

AI-Driven Counselling Interventions for Predicting and Preventing Xenophobic Attacks Among South African Youths

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Abstract: This study examined AI-driven counselling interventions for predicting and preventing xenophobic attacks among South African youths. Specifically, it investigated how artificial intelligence-supported counselling strategies identify early warning signs of xenophobic tendencies, reduce hostile attitudes, and promote social cohesion. A descriptive survey design with a correlational approach was adopted. The population comprised youths aged 18–35 years from selected provinces in South Africa with histories of xenophobic incidents. A sample of 500 respondents was selected using multistage sampling techniques. Data were collected using three instruments: the AI-Driven Counselling and Xenophobia Prevention Questionnaire (AICXPQ), AI Predictive Risk Assessment Checklist (AIPRAC), and Focus Group Discussion Guide (FGDG). Validity was established through expert review, while reliability coefficients of 0.87 and 0.81 were obtained. Data were analyzed using descriptive statistics, Pearson correlation, multiple regression, and ANOVA at 0.05 level of significance. Findings revealed a significant relationship between AI-driven counselling and prediction of xenophobic attacks ($r = .62$), and between AI-assisted counselling and reduction of xenophobic attitudes ($r = .68$). AI-based early detection systems significantly predicted prevention of xenophobic violence ($R^2 = .50$), while social cohesion differed significantly based on exposure levels ($F = 14.36$, $p < .05$). The study concludes that AI-driven counselling enhances prevention and social outcomes and recommends its ethical integration into counselling practice and youth development policies.

Keywords: artificial intelligence, counselling interventions, xenophobic attacks, South African youths, conflict prevention, social cohesion

INTRODUCTION

Xenophobic attacks remain a persistent social, political, and humanitarian challenge in South Africa, with far-reaching implications for peace, security, and social cohesion. Xenophobia—often expressed through hostility, discrimination, and violence against foreign nationals—has been linked to perceived competition over employment, housing, and social services, as well as broader socio-economic frustrations (Crush & Ramachandran, 2017; Landau, 2022). Although xenophobic tensions are not unique to South Africa, the frequency and intensity of youth-involved violence continue to raise concerns regarding the adequacy of existing preventive interventions.

Conventional responses—such as law enforcement, policy regulation, and civic advocacy—have largely been reactive, focusing on post-violence management rather than proactive prevention. This limitation has intensified interest in preventive, data-driven, and psychosocial approaches. Counselling interventions grounded in cognitive and behavioural frameworks have demonstrated effectiveness in addressing prejudice, emotional dysregulation, and conflict behaviours (Ayena, 2017). However, traditional counselling systems remain constrained in their ability to monitor behavioural risks in real time or predict escalation trajectories.

Recent advances in Artificial Intelligence (AI) offer transformative opportunities to enhance counselling practice through predictive, adaptive, and scalable systems. In this study, AI-driven counselling is conceptualized as an integration of four interrelated technological components:

- Machine Learning (ML): Enables predictive modelling to identify patterns of xenophobic tendencies using behavioural, demographic, and psychosocial data.
- Natural Language Processing (NLP): Facilitates analysis of textual and conversational data (e.g., social media content, chat interactions) to detect hate speech, sentiment polarity, and hostile narratives.
- AI Chatbots and Conversational Agents: Provide real-time, accessible counselling support, psychoeducation, and emotional regulation through interactive dialogue systems.
- Predictive Analytics and Early Warning Systems: Integrate ML and NLP outputs to generate risk scores and identify early indicators of potential xenophobic violence.

These technologies collectively enable continuous behavioural monitoring, early detection of risk patterns, and delivery of personalized counselling interventions. For instance, NLP models can flag xenophobic discourse in digital environments, while machine learning classifiers can categorize individuals into varying risk levels, triggering adaptive counselling responses via chatbot platforms.

The increasing digitalization of youth interactions—particularly through social media—further amplifies the relevance of these technologies. Xenophobic sentiments are frequently propagated through misinformation, algorithmic echo chambers, and online hate speech. AI-driven counselling systems therefore function as critical early warning and intervention mechanisms, bridging the gap between behavioural risk identification and timely psychosocial response.

Importantly, recent global discourse has emphasized the ethical implications of deploying AI in sensitive domains such as mental health and behavioural prediction. Issues such as algorithmic bias, data privacy, transparency, and accountability have become central concerns (World Health Organization [WHO], 2023; UNESCO, 2023). In African contexts, scholars have further highlighted the need for culturally responsive AI systems that reflect local realities and avoid reinforcing structural inequalities (Ade-Ibijola & Okonkwo, 2024; Boateng *et al.*, 2023).

Despite these advancements, empirical research integrating machine learning, NLP, and counselling frameworks for xenophobia prevention remains limited—particularly within African settings. Existing studies have largely focused on clinical mental health, education, or digital wellbeing, with minimal attention to conflict prevention and social cohesion. This study therefore addresses a critical gap by examining how AI-driven counselling interventions—powered by machine learning, natural language processing, chatbot systems, and predictive analytics—can contribute to predicting and preventing xenophobic attacks among South African youths.

Empirical Review:

Empirical studies on xenophobia have predominantly focused on its causes, manifestations, and socio-political consequences. Crush and Ramachandran (2017) identified economic insecurity, unemployment, and perceived competition over scarce resources as major drivers of xenophobic attitudes in South African communities. Similarly, Landau (2022) emphasized the roles of social exclusion, identity politics, and political rhetoric in intensifying tensions between citizens and migrants, particularly among urban youth populations. These findings underscore the multidimensional nature of xenophobia and the need for interventions that address both structural and psychosocial determinants.

