

SAND: An AI-Integrated WhatsApp Chatbot Combining a Decision-Game Simulation with the Delphi Technique for Drug-Abuse Awareness Among Youth in Sudan

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Abstract:

Drug abuse is a socio-economic and public health crisis among youth in Sudan, intensified by armed conflict, economic instability, and the limitations of fear-based awareness campaigns. This study developed and evaluated SAND, an artificial intelligence (AI)-driven conversational agent deployed on WhatsApp to provide scalable, interactive, and culturally tailored prevention. SAND integrates a branching Decision-Game simulation with the Delphi technique to promote drug-abuse awareness, critical thinking, and safe decision-making among Sudanese youth aged 18–24. A multidisciplinary panel of 15 experts in addiction prevention, mental health, Islamic counseling, and artificial intelligence completed a three-round Delphi process to develop, validate, and refine culturally sensitive risk scenarios. These scenarios were delivered through WhatsApp, where participant decisions were logged, session-level risk scores were updated, immediate consequence-based feedback was provided, and high-risk users were triaged to confidential, human-reviewed support channels. The system incorporates a four-layer safety architecture comprising a Crisis/Safety filter, Intent-Classification router, Retrieval-Augmented Generation (RAG) knowledge engine, and Anonymized Logging/Escalation layer. Efficacy was assessed using a randomized controlled trial with a pretest-posttest control-group design involving 200 participants. The experimental group interacted with SAND, whereas the control group received non-interactive awareness content. Results showed statistically significant and greater improvements in the experimental group in drug-risk awareness, risk-vulnerability reduction, decision-making self-efficacy, and adaptive coping (all $p < .001$). These findings suggest that combining expert consensus with interactive behavioral learning can support privacy-preserving substance-abuse prevention in crisis-affected, low-resource settings. However, the unusually large effect sizes warrant cautious interpretation, and longer-term, multi-site replication is recommended before broad implementation.

Keywords: Artificial Intelligence in Public Health; AI Chatbots; WhatsApp Interventions; Decision-Game Simulation; Delphi Technique; Drug Abuse Awareness; Substance Use Prevention.

1. Introduction

Drug abuse is one of the most serious challenges facing societies around the world today[1]. Its impact goes far beyond individual health, as it can affect national security, social stability, and economic development. Drug abuse is not simply a health problem that affects individuals; it is a complex social phenomenon influenced by psychological, economic, social, and political conditions[2]. When drug use becomes widespread, it can weaken the human resources that are essential for the progress and development of any society. For this reason, there is an increasing need for more effective approaches to drug prevention and awareness. These approaches should make better use of scientific knowledge and modern technologies rather than relying solely on traditional methods, particularly as communication and social interaction continue to change rapidly and drug-related activities increasingly take place through digital platforms and social media that are widely used by young people[3].

Awareness is an important part of drug prevention because it helps people understand the dangers associated with drug use and encourages healthy behaviors that can reduce the risk of addiction[4]. Effective awareness programs need to consider the differences between age groups and social backgrounds, with particular attention given to young people because they are often more vulnerable to social and environmental influences[5]. In Sudan, the factors contributing to drug use are diverse and closely connected. Economic difficulties, including poverty, unemployment, and low household income, can create conditions that increase vulnerability. Social problems such as family disruption, limited parental supervision, and weakened community relationships can also contribute to the problem. Psychological factors, including anxiety, depression, frustration, and the loss of hope resulting from difficult living conditions, may further increase the risk[6]. At the same time, limited knowledge about the harmful effects of drugs and the spread of misconceptions about substance use can make prevention more difficult. Security challenges, including difficulties in controlling borders and the activities of drug-trafficking networks, may also facilitate the movement of narcotic substances into local communities[7], [8].

The situation has become even more difficult because of the armed conflict that Sudan has experienced. This conflict has resulted in large numbers of displaced people and refugees, disrupted families and communities, and increased psychological and social pressures on individuals[9]. People living under such circumstances may become particularly vulnerable to exploitation by drug-trafficking networks[10]. Economic hardship, displacement, insecurity, and limited access to social and psychological support can create an environment in which vulnerable individuals are more easily exposed to drugs and related criminal activities[11]. The disruption of institutions and weakening of community structures during periods of conflict can therefore make existing prevention efforts even more challenging[12].

In response to the growing problem, government institutions and civil-society organizations in Sudan have used a variety of traditional awareness and prevention methods, including seminars, lectures, printed materials, posters, television and radio programs, and awareness campaigns conducted in schools, markets, and other public places[13]. Although these methods remain useful, their effectiveness can be limited when they are not adapted to the changing needs and behaviors of younger generations. Some campaigns rely heavily on fear and moral messaging, which may not always attract the attention of young people or encourage meaningful engagement. Traditional programs may also have difficulty reaching individuals who spend much of their time online. Another important limitation is the lack of privacy: people who are already having problems with drugs may not want to seek help because they are afraid of being judged or shamed by others. In addition, conventional awareness programs often have limited ability to identify vulnerable individuals or groups and to continuously evaluate the effectiveness of awareness activities using reliable data[14]. The rapid development of online communication and the changing ways in which drugs are promoted through digital platforms further emphasize the necessity of new approaches that can respond more quickly and effectively to emerging risks[15]. Artificial intelligence offers promising opportunities in this context. Its ability to analyze large amounts of information, identify patterns, and support decision-making makes it a potentially valuable tool for drug prevention and awareness[16]. AI-based systems can help researchers and institutions examine patterns associated with drug use, identify factors that may indicate increased vulnerability, and analyze patterns of interaction within digital and social networks[17]. They can also support the development of awareness campaigns that are better suited to different age groups and social contexts. Machine-learning techniques, for example, can be used to analyze patterns of interaction and help

determine which types of awareness content are more likely to attract attention and encourage positive behavior[18].

Another important opportunity is the use of artificial intelligence to develop more engaging forms of awareness content. Interactive educational materials, digital stories, videos, games, and other forms of multimedia content can communicate information about the dangers of drugs in ways that are more familiar and attractive to young people[19]. Instead of relying only on direct warnings, these approaches can encourage users to interact with educational content and think about the possible consequences of their decisions. Artificial intelligence can also support conversational systems that provide general guidance and psychological support in a private and accessible environment, allowing individuals to ask questions and receive information without immediately feeling exposed to social judgement, and, where appropriate, to receive information about available professional services and treatment centers. Such systems should, however, complement rather than replace qualified healthcare and psychological professionals, particularly in situations involving serious substance use or mental-health concerns[20].

Despite these opportunities, the use of artificial intelligence in drug awareness also requires careful consideration. AI systems must be designed responsibly, particularly when they handle sensitive information about individuals; privacy, data protection, accuracy, transparency, and the prevention of bias are essential considerations[21]. In the Sudanese context, technological solutions also need to reflect local cultural and social values and should be developed in a way that is understandable and acceptable to the communities they are intended to serve. Technology alone cannot solve the drug problem; its effectiveness depends on how well it is integrated with education, healthcare, family support, community participation, government policy, and professional intervention[22].

The present study is grounded in two complementary theoretical perspectives. First, it departs from the information-deficit model that underlies most traditional campaigns, which assumes that providing knowledge alone is sufficient to change behavior. Second, it draws on Bandura's Social Cognitive Theory (SCT)[23], which holds that behavior change is more reliably achieved when individuals are given opportunities for mastery experiences, that is, low-stakes rehearsal of a behavior together with observation of its consequences. The Decision-Game component of SAND operationalizes this principle by allowing participants to rehearse refusal and coping responses to realistic risk scenarios and to receive immediate, consequence-based feedback, while the Delphi component ensures that the scenarios rehearsed are scientifically accurate, safe, and culturally appropriate. Against this background, this paper addresses the following central question: how can artificial-intelligence tools be used to strengthen drug awareness and prevention in Sudan and contribute to building a society that is better informed and better prepared to confront the risks associated with drug abuse despite the country's current economic and social challenges? To address this question, the paper examines the current situation of drug awareness in Sudan, discusses the main limitations of traditional awareness approaches, and explores the potential of artificial intelligence as a complementary tool for prevention and education. The paper also presents a smart awareness model that combines modern technology with local knowledge and community values, together with the empirical results obtained from its evaluation. In addition, it presents practical considerations for government institutions, civil-society organizations, and the private sector regarding the responsible use of AI in drug awareness, with particular attention to privacy, data protection, cultural considerations, and cooperation among relevant stakeholders.

