how AI-driven interfaces can complement traditional counseling services to promote more holistic student support [11–13].

The remainder of this paper is organized as follows. Section II reviews prior work on the design and evaluation of well-being conversational agents and highlights the gaps that motivate this study. Section III describes the development of the high-fidelity prototype, including the symptom modules, interaction architecture, and supporting information sources. Section IV outlines the usability evaluation procedures, including participant recruitment, task design, and data collection methods. Section V presents the quantitative and qualitative results, focusing on user acceptance, perceived interaction quality, credibility of information, and privacy considerations. Section VI discusses the implications of these findings for the design and deployment of well-being CAs in educational environments. Finally, Section VII concludes with contributions, limitations, and directions

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for future research.

II. Background and Related Research

The design and adoption of conversational agents for well-being have been explored across multiple domains, with increasing attention to their potential for supporting mental health, emotional regulation, and early-stage screening [2]. While prior studies have described core design principles and identified promising use cases for well-being conversational agents, fewer works have examined how these systems perform when implemented as fully interactive prototypes. The following review highlights research relevant to the design and evaluation of student-focused well-being CAs, placing emphasis on studies that inform usability, interaction quality, and ethical deployment.

A. Designing Well-being CAs

User-centered design approaches play a critical role in developing well-being technologies. Participatory design research has demonstrated that involving users and domain experts can strengthen information presentation, dialog structure, and delivery methods for well-being support tools [3]. In earlier work on student populations, Wang *et al.* [1] collected acceptance and expectation data from 96 students and proposed a conceptual framework for student well-being CAs, emphasizing the importance of ethics, clarity, and trust in shaping user experience.

Other studies have highlighted how individual factors influence well-being CA interactions. Jeong et al. found that personality traits, behavioral tendencies, and perceived social connectedness with the agent affected the success of robot-assisted interventions [4]. Research targeting university students further identified the value of encouragement and self-esteem support in promoting healthy coping behaviors, particularly for those experiencing academic pressure and self-imposed performance expectations [5]. Additional investigations have emphasized contextual alignment, showing that CAs grounded in real-world student experiences and frequently asked questions can enhance personalization and reduce user frustration [6].

Cultural and environmental factors also contribute to design effectiveness. Nelekar *et al.* [7] demonstrated that cultural context, social norms, and students' personal intentions shaped the impact of an embedded CA on stress reduction and emotional well-being. Together, these studies underscore that well-being CA design must combine contextual sensitivity, personalization, and evidence-informed dialog strategies.

B. Evaluation of Well-being Conversational Agents

Evaluation studies have produced mixed but informative results regarding the effectiveness of well-being conversational agents. Several investigations have shown that users respond positively to automated emotional support when systems provide clear guidance, empathetic tone, and structured dialog flows. For example, Inkster et al. evaluated an AI-embedded well-being agent using global user feedback and found that many users valued its accessibility and supportive responses [8]. Narain *et al.* [9] tested a social-focused conversational agent across multiple groups and reported significant improvements in perceived well-being, supported by favorable qualitative feedback.

Targeted populations such as adolescents have also been studied. Gabrielli et al. reported that a coaching-focused conversational agent was well received and considered helpful, although long-term validation was recommended [10]. Complementary work by Ghandeharioun *et al.* [14] examined an emotionally aware conversational agent and found that users appreciated emotion detection capabilities, suggesting that affect-sensitive interpretation can enhance interaction quality.

These evaluations collectively highlight the importance of examining real-time interaction behavior, as usability, trust, and conversational coherence often determine whether CAs can meaningfully support well-being.

C. Ethical, Privacy, and Trust Considerations

Ethical issues are central to well-being CA implementation, particularly in educational environments. Concerns regarding transparency, data handling, user autonomy, and system safety have been well documented [10, 15]. Ma *et al.* [16] analyzed community discussions on well-being applications and identified design practices that risk undermining user trust, including nontransparent data usage and overgeneralized recommendations.

Privacy is especially relevant for students who may hesitate to disclose sensitive information to automated systems. Research on higher education environments has examined responsible data use in mental health contexts, emphasizing the need for secure storage, clear disclosure policies, and appropriate boundaries for automated support [11]. Graham *et al.* [12] further demonstrated that institutional practices and communication norms influence student perceptions of safety and wellness, reinforcing the need for ethical alignment between CA design and campus policies.

These studies collectively show that ethical safeguards and responsible communication practices are essential for designing CAs that students perceive as credible and trustworthy.

The meta-analysis indicates that AI conversational agents show limited improvement in anxiety and depression outcomes, particularly in the absence of structured interventions [2, 16]. In contrast, they tend to demonstrate stronger effects in accessibility and user engagement. Current research is largely based on short-term feedback and self-reported methods [2]. These findings suggest that current conversational agents are promising as supportive tools, yet their effectiveness remains context-dependent.

In recent years, research on Artificial Intelligence (AI) in mental health has increasingly foregrounded ethical concerns alongside performance outcomes. Recent reviews consistently highlight privacy, informed consent, algorithmic bias, transparency, accountability, and human oversight as central challenges, given the sensitivity and longitudinal nature of mental health data [13, 17]. Studies report persistent risks of bias due to demographically narrow training datasets, potentially exacerbating disparities in diagnosis and treatment [18, 19]. While explainable AI is frequently proposed, evidence suggests it is insufficient without clinician training, governance structures, and post-deployment monitoring [20]. The recent expansion of generative AI and conversational agents has intensified ethical debate, particularly regarding safety, crisis handling, and over-reliance, reinforcing calls for ethics-by-design and sustained human oversight [21].

While prior studies have outlined general design principles and explored user expectations, few have evaluated high-fidelity prototypes tailored to student well-being. Building on design insights from earlier exploratory research [1], the current work focuses on implementation and empirical usability testing. This study therefore contributes a practical and evidence-based understanding of how a user-centered well-being CA performs during real interactions, offering insights for future refinement and deployment within university settings.

Taken together, these studies highlight the need for evaluating high-fidelity prototypes within real student interactions. The present work addresses this gap by implementing and analyzing a fully functional well-being CA informed by earlier design insights [1].

III. Prototype Design and Interaction Architecture

The design of the well-being conversational agent is grounded in the insights obtained from earlier work that examined students' expectations, acceptance patterns, and preferred interaction features for a university-based well-being assistant [1]. Based on these findings, a high-fidelity prototype was developed using the open source Juji platform, integrating structured screening sequences, psychoeducational explanations, and links to reputable external resources. The goal of the design process was not to replicate clinical tools, but rather to translate evidence-informed screening logic into a user-centered, ethically responsible conversational experience. The system functions as a step-by-step, rule-based conversational agent that guides users through screening modules using conversational prompts instead of generative responses. Our design intentionally prioritizes standardized assessment accuracy, predictable conversational flow, and knowledge-based feedback to ensure safety and transparency. Instead of open-ended conversational simulation, our goal is to provide structured well-being screening and resource navigation.

The design followed three primary principles:

(1) Evidence grounding by drawing on authoritative health sources such as Anxiety and Depression Association of America (ADAA), Mayo Clinic, and American Academy of Sleep Medicine (AASM) [22–32],

(2) Predictable and transparent interaction that reduces confusion and avoids ambiguous dialog, and

(3) Safety-conscious boundaries that ensure the assistant provides information and resources rather than clinical diagnosis or therapeutic intervention.

