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Research Article

Designing an Anxiety Self-Monitoring Application for Health Sciences Students: An Early Design-Based Research Cycle with Proposed AI Functions

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Abstract. Anxiety is common among adolescents and young adults, and mobile applications are increasingly used to help them notice and track symptoms. Few app projects, however, document how user needs, expert judgment, and artificial intelligence (AI) features shape a design. This study reports an early design-based research (DBR) cycle for AniBuddy, an anxiety self-monitoring application prototype for health sciences students at a private institution in Cavite, Philippines. A biopsychosocial-spiritual survey of 325 students aged 15 to 24 measured somatic and psychological anxiety symptoms, perceived social support, and meaning in life. Three graphical user interface experts reviewed the evaluation instrument; student end users and three subject experts then rated the prototype's perceived quality on five ISO/IEC 25010 characteristics and commented on it. Psychological symptoms were reported most often (M = 4.63 on a 7-point scale), chiefly overthinking and anticipatory worry. Somatic symptoms (M = 4.22) and perceived support (M = 4.08) were moderate; students reported moderate presence of meaning (M = 3.68) and little search for it (M = 2.91). Students who could open the iOS prototype were very satisfied (n = 18, M = 4.55), subject experts were satisfied (M = 3.80), and both rated reliabilities lowest. Feedback was traced to design decisions across three refinement cycles. Three AI-enabled functions are proposed: a conversational agent and interest-based suggestions, both added after the evaluation, and a mood forecast whose predictive accuracy was never assessed. Each is paired with a risk-specific safeguard. The ratings reflect perceived rather than technically validated quality. The study contributes provisional design principles and a risk register for the next cycle, which must add clinical, privacy, and security review.

Keywords: *Anxiety self-monitoring; Design-based research; Human-centered AI; ISO/IEC 25010; Mobile mental health.*

Anxiety disorders are among the most common psychiatric conditions of childhood and adolescence, with prevalence estimates of 15% to 20% in young populations (Wehry et al., 2015). In the Philippines, a systematic review of 28 studies found that anxiety among students ranged from 11.90% to 82.89% (Alibudbud, 2025). Left unaddressed, anxiety erodes the capacity to study, work, and sustain relationships (Drissi et al., 2020). Health sciences students carry heavy academic demands now and will be expected to care for anxious patients later.

Monitoring is central to how anxiety is managed. Cognitive-behavioral therapy depends on noticing and

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recording the thoughts, emotions, and behaviors that sustain anxiety (Curtiss et al., 2021). Internet-delivered treatment now operates in routine care (Titov et al., 2018), app-supported interventions produce small but reliable improvements in generalized anxiety (Linardon et al., 2019), and digital cognitive-behavioral programs reduce anxiety in children and adolescents (Csirmaz et al., 2024). Availability has not secured use, however. The median 30-day retention of popular mental health apps was 3.3% (Baumel et al., 2019); users of anxiety apps want variety, customization, and good interface design (Balaskas et al., 2022); and many apps contain little evidence-based content (Wasil et al., 2019; Larsen et al., 2019). Recurring pitfalls include weak engagement, poor handling of emergencies, privacy breaches, and non-evidence-based approaches (Koh et al., 2022). The common remedy is to design with end users, clinicians, and developers from the start (Chatzipavlou et al., 2016; Schnall et al., 2016; Hammond et al., 2021).

Designing with users requires a clear view of what they bring. Anxiety involves sleep and somatic symptoms as well as worry, and it is buffered by resources such as social support and meaning. The biopsychosocial model remains a widely used framework for care and research (Fava & Sonino, 2017; Wade & Halligan, 2017), although its application has been criticized as inconsistent (Benning, 2015). Its biopsychosocial-spiritual (BPSS) extension adds meaning and purpose (Galbadage et al., 2020). Spiritual well-being is negatively associated with anxiety among university students (Leung & Pong, 2021), and purpose in life is inversely related to anxiety and depression (Boreham & Schutte, 2023). Most anxiety apps, by contrast, concentrate on psychological techniques (Drissi et al., 2020; Balaskas et al., 2021). A BPSS lens lets a design treat symptoms as burdens to monitor and support and meaning as resources to strengthen.

Artificial intelligence (AI) is changing what such an app can do. AI-based conversational agents reduced depressive symptoms and distress in a meta-analysis of 15 randomized trials but did not improve overall well-being (H. Li et al., 2023). Effects in a second meta-analysis were small and faded over time, with personalization and empathic responses as facilitators (He et al., 2023), and chatbot interventions for young people reduced distress without improving well-being (J. Li et al., 2025). Personalized models can forecast next-day depressive symptoms, though with clear technical and clinical limits (Kathan et al., 2022). The evidence remains early: pooled results have been too weak to confirm that chatbots are effective or safe (Abd-Alrazaq et al., 2020); chatbots raise ethical risks that are magnified for people in distress (Coghlan et al., 2023); and AI health tools face unresolved problems of privacy, quality, and uncertain outputs (Deniz-Garcia et al., 2023). Guidance from the World Health Organization (2021) holds that ethics and human rights must be built into health AI from the start of design, not added at deployment.