The main contribution of this paper is the design, implementation, and empirical evaluation of an intelligent assistant, SAND, for drug-abuse awareness. SAND integrates a decision game with the Delphi technique, a structured approach for obtaining and combining expert knowledge through anonymous consultation. This integration supports a more interactive and informed approach to drug awareness while taking into account the social and cultural context of Sudan. The SAND framework, therefore, represents an attempt to move beyond conventional awareness methods by combining artificial intelligence, expert knowledge, and interactive decision support in a single, empirically evaluated awareness-oriented system.

1.1 The Decision Game

The Decision Game[24] is an interactive approach designed to help individuals develop critical thinking and improve their ability to make appropriate decisions when faced with challenging situations. In this study, the game focuses on situations related to drug use and presents participants with realistic scenarios that they may encounter in their daily lives. Within an AI-supported environment, participants are asked to consider each situation and select what they believe is the most appropriate response from several possible choices. The system records and analyzes their decisions and then provides immediate feedback explaining the possible consequences of each choice.

This approach allows participants to understand the health, social, and legal risks associated with drug use while also encouraging them to think carefully about their decisions. By experiencing different situations and seeing the possible outcomes of their choices, participants can develop greater awareness and become better prepared to make safer decisions when faced with similar circumstances in real life.

1.2 The Delphi Technique (Anonymous Expert Consultation)

The Delphi technique[25] is a well-established research method used to collect expert opinions and gradually reach a level of agreement on a particular issue. It is particularly useful when a research problem requires knowledge from specialists with different areas of expertise. In this study, the Delphi process involved a group of experts with experience in drug prevention, mental health, artificial intelligence, and related fields.

The experts participated in several rounds of questionnaires and provided their opinions independently, without knowing the identities or responses of the other participants[26]. After each round, the collected responses were reviewed and summarized, allowing the experts to reconsider their views in subsequent rounds. This process helps reduce the influence of personal status, professional position, or individual relationships on the results and provides a more balanced basis for reaching expert agreement. In the present study, the Delphi technique was used mainly to determine the most appropriate awareness messages, realistic situations, and decision-making scenarios included in the decision game.

1.3 Integration Mechanism: Decision Game and Delphi Technique

The Decision Game and the Delphi Technique were combined in the proposed framework so that expert knowledge and participant experience could complement each other. The process started with the Delphi Technique, through which experts identified and evaluated the awareness messages, situations, and scenarios most relevant to drug prevention. The information obtained from the experts was then used to develop the interactive scenarios within the AI-supported decision game. Participants subsequently interacted with these scenarios by selecting responses to different situations, while the system recorded their decisions and analyzed their responses.

The results obtained from the decision game were then reviewed to determine how effectively the scenarios communicated the intended awareness messages and encouraged appropriate decision-making. These findings were shared with the expert panel for further evaluation and discussion. Based on the experts' feedback, the scenarios and awareness content were refined and improved before being used again. This created a continuous feedback process in which the Delphi technique provided the scientific and expert foundation for the content, while the decision game provided an environment for applying and evaluating that content through participant interaction. The integration of the two methods, therefore, created a link between expert knowledge and practical behavioral responses, allowing the system to be gradually improved based on both professional judgment and real user experiences.

The remainder of the paper is organized as follows: Section 2 reviews related work; Section 3 presents the methodology, including the SAND system architecture and study design; Section 4 presents the empirical results; Section 5 discusses the findings; Section 6 addresses limitations, recommendations, and conclusions; and the final sections present the ethics, funding, and references statements.

2. Related Work

A study conducted by [27] examined the potential of AI to strengthen health communication and drug-abuse prevention in Nigeria. The study was a conceptual/desk-review analysis grounded in the Health Belief Model,

synthesizing literature and case examples (chatbots, social-media sentiment analysis, predictive analytics) rather than collecting primary data. It concluded that AI-driven personalized messaging and predictive analytics hold strong promise, recommending chatbots in local languages delivered via WhatsApp/SMS. Its main limitation is that it remained entirely theoretical: no chatbot was built, no participants were recruited, and no mechanism was proposed to validate content accuracy or cultural safety.

In a related study, [28] developed PsyBot, an AI-driven (GPT-3-based) WhatsApp chatbot delivering Psychological First Aid to reduce loneliness among Indonesian university students. Using a randomized controlled trial (EG $n = 16$, CG $n = 16$) with thematic analysis of transcripts, results showed a significant reduction in loneliness ($p = .006$) and improved well-being ($p = .003$). Its main limitations are a very small sample, a single short session with no follow-up, and the absence of any structured expert-consensus process to validate the chatbot's content before deployment.

Similarly, [29] explored the informational needs of family caregivers of psychiatric patients after hospital discharge in Indonesia and translated these into a rule-based chatbot prototype (KJOL-ITEUNGBOT). Using semi-structured interviews ($n = 8$) and document analysis, analyzed thematically and validated by a six-member expert panel, the study identified nine domains of caregiver need. Its main limitations are that the prototype was never tested for usability or effectiveness, no quantitative outcome data exist, and its purely rule-based architecture limits adaptability.

Together, these studies leave a cumulative gap: a theoretical proposal with no implementation, a tested but under-validated small-scale chatbot, and an expert-validated but untested prototype. SAND resolves this gap in one integrated framework by combining rigorous Delphi expert validation with a full, adequately powered RCT ($N = 200$) that yields statistically significant outcomes, while constraining its generative AI layer through a RAG pipeline grounded strictly in expert-approved content. Beyond closing these methodological gaps, SAND was purpose-built for Sudan: its content was validated by a panel including Islamic and community-counseling experts and tested under real conflict-affected, low-resource conditions, making it a locally grounded intervention genuinely suited to the society it serves.

3. Methodology

The implemented system consists of two complementary components, the Delphi Technique for content validation and the Decision Game for interactive delivery, unified by a single AI-driven conversational layer, SAND, deployed on WhatsApp. Figure 1 illustrates the general workflow: expert-validated content, scenario authoring, AI-mediated interactive delivery, logged decisions, statistical feedback to the expert panel, and iterative refinement.

3.1 The Decision Game Component

The Decision Game presented participants with a sequence of realistic, branching scenarios related to drug-risk situations (e.g., peer pressure[30], exposure to trafficking networks[31], and coping with psychological distress[32]). At each decision point, the participant selected among several plausible alternatives; the system logged the choice, updated an internal risk score, and returned tailored, immediate feedback explaining the health, social, or legal consequences of that choice. This mirrors evidence-based practice in serious-game and simulation-based prevention education, where decision rehearsal in a low-stakes environment supports the transfer of safe decision-making to real-life situations.