To organize the system coherently, the conversational agent is structured into four symptom modules (depression, anxiety, sleep disturbance, and panic symptoms), supported by a set of universal dialog components such as onboarding messages, safety disclaimers, and general well-being resources.

A. System Architecture

The prototype consists of interconnected dialog units that initiate based on user selection. Fig. 1 illustrates the overall architecture used to organize screening sequences, informational segments, and resource referrals.

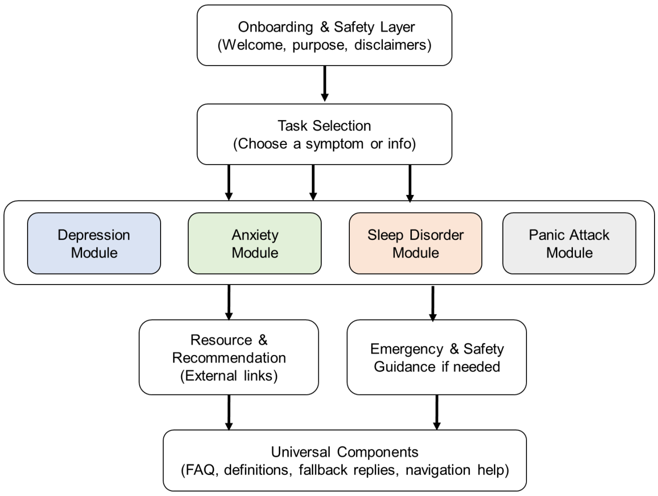


Fig. 1. Overall dialog architecture of the well-being CA prototype.

This architecture allows each symptom module to function independently while sharing common design elements such as user guidance, psychoeducational framing, and external resource links.

B. Symptom Modules and Knowledge Bases

The four primary symptom modules were informed by design requirements collected from students [1] and developed using empirically supported diagnostic and treatment resources drawn from established mental-health research [22–32]. These four areas were selected because they represented the most frequently reported concerns among students in our earlier exploratory work [1]. Also, Depression, anxiety, sleep disorder, and panic symptoms correspond to high-prevalence issues documented in university mental-health research. Each module implements a structured flow consisting of (1) a brief introduction to the topic, (2) a set of evidence-informed screening questions, and (3) links to external information or supportive resources. A summary of the module characteristics is provided in Table 1.

Table 1. Overview of symptom modules incorporated in the prototype

Symptom Module	Key References	Screening Focus	Output
Depression	ADAA; PHQ-9 [22, 24]	PHQ-9-aligned items	Reflective feedback + ADAA links
Anxiety	Mayo Clinic [25]	Situational anxiety indicators	Urgent vs. non-urgent guidance
Sleep Disturbance	AASM [26, 29]	Sleep timing & regularity	Circadian rhythm explanation
Panic Symptoms	ADAA [30, 32]	Panic-related sensations	Urgent-care guidance + resources

1) Depression knowledge base and module

When constructing the knowledge base for depression, we examined the related information from the website of the Anxiety & Depression Association of America [22] and used the information to provide authoritative support for the design of the treatment chat flow for this symptom.

a) Definition of depression

We introduced the definition of depression from the ADAA website to improve the proficiency of the service of our high-fidelity prototype. According to ADAA, depression can be described as "most people feel low and sad at times. However, in the case of individuals who are diagnosed with depression as a psychiatric disorder, the manifestations of the low mood are much more severe, and they tend to persist" [22]. This definition separates depression from short-term feelings and emphasizes severity to recognize the difference. It helps a target user by triggering a self-test on one's condition and deciding whether he/she is willing to make the effort to solve the problem. This is also the first examination for the users in our design of the prototype. We provided the formal definition to let the user decide whether to proceed with the following chat flow for the symptom of depression in the prototype.

b) Examination process of depression

When the requirement of the user has been clarified, a follow-up examination is provided by the prototype. We considered multiple options as the sources to establish our examination process and finally implemented the Patient Health Questionnaire (Fig. 2) as the examination process [23].

	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	○	○	○	○
2. Feeling down, depressed, or hopeless	○	○	○	○
3. Trouble falling or staying asleep, or sleeping too much	○	○	○	○
4. Feeling tired or having little energy	○	○	○	○
5. Poor appetite or overeating	○	○	○	○
6. Feeling bad about yourself—or that you are a failure or have let yourself or your family down	○	○	○	○
7. Trouble concentrating on things such as reading the newspaper or watching television	○	○	○	○
8. Moving or speaking so slowly that other people could have noticed? Or the opposite—being so fidgety or restless that you have been moving around a lot more than usual	○	○	○	○
9. Thoughts that you would be better off dead or of hurting yourself in some way	○	○	○	○

If you clicked on any problems above, how difficult have they made it for you to do your work, take care of things at home, or get along with other people?
Not difficult at all ○ Somewhat difficult ○ Very difficult ○ Extremely difficult ○

Fig. 2. Patient Health Questionnaire-9 (PHQ-9) [23].

The questionnaire provides a convenient check-up for users that scales the possible symptoms, and this sheet can describe the general condition to help doctors or consultants make related judgments. This conversational agent prototype does not provide medical guidance due to limited scope and ethical concerns. Therefore, the examination process in our prototype only serves as a reference before a user has been connected with medical care providers.

c) Suggested treatment resources

We introduced authoritative treatment resources from medical care providers. Since the knowledge base was constructed primarily from the information retrieved from the ADAA website, its treatment suggestion was also introduced into the prototype.

d) Depression logic construction

Our previous paper has described the chat flow process for depression [1]. If the user chooses depression in the task request process, the topics that follow will be guided to complete the depression check process. Notification of incoming questions is provided (Fig. 3), and reference information about these questions is also added to increase the credibility and trust of the questions. For the checking process of depression, we use the Patient Health Questionnaire-9 (PHQ-9) [24].

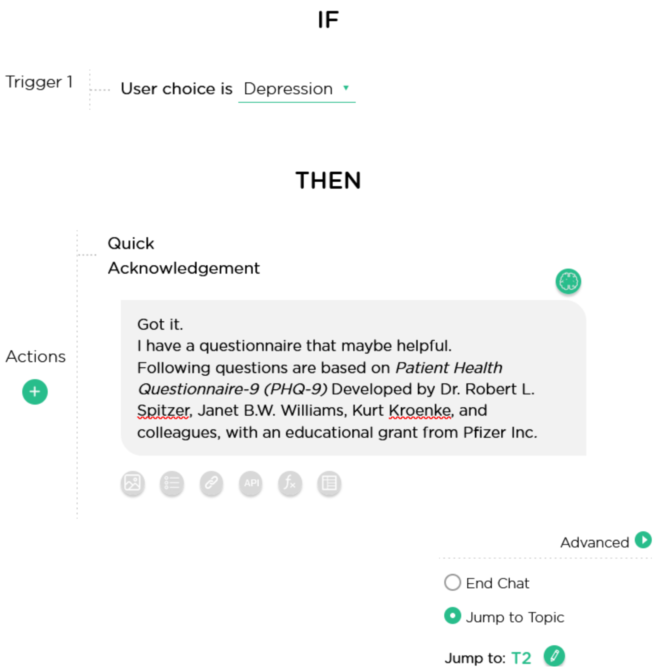


Fig. 3. Topic reply for depression.

