American Journal of Psychiatry and Neuroscience
2026, Vol. 14, No. 3, pp. 69–82
https://doi.org/10.11648/j.ajpn.20261403.13

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Research Article

Neurocognitive and Psychosocial Drivers of Digital Help-seeking Among Kenyan Youth: Self-diagnosis, Affect Regulation, and Algorithm-shaped Symptom Attribution

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Abstract

Digital platforms have become primary spaces through which Kenyan youth interpret distress, search for mental health information, and seek coping support. Yet little Kenya-specific research explains why young people increasingly engage in self-diagnosis and symptom attribution through online environments, or how neurocognitive processes interact with psychosocial drivers and algorithmic exposure to shape help-seeking trajectories. This paper examines the neurocognitive and psychosocial mechanisms underlying digital help-seeking among Kenyan youth, focusing on three linked domains: (i) self-diagnosis as a sense-making strategy, (ii) affect regulation motives that reinforce online searching and scrolling, and (iii) algorithm-shaped symptom attribution, whereby repeated exposure to mental health narratives influences symptom labeling and perceived identity. Using an exploratory design combining digital landscape synthesis, theory-guided review, and stakeholder-informed interpretation, we develop a mechanistic framework explaining how uncertainty reduction, attentional capture, reinforcement learning, social proof, and parasocial trust interact with stigma, service constraints, and peer norms to produce distinctive digital help-seeking patterns. We argue that self-diagnosis is often psychologically adaptive in the short term because it provides emotional relief, coherence, and belonging; however, it can also generate maladaptive cycles through diagnostic anchoring, confirmation bias, and algorithmically amplified symptom salience. The paper proposes an integrated model of digital symptom attribution and identifies governance priorities including credibility cues, algorithm-aware psychoeducation, and referral integration that links high-risk digital trajectories to professional support. The framework offers a foundation for Kenya-specific research, including survey-based measurement of cognitive mechanisms, platform exposure mapping, and longitudinal designs to evaluate whether algorithm-driven symptom narratives intensify distress or improve help-seeking outcomes.

Keywords

Digital Help-seeking, Youth Mental Health, Self-diagnosis, Affect Regulation, Neurocognition, Algorithmic Exposure, Kenya, Social Media

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Received: 24 January 2026; **Accepted:** 11 February 2026; **Published:** 6 August 2026

1. Introduction

Kenyan youth are coming of age in a period of profound social, economic, and technological change, with psychosocial wellbeing increasingly shaped by intersecting stressors such as unemployment and precarity, educational pressure, social inequality, relationship instability, urbanisation, and changing cultural expectations [1-3]. Across sub-Saharan Africa, these pressures have intensified concerns about adolescent and youth mental health, particularly given the persistence of large treatment gaps, limited specialist availability, and the enduring effects of stigma on timely help-seeking [1, 4, 5]. In Kenya, mental health service access remains constrained by affordability, uneven distribution of services, limited integration of mental health into primary and school-based systems, and social norms that frame emotional vulnerability as weakness or moral failure [5-7]. These barriers encourage youth to seek "low-visibility" and socially safe pathways for managing distress, including self-reliance and peer-based coping, but increasingly also through digital platforms that offer privacy, immediacy, and social belonging without formal gatekeeping [8, 9].

Digital environments have therefore become key psychological and behavioural spaces through which Kenyan youth interpret distress, search for mental health information, and construct coping strategies. Globally, systematic reviews show that young people use online spaces for anonymous help-seeking, psychoeducation, peer affirmation, and emotional support, particularly when offline services are inaccessible or socially risky [10, 11]. These online pathways are not simply extensions of formal care; rather, they function as self-directed "sense-making infrastructures" where youth navigate distress by searching symptoms, consuming narratives, and comparing experiences in online communities. At the same time, online help-seeking can expose youth to misinformation, unregulated pseudo-therapy, privacy violations, harmful peer dynamics, and delayed transition to professional support [10-12]. In low- and middle-income contexts where mental health literacy is uneven and service pathways are fragmented, these risks may be intensified by the absence of credible signposting, limited safeguarding protocols, and weak regulation of online counselling practices [13].