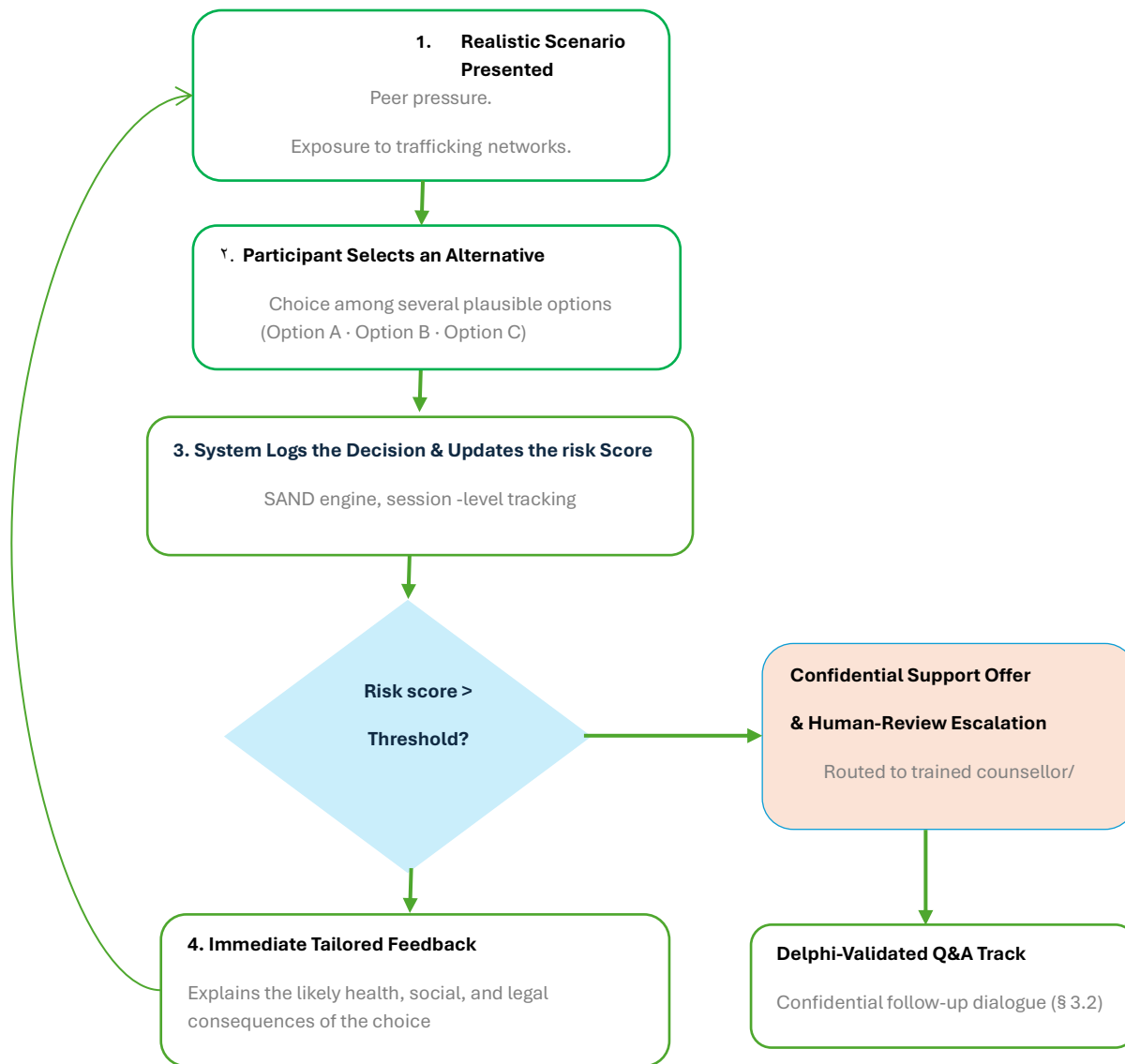


Figure 1. General interaction workflow of the SAND Decision Game

At the operational core of the system sits the Decision Game, whose interaction logic is summarized in Figure 1. Each session began when SAND presented a realistic, Delphi-validated scenario drawn from core risk domains. The participant selected among several plausible alternatives, and the system silently logged the decision while updating a session-level risk score. Rather than resolving every interaction identically, the interaction pipeline branched at a defined decision point: routine choices triggered immediate, consequence-based feedback followed by progression to the next scenario, whereas choices that pushed the accumulated risk score above a pre-set threshold diverted the participant into a confidential, human-reviewed support track. This dual-path structure allowed the game to function simultaneously as a rehearsal tool for safe decision-making and as an early-warning mechanism for participants requiring professional intervention.

3.2 The Delphi (Anonymous Expert) Component

A multidisciplinary panel of $N = 15$ experts spanning addiction prevention, clinical mental-health practice, Islamic and community counseling, and artificial intelligence was recruited. The panel completed three iterative, mutually anonymous questionnaire rounds to:

1. Identify and prioritize the awareness messages and risk scenarios most relevant to the Sudanese socio-cultural context;

2. Validate the scientific accuracy, safety, and cultural appropriateness of the content embedded in each scenario; and
3. Review aggregated, anonymized behavioral data harvested from the Decision Game to refine scenario design in subsequent iterations.

Consensus was quantified using percentage agreement and Kendall's coefficient of concordance (Kendall's W)[33]. A pre-specified stopping rule was enforced, requiring an agreement threshold of $\geq 80\%$ or the stabilization of W across two consecutive rounds before releasing content to the active game engine.

The scenarios and messages populating the interaction loop in Figure 1 did not originate directly from the generative AI model; instead, they were authored and validated beforehand through the Delphi process depicted in Figure 2. The 15 experts completed three successive, mutually anonymous rounds of rating and refinement. As Figure 2 illustrates, each round produced an aggregated, anonymized summary returned to the panel, incorporating behavioral performance data from the Decision Game by the third round to allow experts to evaluate scenario efficacy before finalizing the validated message bank. Content was released for game authoring only upon meeting the pre-specified stopping criteria ($\geq 80\%$ agreement or stable W).

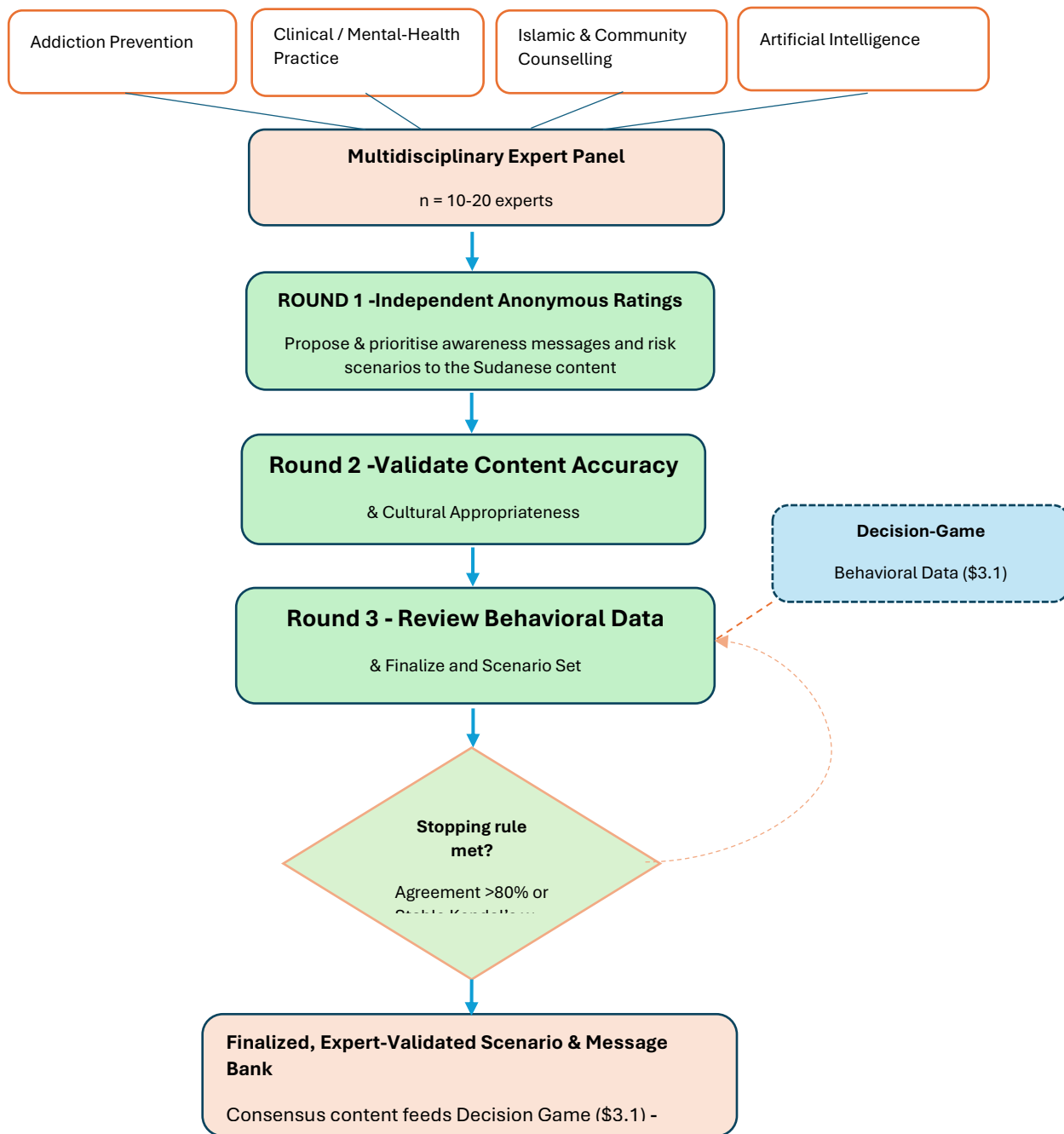


Figure 2. Three-round Delphi consensus-building cycle.