The complete questionnaire contains a total of nine questions that cover daily status at work or study (Fig. 2), including continuing lower mood or emotion, poor sleep quality, physical condition in daytime and appetite, concentration, communication practice with others, and any extreme mental activities that appeared [23]. After the nine questions, the user is also required to reflect on how difficult or easy it is for them to answer the questions. Each of the questions has four options for the user to evaluate the level of severity. We implemented this checklist to be asked one by one during the conversation. However, due to ethical considerations, we can't provide real medical guidance to the user in this prototype. Therefore, we suggested the user keep a record of the choices to be handled by the professional party for further checkups.

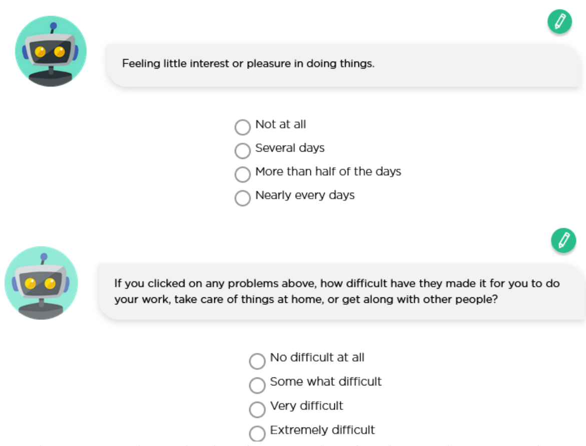


Fig. 4. Questionnaire implementation for depression examples.

Fig. 4 shows how the questions were implemented into the conversational agent. The conversational agent asks one of the questions from the list and provides four options for users to answer based on their circumstances. These questions are to be triggered one after another in a sequence.

After the conversational agent goes through all the above questions, basic suggestions are provided for the user's situation and a URL link for additional information (Fig. 5). The URL link will direct the user to the website of the Anxiety & Depression Association of America [24]. The link allows the users to explore additional information about depression.

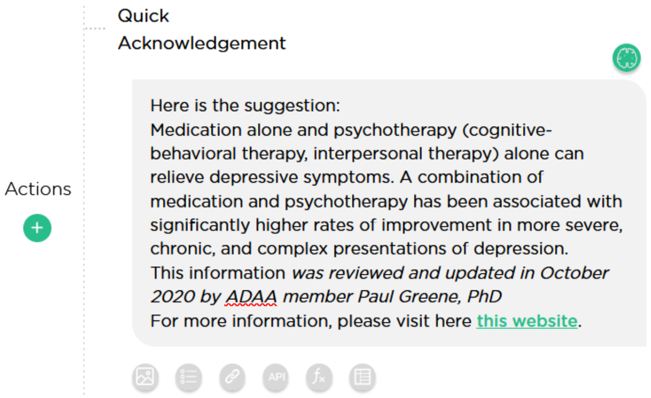


Fig. 5. Reply example for depression.

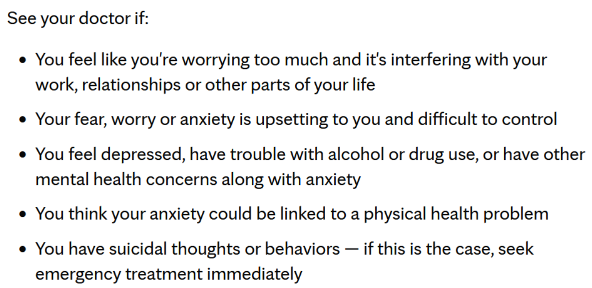
2) *Anxiety knowledge base and module*

a) *Definition of anxiety*

We used the anxiety definition from the Mayo Clinic: "people with anxiety disorders frequently have intense, excessive, and persistent worry and fear about everyday situations [25]". This description identifies the most typical expression of the symptom of anxiety. It allows users to compare their status and have a preliminary impression of their problem and therefore figure out whether they want an examination in this area.

b) *Examination process of anxiety*

Our examination process of anxiety includes several questions related to users' daily conditions (Fig. 6). These questions do not generate medical advice from the conversational agent, but aim to judge whether a user should be introduced to healthcare providers. The questions refer to situations that required a doctor's intervention. Therefore, the informational content was developed based on the Mayo Clinic website [25].


See your doctor if:

- You feel like you're worrying too much and it's interfering with your work, relationships or other parts of your life
- Your fear, worry or anxiety is upsetting to you and difficult to control
- You feel depressed, have trouble with alcohol or drug use, or have other mental health concerns along with anxiety
- You think your anxiety could be linked to a physical health problem
- You have suicidal thoughts or behaviors — if this is the case, seek emergency treatment immediately

Fig. 6. Suggested conditions to see doctor [25].

c) *Suggested treatment resources*

In this module, the suggestion to potential anxiety patients includes a call to users to plan a visit to their doctors. There are also situations where immediate visit is required and is reflected in the buildup. Other than these, a list of local healthcare resources around the user's location is also provided to the user at the end of the consultation.

d) *Anxiety logic construction*

The anxiety module draws on situational markers highlighted by Mayo Clinic [25]. Instead of symptom lists, the design uses short, scenario-based screening items that help users reflect on whether anxiety is interfering with daily functioning. A representative interaction from this module is shown in Fig. 7.

Depending on the user's responses, the conversational agent either provides general non-urgent resources or encourages users to consult a medical professional when appropriate. Situations involving potential harm or acute distress prompt stronger safety-oriented guidance. When the conversational agent finishes with all the questions, the user will have the option to receive suggestions for available well-being resources around the user's area or end the interaction process right after the examination is over.

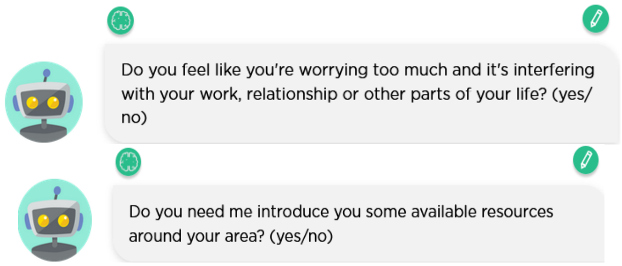


Fig. 7. Example interaction illustrating scenario-based anxiety screening.

Fig. 8 is for the case when the user confirms the existence of any of the situations involving suicidal thoughts or self-abusive behavior. This presents a much more serious situation than other circumstances. Therefore, stronger encouragement from the prototype for the user to reach out for help is required. Fig. 9 is the reply to the user in non-urgent conditions. It is recommended that they reach out to available resources of their own choice. Fig. 10 is for situations when the prototype finds none of the situations listed in the questions. In this case, the prototype does not recommend that the user spend money and time on additional examinations.

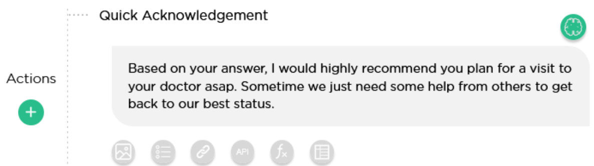


Fig. 8. Reply Example 1 for anxiety.

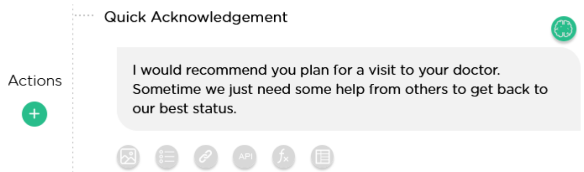


Fig. 9. Reply Example 2 for anxiety.