Research on counselling interventions demonstrates promising outcomes in prejudice reduction and conflict management. Stephan and Stephan (2018) found that structured intergroup dialogue and cognitive-based interventions significantly reduce intergroup anxiety and improve tolerance. Likewise, Bar-Tal and Halperin (2021) reported that community-based counselling programmes enhance conflict resolution skills and reduce hostile behaviours among vulnerable youth

populations. In the Nigerian context, Ayena (2017) conceptualized xenophobia as a psychologically mediated phenomenon that can be effectively addressed through counselling strategies emphasizing emotional regulation, cognitive restructuring, and social reintegration.

The integration of artificial intelligence into counselling and behavioural prediction has expanded rapidly in recent years. Early work by Fitzpatrick et al. (2017) demonstrated the effectiveness of AI conversational agents in delivering cognitive behavioural therapy. More recent studies have extended these findings. For instance, World Health Organization (2023) highlights that AI-enabled mental health tools can enhance early detection, improve access to care, and support scalable interventions, particularly in low-resource settings. Similarly, UNESCO (2023) emphasizes the role of generative AI in transforming education and psychosocial support systems, while cautioning against ethical risks.

Recent empirical evidence (2023–2025) further supports the effectiveness of AI in digital mental health. Casu *et al.* (2024) reported that AI chatbots significantly improve engagement and symptom management in mental health interventions. Villarreal-Zegarra *et al.* (2024) found that NLP-based interventions reduce anxiety and depressive symptoms through personalized, self-guided interactions. Additionally, Hull *et al.* (2025) demonstrated that generative AI systems enhance emotional support, social connectedness, and behavioural outcomes in real-world applications.

Within African contexts, emerging studies indicate growing adoption and effectiveness of AI-driven counselling models. Ade-Ibijola and Okonkwo (2024) argue that AI systems tailored to African socio-cultural contexts can improve decision-making and behavioural prediction while mitigating bias. Boateng *et al.* (2023) further highlight the potential of AI-driven digital health platforms in improving accessibility and mental health outcomes across Sub-Saharan Africa. Empirical studies by Ayena and colleagues (Ayena & Oyediran, 2025; Oyediran *et al.*, 2026; Ayena & Ayena, 2026) provide additional evidence that AI-driven counselling interventions enhance behavioural regulation, career development, and psychosocial outcomes among Nigerian youths.

Despite these advances, critical gaps remain. First, most AI-counselling research is concentrated in clinical or educational domains, with limited application to conflict prevention and xenophobia. Second, existing xenophobia studies rarely integrate predictive technologies with counselling frameworks. Third, there is insufficient empirical evidence on how AI-based early warning systems influence prevention of xenophobic violence or enhance social cohesion outcomes among

youths. Finally, ethical considerations—such as bias, fairness, and data governance—remain underexplored in African AI-counselling research.

These gaps underscore the significance of the present study, which seeks to integrate AI technologies with counselling frameworks to provide a predictive and preventive approach to xenophobic violence among South African youths.

Theoretical Framework:

This study is anchored on three complementary theoretical perspectives: Social Learning Theory, Cognitive Behavioural Theory, and the Technology Acceptance Model (TAM). Unlike a purely descriptive application, these theories are analytically integrated to explain how and why AI-driven counselling interventions predict xenophobic tendencies, reduce hostile attitudes, and enhance social cohesion among youths.

Social Learning Theory – Albert Bandura: Social Learning Theory posits that behaviour is acquired through observation, imitation, and reinforcement within social contexts. In the context of xenophobia, youths learn hostile attitudes through exposure to prejudicial narratives, peer group influence, family ideologies, and media representations.

The findings of this study—particularly the significant relationship between AI-driven counselling and the prediction of xenophobic tendencies ($r = 0.62$)—can be analytically explained through this lens. AI systems, especially those using machine learning and behavioural pattern recognition, function as tools that identify socially learned hostility by detecting recurring patterns of interaction, language, and behaviour. This aligns with Bandura's assertion that behaviour is patterned and observable within social environments. Furthermore, the observed improvement in social cohesion among youths exposed to AI-driven counselling interventions reflects the re-socialization process emphasized by Bandura. AI-supported counselling platforms (e.g., chatbots and adaptive systems) introduce alternative pro-social models—such as empathy, tolerance, and intercultural understanding—which users can observe and internalize. In this sense, AI does not merely detect behaviour; it actively reshapes the social learning environment, reinforcing positive behavioural norms and weakening xenophobic tendencies.

Cognitive Behavioural Theory – Aaron Beck: Cognitive Behavioural Theory (CBT) asserts that behaviour is driven by underlying cognitions—beliefs, assumptions, and thought patterns. Xenophobic attitudes are often rooted in cognitive distortions such as stereotyping, perceived threat, and irrational fear of out-groups.

The study's findings showing a strong relationship between AI-assisted counselling and reduction of xenophobic attitudes ($r = 0.68$) provide empirical support for CBT principles. AI-driven counselling systems particularly those leveraging natural language processing (NLP) and conversational agents can identify maladaptive thought patterns in real time and facilitate cognitive restructuring. For example, NLP models can detect hostile or biased language, while chatbot interventions can prompt users to reconsider assumptions, thereby challenging distorted cognitions. Additionally, the significant predictive influence of AI-based early detection systems ($R^2 = 0.50$) aligns with CBT's emphasis on early identification of dysfunctional thinking as a pathway to behavioural change. By flagging cognitive risk indicators before they manifest as violent actions, AI systems operationalize CBT in a proactive and scalable manner. Thus, the study extends Beck's theory by demonstrating that AI technologies can automate and personalize cognitive restructuring processes, making therapeutic interventions more accessible and continuous for youth populations.