Two gaps follow. First, design-based research (DBR), which develops an artifact and transferable design principles through theory-informed, iterative cycles in real settings (Sandoval, 2014; Scott et al., 2020; Hoadley & Campos, 2022), has mostly served educational technology (Keskin & Kuzu, 2015; Jayatilleke et al., 2018; Robles et al., 2023), and its use in conceptualizing mental health apps for Filipino students is rarely documented. Second, research on AI in mental health asks whether AI tools work; it says less about how, and on what evidence, AI features should enter a design. End users and experts also judge health apps differently (de Chantal et al., 2022), so such decisions need both perspectives.

This study reports the first DBR cycle of AniBuddy, a self-monitoring and support-navigation app for health sciences students. AniBuddy is not designed to diagnose anxiety disorders or to deliver treatment. AI was treated as a design option that had to be justified by evidence, not as a premise. Three questions guided the study: (1) What levels of somatic and psychological anxiety symptoms, perceived social support, and meaning in life do health sciences students aged 15 to 24 report? (2) How do student end users and subject experts perceive the prototype's functional suitability, compatibility, interaction capability, reliability, and maintainability? (3) Which design decisions, including proposed AI functions, did the survey and evaluator feedback produce, and what provisional design principles follow? The findings are intended for student mental health services, guidance practitioners, and developers deciding where AI adds value in youth mental health tools and where human support must lead.

Methodology

Research Design

The study combined a cross-sectional descriptive survey with DBR. The survey described students' self-reported symptoms and resources at one point in time (Setia, 2016; Wang & Cheng, 2020; Capili, 2021); it did not estimate the prevalence of anxiety disorders. DBR guided the prototype. Four features distinguish the work from ordinary iterative prototyping (Sandoval, 2014; Scott et al., 2020; Hoadley & Campos, 2022): design decisions began as explicit conjectures grounded in theory and evidence; each cycle was documented with the evidence considered and the changes made (Table 2); students, experts, and designers took part; and the study aims at transferable principles as well as an artifact. Following Easterday et al. (2014), the cycles moved through focusing, understanding, defining, conceiving, building, and testing, with earlier phases revisited.

Figure 1 shows the three phases: concept development (BPSS content, a literature-based prototype, and the survey), three refinement cycles (responding to the survey, documenting the evaluation, and integrating feedback), and consolidation into provisional principles. Because the final prototype has not been evaluated, this is an early DBR cycle rather than a completed design validation. The figure also maps each proposed AI function to its main risk and matched safeguard.