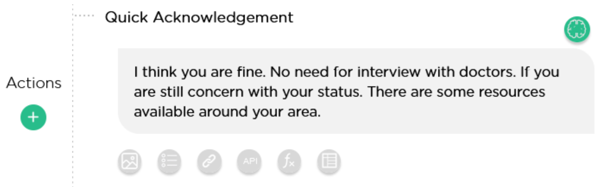


Fig. 10. Reply Example 3 for anxiety.

3) Sleep disorder knowledge base and module

This module focuses on circadian rhythm sleep-wake disturbances as described by AASM [26–29]. The conversational agent asks about sleep timing, regularity, and the degree to which sleep patterns affect functioning. Based on user input, the system identifies whether the description most closely resembles delayed, advanced, or irregular sleep patterns. An illustration of the typical interaction for this module is shown in Fig. 9. The assistant provides concise definitions adapted from AASM and links to corresponding Sleep Education pages for detailed guidance.

a) Definition of sleep disorders

Sleep disorders are one important problem that affect students who depend on a well-arranged schedule for good performance. There are several classifications of sleep disorders, and each covers multiple conditions that make sleep irregular or subpar [26]. It should be noted that users may mix it with external factors that cause sleep disorders. These may include environmental factors that affect sleep quality and intentional/unintentional stimuli that cause sleep disorders. A correct understanding of sleep disorders is necessary to identify the problem [26].

b) Examination of sleep disorder

Our examination process for sleep disorders is limited to circadian rhythm sleep-wake disorder which refers to conditions in which the sleep times are out of alignment [26]. We focused on the examination process of irregular, delayed, and advanced sleep-wake rhythm by asking directly about the sleep conditions of the participants.

c) Suggested treatment resources

After the symptoms of the participants are confirmed, the design provides the full description of their matched symptoms from AASM [26]. Furthermore, treatment suggestions are provided at the end of the response according to AASM. An outside official link was provided so that users can check and proceed as needed.

d) Sleep disorder logic construction

The chat flow for sleep disorder examination was described in our previous paper [1]. Below is a question from the conversational agent that asks about the sleep quality of the user (Fig. 11). It is positioned at the beginning when the examination begins. Users are able to choose one of the options listed. There are several more kinds of sleep disorders as introduced by Sleep Education [26]. This conversational agent focuses on late, early, and irregular sleep disorders.

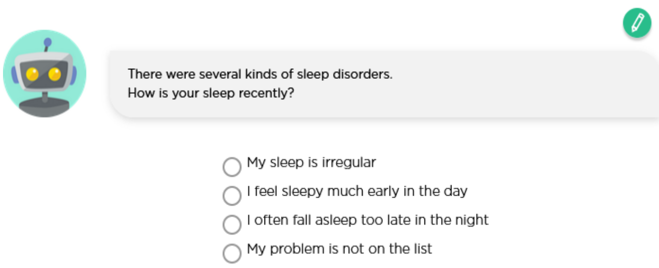


Fig. 11. Question implementation for sleep disorder example.

For users who have irregular sleep, the prototype will provide a brief description that explains the symptoms of irregular sleep disorder (Fig. 12). According to the definition of AASM Sleep Education, irregular sleep disorder refers to the situation in which a person needs three or more periods of sleep in 24 h [27]. Users will be able to check their actual status with the description. A reference to AASM Sleep Education is added to increase the credibility of the information. At the end of the reply, a link to the information page on irregular sleep on their official website is provided [27]. Users can access it for additional help and information.

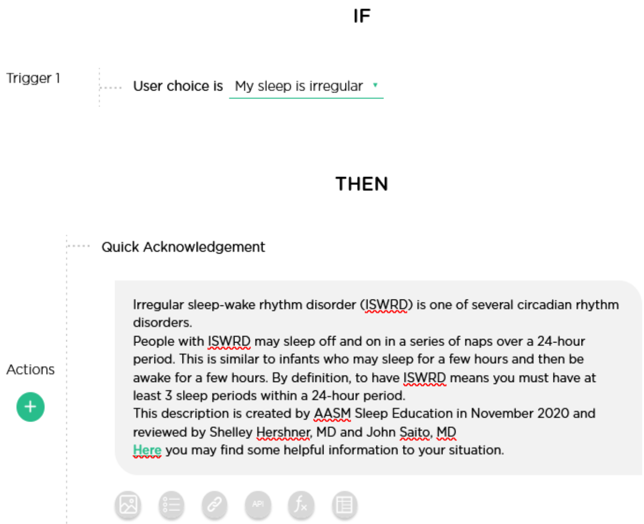


Fig. 12. Reply Example 1 for sleep disorder.

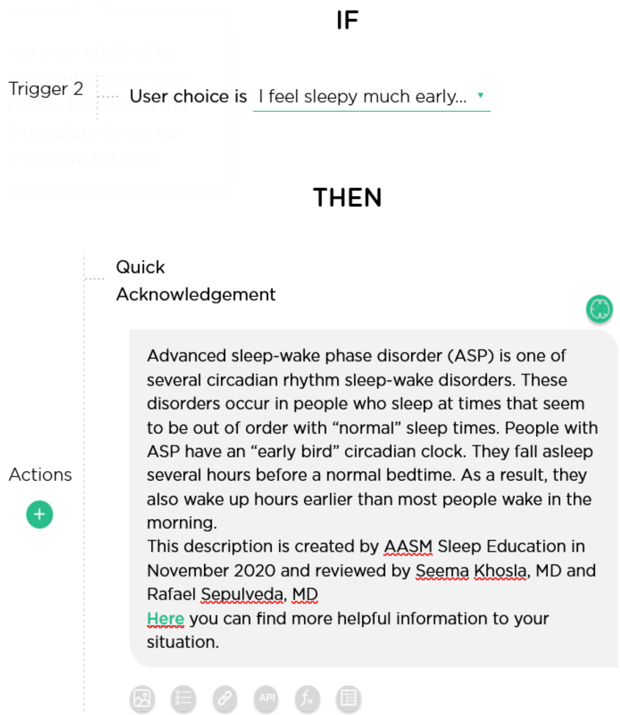


Fig. 13. Reply Example 2 for sleep disorder.

For users who sleep much earlier during the day, the prototype provides a description that briefly explains the details of early sleep disorder (Fig. 13). Early sleep refers to the situation when people sleep much earlier than normal period and resulting in an early wake-up in the morning [28]. Such information is provided as well as for the other two symptom check processes for the user to compare with their status. A reference to AASM Sleep Education is added to increase the credibility of the information [28]. At the end of the reply, a link to the information page of early sleep on their official website is provided. Users can access it for additional help and information.

The last reply is for users who sleep too late during the night. A description of late sleep disorder is provided for the user to self-check (Fig. 14). Late sleep disorder refers to people who have a late sleep period and delay the sleep schedule, which can impact the person's social life [29]. A reference to AASM Sleep Education is added to increase the credibility of the information [29]. At the end of the reply, a link to the information page on late sleep on their official website is provided. Users can access it for additional help and information.