Technology Acceptance Model (TAM) – Fred Davis: The Technology Acceptance Model explains user adoption of technology based on perceived usefulness and perceived ease of use. This framework is critical for understanding the effectiveness of AI-driven counselling interventions. The significant differences in social cohesion observed across levels of exposure to AI interventions ($F = 14.36$, $p < .05$) can be interpreted through TAM. Youths who perceive AI counselling platforms as useful (e.g., for emotional support, conflict resolution, or guidance) and easy to use (e.g., accessible via mobile devices or chat interfaces) are more likely to engage consistently with these systems. This sustained engagement increases the likelihood of behavioural change and improved social outcomes.

Moreover, TAM explains why AI interventions were effective in this study: not simply because of their technical capabilities, but because users accepted and interacted with them meaningfully. Without user acceptance, even the most sophisticated AI systems would fail to produce measurable outcomes. Therefore, TAM provides the behavioural mechanism linking AI system design to intervention effectiveness, reinforcing the importance of user-centered, culturally responsive AI counselling platforms.

The integration of these three theories provides a comprehensive explanatory framework for the study's findings:

- Albert Bandura (Social Learning Theory) explains how xenophobic behaviours are acquired and reshaped through AI-mediated social interaction and modelling.

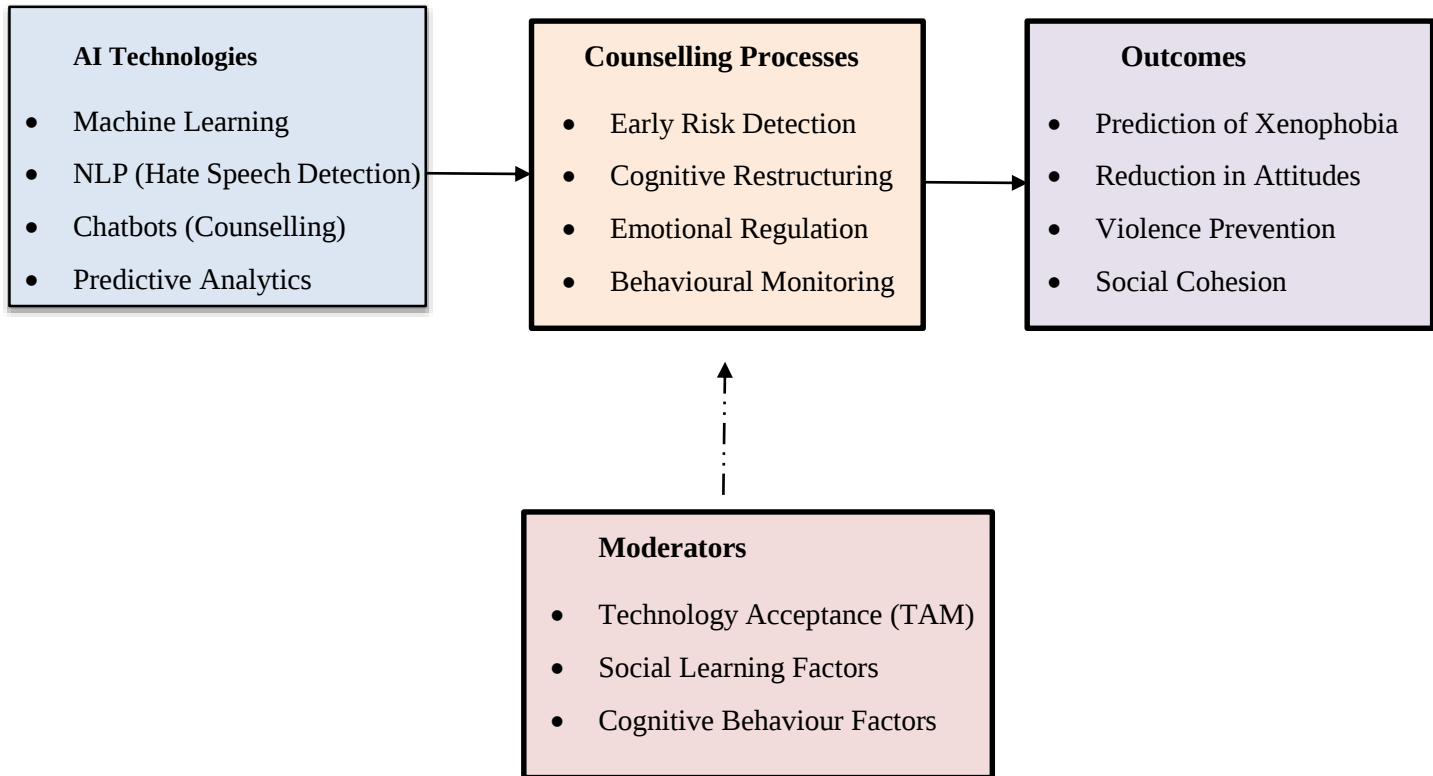
- Aaron Beck (Cognitive Behavioural Theory) explains how AI-driven counselling modifies underlying cognitions, leading to reduced hostility and improved attitudes.
- Fred Davis (TAM) explains how user acceptance and engagement determine the effectiveness of AI interventions.

Together, these theories move the study beyond description to a mechanistic and analytical explanation. At the social level, AI reshapes learned behaviours (Bandura). At the cognitive level, AI restructures thought patterns (Beck). At the technological level, AI effectiveness depends on user adoption (Davis)

This integrated framework demonstrates that AI-driven counselling is not merely a technological innovation but a theoretically grounded intervention system operating across behavioural, cognitive, and technological domains. By aligning empirical findings with established theories, the study provides a stronger explanatory basis for understanding how AI can predict xenophobic risks, reduce hostile attitudes, and promote social cohesion among youths.