A distinctive feature of contemporary digital help-seeking is the rise of self-diagnosis and symptom attribution through online platforms. Kenyan youth, like peers globally, increasingly encounter mental health language through search engines, social media feeds, and influencer narratives that frame distress using psychiatric or therapeutic labels (e.g., "depression," "anxiety," "trauma," "burnout," "ADHD," "attachment issues"). Such labels can be psychologically useful by giving distress a name, providing coherence, and reducing isolation through normalisation and belonging [10, 14]. However, the meaning and accuracy of these labels are often unstable. In algorithm-driven environments, youth may encounter repeated symptom narratives that amplify salience, promote diagnostic anchoring, and strengthen confirmation bias, particularly when content is emotionally resonant and socially validated through comments, likes, and shares [15, 16]. Systematic evidence suggests that mental health information quality on short-form platforms varies widely, with risks of misleading guidance, oversimplified causal explanations, and inconsistent or inaccurate advice, despite the potential for increased awareness and peer support [17]. These dynamics have special relevance in Kenya, where youth may adopt digital self-diagnosis as a substitute for professional consultation due to cost and stigma, thereby increasing vulnerability to mislabeling and delayed care escalation.

Understanding digital help-seeking therefore requires attention not only to social drivers but also to the neurocognitive and psychosocial mechanisms that shape online behaviour under distress. Distress is typically accompanied by uncertainty, heightened arousal, and cognitive narrowing, which can motivate information-seeking as a form of uncertainty reduction and emotion regulation [18]. Online searching and scrolling may offer immediate relief through reassurance, narrative coherence, and perceived control, reinforcing repeated engagement. In neurocognitive terms, this resembles affect regulation supported by reward-based learning, where "relief" and validation serve as reinforcing outcomes that sustain the behaviour [18]. Once a youth encounters a resonant symptom narrative, repeated algorithmic exposure can strengthen attentional capture and memory accessibility, increasing the likelihood that subsequent distress is interpreted through the same diagnostic frame. The result is an emergent phenomenon that can be described as algorithm-shaped symptom attribution a process in which platform recommendation systems, combined with youth cognitive biases, increase the perceived relevance and frequency of particular symptom categories. This may promote adaptive outcomes such as early recognition and help-seeking intentions, but also maladaptive outcomes including rumination, heightened symptom monitoring, misdiagnosis identity fixation, and increased anxiety through exposure to distress-themed content clusters [15, 19].

Trust processes further mediate these dynamics. Adolescents and young adults rarely evaluate online mental health content solely by evidence quality. Instead, trust is frequently constructed through relational cues such as relatability, shared lived experience, perceived empathy, tone, responsiveness, and community endorsement [20]. Influencers or peer creators may therefore become powerful interpretive authorities in the mental health space, shaping how youth understand symptoms, what coping actions are legitimate, and whether professional services are seen as necessary or avoidable. Public engagement research shows that social media mental health messaging is strongly shaped by resonance and platform dynamics, meaning that content reach and influence depend as much on social and emotional appeal as on clinical accuracy [21]. These realities raise urgent ethical questions in Kenya about privacy, safeguarding, misinformation, and exploitation risks, especially in environments where counselling practices may operate without clear standards and where minors can engage in emotionally intimate exchanges in poorly moderated spaces [13, 22].

Despite growing policy interest in youth mental health and digital innovation, Kenya-specific research remains limited in explaining the mechanisms by which youth engage in self-diagnosis and algorithm-shaped symptom attribution, and how these processes influence distress outcomes and care pathways. Existing intervention studies indicate that structured psychosocial and digital programmes can be effective among Kenyan adolescents, especially within school contexts [23, 24]. However, these interventions represent only a small part of the everyday digital mental health ecology. Most youth experiences occur in mainstream platforms whose design optimises engagement rather than wellbeing and whose algorithmic dynamics may generate unintended cognitive and emotional effects. There is therefore a need for a mechanistic framework that connects neurocognitive processes (uncertainty reduction, attentional capture, reinforcement learning, bias-driven interpretation) with psychosocial drivers (stigma, belonging needs, peer norms, service constraints) and algorithmic platform conditions to explain digital help-seeking trajectories in Kenya.

Accordingly, this paper examines the neurocognitive and psychosocial drivers of digital help-seeking among Kenyan youth, with specific attention to self-diagnosis, affect regulation, and algorithm-shaped symptom attribution. The paper addresses three guiding questions: (i) how do Kenyan youth use digital self-diagnosis as a sense-making strategy during distress; (ii) what affect regulation motives and reinforcement processes sustain repeated searching and scrolling; and (iii) how does algorithm-shaped exposure contribute to symptom attribution, diagnostic anchoring, and identity framing? By integrating targeted literature synthesis with digital ecosystem scanning and stakeholder-informed interpretation, the study offers a context-grounded conceptual framework for understanding youth digital help-seeking in Kenya and proposes priorities for safe design, credibility supports, and referral integration.