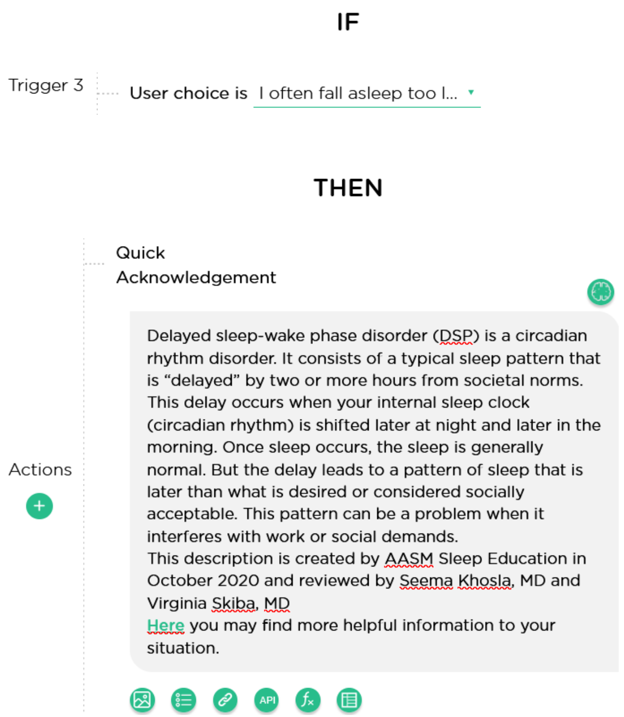


Fig. 14. Reply Example 3 for sleep disorder.

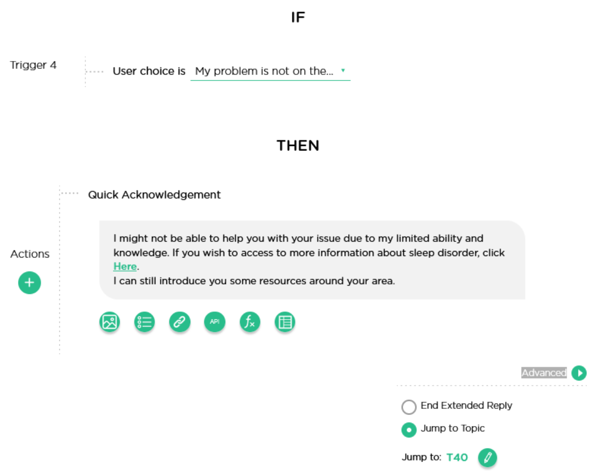


Fig. 15. Reply Example 4 for sleep disorder.

Considering the possibility that users may not find their problems on the list, we provide the link to the root information page on sleep disorder for further understanding and details (Fig. 15). Accessible resources around the user's location and general resources are still provided.

4) Panic symptoms knowledge base and module

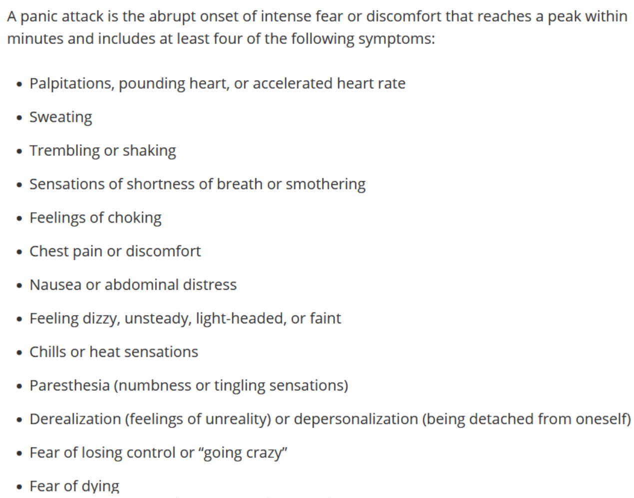
a) Definition of a panic attack

The last symptom in the conversational agent is a panic attack or panic disorder. The authoritative definition is from the website of the Anxiety & Depression Association of America [30]:

"Panic disorder is diagnosed in people who experience spontaneous seemingly out-of-the-blue panic attacks and are very preoccupied with the fear of a recurring attack. Panic attacks occur unexpectedly, sometimes even when waking up from sleep. Panic disorder usually begins in adulthood (after age 20), but children can also have panic disorder and many children experience panic-like symptoms" [31].

a) Examination of a panic attack

For the examination process, we introduced the symptoms associated with panic attacks from the ADAA website to help identify the issue [30]. It includes a list of physical feelings that people may have within a few minutes when a panic attack takes place (Fig. 16). People with at least four of the listed symptoms are considered to contain panic attacks.


A panic attack is the abrupt onset of intense fear or discomfort that reaches a peak within minutes and includes at least four of the following symptoms:

- Palpitations, pounding heart, or accelerated heart rate
- Sweating
- Trembling or shaking
- Sensations of shortness of breath or smothering
- Feelings of choking
- Chest pain or discomfort
- Nausea or abdominal distress
- Feeling dizzy, unsteady, light-headed, or faint
- Chills or heat sensations
- Paresthesia (numbness or tingling sensations)
- Derealization (feelings of unreality) or depersonalization (being detached from oneself)
- Fear of losing control or "going crazy"
- Fear of dying

Fig. 16. Panic attack symptoms [30].

b) Suggested treatment resources

We direct users who are detected with panic attacks to the treatment page of panic disorder on the ADAA website. It contains primarily self-help steps that are created by experts and doctors in the area. The suggested treatment for panic attacks is included at the end of the interaction to ensure credibility [32]. The user is also encouraged to contact their doctor for consultation when in need or call 911 in an emergency.

c) Panic attack logic construction

The panic module presents a simplified checklist that reflects common panic-related sensations identified by ADAA [30–32]. The general interaction sequence for the examination process of panic attacks was explained in our previous paper [1]. Unlike the question list for depression, a panic attack is defined as a short period of intense fear and is associated with a minimum of four of the symptoms listed below (Fig. 17) [30]. Users select the sensations they have experienced recently, allowing them to compare their experiences with known patterns of panic episodes.

If users select multiple sensations or indicate acute distress, the assistant prompts them to seek professional evaluation and provides ADAA links for further reading. Emergency guidance is given for situations involving severe or escalating symptoms (Fig. 18).

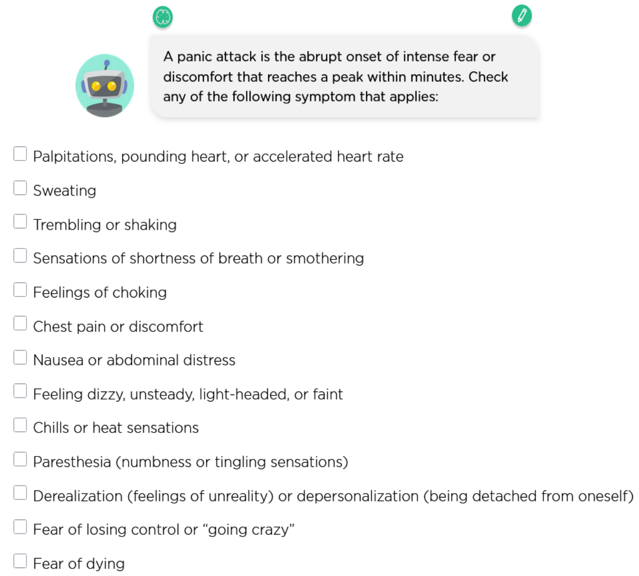


Fig. 17. Panic attack symptom checklist implementation [30].