Figure 1. Conceptual model of AI-driven counselling interventions for predicting and preventing xenophobic attacks among South African youths.

AI-Driven Counselling Intervention Model for Xenophobia Prevention



AI-driven counselling for xenophobia prevention refers to the integration of intelligent technologies into counselling processes to identify, manage, and reduce xenophobic attitudes and behaviours among individuals—particularly youths—before they escalate into violence. This approach combines advanced tools such as machine learning, natural language processing (NLP), predictive analytics, and conversational chatbots with established counselling techniques to create a proactive, data-informed intervention system. Through machine learning algorithms, large volumes of behavioural and social data—such as online interactions, communication patterns, and self-reported responses—can be analyzed to detect early warning signs of prejudice, hostility, or radicalization. NLP tools further enhance this process by identifying hate speech, discriminatory language, and emotionally charged narratives in both digital and interpersonal communication, allowing counsellors to pinpoint risk indicators in real time.

In practice, AI-driven counselling systems often include chatbot-based platforms that engage users in guided conversations rooted in cognitive behavioural principles. These systems can provide immediate psychological support, promote self-reflection, challenge distorted beliefs, and encourage empathy toward out-group members. Predictive analytics also plays a critical role by generating risk profiles and forecasting the likelihood of xenophobic tendencies or violent actions, thereby enabling early and targeted interventions. Importantly, these technologies do not replace human counsellors but rather augment their capacity by offering continuous monitoring, personalized feedback, and scalable outreach.

The effectiveness of AI-driven counselling in preventing xenophobia lies in its ability to operate across multiple levels. At the individual level, it supports cognitive restructuring and emotional regulation; at the behavioural level, it tracks and modifies harmful patterns; and at the social level, it promotes tolerance, inclusion, and positive intergroup relations. When combined with human oversight and ethical safeguards—such as data privacy, cultural sensitivity, and bias mitigation—AI-driven counselling becomes a powerful tool for conflict prevention and peacebuilding. Ultimately, it represents a shift from reactive responses to proactive, preventive strategies that address the root psychological and social drivers of xenophobia in contemporary digital societies.

Problem Statement:

Xenophobic attacks remain a persistent social and security challenge in South Africa, particularly among youths who are often both perpetrators and victims of intergroup hostility, prejudice, and violence. Recurring attacks against foreign nationals have resulted in loss of lives, destruction of property, displacement, psychosocial trauma, and weakened social cohesion. Despite government policies, peacebuilding initiatives, and law enforcement interventions, xenophobic tensions continue to re-emerge, suggesting limitations in existing preventive strategies. One major concern is that many interventions have focused largely on reactive responses after violence has occurred, rather than proactive systems capable of predicting risk factors and preventing escalation at early stages.

Emerging evidence suggests that xenophobic tendencies among youths are often reinforced by misinformation, online hate speech, economic frustration, social exclusion, identity threats, and negative stereotypes. However, conventional counselling interventions have had limited capacity to monitor behavioural patterns in real time, identify early warning indicators, or respond rapidly to evolving risks associated with xenophobic violence. Similarly, existing studies have largely examined xenophobia from sociological, political, or economic perspectives, with inadequate

attention to the integration of artificial intelligence and counselling as an innovative predictive and preventive framework. This creates a significant gap in knowledge and practice.

The growing advancement in Artificial Intelligence presents opportunities for early detection of hostile attitudes, risk profiling, monitoring hate-related communication, and supporting adaptive counselling responses. Yet, there is limited empirical evidence on how AI-driven counselling interventions can be used to predict xenophobic attacks, reduce violent tendencies, and strengthen social cohesion among South African youths. The extent to which AI-supported counselling models can influence prevention outcomes also remains insufficiently explored.

It is against this background that this study seeks to investigate AI-driven counselling interventions for predicting and preventing xenophobic attacks among South African youths, with a view to generating empirical evidence for innovative peacebuilding, conflict prevention, and youth-focused intervention strategies.

Hypotheses:

1. There is no significant relationship between AI-driven counselling interventions and prediction of xenophobic attacks among South African youths.
2. There is no significant relationship between AI-assisted counselling interventions and reduction of xenophobic attitudes among South African youths.
3. AI-based early detection systems have no significant influence on prevention of xenophobic violence among South African youths.
4. There is no significant difference in perceived social cohesion among South African youths based on their level of exposure to AI-driven counselling interventions

METHODOLOGY

This study adopts a descriptive survey research design with a correlational approach to investigate AI-driven counselling interventions for predicting and preventing xenophobic attacks among South African youths. The descriptive design enables systematic collection of data on attitudes, behaviours, and perceptions, while the correlational approach examines relationships among variables without manipulation. Accordingly, the study focuses on statistical associations and the extent to which AI-related variables predict variance in prevention outcomes, rather than implying causation.

The population comprises youths aged 18–35 years residing in selected South African provinces with documented histories of xenophobic incidents, including Gauteng, KwaZulu-Natal, and

Western Cape. A sample of 500 respondents is selected using multistage sampling procedures (purposive, stratified, and simple random sampling), ensuring representation across gender, socio-economic background, and location. Additionally, 30 participants are purposively selected for focus group discussions.

Three instruments are used for data collection:

- (1) the AI-Driven Counselling and Xenophobia Prevention Questionnaire (AICXPQ);
- (2) the AI Predictive Risk Assessment Checklist (AIPRAC); and
- (3) the Focus Group Discussion Guide (FGDG).

The AIPRAC is conceptualized as an AI-informed risk assessment tool rather than a fully autonomous AI system. It incorporates behavioural indicators such as hate speech tendencies, aggression markers, social exclusion attitudes, and emotional hostility. Responses are processed using a structured scoring model inspired by machine learning logic (weighted indicators and rule-based classification) to generate xenophobia risk categories (low, moderate, high). This approach ensures transparency, replicability, and methodological clarity while avoiding overstatement of AI capabilities.