2. Methodology

2.1. Study Design

This study employed a convergent mixed-methods design to examine the neurocognitive and psychosocial drivers of digital help-seeking among Kenyan youth, with specific attention to self-diagnosis, affect regulation motives, and algorithm-shaped symptom attribution. A mixed-methods approach was considered necessary because digital help-seeking is simultaneously behavioural and interpretive: it involves measurable patterns (e.g., frequency of symptom searching, platform switching, adoption of diagnostic labels) as well as psychological and social mechanisms (e.g., uncertainty reduction, stigma avoidance, diagnostic anchoring, and identity framing) that cannot be adequately captured through a single method. Convergent mixed-methods designs are widely recommended for complex psychosocial and digital health phenomena because they allow parallel data collection, triangulation across data types, and integration that strengthens inference and explanatory validity [25-27]. In this study, quantitative survey data and qualitative evidence (key informant interviews and document/platform analysis) were collected concurrently and integrated during analysis using convergence mapping and mixed-methods joint displays [26, 28].

Both the quantitative and qualitative strands were accorded equal analytic priority in order to support explanatory integration rather than methodological dominance by a single data source.

2.2. Research Questions

The study was guided by four research questions. First, it examined the dominant platform pathways and entry routes used by Kenyan youth for psychosocial support seeking, and estimated the prevalence of self-diagnosis behaviours across common platforms. Second, it assessed which neurocognitive and psychosocial drivers particularly uncertainty reduction, affect regulation motives, and heuristic-based credibility judgment were associated with repeated searching and scrolling during distress episodes. Third, it investigated how algorithmic exposure contributes to symptom attribution and diagnostic identity framing, including whether repeated exposure to specific symptom narratives increases diagnostic certainty and self-monitoring. Fourth, the study explored ethical risks and safeguarding gaps arising from digital self-diagnosis and algorithm-shaped attribution, and assessed stakeholder perspectives on feasible ecosystem governance mechanisms.

2.3. Study Population and Setting

The study focused on Kenyan youth, broadly defined to include older adolescents and young adults, reflecting common demographic and programmatic definitions used in youth mental health and psychosocial support contexts. This framing aligns with youth classifications commonly applied in Kenyan mental health policy, education systems, and youth-focused psychosocial programming, rather than relying on a rigid age-based threshold. Recruitment prioritised youth who actively use mainstream social and content platforms such as Google Search, YouTube, TikTok, Instagram, Facebook and WhatsApp, because these platforms have been repeatedly identified in the literature as primary pathways for youth online help-seeking, particularly where offline services are constrained by stigma and access barriers [10-12]. The conceptual framing treated digital help-seeking not as a bounded "app use" behaviour, but as a multi-platform ecosystem practice shaped by constraints, platform affordances, and socially constructed trust.

2.4. Data Sources and Data Collection Procedures

Three complementary evidence streams were used: a youth questionnaire, key informant interviews, and document/platform analysis. First, a structured youth questionnaire was administered to capture self-reported digital help-seeking behaviours and associated psychological drivers. The survey collected demographic variables and assessed the frequency of platform use, entry routes (search-led vs feed-led vs peer referral), symptom searching practices, adoption of diagnostic labels, and self-reported diagnostic certainty. It also measured affect regulation motives for online engagement such as reassurance seeking, mood repair, emotional validation, and belonging. Credibility judgement cues were assessed using items capturing perceived relatability, confidentiality, professional legitimacy, verification signals, and social proof cues (likes, comments, shares). Items were rated on Likert scales and were used to compute descriptive indices for key constructs such as self-diagnosis intensity, affect regulation reliance, and perceived algorithmic exposure salience. The survey constructs were aligned with established evidence on youth online help-seeking behaviour and adolescent credibility judgments in social media health contexts [10, 11, 20].

Operationalisation of key constructs: Self-diagnosis intensity was operationalised as a composite index derived from questionnaire items capturing (i) frequency of symptom searching, (ii) adoption of diagnostic labels following online exposure, and (iii) perceived certainty regarding self-attributed mental health conditions. Higher values reflected greater reliance on digital self-diagnosis as a sense-making strategy rather than clinical confirmation. Perceived algorithmic exposure salience was operationalised using self-reported indicators of repeated exposure to similar mental health content, including perceived content recurrence following interaction (e.g., likes, comments, viewing duration), prominence of specific diagnostic narratives in platform feeds, and reliance on social proof cues when evaluating symptom relevance. This construct reflects perceived and behaviourally inferred exposure rather than direct measurement of platform algorithms.