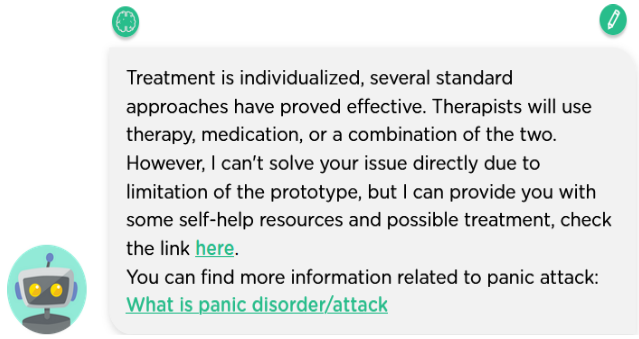


Fig. 18. Disclaimer and reply example for prototype.

5) Universal components and safety measures

Across all modules, the prototype includes global dialog components that serve three purposes:

(1) Reinforce the educational scope of the system,

(2) Provide immediate access to general well-being resources, and

(3) Offer fail-safe responses when the system lacks information.

Examples include quick definitions, campus resource listings, and standard replies when users ask questions outside the system's knowledge base. Fig. 19 depicts a universal support message that may appear at any point in the interaction. These components ensure consistency in tone and safety across the system while also providing structure for future expansion.

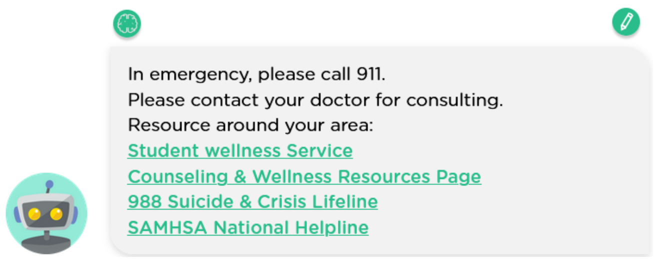


Fig. 19. Example universal support message offering well-being resources.

There are also explanatory Q&As set up for the user to address quick questions (Fig. 20). When the user is asked about the definition of the four symptoms, the conversational agent will provide a formal description of those involved in this prototype. These quick answers will be provided straightforwardly whenever asked during the interaction.

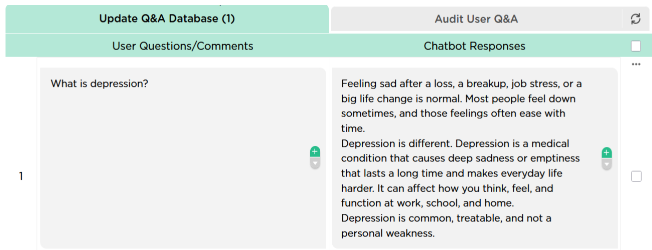


Fig. 20. Example for an answer to quick questions

IV. Usability Evaluation of the Prototype

The primary aim of this work is to examine how students interact with the well-being conversational agent and to understand whether the implemented design supports clarity, accessibility, and responsible information delivery. The prototype integrates structured screening sequences and evidence-based psychoeducational content to help students identify potential well-being concerns and locate credible resources in a more efficient way. The usability study focuses on how students engaged with these functions during real-time interaction and what design improvements can be informed by their experiences.

A. Participants

Twenty students from a Midwestern university participated in the study (mean age = 23, SD = 2.33). Fourteen participants identified as male and six as female. Most students were enrolled in Information Systems or Information Assurance programs. Institutional Review Board approval was obtained before recruitment, and all students provided informed consent. Nineteen participant datasets were retained for analysis after quality checks. The participants were invited through course announcements. Participation was voluntary, with no credit given in order to minimize coercion. The participants' responses did not influence their academic performance.

To increase sample diversity, we additionally invited five students from a university on the East Coast to interact with the prototype and provide qualitative feedback. These additional participants did not complete the Likert-scale quantitative questions and were included to broaden contextual perspectives. Among them, four were female and one was male. All were Geography majors.

B. Tasks and Procedure

Participants were asked to interact with the conversational agent by selecting one of the available well-being screening modules. The task required them to navigate the conversational flow, respond to screening questions, and review the resources or feedback presented by the system. They were designed to illustrate common student well-being concerns reported in our previous study [1]. To ensure that participants focused on interaction quality, they were advised to reflect on the clarity, tone, and helpfulness of the responses during the task.

After completing the interaction, participants answered a set of Likert-scale items measuring perceived usability and user experience [33, 34]. Semi-structured interviews followed, exploring participants' impressions of the system, expectations for future design improvements, and any ethical or privacy-related considerations that emerged during the interaction. This mixed-method approach enabled a deeper understanding of both functional performance and user perceptions. Fig. 21 illustrates the general structure of the usability session, from onboarding to post-task reflection.

The participants were required to report their honest and critical responses to minimize social desirability bias. We encouraged participants to provide both positive and negative comments to improve the prototype design.

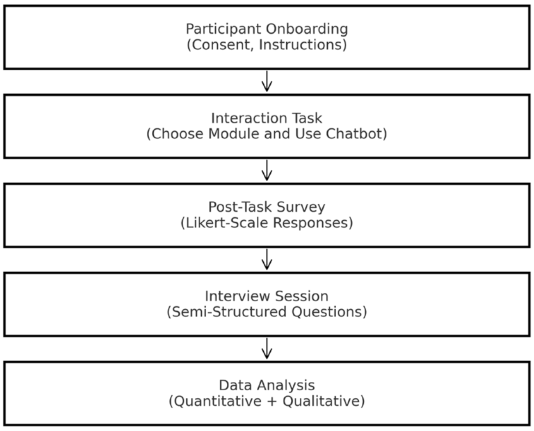


Fig. 21. Overview of the usability evaluation procedure.

C. *Data Analysis*

Likert-scale responses were summarized using descriptive statistics, including mean and standard deviation, to evaluate perceived usability and interaction satisfaction. Interview transcripts were coded using an inductive qualitative content analysis approach. Due to the brevity and task-oriented nature of participant feedback, the analysis focused on identifying recurring usability-related themes including ease of use, clarity of dialog, trust, emotional comfort, and privacy concerns, instead of conducting a deeply interpretive thematic analysis. Interview responses were anonymized prior to analysis. .

To strengthen the validity of the findings, a second researcher independently reviewed the coded data to check for interpretive consistency and potential bias. Following traditional qualitative analysis procedures, themes were then refined through discussion and integrated into a synthesized set of considerations for improving the next version of the prototype. Due to collaborative refinement during the coding process, inter-rater reliability coefficients were not calculated. This consensus-based coding process reduced individual bias in qualitative analysis.

V. USABILITY EVALUATION RESULTS

The usability study examined how students interacted with the well-being conversational agent and evaluated whether the implemented features aligned with user expectations identified in prior research [1]. Quantitative ratings and qualitative feedback were analyzed to understand the prototype's usability, interaction quality, and perceived value as a support tool. The findings reveal patterns related to user acceptance, perceived intelligence, interaction design, information credibility, and concerns about privacy and security.