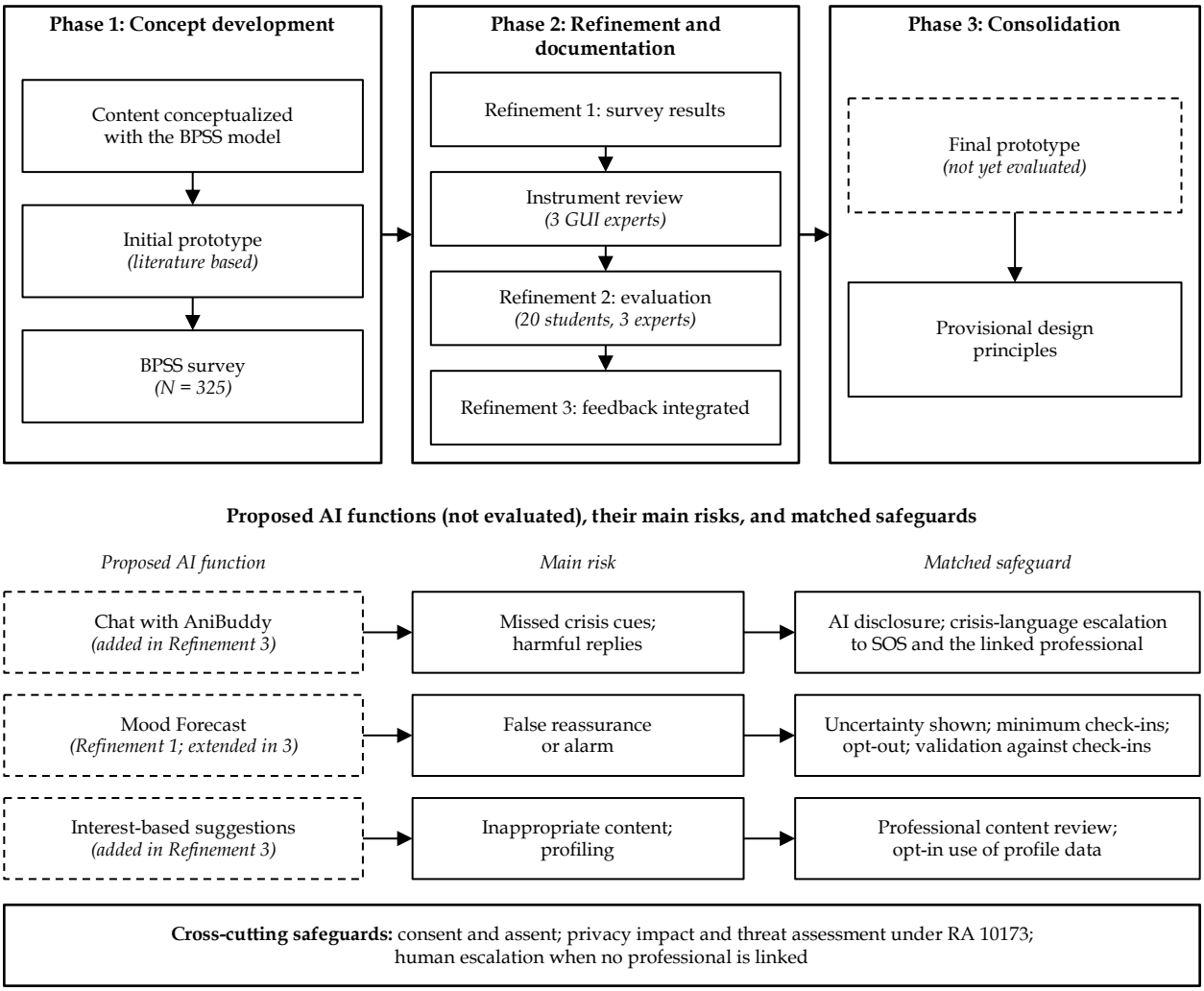


Figure 1. *Early Design-Based Research Cycle for AniBuddy with Proposed AI Functions and Risk-Specific Safeguards*

Note. Phases 1 to 3 show the design cycle. The lower panel maps each proposed AI function to its main risk and the safeguard meant to address it; dashed borders mark components that were not evaluated. Cross-cutting safeguards apply to all functions.

Participants and Sampling Technique

The survey involved 325 students aged 15 to 24 enrolled in the senior high school and college programs of De La Salle Medical and Health Sciences Institute, a private health sciences institution in Dasmariñas City, Cavite, Philippines. Non-proportional quota sampling drew respondents from class sections until a minimum of 300 was reached (Iliyasu & Etikan, 2021). Because no subgroup comparisons were planned, the target was set for precision: with N = 325, the 95% confidence interval around an indicator mean is about ±0.16 points even if the standard deviation is 1.50, well within the 0.85-point width of each interpretive band. Eligible students were enrolled, within the age range, and gave consent or, for minors, assent with guardian consent. The study record does not include the source population size, a breakdown by age, sex, program, or level, section quotas, the number invited, or response rates.

Twenty senior high school students evaluated the prototype as end users, against a planned minimum of 10. They were recruited through a separate invitation, and because the survey recorded no names, their overlap with the 325 respondents cannot be determined. Three subject experts from the institution's personality development and health education faculty also evaluated it, and three graphical user interface (GUI) experts reviewed the evaluation instrument. All evaluators were selected purposively. The experts' licenses and years of experience were not documented, and no clinical-safety, data-privacy, or software-security specialist took part, a gap addressed in the next cycle.

Research Instrument

The 43-item survey used a 7-point agreement scale (1 = strongly disagree to 7 = strongly agree), and each BPSS dimension was operationalized as a distinct indicator with its own score direction. The biological indicator (12 items) measured somatic anxiety symptoms with nine items adapted from the Physical Health Questionnaire (Schat et al., 2005) and three from the Beck Anxiety Inventory (Beck et al., 1988); item 4, on peaceful sleep, was reverse-keyed. The psychological indicator (10 items) consisted of first-person self-report statements written from the symptom domains of the clinician-rated Hamilton Anxiety Rating Scale (Hamilton, 1959; Thompson, 2015). They are not a validated self-report form of that scale and yield neither a severity score nor a diagnosis. The social indicator (11 items) measured perceived social support with items adapted from the Social Support Questionnaire (Sarason et al., 1983); six items describing a lack of support (1, 2, 7, 8, 10, and 11) were reverse-keyed so that higher scores mean more support. The spiritual indicator used the 10-item Meaning in Life Questionnaire, scored as its two subscales: presence of meaning (items 1, 4, 5, 6, and reverse-keyed item 9) and search for meaning (items 2, 3, 7, 8, and 10; Steger et al., 2006; Rose et al., 2017). Social support and meaning are protective constructs, so their scores are not need scores, and no overall BPSS score was computed. Items were rephrased as first-person statements on the common scale and reviewed qualitatively by the research adviser, a statistician, a language proofreader, and three instrument validators (Taherdoost, 2016). No content validity index was computed, no pilot test was run, and permission from the source developers was not documented. The 43 items are listed in Supplementary File S1, which is also available from the corresponding author.