Second, semi-structured key informant interviews (KIIs) were conducted with mental health and youth-support stakeholders, including psychologists, counsellors, educators, youth NGO program staff, safeguarding professionals and digital health implementers. KIIs explored observed patterns of youth digital self-diagnosis, reasons youth prefer digital help-seeking to formal services, and how algorithmic feeds shape symptom interpretation and diagnostic identity narratives. Interviews further examined ethical vulnerabilities including misinformation, pseudo-therapy practices, privacy leakage, coercive DM-based interactions, stigma amplification, and the absence of crisis response or referral integration. Key informant interviewing was selected because it provides expert interpretation of system-level behaviours, governance gaps, and feasible interventions, especially in emerging fields where empirical studies are limited [29, 30]. Interviews were audio-recorded where consent was granted, complemented by expanded field notes, and anonymised during transcription and reporting.

Third, document analysis and platform content analysis were conducted to situate findings within governance and policy contexts. Document analysis reviewed policy, strategy and guidance materials relevant to digital mental health, youth wellbeing, online safety and referral systems. Document analysis was included because it strengthens contextual validity by identifying what institutional safeguards exist and where governance gaps remain [31]. In parallel, a structured digital landscape scan was conducted across publicly available content environments on Google Search, YouTube, TikTok, Instagram, Facebook and X/Twitter. The scan examined diagnostic framing patterns (e.g., symptom checklists and "signs you have…" narratives), algorithmically reinforced topic clusters, credibility cue structures (verification, titles, organisational affiliation), and observable risk cues such as harmful advice, stigma-laden discourse, and invitations to unregulated DM-based "counselling." The scan design drew on netnography and digital ethnography principles which conceptualise social platforms as culturally embedded meaning-making spaces shaped by interaction norms and recommendation systems [32, 33]. Only public content was analysed, and no covert access to closed peer groups was undertaken, consistent with ethical guidance for internet-mediated research [13, 34].

2.5. Sampling and Recruitment

Youth survey participants were recruited purposively through educational institutions, youth networks, and online recruitment to capture digitally active youth. Key informants were purposively selected based on professional roles directly relevant to youth psychosocial support, safeguarding, counselling, digital mental health implementation, or youth mentorship. Qualitative sampling adequacy was guided by the principle of information power, whereby sample size is determined by analytic depth, study aim specificity, and participant relevance rather than fixed numerical targets [35]. This approach is appropriate in mechanism-focused exploratory studies that aim to build conceptual frameworks rather than estimate population prevalence.

2.6. Data Analysis and Integration

Quantitative data were analysed using descriptive statistics including frequencies, proportions, means and standard deviations. Platform comparisons were explored through cross-tabulations, particularly examining differences between search-led entry and feed-led entry. Where composite indices were constructed (e.g., affect regulation reliance score; algorithm exposure salience score), internal consistency was checked using standard reliability approaches. Qualitative data from KIIs were analysed thematically following established procedures including familiarisation, coding, theme development, and interpretation, with both deductive categories (self-diagnosis, affect regulation, algorithmic attribution) and inductive themes emerging from participants' accounts [36, 37]. Document and platform scan evidence were analysed using directed qualitative content analysis to identify recurring diagnostic narratives, credibility cue patterns, and risk mechanisms [38]. All composite indices used in quantitative analysis were derived from the operational definitions specified in Section 2.4.

Integration occurred through triangulation and convergence mapping, comparing quantitative patterns with qualitative explanations and observational evidence. Mixed-methods integration followed recommended convergence procedures, including joint display logic where quantitative trends (e.g., frequency of self-diagnosis) were interpreted alongside qualitative explanatory mechanisms (e.g., stigma avoidance, uncertainty reduction, diagnostic anchoring) and platform structures (e.g., recommendation clustering, social proof dynamics) [26, 28]. Divergences were treated analytically as informative, especially where youth reported trust in certain platforms despite high risk exposure.

2.7. Rigour and Trustworthiness

Rigour was strengthened through methodological triangulation across survey, KIIs and document/platform analysis. An audit trail was maintained through structured survey instruments, KII guides, and extraction templates for platform scan observations. Peer debriefing was conducted through expert consultation to validate emergent interpretations and reduce single-analyst bias. Negative case attention was applied by examining instances where youth reported avoiding diagnosis labels, seeking professional support early, or disengaging from algorithmic content due to perceived harm. These strategies align with widely cited standards for qualitative trustworthiness and mixed-method inference strengthening [27, 37].