3.3 Integration Workflow

The integration between the Delphi Technique and the Decision Game followed a structured, closed-loop execution cycle:

1. Round 1 (Delphi): The 15 experts independently proposed and rated candidate risk scenarios and awareness messages.
2. Content Synthesis: The research team aggregated expert input into a structured candidate scenario bank, removing identifying information to preserve anonymity.

3. Rounds 2-3 (Delphi): Experts reviewed aggregated results and re-rated items until the pre-specified consensus threshold ($\geq 80\%$ agreement) was reached across the three rounds.
4. Scenario Authoring: Validated content was converted into branching dialogue trees, decision nodes, and risk-scoring rules for the Decision Game.
5. AI-Mediated Delivery: SAND delivered the game and free-text Q&A to participants over WhatsApp, logging every decision and interaction.
6. Empirical Feedback Loop: Aggregated, anonymized participant performance data (e.g., proportion of correct decisions per scenario) was returned to the expert panel to inform iterative refinement of weak-performing scenarios.

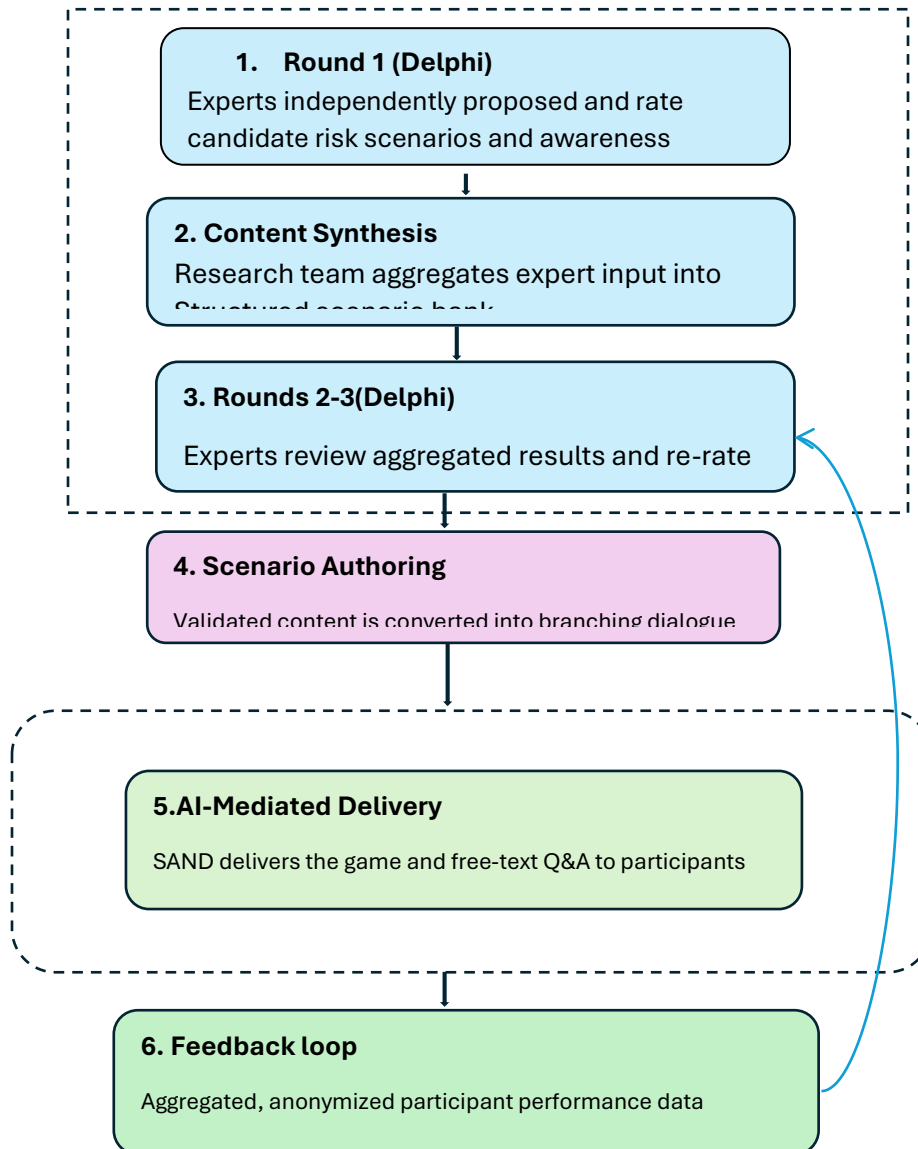


Figure 3. Closed-loop integration of the Delphi cycle and the Decision-Game loop.

Figure 3 makes explicit the relationship between Figures 1 and 2: it presents the Delphi cycle and the Decision Game loop as a single closed system. The upper cluster reproduces the consensus-building stages, culminating in a validated scenario bank; the scenario-authoring step converts approved content into branching dialogue trees. Aggregated, anonymized performance data from the Decision Game was routed back into subsequent Delphi rounds, enabling the expert panel to iteratively refine weak scenarios.

3.4 SAND: System Architecture

SAND is an AI-driven conversational agent deployed on WhatsApp, the predominant messaging platform among Sudanese youth, chosen to minimize adoption barriers and make the system easier to access. Its architecture integrates four functional layers, each responsible for a specific part of the interaction and support process.

Crisis / Safety Layer: A keyword- and intent-based filter screens every incoming message for crisis indicators (e.g., expressions of self-harm or suicidal ideation) prior to any further processing. A match immediately triggers an emergency-response template with hotline contacts and flags the session for urgent human review, bypassing the normal conversational flow.

Intent-Classification Layer: After the safety check, the system routes each message into a dedicated track: menu navigation, Decision Game play, informational Q&A, requests for emotional support or treatment referral, or requests for information that could facilitate harmful behavior. The latter are not answered with operational details; instead, SAND returns a safe response and redirects the user toward appropriate support and prevention information.

Retrieval-and-Generation Layer: For conversational questions, SAND uses a lightweight Retrieval-Augmented Generation (RAG) pipeline. The generative component was a locally hosted, open-weight instruction-tuned language model (Llama-3-8B-Instruct class), selected to preserve data sovereignty over sensitive health conversations rather than routing raw user messages to a third-party cloud API. The system retrieves relevant passages from a vector index (FAISS) built exclusively from the Delphi-approved knowledge base, and the model is constrained to generate responses grounded in the retrieved context. This design reduces unsupported or inaccurate responses and limits the possibility of generating advice that has not been reviewed by the expert panel.

Logging, Anonymization, and Escalation Layer: Interaction records are hashed and anonymized prior to analysis, with identifying information handled separately from behavioral data. A cumulative session risk score exceeding 70% of the maximum attainable score, or any single crisis-filter match, automatically diverted the participant to a confidential, human-reviewed support track. Escalations were reviewed by trained peer-counselors and a supervising clinical psychologist affiliated with the university's student wellness unit, available through an on-call rotation for the duration of the trial. When relevant, SAND also appended official referral information (hotlines and treatment-center contacts) to the exchange.