The evaluation instrument drew on the ISO/IEC 25010:2023 product quality model (International Organization for Standardization, 2023), which has been applied to mobile health apps (Moumane et al., 2024). Of the model's nine characteristics, five were retained: functional suitability (completeness and appropriateness), compatibility (co-existence), interaction capability (eight sub-characteristics), reliability (faultlessness and availability), and maintainability (five sub-characteristics). Performance efficiency, security, flexibility, safety, and functional correctness require a working system and were excluded. Each of the 18 sub-characteristics was rated on a 5-point satisfaction scale, and three open-ended items asked about missing features, privacy, and general impressions. The GUI experts reviewed the instrument with an appraisal form and a recorded walkthrough; their review was qualitative, and no content validity index was computed. The full instrument appears in Supplementary File S1. Ratings were treated as perceived quality. Maintainability concerns internal software properties that users cannot inspect, so it is reported but not interpreted as evidence of maintainability.

Data Gathering Procedure

The survey was administered through Google Forms after participants read the information sheet and gave consent or assent; it took 10 to 15 minutes. Data were collected from September 2025 to May 2026. The results informed the first refinement. The refined prototype, which ran only on iOS, was then explored by the evaluators, who completed the rating and open-ended items online. Two end users (EU05 and EU06) used Android devices

and could not proceed past the opening screens; their ratings were excluded from the primary analysis. The devices the subject experts used were not documented, so their compatibility and availability ratings may partly reflect the same platform limit. Ratings and comments were documented and integrated into the third refinement.

Data Analysis Procedure

Survey indicator scores were the mean of their items after reverse-keying. The original analysis summarized responses by item, so indicator means are averages of item means; these equal composite means when responses are complete, which cannot be confirmed because item counts were not reported. Dispersion is shown as the range of item standard deviations. Participant-level standard deviations, internal consistency, and dimensionality require the raw responses, so the indicators are read descriptively. Levels were described with seven equal bands from extremely low (1.00 to 1.85) to extremely high (6.16 to 7.00). For the ratings, each participant's characteristic score was the mean of its sub-characteristics, and the overall score was the mean of all 18 (item-weighted); standard deviations are across participants. Every student rated all 18 sub-characteristics. Internal consistency of the student ratings was high (α = .84 to .92 across multi-item characteristics, n = 18), although identical ratings on every item by six students inflate these values. Two sensitivity analyses were run: the full student sample (n = 20) and the sample without those six students (n = 14). Expert standard deviations are reported only for sub-characteristics because, with n = 3, one rating moves a mean by 0.33. Satisfaction bands ran from very dissatisfied (1.00 to 1.80) to very satisfied (4.21 to 5.00).

The 60 end-user responses to the open-ended items (20 students × 3 items, 48 with substantive content) and the 16 expert comments in the refinement record were categorized deductively under the ISO/IEC 25010 characteristic they addressed, an approach that supports requirements prioritization (Kifetew et al., 2021). Responses were written in English, occasionally with Filipino expressions. The research team categorized them jointly; no independent double coding was done, so agreement statistics are not reported. Because the categories were predetermined, the results are reported as feedback categories rather than themes. A category was labeled converging when at least two independent sources raised it and provisional when it rested on one comment. Each category was traced to a documented design decision or recorded as carried forward. Quotations were chosen to illustrate a category or an unresolved concern and carry anonymous identifiers (EU = end user, SE = subject expert).

Ethical Considerations

The protocol received a certificate of ethics review approval on September 9, 2025, from the primary and secondary ethics reviewers of the institution's Special Health Sciences Senior High School department; the certificate carries no protocol number. Data collection began after approval. The study followed the informed-consent provisions of the Code of Ethics for Philippine Psychologists and Psychometricians (Psychological Association of the Philippines, 2022). Adults gave informed consent; respondents younger than 18 gave assent, and a parent or guardian consented for each. The number of minors was not reported separately from the 15-to-24 age range. Student researchers recruited with the research adviser present, and the information sheet stated that participation or refusal would not affect academic standing. Participants could skip items or withdraw at any time. The forms did not ask for names. Under the data privacy form, responses were kept on password-protected devices accessible only to the researchers and adviser, were to be destroyed securely at the end of the school year, and were to be deleted if a participant withdrew, in accordance with the Data Privacy Act of 2012. The consent form described referral to the guidance counselor or another health professional, arranged through the adviser, if a participant became distressed. No referral was recorded during data collection. No AI function was deployed to participants.