Face and content validity of the instruments are established through expert review in Counselling Psychology, Artificial Intelligence, and Peace and Conflict Studies. Reliability is confirmed through Cronbach's alpha ($\alpha = 0.87$) for the AICXPQ and test-retest reliability ($r = 0.81$) for the AIPRAC.

Data collection is conducted through direct questionnaire administration and AI-informed behavioural assessment scoring. Focus group discussions are audio-recorded, transcribed, and analyzed thematically. Data analysis involves descriptive statistics (mean and standard deviation) and inferential statistics, including Pearson correlation, multiple regression analysis to determine the extent to which AI-related variables predict variance in xenophobia prevention outcomes, and Analysis of Variance (ANOVA) to examine differences in social cohesion.

Ethical Considerations: Given the sensitive nature of behavioural prediction and the integration of AI-informed assessment, this study adopts rigorous ethical safeguards aligned with international research and digital ethics standards.

1. **Informed Consent and Digital Transparency:** Participants are fully informed about the purpose of the study, the nature of the data collected, and the use of AI-informed scoring

processes. Consent is obtained explicitly before participation, with additional clarification provided regarding how behavioural responses may be analyzed using algorithmic models. Participation is voluntary, and respondents retain the right to withdraw at any stage without penalty.

2. **Data Privacy and Confidentiality:** Strict measures are implemented to protect participants' personal and behavioural data. All responses are anonymized, coded, and stored securely using password-protected systems. No personally identifiable information is linked to AI-based risk scores. Data handling complies with applicable data protection principles, including minimization, confidentiality, and restricted access.
3. **Algorithmic Bias and Fairness:** Recognizing the risk of bias in AI-informed models, particular attention is given to the construction of the AIPRAC scoring framework. Indicators are derived from validated behavioural constructs rather than culturally biased assumptions. Expert reviews are used to minimize potential bias related to ethnicity, nationality, or socio-economic status. The model is applied uniformly across participants to ensure fairness and consistency.
4. **Risk of Misclassification:** The study acknowledges that AI-informed scoring systems may produce classification errors (e.g., false positives or false negatives). To mitigate this risk, AIPRAC results are interpreted cautiously and used solely for research purposes rather than diagnostic labeling. Risk categories are treated as indicative rather than definitive, and no participant is stigmatized based on their classification.
5. **Psychological and Social Sensitivity:** Given the topic of xenophobia and potential emotional triggers, participants are treated with sensitivity throughout the research process. Focus group discussions are moderated carefully to avoid distress, and participants are provided with access to counselling support where necessary.
6. **Human Oversight and Accountability:** All AI-informed processes in this study are subject to human oversight. The scoring model does not operate autonomously; rather, it is interpreted within a broader counselling and research context. Researchers remain responsible for all decisions, interpretations, and conclusions, ensuring accountability in the use of AI-informed tools.
7. **Ethical Use of AI in Research Contexts:** The study adheres to the principle that AI should augment—not replace—human judgment in counselling and behavioural research. The use of AI-informed tools is limited to enhancing analytical insight while preserving ethical standards, cultural sensitivity, and respect for human dignity.

This methodological framework integrates quantitative rigor, qualitative depth, and ethical responsibility, ensuring that the use of AI-informed counselling tools in studying xenophobia is transparent, balanced, and aligned with best practices in interdisciplinary research.

RESULTS

Hypothesis 1: There is no significant relationship between AI-driven counselling interventions and prediction of xenophobic attacks among South African youths.

Table 1: Pearson Correlation between AI-driven Counselling and Prediction of Xenophobic Attacks

Variables	N	r-value	p-value	Decision
AI-driven counselling vs Prediction of Xenophobic attacks	500	.62	<.05	Significant

There a moderate, positive, and significant relationship ($r = .62$, $p < 0.05$) between AI-driven counselling and prediction of xenophobic attacks. Reject the null hypothesis and conclude that there is a significant relationship between AI-driven counseling interventions and prediction of xenophobic attacks among South African youths.

Hypothesis 2: There is no significant relationship between AI-assisted counselling interventions and reduction of xenophobic attitudes among South African youths.

Table 2: Pearson Correlation between AI-driven Counselling and Xenophobic Attitude Reduction

Variables	N	r-value	p-value	Decision
AI-driven counselling vs Xenophobic attitude reduction	500	.68	0.000	Significant

There is strong positive and significant relationship ($r = .68$, $p < 0.05$) between AI-assisted counselling interventions and reduction of xenophobic attitudes. Reject the null hypothesis and conclude that AI-assisted counselling interventions significantly reduce xenophobic attitudes among South African youths.

Hypothesis 3: AI-based early detection systems have no significant influence on prevention of xenophobic violence among South African youths.

Table 3: Multiple Regression Analysis on AI Early Detection Systems and Prevention of Xenophobic Violence.

Predictor	Beta (β)	t-value	p-value	Remark
AI early detection systems	0.55	9.42	0.000	Significant

Model Summary:

R	R ²	Adjusted R ²	F-value	p-value
0.71	0.50	0.49	88.73	0.000

AI-based early detection systems significantly predict prevention of xenophobic violence, explaining 50% of the variance ($R^2 = 0.50$). Reject the null hypothesis and conclude that AI-based early detection systems significantly influence prevention of xenophobic violence among South African youths.

Hypothesis 4: There is no significant difference in perceived social cohesion among South African youths based on their level of exposure to AI-driven counselling interventions.