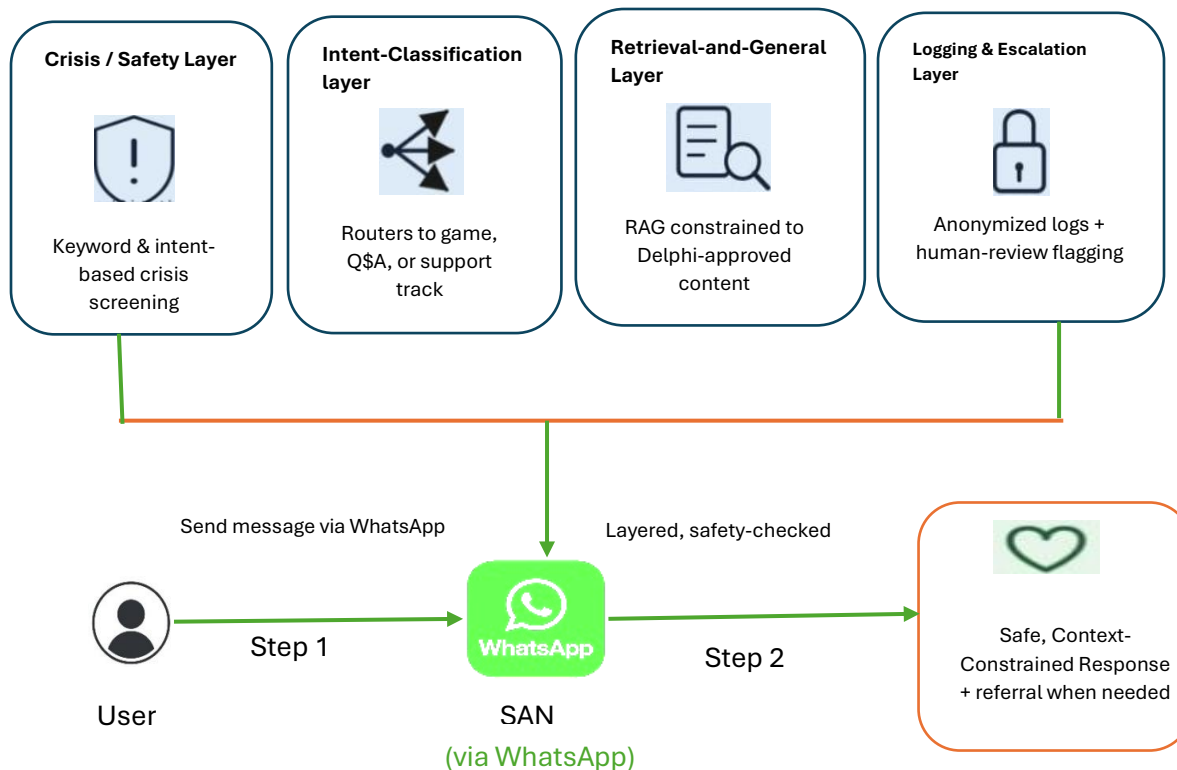


Figure 4. The four-layer SAND system architecture.

This layered architecture (Figure 4) reflects the principle that AI systems addressing substance use should serve as a bridge to human and institutional support rather than a standalone replacement, maintaining explicit human-in-the-loop review for elevated-risk interactions. On average, a full Decision-Game session, comprising scenario progression, feedback, and optional free-text Q&A, lasted approximately 35-40 minutes.

3.5 Study Design

The evaluation of SAND employed a mixed-methods randomized controlled trial (RCT) with a pretest-posttest control-group design. This design directly tests the causal claim underlying the model: that structured, expert-validated interaction with the Decision Game drives improvements in drug-risk awareness and decision-making quality relative to non-interactive exposure.

Participants were randomly assigned to either an experimental group (EG, $n = 100$), which interacted with SAND's Decision Game over WhatsApp, or a control group (CG, $n = 100$), which received a neutral, non-interactive awareness activity of identical duration. Allocation concealment was maintained using a computer-generated randomization sequence administered by an independent research assistant not involved in recruitment or intervention delivery.

Ethical approval was obtained from the Research Ethics Committee, Faculty of Computer Sciences and Information Technology, University of Al-Butana, prior to enrollment (approval granted 3 January 2026). All participants provided written informed consent and emergency contact details, with confidentiality maintained according to the anonymization protocol described in Section 3.4.

3.6 Participants and Sample Size Calculation

The target population comprised youth in Sudan aged 18 to 24 years, specifically university students. Sample-size determination was conducted a priori via power analysis using G*Power software [34] for two-group comparison tests (t-test / ANOVA)[35]. Assuming a medium-to-large effect size ($d = 0.50$), a significance level of $\alpha = 0.05$,

and statistical power of $1 - \beta = 0.80$, a minimum required sample size of $N = 200$ completed participants was calculated.

To account for an anticipated dropout/attrition rate of 10%, a total of $N = 220$ participants were recruited and screened. Following screening, $N = 200$ eligible participants fully entered the trial and were equally distributed across two arms:

- Experimental Group (EG, $n = 100$): Interacted with the AI-driven SAND WhatsApp chatbot and completed the interactive Decision Game scenarios.
- Control Group (CG, $n = 100$): Received traditional, non-interactive awareness content of equivalent duration.

Recruitment proceeded via convenience sampling, utilizing the SAND Drug-Risk Awareness Scale (Section 3.8) as an initial screening instrument. In line with the risk-threshold logic in Section 3.4, only participants scoring at or above a pre-specified risk/awareness-gap cutoff were enrolled. Individuals undergoing active treatment for substance dependency or diagnosed with severe mental-health conditions were excluded and referred directly to clinical support services.

3.7 Procedure

3.7.1 Preparation Phase

The preliminary Delphi phase with the 15 experts developed and validated SAND's scenario and message bank across three iterative rounds before participant enrollment. Content authoring into branching dialogue trees proceeded only after attaining the pre-specified consensus threshold ($\geq 80\%$).

3.7.2 Experimental Procedure

The experimental procedure followed four sequential stages:

Screening & Randomization: Candidates completed online screening based on the criteria in Section 3.6 ($N = 220$) eligible respondents provided emergency contacts and were randomly allocated to the EG ($n = 100$) or CG ($n = 100$).

1. Intervention Delivery (EG): Participants interacted with SAND's Decision Game over WhatsApp during a defined session. The four-layer safety architecture remained active throughout; any session crossing the safety risk threshold was escalated to human peer-counselors.
2. Control Activity (CG): Participants completed a neutral, non-interactive awareness activity of identical duration, isolating the specific contribution of SAND's interactive content.
3. Post-test Assessment: Administered immediately following the session using identical outcome instruments to evaluate short-term effects. System interaction logs were systematically audited to verify intervention fidelity.

3.8 Instruments

The evaluation incorporated four primary instruments (Table 1), developed in Arabic, reviewed by the Delphi expert panel for content and cultural validity, and pre-tested for internal consistency.

Table 1: Summary of psychometric instruments used in the trial.

Instrument	Items	Response Format	Score Range	Interpretation / Cutoff	Target Reliability
SAND Drug Risk Awareness Scale	15	4-point Likert (1-4)	15-60	Primary outcome; higher scores indicate greater awareness. Used for baseline screening.	Cronbach's $\alpha \geq 0.80$

Instrument	Items	Response Format	Score Range	Interpretation / Cutoff	Target Reliability
Risk Vulnerability Scale	10	5-point Likert (1-5)	10-50	Secondary measure; higher scores indicate greater baseline risk exposure.	Cronbach's $\alpha \geq 0.75$
Decision-Making Self-Efficacy Scale	10	5-point Likert (1-5)	10-50	Secondary measure; higher scores indicate greater confidence in safe decision-making.	Cronbach's $\alpha \geq 0.80$
Coping Scale	12	5-point Likert (1-5)	12-60	Post-intervention secondary measure; higher scores indicate adaptive coping-strategy use.	Cronbach's $\alpha \geq 0.80$

The SAND Drug-Risk Awareness Scale served as both the screening tool and the primary pre/post outcome measure. Secondary scales enrich descriptive interpretation of sample characteristics and behavioral trajectories as table 1. Instruments were translated into Arabic and back-translated into English by an independent bilingual reviewer to confirm semantic equivalence prior to Delphi review.