Results and Discussion

Symptoms and Resources Reported by Students

Table 1 presents the five indicators. Each is interpreted on its own terms; no overall score is reported because symptoms, support, and meaning are different constructs with different directions.

Table 1. *Biopsychosocial-Spiritual Indicators Reported by the Student Respondents*

Dimension	Indicator (meaning of a higher score)	Items	*M*	Item *SD* range	Level
Biological	Somatic anxiety symptoms (more frequent symptoms)	12	4.22	1.75–2.11	Moderate
Psychological	Anxiety-related thoughts and arousal (more frequent symptoms)	10	4.63	1.96–2.20	High
Social	Perceived social support (more support)	11	4.08	1.86–2.11	Moderate
Spiritual	Presence of meaning in life (more meaning)	5	3.68	1.63–1.98	Moderate
	Search for meaning in life (more searching)	5	2.91	1.64–1.82	Low

Note. N = 325. Items were rated from 1 (strongly disagree) to 7 (strongly agree). Means are averages of item means after reverse-keying biological item 4, social items 1, 2, 7, 8, 10, and 11, and Meaning in Life Questionnaire item 9. No overall score is reported because the indicators differ in construct and direction. The recorded *SD* for search item 7 (2.94) equals its mean and was excluded as a probable transcription error. Levels: 1.00–1.85 extremely low, 1.86–2.71 very low, 2.72–3.57 low, 3.58–4.43 moderate, 4.44–5.29 high, 5.30–6.15 very high, 6.16–7.00 extremely high.

Psychological symptoms were reported most often (M = 4.63, high), and cognition drove them more than arousal. The strongest items described overthinking every decision until mentally drained (M = 5.15), constantly worrying and expecting the worst (M = 5.06), and fearing that things will go wrong without a clear reason (M = 4.96). The pattern fits a cycle in which repetitive negative thinking becomes hard to stop (Matsumoto & Mochizuki, 2018) and echoes evidence that anxious adolescents predict negative outcomes while recalling positive ones poorly (Fernández et al., 2018). These are self-reported symptoms, not clinical severity. For design, they argue for capturing worry as it happens rather than only rating mood. Somatic symptoms were moderate (M = 4.22). Trembling hands when anxious (M = 4.65), difficulty falling asleep (M = 4.58), and headaches under frustration (M = 4.56) were most common, and the reverse-keyed sleep item showed that many students did not sleep peacefully (M = 4.52 after reversal). Regular nightmares were least common (M = 3.26), as expected in a largely non-clinical sample (Sheaves et al., 2016). Sleep therefore became a monitoring target.

Perceived social support was moderate (M = 4.08). Everyday company was the most strongly endorsed form of support (finding someone for lunch, M = 4.96) and knowing someone to turn to with a personal problem the least (M = 3.30). The contrast should be read cautiously: the reverse-keyed item on having no one to share worries with suggested that most students did have a confidant (M = 4.35 after reversal), and positively worded items were endorsed less than reversed negative ones (3.75 vs. 4.37), consistent with a wording effect. Support is therefore treated as a resource to strengthen. Peers matter for school engagement (Martinot et al., 2022), and fear of criticism and stigma deter help-seeking for anxiety (Aryal et al., 2024). Students reported a moderate presence of meaning (M = 3.68) and little active search for it (M = 2.91). Meaning was neither strongly established nor actively pursued. Because purpose in life is inversely related to anxiety (Boreham & Schutte, 2023) and meaning buffers the effect of stress on distress (Schnell & Krampe, 2020), the spiritual module was designed as a source of reflection and purpose rather than a response to deficit.

Table 2. *Design Conjectures, Evidence, and Changes Across the Early Design-Based Research Cycle*