2.8. Ethical Considerations

Participation in the questionnaire and KIIs was voluntary and based on informed consent, with strict anonymisation of participants. Given the sensitivity of psychosocial distress, participants were not required to provide clinical diagnoses or disclose traumatic details. For the digital landscape scan, only publicly accessible content was reviewed, and all illustrative examples were paraphrased and de-identified to prevent traceability. Algorithmic systems were not directly interrogated or reverse-engineered; platform influence was examined through self-reported exposure patterns and observable content clustering, consistent with ethical guidance for internet-mediated research. The study followed professional ethical guidance for internet-mediated research, with emphasis on minimisation of harm, respect for privacy expectations, and safeguarding considerations for vulnerable youth populations [13, 34].

This section presents findings from the convergent mixed-methods analysis of neurocognitive and psychosocial drivers of digital help-seeking among Kenyan youth. Results integrate quantitative survey patterns with qualitative evidence from key informant interviews (KIIs) and document/platform analysis. Findings are organised into four domains aligned to the study questions: youth digital help-seeking pathways and prevalence of self-diagnosis practices; affect regulation motives and neurocognitive drivers sustaining repeated online engagement; algorithm-shaped symptom attribution and diagnostic identity framing; and ethical risks, safeguarding gaps, and governance mechanisms.

3. Results

3.1. Digital Help-seeking Pathways and Prevalence of Self-diagnosis Practices

Survey findings indicate that digital help-seeking among Kenyan youth most commonly begins with search-first self-triage, where distress is interpreted through symptom searches (Google) and extended psychoeducation (YouTube), followed by platform switching into short-form and interactive spaces (TikTok/Instagram) for relatable narratives, coping tips, and comment-based peer reassurance. Youth reported that movement between platforms is shaped by privacy needs, emotional intensity, and stigma concerns. These multi-step pathways are summarised in Figure 1, which maps the dominant route structure from distress triggers, through decision filters (privacy, cost, stigma, urgency), to entry points and outcomes.

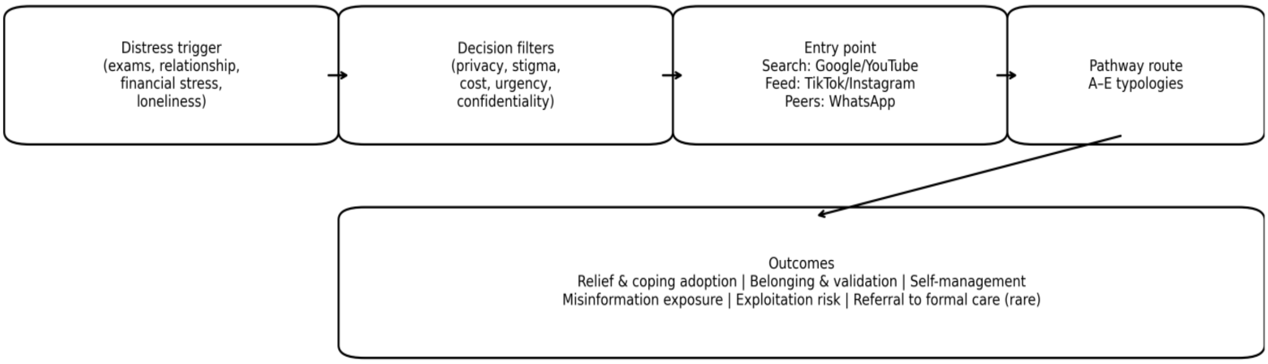

Figure 1. *Conceptual map of youth digital help-seeking pathways and decision filters in Kenya.*

Table 1. *Digital help-seeking pathway entry points and prevalence of self-diagnosis practices among Kenyan youth (survey synthesis).*

Entry route / platform pathway	Typical first step	% reporting symptom search ("what condition do I have?")	% adopting a diagnostic label after exposure	% reporting "this content describes me" identity-framing	Qualitative corroboration (KII summary)
Search-led self-triage (Google → YouTube)	Search symptoms / "signs of…"	78	54	31	"Youth come already saying *I have anxiety/trauma* after YouTube searching."
Feed-led discovery (TikTok/Instagram)	Scroll; short videos; comments	51	47	72	"TikTok labels stick; youth interpret stress through popular labels."
Peer-led confidential support (WhatsApp)	Friend/group referral	36	29	44	"WhatsApp is where youth disclose first diagnosis comes later."
Influencer-guided meaning-making	Follow a creator; DM	41	46	65	"Creators become trusted authorities even without credentials."
Crisis-to-professional referral	Hotline/clinic link	12	8	6	"Referral pathway exists but is weakly embedded in youth routines."