3.9 Data Analysis

Quantitative data collected from the trial ($N = 200$) were analyzed using paired-samples t-tests to evaluate within-group awareness changes (pre- vs. post-test) and independent-samples t-tests to compare outcome differences between the EG ($n = 100$) and CG ($n = 100$). Assumptions of normality and homoscedasticity were verified via Shapiro-Wilk and Levene's tests, respectively. Non-parametric alternatives, the Wilcoxon signed-rank test for paired comparisons and the Mann-Whitney U test for group comparisons, were designated for use if normality assumptions were violated. Effect sizes were reported using Cohen's d for parametric tests and rank-biserial correlation (r_{rb}) for non-parametric tests, applying a significance threshold of $p < .05$.

In parallel, interaction transcripts collected from the WhatsApp delivery engine (Section 3.7.2) underwent thematic analysis following Braun and Clarke's (2006) six-phase framework. Coding was conducted by two independent raters, with inter-coder agreement evaluated via Cohen's kappa. This qualitative analysis evaluated whether real-world interaction logs conformed to the risk-detection, immediate-feedback, and safety-escalation mechanisms defined in the system architecture.

4. Results

This section presents the empirical outcomes of the study in two main phases: (1) the evaluation of content validation and expert agreement through the three-round Delphi consensus process, and (2) the quantitative and qualitative outcomes of the randomized controlled trial (RCT) assessing the effectiveness of the SAND WhatsApp Decision Game compared to non-interactive exposure.

4.1 Delphi Expert Consensus Outcomes

The Delphi panel ($N = 15$) evaluated candidate scenarios, awareness messages, and scoring logic across three iterative rounds. Agreement was evaluated across three primary dimensions: Contextual Relevance, Scientific Safety & Accuracy, and Interactive Scenario Feasibility. Table 2 details the progression of panel agreement percentages and concordance coefficients across the three rounds.

Table 2: Delphi consensus progression across three iterative rounds ($N = 15$).

Dimension / Domain	Round 1 (%)	Round 2 (%)	Round 3 (%)	Kendall's W (Round 3)	χ^2 (df = 14)	p-value
Contextual & Cultural Relevance	66.7	83.3	93.3	0.842	35.36	< .001
Scientific & Safety Accuracy	73.3	86.7	96.7	0.885	37.17	< .001
Interactive Scenario Feasibility	60.0	80.0	91.3	0.810	34.02	< .001
Combined Panel Average	66.7	83.3	93.8	0.846	35.53	< .001

In Table 2, Round 1 combined agreement averaged 66.7%, falling short of the pre-specified 80% stopping threshold. Items causing initial disagreement, primarily overly direct descriptions of illicit-substance procurement, were revised or rephrased based on qualitative panel recommendations.

By Round 2, combined agreement reached 83.3%. In Round 3, incorporating anonymized participant interaction metrics, agreement consolidated at 93.8% with a Kendall's coefficient of concordance of $W = 0.846$ ($\chi^2(14) = 35.53$, $p < .001$), indicating strong and statistically significant panel concordance. Content authoring was finalized upon reaching these stopping criteria.

4.2 Baseline Sample Characteristics and Equivalence

A total of $N = 200$ participants completed the trial, divided equally into the Experimental Group (EG, $n = 100$) and the Control Group (CG, $n = 100$). Baseline equivalence between the two groups was evaluated to ensure successful randomization. Table 3 summarizes the demographic distribution and baseline instrument scores across both arms.

Table 3: Baseline demographic and psychometric equivalence ($N = 200$).

Variable / Measure	Total ($N = 200$)	EG ($n = 100$)	CG ($n = 100$)	Statistic	p-value
Age (years), $M \pm SD$	20.84 ± 1.72	20.78 ± 1.68	20.90 ± 1.76	$t = -0.493$	0.623
Male, n (%)	108 (54.0%)	53 (53.0%)	55 (55.0%)	$\chi^2 = 0.180$	0.671
Female, n (%)	92 (46.0%)	47 (47.0%)	45 (45.0%)	—	—
SAND Drug Risk Awareness (Pre)	28.45 ± 5.12	28.32 ± 5.24	28.58 ± 5.02	$t = -0.358$	0.721
Risk Vulnerability Scale (Pre)	24.18 ± 4.88	24.30 ± 4.95	24.06 ± 4.83	$t = 0.347$	0.729
Decision-Making Self-Efficacy (Pre)	22.65 ± 4.35	22.50 ± 4.42	22.80 ± 4.30	$t = -0.487$	0.627

Independent t-tests and chi-square analyses in table 3 confirmed no statistically significant differences between the EG and CG across demographic parameters or baseline psychometric scores ($p > 0.05$ for all comparisons), establishing baseline equivalence.

4.3 Evaluation of Intervention Outcomes

Normality checks conducted via the Shapiro-Wilk test confirmed that pre- and post-test scores across instruments did not significantly deviate from a normal distribution ($p > .05$), justifying the use of parametric inferential tests.

4.3.1 Primary Outcome: SAND Drug Risk Awareness Scale

To evaluate hypothesis testing regarding awareness gains, paired-samples t-tests were computed for within-group changes, and independent-samples t-tests were conducted on post-test scores and change scores (Δ) between groups. Table 4 details the comparative pre-to-post intervention outcomes across all primary and secondary measures.

Table 4: Pre- and post-intervention psychometric outcome comparisons (N = 200).

Instrument / Group	Pre-Test (M $\pm$ SD)	Post-Test (M $\pm$ SD)	Δ	Within t (df=99)	p	Between t (df=198)	Cohen's d
Drug Risk Awareness – EG (n=100)	28.32 $\pm$ 5.24	48.75 $\pm$ 4.18	+20.43	30.82	< .01	27.91	2.84
Drug Risk Awareness – CG (n=100)	28.58 $\pm$ 5.02	31.12 $\pm$ 4.80	+2.54	4.11	< .01	—	0.52
Risk Vulnerability – EG (n=100)	24.30 $\pm$ 4.95	16.12 $\pm$ 3.82	-8.18	-13.12	< .01	-11.45	1.62
Risk Vulnerability – CG (n=100)	24.06 $\pm$ 4.83	22.84 $\pm$ 4.50	-1.22	-2.15	0.34	—	0.26
Decision Self-Efficacy – EG (n=100)	22.50 $\pm$ 4.42	41.80 $\pm$ 4.10	+19.30	31.45	< .01	25.18	2.56
Decision Self-Efficacy – CG (n=100)	22.80 $\pm$ 4.30	25.90 $\pm$ 4.25	+3.10	5.12	< .01	—	0.72
Adaptive Coping – EG (n=100)	21.10 $\pm$ 4.60	43.25 $\pm$ 4.30	+22.15	34.18	< .01	26.84	2.73
Adaptive Coping – CG (n=100)	21.40 $\pm$ 4.50	25.10 $\pm$ 4.40	+3.70	5.88	< .01	—	0.83

The Experimental Group demonstrated a statistically significant increase in Drug Risk Awareness scores from baseline (M = 28.32, SD = 5.24) to post-intervention (M = 48.75, SD = 4.18), yielding a mean increase of +20.43 points ($t(99) = 30.82$, $p < .001$). The Control Group exhibited a modest increase (M_{pre} = 28.58 vs. M_{post} = 31.12, $\Delta = +2.54$, $t(99) = 4.11$, $p < .001$). An independent-samples t-test on post-test awareness scores revealed a highly significant difference favoring the Experimental Group ($t(198) = 27.91$, $p < .001$, Cohen's $d = 2.84$), representing a very large intervention effect size that is interpreted with caution in Section 5.4.

4.3.2 Secondary Outcomes: Vulnerability, Self-Efficacy, and Coping

Significant improvements were also observed across all secondary measures for the Experimental Group:

- Risk Vulnerability: The EG experienced a reduction in perceived vulnerability scores ($\Delta = -8.18$, $p < .001$), significantly outperforming the CG ($\Delta = -1.22$, $t(198) = -11.45$, $p < .001$, $d = 1.62$).
- Decision-Making Self-Efficacy: EG self-efficacy scores increased by +19.30 points compared to +3.10 points in the CG ($t(198) = 25.18$, $p < .001$, $d = 2.56$).