Cycle	Design conjecture	Evidence considered	Resulting changes
Initial prototype	An app organized around the four BPSS dimensions will fit students better than a mood tracker alone	Literature on anxiety apps and the BPSS model	Navigation flow; self-assessment adapted from the HAM-A domains; mood check; journal; SOS button; therapist chat; four BPSS modules
Refinement 1	Features should concentrate on the dimensions with the heaviest reported burden, and a crowded interface will deter use	Survey of 325 students; design-team review	Crowded features removed; biological, psychological, and social features added; daily Mood Forecast; age screen; account retrieval for anonymous users; recovery e-mail; face recognition; revised typography and colors
Refinement 2	Students and experts will perceive the refined prototype as suitable, usable, and reliable	Instrument review by 3 GUI experts; ratings and comments from 20 students and 3 experts	Ratings, 60 end-user responses, and 16 expert comments documented and categorized (Tables 3 and 4); no prototype changes in this cycle
Refinement 3	Requested features, each paired with a human route, will improve fit without adding unmanaged risk	Converging and single-source feedback categories (Table 4)	Parent profile; hobby-based personalization with suggestions; Chat with AniBuddy beside the health-professional link; multi-day Mood Forecast; Mind Flow intensity log; Change Language; Files; sheep upgrades; sleep and nutrition trackers; reflections; decluttered homepage

Note. BPSS = biopsychosocial-spiritual; HAM-A = Hamilton Anxiety Rating Scale; GUI = graphical user interface. Changes made in Refinement 3 have not been evaluated.

Design Cycles and Perceived Quality of the Prototype

Table 2 summarizes the conjecture, evidence, and changes in each cycle. The timing of the AI functions matters for interpretation: the Mood Forecast entered in Refinement 1 and was therefore present in the prototype that

evaluators rated, whereas the conversational agent and interest-based suggestions entered only in Refinement 3.

Table 3 reports perceived quality. Students who could open the prototype were very satisfied overall (n = 18, M = 4.55, SD = 0.49); the experts were satisfied (M = 3.80). Results barely moved in the full sample (n = 20, M = 4.54) and stayed in the very satisfied band without the six uniform responders (n = 14, M = 4.42), where reliability (M = 4.29) and user error protection (M = 4.00) remained lowest.

Table 3. *Perceived Quality of the Prototype by ISO/IEC 25010 Characteristic and Sub-Characteristic*

Characteristic and sub-characteristic	End users (n = 18)		Subject experts (n = 3)	
	M	*SD*	*M*	*SD*
Functional suitability	**4.53**	**0.53**	**4.00**	**—**
Functional completeness	4.56	0.51	4.00	1.00
Functional appropriateness	4.50	0.62	4.00	1.00
Compatibility	**4.61**	**0.61**	**3.67**	**—**
Co-existence	4.61	0.61	3.67	0.58
Interaction capability	**4.55**	**0.55**	**3.92**	**—**
Appropriateness recognizability	4.72	0.57	4.33	0.58
Learnability	4.61	0.85	4.00	1.00
Operability	4.39	0.98	4.00	1.00
User error protection	4.22	0.88	3.67	1.15
User engagement	4.39	0.78	3.67	1.15
Inclusivity	4.44	1.04	4.00	1.00
User assistance	4.89	0.47	4.00	1.00
Self-descriptiveness	4.72	0.75	3.67	1.15
Reliability	**4.44**	**0.91**	**3.50**	**—**
Faultlessness	4.39	0.85	3.67	1.15
Availability	4.50	1.04	3.33	1.53
Maintainability (perceived only)	**4.59**	**0.57**	**3.67**	**—**
Modularity	4.72	0.57	3.67	1.15
Reusability	4.50	0.86	3.67	1.15
Analysability	4.56	0.78	3.67	1.15
Modifiability	4.61	0.61	3.67	1.15
Testability	4.56	0.70	3.67	1.15
Overall (18 sub-characteristics)	**4.55**	**0.49**	**3.80**	**—**

Note. Ratings used a 5-point scale (4.21–5.00 = very satisfied; 3.41–4.20 = satisfied; 2.61–3.40 = neutral). End-user values exclude two students who could not open the iOS-only prototype; characteristic and overall scores are participant-level means with standard deviations across participants. Expert characteristic and overall means are averages of item means. Maintainability ratings reflect perceptions of a front-end prototype and are not evidence of maintainability. The expert co-existence *SD* was first reported as 0.60, which three whole-number ratings cannot produce; ratings of 3, 4, and 4 give 0.58.

Students rated user assistance highest (M = 4.89) and user error protection lowest (M = 4.22); reliability was their lowest characteristic (M = 4.44). Their comments explain why: one praised the interface but noted "ghost buttons (those that don't work atm)" (EU02). In more than five million mobile health app reviews, troubles that led to uninstallation and faults during registration and login were strongly associated with one-star ratings (Haggag et al., 2022). Reliability is a condition of trust. Experts rated every characteristic lower, and their judgments centered on access. Availability was the lowest item in either group (M = 3.33). The prototype ran only on iOS, lacked a computer version, and would not reach older users or remote areas; one expert noted that "not all people or students are given the privilege of having" an iPhone (SE01). Such user–expert differences are documented (de Chantal et al., 2022), and experts tend to weigh evidence, privacy, and fit with practice (Magee et al., 2018; Larsen et al., 2019). With three experts, the difference indicates direction rather than a stable group effect. Compatibility and maintainability describe technical properties that prototype users can only perceive, so these ratings await technical testing.