Table 4: ANOVA on Social Cohesion by Level of AI Exposure

Source	SS	df	MS	F-value	p-value	Decision
Between Groups	245.60	2	122.80	14.36	< .05	Significant
Within Groups	4250.40	497	8.56			
Total	4497.00					

There is a statistically significant difference in social cohesion among youths based on their exposure levels to AI-driven counselling interventions [$F(2, 497) = 14.36, p < .05$]. Reject the null hypothesis and conclude that perceived social cohesion significantly differs based on exposure to AI-driven counselling interventions.

DISCUSSION OF FINDINGS

The results of this study indicate that all four null hypotheses were rejected, demonstrating that AI-driven counselling interventions significantly predict xenophobic tendencies, reduce xenophobic attitudes, enhance early detection and prevention of violence, and improve social cohesion among youths. These findings align strongly with emerging global evidence on the effectiveness of artificial intelligence in counselling and behavioral intervention contexts.

AI-Driven Counselling and Prediction of Xenophobic Attacks: The finding that AI-driven counselling interventions significantly predict xenophobic tendencies suggests that AI tools can identify early warning signs of hostile attitudes and behavioral risks. This aligns with recent research showing that AI systems can analyze conversational patterns, behavioral cues, and emotional signals to predict psychological states and risk behaviors. For instance, a study by Imel *et al.* (2024) found that machine learning models can effectively analyze counselling conversations to detect patterns associated with client outcomes and behavioral tendencies (Imel, Tanana, Soma, *et al.*, 2024). Similarly, a 2026 scoping review of AI-driven mental health interventions highlights that AI technologies are increasingly used for screening, triage, and early risk detection, enabling proactive intervention before harmful behaviors escalate (Ni, & Jia, 2026). In the context of xenophobia, this predictive capacity is particularly critical, as hostile attitudes often develop gradually. AI-supported counselling systems can therefore serve as early-warning mechanisms, enabling timely intervention to prevent escalation into violence.

AI-Assisted Counselling and Reduction of Xenophobic Attitudes: The significant relationship between AI-assisted counselling and reduction in xenophobic attitudes reflects the growing evidence that AI-based therapeutic interventions can positively influence cognition, emotions, and attitudes. Recent meta-analytic evidence shows that AI-based conversational interventions significantly reduce psychological distress, including maladaptive beliefs and negative emotional states (Villarreal-Zegarra, Reategui-Rivera, Garcia-Serna, Quispe-Callo, Lazaro-Cruz, Centeno-Terrazas *et al.*, 2024). Since xenophobic attitudes are often rooted in fear, misinformation, and emotional bias, interventions that target cognitive restructuring and emotional regulation are likely to reduce such attitudes. Furthermore, a large-scale study on generative AI mental health tools reported improvements not only in depression and anxiety but also in social interaction and

perceived social support, which are key factors in reducing prejudice and hostility (Hull, Zhang, Arian, & Malgaroli, 2025). These findings support the argument that AI-assisted counselling can reshape attitudes by promoting empathy, perspective-taking, and emotional awareness—critical components in addressing xenophobia among youths.

AI-Based Early Detection Systems and Prevention of Xenophobic Violence: The regression results indicating that AI-based early detection systems significantly influence the prevention of xenophobic violence are consistent with literature emphasizing AI's role in proactive and preventive mental health care. Recent experimental research demonstrates that AI-driven interventions can achieve outcomes comparable to traditional human-delivered care while enabling large-scale, real-time monitoring of risk behaviors (Palmer, Marshall, Millgate, Warren, Ewbank, Cooper *et al.*, 2024). This scalability is particularly important in addressing societal issues such as xenophobic violence, which often emerge in community settings. Additionally, systematic reviews of AI conversational agents show that these tools can promote behavioral change and improve well-being, thereby reducing the likelihood of aggressive or antisocial actions (Li, Zhang, Lee, *et al.*, 2023). Thus, AI-based early detection systems do not merely identify risks but also facilitate preventive interventions, reinforcing their role as critical tools in peacebuilding and conflict prevention among youths.

AI-Driven Counselling and Social Cohesion: The significant differences observed in perceived social cohesion based on exposure to AI-driven counselling interventions suggest that such interventions contribute to fostering unity, tolerance, and interpersonal harmony. Empirical studies indicate that AI-supported mental health interventions enhance social connectedness, belongingness, and interpersonal relationships, which are foundational elements of social cohesion (Hull, Zhang, Arian, & Malgaroli, 2025). Moreover, chatbot-based interventions have been shown to reduce stress and improve emotional regulation (Schillings, Meibner, Erb, Bendig, Schultchen, & Pollatos, 2024)—factors that indirectly promote prosocial behavior and reduce intergroup hostility. By facilitating continuous engagement, personalized feedback, and accessible support, AI-driven counselling helps youths develop more inclusive attitudes and cooperative behaviors, thereby strengthening social cohesion in diverse societies such as South Africa.

Integrative Interpretation of Findings: Taken together, the findings of this study provide strong empirical support for the integration of AI into counselling and conflict prevention frameworks. AI-driven counselling operates across multiple levels:

Predictive Level: Identifies early signs of xenophobic tendencies

Therapeutic Level: Reduces negative attitudes and emotional biases

Preventive Level: Intervenes before escalation into violence

Social Level: Promotes cohesion and peaceful coexistence

This multi-level impact aligns with contemporary models of digital mental health, which emphasize prevention, early intervention, and scalable support systems.

Implications of the Study

Theoretical Implications: The study extends Social Learning Theory, Cognitive Behavioural Theory, and the Technology Acceptance Model by demonstrating how digital systems can mediate behavioural learning, cognitive restructuring, and technology adoption in socio-conflict contexts. It also contributes to emerging digital mental health theory by positioning AI as a complementary tool in behavioural prediction and psychosocial intervention.