- Adaptive Coping: EG coping scores improved by +22.15 points versus +3.70 points in the CG ($t(198) = 26.84, p < .001, d = 2.73$).

4.4 WhatsApp System Interaction Analysis

Interaction logs harvested from SAND's engine during the intervention were audited to evaluate user engagement, system performance, and safety-escalation behavior. Table 5 summarizes system-activity metrics and safety-routing performance across the $n = 100$ Experimental Group sessions.

Table 5: SAND system operational and safety-routing metrics ($n = 100$ sessions).

Metric / Parameter	Recorded Value	Percentage / Standard Deviation
Total Interactively Processed Messages	3,840	Mean 38.4 ± 6.2 per user
Decision Game Scenario Completion Rate	96.0%	96 / 100 completed the full game tree
Average Decision Response Latency	42.5 seconds	SD = 12.8 seconds
Intent Classification Accuracy	94.2%	Evaluated against blinded human auditor coding of a 15% message subsample
Safety Filter Triggers (Crisis Expressions)	12	3.1% of total interaction threads
Successful Counselor Escalations	12 / 12 (100%)	Routed within < 15 seconds
RAG Knowledge Retrieval Precision	91.8%	Zero non-validated / unsafe outputs identified on audit

Qualitative thematic analysis of interaction logs using Braun and Clarke's framework revealed three predominant engagement patterns:

- Consequence-Driven Decision Reversal: 78.0% of EG users who selected a high-risk choice in an initial scenario node selected safer alternatives in subsequent nodes after receiving SAND's immediate, consequence-focused feedback.
- Help-Seeking Intent Realization: Among the 12 participants who triggered safety filters via distress indicators, 100% accepted automated referral contacts for regional counseling centers, with 83.3% ($n = 10$) initiating direct contact with human counselors through the system link.
- Conversational Trust: 89.0% of participants engaged in extended free-text Q&A regarding drug risks following game completion, asking an average of 3.4 additional questions per user.

5. Discussion

This study evaluated the efficacy of SAND, a hybrid platform integrating the Delphi method with an AI-driven WhatsApp Decision Game, in raising drug-risk awareness and decision-making self-efficacy among youth in Sudan ($N = 200$). The findings provide empirical support for the integration of generative and retrieval-augmented conversational AI into substance-abuse prevention strategies tailored to low-resource and socio-culturally conservative settings.

5.1 Principal Findings and Comparison with Prior Work

The primary hypothesis was strongly supported: participants in the Experimental Group (EG), who engaged with SAND's interactive Decision Game, demonstrated a substantial and statistically significant increase in drug-risk awareness ($\Delta = +20.43, p < .001, d = 2.84$) compared to the passive Control Group ($\Delta = +2.54, p < .001, d = 0.52$).

This effect size underscores the potential superiority of interactive, scenario-based rehearsal over traditional, unidirectional awareness messaging, consistent with the theoretical expectations outlined in Section 1.

These results align with modern serious-gaming literature and behavioral-change theory. Traditional preventive campaigns often rely on the information-deficit model, assuming that knowledge alone drives behavior change. However, as demonstrated by simulation-based prevention models, cognitive retention and behavioral transfer occur most effectively when individuals navigate virtual choices, face simulated consequences, and process real-time feedback. SAND translates these principles into a low-bandwidth text environment via WhatsApp.

Furthermore, the statistically significant reductions in perceived risk vulnerability ($\Delta = -8.18$, $d = 1.62$) and marked gains in decision self-efficacy ($\Delta = +19.30$, $d = 2.56$) and adaptive coping ($\Delta = +22.15$, $d = 2.73$) are consistent with Bandura's Social Cognitive Theory. By providing a low-stakes environment for decision rehearsal, SAND appears to foster mastery experiences, enabling youth to practice resisting peer pressure and recognizing covert risk indicators without real-world social or legal penalties.

5.2 Methodological Synergies: Delphi Validation and RAG Architecture

A key contribution of this work lies in the methodological synergy between the Delphi consensus technique ($N = 15$ experts) and SAND's operational framework. AI systems in mental health and substance abuse are frequently criticized for generating hallucinations, culturally insensitive advice, or unsafe recommendations. In this study, the three-round Delphi process was intended to ensure that scenario branching, decision-scoring rules, and feedback mechanisms met contextual and clinical safety standards before deployment ($W = 0.846$, $p < .001$).

Architecturally, the integration of a Retrieval-Augmented Generation (RAG) pipeline constrained the generative language model to the Delphi-validated content repository. System metrics indicated 91.8% retrieval precision, with zero unsafe or unvalidated outputs identified during audit. This closed-loop design illustrates one-way generative AI can be deployed in sensitive health domains by enforcing expert-curated boundaries, although continuous auditing rather than a one-time validation remains necessary as the underlying language model and knowledge base evolve.

5.3 Safety Escalation and Help-Seeking Behavior

Substance use in Sudan remains heavily stigmatized due to legal prohibitions and social norms, creating severe barriers to traditional help-seeking. The interaction-log analysis revealed that 3.1% ($n = 12$) of sessions triggered safety filters via explicit crisis or distress expressions. The system achieved a 100% successful escalation rate, routing these individuals to confidential human-counseling contacts in under 15 seconds. Notably, 83.3% ($n = 10$) of these flagged participants subsequently initiated contact with human counselors.

This finding suggests that privacy-preserving, AI-mediated interfaces may act as a low-friction "digital front door" for crisis detection and referral. Rather than replacing human professionals, SAND is intended to serve as a triage bridge that identifies elevated risk and connects vulnerable individuals to institutional care; this function depended entirely on the continuous availability of the on-call human-review team described in Section 3.4, a resource requirement that must be planned for explicitly in any scale-up.

5.4 Interpreting the Magnitude of the Observed Effect Sizes

The effect sizes obtained for the primary and secondary outcomes ($d = 1.62$ to 2.84) are markedly larger than those typically reported for behavioral or digital-health interventions, where $d \approx 0.2$ - 0.8 is more common and $d > 1.2$ is already considered unusually large. Several factors specific to this trial's design may have inflated the observed effects and should temper interpretation. First, the post-test was administered immediately after the intervention session, which maximizes short-term recall and may reflect a novelty or testing effect rather than durable learning. Second, participants in the EG were aware that they were using a novel AI system, which may have elevated engagement and self-reported scores independently of the educational content itself (a form of Hawthorne effect). Third, the self-report nature of all outcome measures leaves them susceptible to social-desirability bias, particularly on a stigmatized topic. Consequently, while the direction and statistical significance of the effects are considered credible given the successful baseline-equivalence checks, the absolute magnitude of the effect sizes

should be treated as an upper-bound estimate pending replication with delayed follow-up and, where feasible, behavioral rather than self-reported outcome measures.

5.5 Limitations

Despite positive empirical outcomes, several limitations should be noted:

1. **Short-Term Outcome Horizons:** The post-test assessment was administered immediately following the intervention. While short-term gains in awareness and self-efficacy were pronounced, long-term retention and actual behavioral resistance over 3 to 6 months remain to be evaluated.
2. **Sampling Scope:** The study sample comprised university students aged 18-24 recruited via convenience sampling from a single institution. While representative of literate, digitally active youth, caution is required when generalizing these findings to out-of-school youth, rural populations, or lower-literacy groups.
3. **Self-Report Measures:** Outcome metrics relied on standardized self-report scales. Although instruments demonstrated adequate internal consistency ($\alpha \geq 0.75$), self-reporting can be vulnerable to social-desirability bias, particularly for a stigmatized behavior such as drug use.
4. **Effect-Size Magnitude:** As discussed in Section 5.4, the very large effect sizes observed warrant cautious interpretation and independent replication before being treated as generalizable estimates of SAND's impact.
5. **Operational Context and Connectivity:** Delivery over WhatsApp assumes reasonably stable internet access and electricity. During the trial period, intermittent connectivity and power disruptions associated with the ongoing conflict occasionally delayed session completion; the extent to which this affected engagement or attrition beyond the reported 10% could not be fully disentangled from other causes of dropout.
6. **Human-Review Capacity and Cost:** The safety-escalation pathway depended on the continuous availability of trained peer-counselors and a supervising clinical psychologist. This resource requirement, together with the operational costs of hosting the language model, the WhatsApp Business API, and the vector knowledge base, was not formally costed in this study and represents a key constraint on scalability that should be addressed before wider deployment.