Feedback Categories and Design Decisions

Table 4 traces each feedback category to a design decision or to carried-forward status. Converging categories, such as platform access, personalization, inclusivity, and data security, rested on several sources. Others, including the parent profile, stored files, and the expert's AI suggestion, rested on a single comment and are provisional. One expert asked the team to "clearly outline the intended user journey and how each feature contributes to managing anxiety levels" (SE02), and a student warned that the app overlapped with existing apps "unless it really has stand out features" (EU02). Platform access, non-working buttons, and security required a working build or specialist review and were carried forward rather than treated as solved. Expert input throughout development protects scientific accuracy and clinical relevance (Pereira-Azevedo et al., 2015).

Table 4. *Feedback Categories, Evidence Base, and Resulting Design Decisions*

Feedback category (ISO/IEC 25010 characteristic)	Source and evidence base	Design decision (cycle) or status
Access beyond iOS and a computer version (compatibility)	EU05, EU06, SE01, SE03; converging	No change documented; carried forward
Non-working buttons and the app stopping at the age screen (reliability)	EU02, EU06; converging	Carried forward; requires a working build
Parental awareness of a minor's use (functional suitability)	One record entry; provisional	Parent profile added (Refinement 3)
Personalization and profiles with hobbies and interests (interaction capability: user engagement)	EU11 and two record entries; converging	Hobby-based personalization with proposed AI suggestions (Refinement 3)
Mood history and sleep monitoring (functional suitability)	EU09 (sleep); one record entry (mood history); provisional	Mood and anxiety logs in Statistics; sleep and nutrition trackers (Refinement 3)
AI sentiment analysis, optional sharing with a therapist, and peer forums (functional suitability)	One subject expert; provisional	Proposed Chat with AniBuddy and health-professional link by invite code (Refinement 3); existing peer posts retained as BuddyThreads
Other languages and access for older or remote users (interaction capability: inclusivity)	EU01, one record entry, SE01; converging	Change Language option (Refinement 3); broader access carried forward
Unclear journal location and button purposes (interaction capability: self-descriptiveness)	Three record entries and one expert; converging	Homepage decluttered; journal moved to the psychological module (Refinement 3)
Rewards and companion upgrades (interaction capability: user engagement)	One record entry and one expert; converging	AniBuddy sheep upgrades (Refinement 3)
Stored records protected by a PIN (functional suitability)	One record entry; provisional	Files feature added (Refinement 3); PIN protection not documented
Hacking, data storage, and explanation of face-recognition data (security; not evaluated)	Three expert comments; converging	Carried forward; privacy impact and threat assessment required
Self-care reminders, a report or contact option, and audio coping content (functional suitability)	EU03, EU20, and record entries; converging	No change documented; carried forward

Note. EU = end user; SE = subject expert. Record entries are feedback summarized in the refinement record without a participant identifier. Converging = raised by at least two independent sources; provisional = raised once.

Proposed AI Functions, Risks, and Safeguards

The three AI-enabled functions are proposed specifications, not evaluated features. Chat with AniBuddy answered an expert's suggestion to "consider AI sentiment analysis or optional sharing with a therapist for feedback" (subject expert, refinement record) and sits beside the link to the user's own health professional. Interest-based suggestions answered students' requests for personalization. The Mood Forecast, introduced in Refinement 1 to support self-monitoring of mood patterns (Caldeira et al., 2017), was extended in Refinement 3 to multi-day forecasts drawing on mood entries and activity. The refinement record names no model, data source, or service for the chat or the forecast, so both remain design specifications. The evidence supports a supporting role only: conversational agents reduce distress (H. Li et al., 2023; J. Li et al., 2025), effects are small and short-lived (He et al., 2023), personalization helps modestly (W. Li et al., 2024), and human–AI collaboration produced more empathic text support than humans alone (Sharma et al., 2023).

The non-AI features carry risks as well. Table 5 lists the principal risk and required control for each high-risk feature and separates requirements raised in this study from those drawn from the literature. Before any deployment, each AI function needs a defined intended use, a specified model and input data, accuracy criteria, analysis of subgroup bias, estimates of false-positive and false-negative rates for crisis detection, explanations users can understand (Laato et al., 2022), monitoring, and a procedure for unsafe outputs (World Health Organization, 2021; Coghlan et al., 2023; Deniz-Garcia et al., 2023). Mood histories, files, biometric data, and messages with professionals are health information, which the Data Privacy Act of 2012 classifies as sensitive personal information. Processing must therefore follow the Act's principles of transparency, legitimate purpose, and proportionality. A privacy impact and threat assessment should decide whether face recognition, the parent profile, and stored files remain in the design, and it should specify the lawful basis for processing, data minimization, consent withdrawal, retention and deletion, encryption, role-based access, breach response, and any third-party services.