A. *Quantitative Findings*

Participants generally reported positive experiences with the conversational agent (Fig. 22). As shown in Table 2, students rated the system as easy to learn and use, and most agreed that the conversational agent helped them locate relevant information and consider potential solutions. Measures related to satisfaction and comfort also scored above the midpoint, although ratings for problem-solving usefulness were slightly more variable. The Cronbach's alpha results demonstrated the internal consistency of the evaluation. The coefficients for user satisfaction (0.84), usability (0.83), and privacy (0.75) indicated high reliability. Moreover, an independent samples t-test was conducted to examine variances based on gender. There were no significant differences between male and female participants ($t = -0.05$, $p = 0.96$), demonstrating robust performance across user demographics.

Table 2. Usability ratings from Likert-scale responses

Item	Mean	SD
The chatbot is successful in helping me solve my issue.	4.32	0.89
This chatbot's chat flow helps me with my issues.	4.05	0.91
This chatbot is useful in solving my problems.	3.84	1.21
It is easy to learn how to use this chatbot.	4.74	0.56
It is easy to remember how to use this chatbot.	4.84	0.37
I am satisfied with the interaction with the chatbot.	4.50	0.83
The conversation with the chatbot is comfortable.	4.37	1.01
The chatbot helps me find information and possible solutions.	4.00	0.88
I receive appropriate information from this chatbot.	4.19	0.61

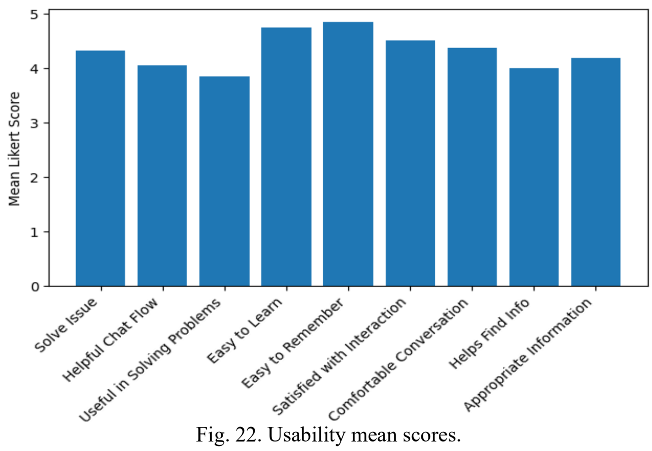


Fig. 22. Usability mean scores.

Overall, ratings indicate that the system provides a smooth onboarding experience and is accessible even to first-time users. The lower variability in ease-of-use scores suggests that interaction mechanics were intuitive for most participants.

B. *User Acceptance*

Interview responses revealed diverse attitudes toward using an AI-based well-being assistant. Many students appreciated the accessibility and clarity of the screening sequences, noting that the system delivered structured guidance and helped them reflect on their concerns.

One participant emphasized the usefulness of the depression module:

Participant 16: "For the specific situations I put the conversational agent in. I did a lot of depression testing and the conversational agent with very clear and helped give good input and give good options/ decisions while also trying to comfort me."

Participant 7: "I need suggestions for how I can improve my mental health and try to be the guy who can live like a 22-year-old person. I overthink a lot and worry about things that should not be bothering me. I just want to overcome those feelings."

Participant 15: "I would want the conversational agent to help me come up with ways to get out of a slump I had or look at the bright side of things."

Participant 8: "Very comfortable. The chatbot didn't get too personal and at the same time didn't ask any irrelevant questions."

Participant 5: "This chatbot is generally comfortable to chat with, as it responds promptly and provides relevant information… there were instances where the chatbot struggled to comprehend complex questions or express empathy."

Participant 3: "It would be interesting to be linked with conversational agent as they will analyze your thought process and may give you rational solution. It should fulfill the user's requirements and interests and build a trustworthy relationship."

Participant 21: "Very good, gives you clear answers."

Others described the conversational agent as a complementary tool rather than a substitute for personal relationships:

Participant 6: "I don't think I will because I always have my siblings and friends to go to when I have an issue. I will say however it isn't a total no, and I might be interested in using it one day."

Participant 20: "Yes I would consider it but would probably not rely on it."

A smaller group preferred human interaction due to emotional connection or dialog richness:

Participant 16: "I would not use the chatbot for any issues I have at the moment. I am very close to my family so I just think that I would want to talk to people that know me and who I am."

Participant 12: "No, the conversational flow is not good for me. I like a conversation with a back-and-forth interaction. I would much rather prefer a person. This bot also has templates that it keeps reusing."

These responses indicate that acceptance depends on personal preferences, emotional needs, and the perceived role of the agent in relation to a user's existing support network.

C. Perceived Intelligence and Interaction Quality

Participants frequently evaluated the system's intelligence based on its language clarity, dialog structure, and ability to provide concise explanations. Some students saw the conversational agent as an efficient way to obtain information:

Participant 19: "Compared with traditional search browsers, this chatbot is more intelligent, can extract more concise content, and makes it easier for me to understand the answer to the question…"

Other participants appreciated conversational friendliness but noted limitations in depth and variability:

Participant 17: "The chatbot is extremely user-friendly. I did enjoy that it could have quick quips for its responses as well as creating fun answers. It also has clear lines of dialog created within itself to protect information. Although some lines are repetitive and it's still in a learning environment, I think the chatbot has a large room to grow and become more complex."

Students also commented on gaps in emotional attunement:

Participant 5: "This chatbot is generally comfortable to chat with, as it responds promptly and provides relevant information. There were instances where the chatbot struggled to comprehend complex questions or express empathy…"

And some contrasted the system with human interaction:

Participant 10: "Chatbots often follow predetermined communication patterns… Human relationships… are more fluid and adaptive…"

These findings suggest that while the system's structure supports clarity, improvements in adaptiveness, emotional expression, and contextual comprehension would strengthen trust and engagement.

D. Feedback on Design Features

Participants identified several design elements that positively affected usability. They appreciated the focus on maintaining a comfortable interaction space:

Participant 8: "Very comfortable. The chatbot didn't get too personal and at the same time didn't ask any irrelevant questions."

Participant 23: "Yes, decent."

Participant 24: "It's much more defined with answers."

Others highlighted the benefit of curated information:

Participant 9: "It is a very beneficial and informative way of collecting information. On a Search, a user has to find the result that will work best but on a chatbot, the best result is generated by Artificial Intelligence."

Meanwhile, users encountered issues when asking questions outside the prepared knowledge base and experienced problems with interaction transitions.

Participant 12: "When I asked the bot questions, it took some time, and replied when I followed up with another question…"

Participant 22: "No just one thing then another, no transition."

These insights underscore the importance of expanding the knowledge base and improving fallback responses to support more flexible inquiries.

E. Credibility and Information Trustworthiness

Trust in information accuracy varied across participants. Some students recognized the screening items and associated them with authoritative sources:

Participant 7: "Yes, I do trust this chatbot because of the information it provided, and another reason is CAPS having the same questionnaire…"

Others expressed skepticism:

Participant 13: "Not really, I don't know for sure the information it provides is accurate."

Concerns also emerged when users encountered limitations in the system's responses:

Participant 12: "I do not trust the chatbot because it clearly states… 'my human teammates are improving me constantly.'"

Participant 10: "In some cases, human expertise or context-specific knowledge may be necessary…"

These responses indicate that credibility is strongly influenced by transparency, perceived expertise, and consistency in the quality of information provided.