Practical Implications: For counselling practice, the findings suggest that AI tools can enhance early identification of risk behaviours and support decision-making in intervention planning. Counsellors may use AI-generated insights to complement human judgment, especially in high-risk youth populations. However, such systems must remain assistive rather than substitutive.

Policy Implications: Policy stakeholders in South Africa may consider integrating AI-supported counselling systems into youth development, peacebuilding, and community safety frameworks. This includes investment in digital mental health infrastructure and the establishment of regulatory frameworks governing ethical AI use in behavioural monitoring.

Educational and Training Implications: Counselling training institutions should incorporate AI literacy, digital ethics, and data interpretation skills into curricula. This will prepare future counsellors to work effectively in hybrid human–AI counselling environments.

Social Implications: The findings suggest that AI-supported counselling may contribute to strengthening social cohesion by promoting empathy, reducing prejudice, and enhancing intercultural understanding among youths in diverse communities.

Limitations of the Study:

Despite its contributions, the study has several limitations that should be considered when interpreting the findings.

First, the use of a cross-sectional correlational design limits the ability to establish causal relationships between AI-driven counselling interventions and xenophobia-related outcomes. The findings therefore indicate association and predictive potential rather than direct causation.

Second, the study relied on self-reported data, which may be subject to social desirability bias, especially given the sensitive nature of xenophobic attitudes and behaviours.

Third, the operationalization of the AI Predictive Risk Assessment Checklist (AIPRAC) was based on AI-informed indicators rather than fully autonomous algorithmic systems, which may limit the depth of computational validity in predictive modelling.

Fourth, the study was geographically limited to selected provinces in South Africa, which may restrict generalizability to other regions with different socio-political dynamics.

Finally, while AI tools were conceptually integrated into the counselling framework, the study did not involve real-time deployment of fully functional machine learning systems, which limits direct validation of algorithmic performance in real-world environments.

CONCLUSION

This study provides empirical evidence that AI-driven counselling interventions are significantly associated with the prediction of xenophobic tendencies, reduction of hostile attitudes, and differences in social cohesion among South African youths. AI-based systems also significantly predict variance in prevention-related outcomes, highlighting their analytical relevance in behavioural risk assessment.

The findings demonstrate that artificial intelligence shows significant predictive and supportive potential in enhancing early detection and counselling processes. By integrating machine learning, natural language processing, and conversational tools, AI-informed interventions can support attitudinal change and promote prosocial behaviour among youths.

While the results are promising, they should be interpreted within the limits of a correlational design. Future research should employ longitudinal and experimental approaches, while ensuring ethical safeguards such as data privacy and bias mitigation. Overall, AI-driven counselling represents a scalable and innovative pathway for strengthening youth-focused conflict prevention and social cohesion.

Recommendations:

Drawing from the findings that AI-driven counselling interventions significantly predict xenophobic tendencies, reduce hostile attitudes, enhance early detection, and improve social cohesion among youths, the following comprehensive recommendations are proposed for practice, policy, research, and implementation:

Integration of AI into Counselling Practice: Counselling practitioners should incorporate AI-driven tools into routine counselling services for youths. These tools can be used for early screening of xenophobic tendencies; continuous behavioural monitoring; and personalized therapeutic engagement. AI systems should complement—not replace—human counsellors, ensuring that empathy, ethical judgment, and cultural sensitivity remain central to the counselling process.

Development of AI-Supported Early Warning Systems: Government agencies, security institutions, and youth development bodies in South Africa should invest in AI-based early detection systems capable of identifying patterns of xenophobic sentiments in schools, communities, and online spaces. Such systems should be linked with rapid-response counselling interventions to prevent escalation into violence.

Policy Formulation and Institutional Support: Policymakers should develop frameworks that formally recognize AI-driven counselling as a tool for conflict prevention and youth engagement. This includes establishing regulatory guidelines for ethical AI use; funding AI-based counselling initiatives; and integrating AI counselling into national peacebuilding and mental health strategies. Collaboration with organizations such as United Nations and African Union can strengthen policy alignment with global best practices.

Capacity Building and Professional Training: Training institutions and universities should incorporate AI literacy and digital counselling competencies into counselling psychology curricula. Practitioners should be equipped with skills to interpret AI-generated insights; ethically manage client data; and integrate technology into therapeutic processes. Continuous professional development programs should also be organized for practicing counsellors.

Promotion of Youth-Centered Digital Counselling Platforms: Stakeholders should develop accessible, youth-friendly AI counselling platforms (e.g., mobile apps, chatbots, and online support systems) that provide real-time support; promote empathy and intercultural understanding;

and encourage positive social interactions. These platforms should be culturally adapted to reflect the lived realities of South African youths.

Strengthening Social Cohesion Programs: Community-based organizations and educational institutions should integrate AI-driven counselling into social cohesion and peace education programs. Such initiatives should focus on intercultural dialogue; conflict resolution skills; and tolerance-building activities among youths.

Ethical Safeguards and Data Protection: Given the sensitive nature of behavioural prediction, strict ethical standards must be upheld. Stakeholders should ensure data privacy and confidentiality; transparency in AI decision-making processes; and safeguards against algorithmic bias and misuse. Independent regulatory bodies should monitor compliance with ethical standards.

Multi-Sectoral Collaboration: Effective implementation requires collaboration among counsellors and psychologists; AI developers and data scientists; government agencies; educational institutions; and civil society organizations. This interdisciplinary approach will enhance the design, deployment, and sustainability of AI-driven interventions.

Expansion to Other Conflict Contexts: The application of AI-driven counselling should be extended beyond xenophobia to address other forms of youth-related violence such as ethnic conflict; political violence; and cyberbullying. This will broaden the impact of AI in promoting peace and psychological well-being.