The survey further showed that self-diagnosis behaviours were common across the sample, with large differences by entry route. Table 1 presents prevalence estimates of symptom searching and diagnostic label adoption across pathway entry points. Search-led entry was the strongest indicator of self-diagnosis: 78% of respondents reporting search-led entry (Google → YouTube) indicated that they had searched symptoms to determine "what condition I may have," and 54% reported adopting a diagnostic label after exposure. In contrast, feed-led discovery (TikTok/Instagram) was more strongly associated with identity framing: while 51% reported symptom searching, the proportion reporting "this content describes me" was substantially higher (72%) than in search-led entry (31%). Peer-led confidential support routes (WhatsApp) showed lower self-diagnosis rates (36%) and reduced diagnostic label adoption (29%), although identity-framing remained notable (44%). Finally, crisis-to-professional referral pathways were reported infrequently, with only 12% reporting symptom searching and 8% reporting label adoption in this pathway.

Qualitative data reinforced these quantitative trends. KIIs consistently described youth presenting with distress narratives framed through online diagnostic terms (e.g., anxiety, trauma, ADHD, attachment issues). Informants emphasised that diagnostic language was commonly introduced before engagement with formal support systems and was frequently linked to search-led and feed-led exposure. Document review and platform analysis showed that while Kenya has emerging digital mental health innovation and intervention activity, direct referral integration into youth's everyday platform routines remains limited, corresponding to the weak crisis-to-professional trajectory observed in Table 1.

3.2. Affect Regulation Motives and Neurocognitive Drivers Sustaining Repeated Help-seeking

Survey findings show that digital help-seeking is strongly driven by affect regulation motives, not only information seeking. Table 2 ranks affect regulation motives and reports mean scores, demonstrating that relief-seeking and belonging motives were consistently endorsed at higher levels than motives relating to professional referral. The strongest motive was reassurance seeking ("I feel calmer after watching/reading"), with a mean score of 4.31 (SD 0.74). Belonging and validation (relief from loneliness through comments and shared experiences) was also highly rated (4.18, SD 0.80). Narrative coherence (distress becoming clearer after symptom explanations) scored 4.02 (SD 0.86). Mood repair motives remained elevated (3.88, SD 0.92), while practical coping adoption scored 3.67 (SD 0.96). By contrast, professional referral motivation was notably lower (2.41, SD 1.05), indicating that online engagement was more frequently oriented toward emotional relief and meaning-making than offline escalation.

Table 2. *Affect regulation motives and neurocognitive drivers of repeated online help-seeking (mean scores and qualitative examples).*

Affect regulation driver / motive	Mean (SD)	Interpretation for help-seeking behaviour	Illustrative qualitative evidence (youth/KII synthesis)
Reassurance seeking ("I feel calmer after watching/reading")	4.31 (0.74)	Immediate emotional relief reinforces repeated engagement	"I just want to settle my mind scrolling helps."
Belonging and validation (comments/peer stories reduce loneliness)	4.18 (0.80)	Peer resonance strengthens disclosure and trust	"If many people say same, you feel normal."
Narrative coherence (distress feels clearer after symptom explanation)	4.02 (0.86)	Supports uncertainty reduction and symptom attribution	"Once I understand what it is, I can cope."
Mood repair (music/reels/affirmations regulate affect)	3.88 (0.92)	Maintains continued platform use even without solutions	"Sometimes it's not advice, it's just encouragement."
Practical coping adoption (try techniques suggested online)	3.67 (0.96)	Facilitates coping behaviours but quality varies	"Breathing tips help sometimes, but not always."
Professional referral motivation ("I was encouraged to seek counselling")	2.41 (1.05)	Weak bridge from online to formal care	"Youth fear being judged offline; they stay online."

Scale: 1 = strongly disagree; 5 = strongly agree.

KIIs provided consistent supporting evidence. Youth were described as using online searching and scrolling to "settle the mind," gain reassurance, and restore perceived control when distressed, with repeated engagement described as common in fear-based or ruminative episodes. Platform analysis also showed that high-engagement mental health content frequently uses emotionally salient hooks (symptom lists, label-based narratives, "signs you are…" framing), consistent with survey evidence of reassurance-driven searching.

The reinforcement structure of this process is summarised in Figure 2, which illustrates how distress and uncertainty precede repeated online searching/scrolling, leading to short-term relief and belonging and strengthening future reliance on online ecosystems.