F. Privacy, Security, and Platform Concerns

Students also reflected on data security and personal information risks. Some worried about potential cyberattacks:

Participant 20: "Yes I do as far as security but ultimately the truth is this chatbot is online and it can be hacked…"

Others were cautious about sharing personal information:

Participant 11: "Yes, I would trust it. But at the same time, I will not provide personal information just in case."

A few participants expressed concern about data misuse by organizations:

Participant 19: "Collect and sell some of your personal information."

Participant 3: "I will confide my worries to CA, but still have privacy concerns."

Participant 9: "Yes, I do sometimes. I do have privacy concerns."

Participant 8: "No, I don't have security or privacy concerns."

Participant 2: "Considering the fact that there might be a third party involved who is managing and organizing conversational agent, I will be hesitant to confide my worries to it. More security mechanisms such as encryption should be applied for privacy concerns."

Participant 1: "When developing and utilizing CA, it's crucial to take security and privacy issues into account… proper security precautions must be taken."

These findings highlight the importance of explicit privacy policies and secure data handling practices.

G. Expectations for Future Development

Participants offered suggestions for improving personalization, emotional responsiveness, and system integration with university platforms. For example:

Participant 5: "To better serve students, the chatbot should offer personalized recommendations…"

Participant 16: "Personality is always something you strive for in things like a chatbot…"

Participant 8: "…the AI can be improved by adding an element of fake emotion and more deep questions…"

A student also suggested linking the system with existing academic platforms:

Participant 3: "To better serve students, the chatbot should offer personalized recommendations…"

Collectively, these suggestions point to opportunities for improving adaptive responses, personalization, and ecosystem integration.

Overall, these quotes demonstrated diverse perspectives among the participants, instead of indicating uniform agreements. The usability findings indicate strong acceptance of the prototype's ease of use, clarity, and structured guidance, yet several tensions emerged across themes. Students generally trusted the credibility of content when it aligned with known resources, but concerns about privacy, data security, and platform transparency reduced their willingness to disclose sensitive information. In addition, participants valued the system's efficiency and consistency, but noted limitations in emotional expressiveness and adaptive intelligence during dialog. These patterns highlight the need for balancing structured symptom-focused design with more flexible, emotionally responsive interactions, setting the stage for the broader implications discussed in the next section.

VI. Discussion

Despite their advantages, conversational agents operating in well-being contexts face several important limitations that must be mentioned. Certain situations require human expertise, deeper contextual understanding, or professional clinical judgment that automated systems cannot replicate. Ambiguous or context-dependent queries pose a particular challenge: a single medical term may carry multiple meanings, and incorrect interpretation can lead to misunderstanding or reduced user trust. To strengthen credibility and transparency, our design relied on an expert-validated knowledgebase drawn exclusively from credible medical sources, with direct references to the source pages. While this approach improves reliability, it also introduces constraints, including limited coverage and the inability to answer certain user questions, which may undermine user confidence when the conversational agent openly acknowledges its limitations. Additional considerations include the ethical and legal implications of providing health-related information, highlighting the need for strong disclaimers clarifying that the conversational agent is not a substitute for professional medical consultation. Equally important are user data privacy and security requirements, such as encryption and regulatory compliance such as HIPAA and GDPR when handling sensitive information. Because this study only designed and evaluated a prototype rather than a fully industrialized application, advanced technical safeguards such as encryption mechanisms, data anonymization, and audit trails will be addressed in future implementation research.

Maintaining the manually compiled knowledgebase necessitates continuous updates to ensure currency, yet transitioning to generative AI could minimize upkeep efforts at the cost of increased risks related to erroneous outputs, lack of transparency, hallucination, and difficulty in validating information sources. These generative systems also function as a black box, making it difficult to provide traceable reasoning which is essential for user trust in medical contexts. Finally, the system must incorporate mechanisms for capturing user feedback to identify gaps, correct errors, and guide continuous improvement. Considering these factors, future development should weigh the trade-offs between expanding the curated knowledgebase and transitioning to a generative model with stronger guardrails, transparency features, and medical-grade safety controls.

Our prototype demonstrates a knowledge-based design tailored for university students in contrast to contemporary well-being conversational agents such as Wysa, Woebot, and Replika. A secondary analysis of previously collected Replika data suggested moderate overall performance (M = 4.99/7). Users reported that it was conversationally friendly and that its chat flow was natural. However, the qualitative analysis revealed indirect or incomplete responses during interactions. While conversational agents in the market focus on natural chat flow and emotional support, our prototype emphasizes structured screening, authoritative medical references, and institutional alignment. It reflects ethical and contextual requirements in higher education, focusing on credibility and safety.

Although ethical and legal concerns have been discussed in the previous paragraph, careful consideration is still required before institutional deployment. Using the conversational agent may prevent students from seeking professional help. Structured screening information such as the PHQ-9 may also provide incorrect judgements. Therefore, clear disclaimers and escalation responses were provided such as “Please consult your doctor” or “Please call 911”. Moreover, as the screening materials are based on America university culture, cultural and contextual bias should be considered. While the sample size was increased to 25 participants across two universities, there are limitations regarding demographics and diversity. The participants are university students, which limits the generalizability of the findings. However, from a human-computer interaction perspective, a sample size of 25 participants is considered robust for usability testing, as Nielsen [35] pointed out that five participants could identify 85% of the usability problems.

Our future study will consider institutional implementation, with compliance with HIPAA and GDPR. Institutional review board approval and informed consent are necessary to ensure accountability and ethics. Overall, deployment in future studies is beyond the scope of the current design and requires governance and ethical review. In future research, we will explore hybrid AI-human deployment models, institutional policy frameworks, and broader societal implications, including stigma reduction and potential digital access disparities.

VII. Conclusion

This work aims to advance the development of well-being conversational agents by implementing and evaluating a user-centered prototype designed to support students who experience common well-being challenges during their studies. The system focuses on four symptom areas frequently reported by university students and incorporates information from reputable well-being resources. Using these sources, we designed a structured screening and information-delivery workflow that provides students with guided reflection and access to credible resources.

To assess the design in practice, student participants interacted with the prototype and provided detailed feedback on its usability, interaction quality, and perceived value. Their responses revealed both strengths and areas that require refinement, offering insights that were not evident during the initial design process. This evaluation allowed us to understand user acceptance of a CA-based approach and to identify expectations that can inform future iterations.

The current study designed and evaluated a high-fidelity prototype. Considerations such as scalability, integration with university systems, multilingual support, accessibility compliance, and the trade-offs between rule-based and generative AI approaches are important for future studies.

This work extends prior research that gathered acceptance patterns and design expectations from 96 students by translating those insights into a high-fidelity prototype and conducting a systematic usability evaluation with 20 participants. The findings contribute to user-centered design practices for well-being CAs by highlighting how students interact with real implementations, what features support engagement, and what concerns need to be addressed to build trust and credibility. Although the prototype focuses on student needs, the underlying design principles may also apply to broader populations who face similar well-being concerns. As AI-based assistants continue to evolve, this work offers guidance for developing responsible, knowledge-based, and accessible well-being support tools.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Jieyu Wang and Dingfang Kang conducted the research and data collection. Jieyu Wang, Li Zhang, Abdullah Abuhussein, and Dingfang Kang wrote the manuscript. Katherina G. Pattit provided overall supervision and project administration. All authors have read and approved the final version of the manuscript.

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