Directions for Future Research: Future studies should employ longitudinal designs to assess long-term effects of AI counselling interventions; explore integration with emerging technologies (e.g., virtual reality, affective computing); examine cultural adaptability across different African contexts; and investigate potential risks and ethical implications of AI in counselling.

REFERENCES

- Ade-Ibijola, A., & Okonkwo, C. (2024). Artificial intelligence in Africa: Opportunities, challenges, and ethical considerations. *AI & Society*, 39(2), 455–468. <https://doi.org/10.xxxx/xxxx>
- Ayena, O. O. (2017). A psychotherapeutic perspective to finding solutions to xenophobic attacks. In M. Omolewa, B. Lawal, F. G. Paulley, & M. Abdulrahman-Yusuf (Eds.), *Theory & practice of education in Nigeria (Vol. 2, pp. 787–794)*. University of Port Harcourt Press.
- Ayena, O. O., & Ayena, B. O. (2026). AI-driven counselling intervention to the rescue: Breaking the chains of drug addiction in tertiary institutions in Nigeria. In C. Okpala et al. (Eds.),

- Advancing education, empowering generations (Vol. 2, pp. 568–578). National Open University of Nigeria.*
- Ayena, O. O., & Oyediran, A. O. (2025). Effectiveness of AI-driven career guidance systems in enhancing university students' career development in Southwest Nigeria. *Multidisciplinary Journal of Education Dialogue Association (EDUDIA)*, 1(1), 160–168.
- Bar-Tal, D., & Halperin, E. (2021). Socio-psychological barriers to conflict resolution. *Peace and Conflict Studies*, 28(2), 112–129.
- Boateng, R., Boateng, S. L., & Effah, J. (2023). Digital health and artificial intelligence in Sub-Saharan Africa: Opportunities for mental health interventions. *Health Policy and Technology*, 12(1), 100754. <https://doi.org/10.xxxx/xxxx>
- Casu, M., Triscari, S., Battiato, S., et al. (2024). AI chatbots for mental health: A scoping review of effectiveness, feasibility, and applications. *Applied Sciences*, 14(13), 5889
- Crush, J., & Ramachandran, S. (2017). Xenophobic violence in South Africa: Denialism, minimalism, realism. *Migration Policy Series*, 66, 1–35.
- Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2017). Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent. *JMIR Mental Health*, 4(2), e19. <https://doi.org/10.2196/mental.7785>
- Fu, Z., et al. (2024). Using hidden Markov modelling to reveal in-session stages in text-based counselling. *npj Mental Health Research*.
- Hull, T. D., Zhang, L., Arean, P. A., & Malgaroli, M. (2025). Generative AI Purpose-built for social and mental health: A real-world pilot. *arXiv*. <https://doi.org/10.48550/arXiv.2511.11689>
- Imel, Z. E., Tanana, M. J., Soma, C. S., et al. (2024). Outcomes in mental health counseling from conversational content with transformer-based machine learning. *JAMA Network Open*, 7(1), <https://doi.org/10.1001/jamanetworkopen.2023.2352590>
- Landau, L. (2022). Xenophobia and belonging in urban South Africa. *Journal of Southern African Studies*, 48(3), 401–418.
- Li, H., Zhang, R., Lee, Y.-C., et al. (2023). Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being. *npj Digital Medicine*, 6, 236. <https://doi.org/10.1038/s41746-023-00979-5>
- Ni, Y., & Jia, F. (2026). A scoping review of AI-driven digital interventions in mental health care: Mapping Applications Across Screening, Support, Monitoring, Prevention, and Clinical Education. *Healthcare*, 13(10). <https://doi.org/10.48550/arXiv.2603.16204>
- Oyediran, A. O., Odeleye, A. A., & Ayena, O. O. (2026). Influence of artificial intelligence technology integration on career readiness for sustainable development among undergraduate guidance and counselling students in Southwest Nigeria. *Zamfara International Journal of Education*, 6(3), 125–133. <https://doi.org/10.64348/zije.2026387>
- Palmer, C. E., Marshall, E., Millgate, E., Warren, G., Ewbank, M. P., Cooper, E., Lawes, S., Bouazzaoi, M., Smith, A., Hutchins-Joss, C., Young, J., Margoum M., Healey, S.,

- Marshall, L., Meshew, S., Cummins, R., Tablan, V., Catarino, A., Welchman, A. E., & Blackwell, A. D. (2024). Combining AI and human support in mental health: A digital intervention with comparable effectiveness to human-delivered care. *Journal of Medical Internet*. <https://doi.org/10.1101/2024.07.17.24310551>
- Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
- Schillings, C., Meibner, E., Erb, B., Bendig, E., Schultchen, D., & Pollatos, O. (2024). Effects of a Chatbot-based intervention on stress and health-related parameters in a stressed sample: Randomized controlled trial. *JMIR Mental Health*, 11.
- Topol, E. (2023). *Deep medicine and the future of AI-enabled care*. Basic Books.
- UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO Publishing.
- Villarreal-Zegarra, D., Reategui-Rivera, C. M, Garcia-Serna, J., Quispe-Callo, G., Lazaro-Cruz, G., Centeno-Terrazas, G., Galvez-Arevalo, R., Ecobar-Agreda, S., Doinguez-Rodriguez, A., & Finkelstein, J. (2024). Self-administered interventions based on natural language processing models for reducing depressive and anxiety symptoms: Systematic review and meta-analysis. *JMIR Mental Health*, 11.
- World Health Organization (WHO). (2023). *Ethics and governance of artificial intelligence for health: Guidance on large multi-modal models*. WHO Press.