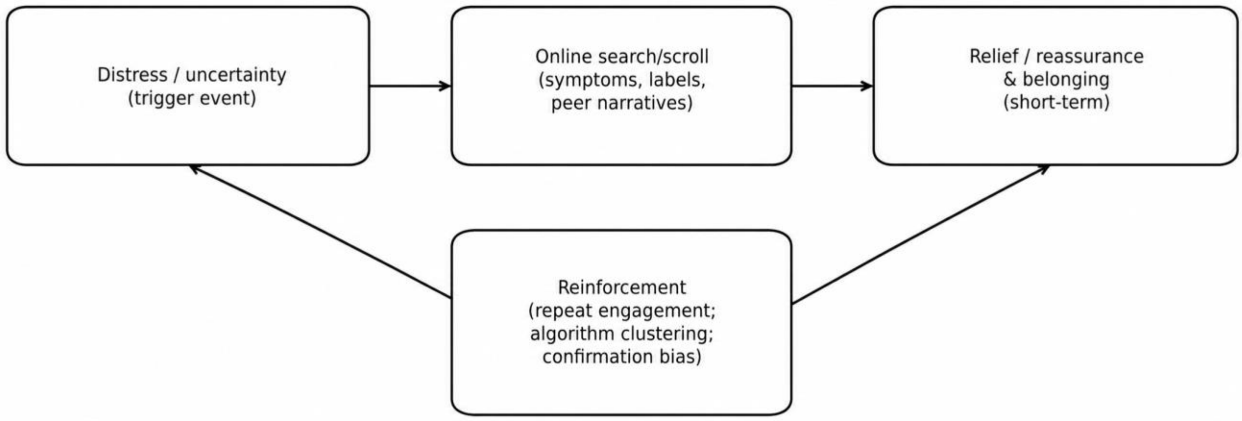

Figure 2. *Affect regulation loop and reinforcement cycle in youth digital help-seeking.*

3.3. Algorithm-shaped Symptom Attribution and Diagnostic Identity Framing

A major quantitative finding is that symptom attribution among youth is strongly shaped by algorithm-shaped exposure, including repeated encounters with diagnostic labels even when respondents were not actively searching. Table 3 summarises indicators of algorithmic reinforcement and perceived influence on symptom attribution. The most prevalent indicator was intensified exposure after interaction: 71% reported that clicking on or interacting with a mental health post increased similar content in subsequent feeds. A large majority (69%) reported repeated appearance of the same diagnosis category (e.g., anxiety/ADHD/trauma). Social proof was particularly prominent: 74% reported using likes/comments as a credibility cue. Exposure to distress content repeatedly in feeds was reported by 63%, while symptom checklist formats ("signs you have…") were reported by 58%. Identity framing narratives ("ADHD brain," "you are traumatised") were reported by 47%.

Table 3. Algorithm exposure indicators and perceived influence on symptom attribution and diagnostic identity framing.

Algorithm exposure indicator	% reporting exposure	Perceived psychological effect	Platform scan evidence
Repeated appearance of the same diagnosis category (e.g., ADHD/anxiety/trauma)	69	Increased perceived relevance of labels; diagnostic anchoring	Mental health clusters form rapidly after likes/comments
"For You" feed showing distress content repeatedly	63	Rumination loop and heightened self-monitoring	Short-form feeds show topic persistence
Social proof (likes/comments as credibility cue)	74	"If many agree, it must be true"; confirmation bias	Comment sections validate self-diagnosis
Symptom checklist videos ("signs you have…")	58	Self-assessment using non-clinical criteria	High-engagement symptom-list formats common
Identity framing ("you are traumatised/ADHD brain")	47	Mental health identity adoption and label fixation	Label-as-identity narratives prominent
Intensification after interaction (clicking once increases similar content)	71	Reinforcement cycle strengthening exposure	Recommendation clustering consistent

KIIs converged with these results in describing recurring diagnostic narratives among youth and increased self-monitoring following repeated exposure. Platform scan findings further supported the quantitative results by documenting rapid clustering of mental health content once users engage with related posts and frequent amplification of diagnostic certainty in comment sections (e.g., "this is me," "now I understand why I am like this"). Across sources, algorithmic recurrence and social proof were consistently identified as the strongest cues that increased perceived relevance of symptom labels.