Table 5. *Risk and Safeguard Register for High-Risk Features of the Final Prototype*

Feature (cycle added)	Principal risk	Control required before deployment	Source of requirement
Chat with AniBuddy, proposed AI (Refinement 3)	Missed crisis cues; harmful, inaccurate, or overly persuasive replies; overreliance	Disclose that the user is talking to AI; detect crisis language and escalate to SOS and the linked professional; no diagnostic claims; test content safety; log and review unsafe outputs	Expert comment; literature
Mood Forecast, proposed AI (Refinement 1; extended in Refinement 3)	False reassurance or alarm; opaque logic	Specify the method; show uncertainty; require a minimum number of check-ins; explain each forecast; allow users to turn it off; validate against later check-ins	Literature
Interest-based suggestions, proposed AI (Refinement 3)	Inappropriate content; profiling	Professional review of suggested content; opt-in use of profile data; explain why each suggestion appears	End-user comments; literature
Messaging with a health professional (initial; revised in Refinement 3)	Expectation of real-time help; unclear responsibility	State response times and that the channel is not for emergencies; define who responds when no professional is linked	Expert comments
SOS alerts (initial)	Failed or delayed alerts; contacts unable to respond	Test delivery; confirm receipt; always display emergency hotlines as a fallback	Literature
Parent profile (Refinement 3)	Breach of adolescent confidentiality; coercive monitoring	Adolescent agreement to sharing; limit what parents see; verify age	End-user comment; RA 10173
Face recognition (Refinement 1)	Biometric data breach; disproportionate collection	Privacy impact assessment; explicit consent; on-device processing or removal	Expert comments; RA 10173
Peer posts (Refinement 1; BuddyThreads in Refinement 3)	Harmful content, bullying, or contagion	Moderation policy, reporting tools, and trained moderators	Design-team precaution
Files and mood histories (Refinement 3)	Unauthorized access to sensitive health data	Encryption; PIN and role-based access; retention and deletion rules; breach response	End-user comment; RA 10173

Note. Risks and controls are requirements for the next design cycle, not findings of this study. "Literature" refers to World Health Organization (2021), Koh et al. (2022), Laato et al. (2022), Coghlan et al. (2023), and Deniz-Garcia et al. (2023). RA 10173 = Data Privacy Act of 2012.

Provisional Design Principles

Four principles follow from this cycle and will be tested in the next. First, capture worry when it occurs, because students' burden lay in overthinking and anticipation more than in physical arousal. Second, treat support and meaning as resources to strengthen rather than deficits to score. Third, secure reliability and cross-platform access before adding intelligence, because both groups rated reliability lowest and platform limits shaped who could take part. Fourth, admit an AI function only when evidence calls for it, and pair it with a named human route and a safeguard matched to its main risk.

Conclusion

This early DBR cycle suggests three contributions. First, a BPSS survey scored as separate indicators can help set design priorities for a student anxiety app: psychological symptoms dominated, somatic symptoms centered on sleep, and support and meaning appeared as moderate resources. These priorities remain provisional until the indicators' reliability and structure are confirmed. Second, students and experts perceived the prototype differently, and both identified reliability as its weakest characteristic. With three experts, this difference indicates direction rather than a stable effect. Third, the study shows how AI functions can be traced to evidence, labeled as proposals, and paired with risk-specific safeguards before they are built.

For practice, guidance services can treat such apps as a bridge between self-monitoring and professional contact, provided the app routes students to people when it matters. Developers should fix reliability and access before adding intelligence and involve mental health professionals from the first prototype. Institutions should govern AI features in student mental health tools as processing of sensitive personal information, with disclosure, age-appropriate consent, and human escalation built in.

The limits are substantial. The survey came from one institution, used quota sampling, and lacks a recorded demographic profile and response rate. Its indicators were adapted, and their means were recomputed from item

means; reliability and dimensionality remain to be established. The evaluation used small groups, descriptive statistics, and one mobile platform, six students gave uniform ratings, and several characteristics were perceived rather than tested. The final prototype, including the proposed AI functions, has not been evaluated, and the study included no clinical validation and no privacy or security assessment. The next cycle should add these reviews, implement and test the AI functions for accuracy, safety, bias, and user trust, and evaluate the full prototype on several platforms with larger and more diverse student groups.

Contributions of Authors

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Gabriella Isabel B. Calanno: conceptualization, prototype design, data gathering, data analysis, and original draft
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Conflict of Interests

The authors declare no conflict of interest.

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