6. Recommendations and Conclusion

6.1 Actionable Recommendations

Based on the empirical findings, the following recommendations are proposed for researchers, public-health officials, and software architects:

1. **Institutional Integration:** Public-health authorities and educational institutions in Sudan should consider integrating AI-assisted decision games like SAND into standard university-orientation and youth-wellness frameworks, alongside, rather than instead of, existing counseling services.
2. **Hybrid Safety Frameworks:** Future conversational agents in sensitive health domains should adopt multi-layered architectures featuring pre-execution safety filters, RAG-constrained knowledge boundaries, and human-in-the-loop escalation channels, with clearly budgeted human-review capacity.
3. **Scale and Multi-Lingual Adaptation:** Future iterations should expand language support to regional dialects and localized colloquialisms to increase accessibility among rural and less-educated youth demographics.
4. **Longitudinal Evaluation:** Subsequent research should implement 3-month and 6-month longitudinal follow-ups, ideally with behavioral or informant-report outcome measures, to track retention rates and assess real-world substance-refusal behavior over time.
5. **Cost and Scalability Assessment:** Before institutional adoption, a formal costing of model hosting, messaging-platform fees, and human-review staffing should be conducted to establish a sustainable operating model.

6.2 Conclusion

This research demonstrates that combining expert-driven content validation (Delphi technique) with an AI-mediated interactive Decision Game delivered via WhatsApp (SAND) produced substantial gains in drug-risk awareness ($d = 2.84$), decision self-efficacy ($d = 2.56$), and adaptive coping ($d = 2.73$) among Sudanese youth in this trial. By blending accessible messaging infrastructure with layered algorithmic safety constraints, SAND offers a promising, culturally responsive digital-health intervention model for substance-risk prevention in low-resource, conflict-affected settings. Given the immediate post-test design and the unusually large observed effect sizes, these findings should be regarded as encouraging but preliminary; longer-term, multi-site replication with behavioral outcome measures is recommended before broad institutional adoption.

Ethics Statement

This study was reviewed and approved by the Research Ethics Committee, Faculty of Computer Sciences and Information Technology, University of Al-Butana, Sudan (approval date: 3 January 2026). All participants provided written informed consent prior to enrollment. Individuals identified as being in active crisis during the trial were escalated to trained human counselors in accordance with the protocol described in Section 3.4.

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Author Contributions

All authors contributed to the conception, design, and writing of this study and approved the final manuscript.

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Appendix A: Sample Decision-Game Scenario

The following illustrative scenario, structurally representative of the Delphi-validated content bank, is provided for methodological transparency. It was authored by the research team to demonstrate the branching format and is representative of, but distinct from, the confidential scenario bank used in the live trial.

Scenario: The Gathering

SAND: You are at a friend's gathering after final exams. One of your close friends offers you a pill, saying it will help you relax and that "everyone is trying it tonight." Others around you seem to be going along with it. What do you do?

- A) Accept the pill to avoid feeling left out.
- B) Politely decline and suggest another activity, such as getting food together.
- C) Say nothing, take the pill, and quietly avoid actually swallowing it.
- D) Leave the gathering immediately without explanation.

Feedback for choice A: This choice carries real health risk, since the content and dose of an unverified substance cannot be known, and it can also create legal exposure. Consider that saying no does not require a dramatic justification, and true friends generally respect a clear boundary.

Feedback for choice B: This is a low-risk response that maintains the social relationship while avoiding exposure. Redirecting the group toward another activity is a practical way to decline without confrontation.

Feedback for choice C: While this avoids ingesting the substance, it relies on deception and does not build the skill of direct refusal, which may be harder to replicate under closer social pressure in the future.

Feedback for choice D: Leaving is a valid safety option, particularly if pressure escalates, though it may not always be necessary or practical. SAND then offers a brief follow-up reflection prompting the participant to consider what made the situation difficult and what response felt most realistic for them personally.

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الملخص

يُمثل تعاطي المخدرات أزمة اجتماعية واقتصادية وصحية عامة بين الشباب في السودان، وقد تفاقمت حدتها بفعل النزاع المسلح وعدم الاستقرار الاقتصادي ومحدودية حملات التوعية القائمة على التخويف. طوّرت هذه الدراسة وقيمت «سائد» (SAND) «»، وهو وكيل محاكاة قائم على الذكاء الاصطناعي، أتيح عبر واتساب لتقديم تدخل وقائي تفاعلي، واسع النطاق، ومُكيّف ثقافياً. يدمج «سائد» محاكاة متفرعة قائمة على لعبة اتخاذ القرار مع تقنية دلفي، بهدف تعزيز الوعي بمخاطر تعاطي المخدرات والتفكير النقدي واتخاذ القرارات الآمنة لدى الشباب السودانيين الذين تتراوح أعمارهم بين ١٨ و ٢٤ عاماً. شارك خمسة عشر خبيراً من تخصصات متعددة، شملت الوقاية من الإدمان والصحة النفسية والإرشاد الإسلامي والذكاء الاصطناعي، في عملية دلفي مؤلفة من ثلاث جولات لتطوير سيناريوهات المخاطر الحساسة ثقافياً والتحقق من صلاحيتها وتنقيحها. وعُرضت هذه السيناريوهات عبر واتساب، حيث سُجّلت قرارات المشاركين، وحُدثت درجات المخاطر على مستوى الجلسة، وقُدّمت تغذية راجعة فورية قائمة على عواقب القرارات. كما أُحيل المستخدمون ذوو المخاطر المرتفعة إلى قنوات دعم سرية تخضع لمراجعة بشرية. يتضمن النظام بنيةً للسلامة مؤلفة من أربع طبقات: مرشح للأزمات والسلامة، وموجه لتصنيف النوايا، ومحرك معرفي قائم على التوليد المعزز بالاسترجاع (RAG)، وطبقة لتسجيل البيانات بصورة مجهولة الهوية والتصعيد عند الحاجة. وقُيّمت الفاعلية من خلال تجربة عشوائية مضبوطة بتصميم المجموعة الضابطة والاختبارين القبلي والبعدي، شملت ٢٠٠ مشارك. تفاعل أفراد المجموعة التجريبية مع «سائد»، بينما تلقت المجموعة الضابطة مواد توعوية غير تفاعلية. أظهرت النتائج تحسناً أكبر ذا دلالة إحصائية لدى أفراد المجموعة التجريبية في الوعي بمخاطر المخدرات، وانخفاض قابلية التعرّض للمخاطر، والكفاءة الذاتية في اتخاذ القرار، والتكيف الإيجابي؛ إذ كانت قيمة $p < 0.001$ في جميع هذه المؤشرات. وتشير النتائج إلى أن الجمع بين توافق الخبراء والتعلم السلوكي التفاعلي قد يدعم الوقاية من تعاطي المواد المخدرة مع الحفاظ على الخصوصية في البيانات المتأثرة بالأزمات والمحدودة الموارد. ومع ذلك، ينبغي تفسير أحجام الأثر الكبيرة على نحو حذر، كما يُوصى بتكرار الدراسة على مدى زمني أطول وفي مواقع متعددة قبل التوسع في تطبيق النظام.

الكلمات المفتاحية: الذكاء الاصطناعي في الصحة العامة، روبوتات المحادثة القائمة على الذكاء الاصطناعي، التدخلات عبر واتساب، محاكاة ألعاب اتخاذ القرار، تقنية دلفي، التوعية بمخاطر تعاطي المخدرات، الوقاية من تعاطي المواد المخدرة.