3.4. Ethical Risks, Safeguarding Gaps, and Governance Mechanisms

Ethical risks were reported frequently and were evident across both survey and qualitative evidence. Table 4 summarises reported risk exposure prevalence and contextualises each risk using KII and platform scan evidence. The most common reported governance gap was weak crisis escalation and referral prompting: 61% reported encountering situations where distress-related content lacked clear pathways to helplines or professional support. Misinformation exposure was also high (57%), particularly within TikTok and YouTube content environments. Privacy leakage risks were substantial (44%), especially in WhatsApp and Facebook group settings where forwarding and screenshots were commonly described. Unregulated pseudo-counselling and boundary violations were also reported (39%), particularly in DM-based environments (Instagram/Telegram). Predatory exploitation risks were reported by 28%, especially within anonymous confession spaces and DM interactions. Cyberstigma and public shaming appeared frequently (33%), often linked to public comment threads.

Table 4. Ethical risks and safeguarding gaps in youth digital help-seeking ecosystems: prevalence and qualitative evidence.

Ethical risk / governance gap	% youth reporting exposure	High-risk platforms/spaces	Qualitative evidence (KII synthesis)	Safeguarding priority
Misinformation / harmful coping scripts	57	TikTok, YouTube	"Youth are given confident but inaccurate advice."	Verified content + accuracy labelling
Privacy leakage (screenshots, forwarding)	44	WhatsApp, FB groups	"Disclosures are used for shaming; youth retreat."	Group norms + reporting pathways
Unregulated pseudo-counselling	39	IG DMs, Telegram	"Someone claims therapist status no accountability."	Professional boundary standards

Ethical risk / governance gap	% youth reporting exposure	High-risk platforms/spaces	Qualitative evidence (KII synthesis)	Safeguarding priority
Predatory exploitation (coercive DMs)	28	Confession pages, DMs	“Support becomes emotional grooming.”	Anti-DM safeguarding rules
Cyberstigma / shaming in comments	33	TikTok/IG comments	“Public ridicule worsens distress.”	Comment moderation + stigma-free rules
Weak crisis escalation / referral prompts	61	All platforms	“No pathway to helplines when youth are high-risk.”	Crisis prompts + helpline integration

Qualitative evidence reinforced the ecosystem nature of these risks. KIIs highlighted that informal peer support spaces may be treated as “safe,” but disclosure leakage practices (forwarding, screenshots) increase vulnerability to shame and cyberbullying. Key informants also emphasised that pseudo-support accounts sometimes mimic counselling identities while operating outside professional regulation. Document analysis further indicated that although international digital health guidance and online research ethics standards exist, youth-specific safeguarding integration (e.g., crisis prompts, structured referral links) remains inconsistently implemented within everyday mainstream platform contexts.

4. Discussion

4.1. Digital Help-seeking as a Distributed Psychosocial Support System

The results demonstrate that youth psychosocial help-seeking in Kenya is best understood as a distributed, informal, multi-platform support system rather than a bounded “digital mental health intervention.” The dominance of mainstream platforms in Table 1 and the pathway architecture in Figure 1 align with international evidence that young people frequently seek mental health information and emotional support online because it is immediate, private, and socially accessible, particularly where offline stigma and service barriers persist [39]. This broader pattern has been repeatedly observed in systematic synthesis showing that online help-seeking offers anonymity, convenience and self-reliant coping pathways but often lacks structured escalation to formal services [39, 40]. Our findings extend this evidence by identifying the specific pathway logic within the Kenyan context: youth commonly begin with symptom searching, then shift into algorithm-mediated spaces where diagnostic labels become identity narratives and credibility is socially constructed.

A central implication of the current findings is that the digital ecosystem youth rely on is not designed as a care infrastructure; rather, it is a commercial attention infrastructure. In such systems, help-seeking behaviour is shaped by platform affordances and recommendation engines that reward emotional salience and engagement. This helps explain why the crisis-to-professional pathway remained weak in Table 1 and why governance gaps in Table 4 were prominent. The results therefore suggest that Kenya’s digital youth psychosocial landscape should be framed not only as an opportunity for innovation but also as a high-exposure risk environment requiring safeguarding, credibility, and referral mechanisms.

4.2. Pathways and Self-diagnosis: Sense-making Under Constraint

Table 1 shows that self-diagnosis is widespread and strongly associated with search-led entry points, while feed-led entry points are strongly associated with diagnostic identity framing. These patterns correspond closely with evidence that online help-seeking frequently begins with symptom searching and self-triage when stigma, cost, and confidentiality concerns limit offline disclosure [39]. In many settings, search engines serve as the first interpretive gateway during distress, providing rapid psychoeducation and “possible explanations” that may reduce uncertainty. However, the Kenyan findings emphasise that this process is rarely linear; youth frequently shift from factual information spaces (Google/YouTube) into highly socialised narrative environments (TikTok/Instagram/WhatsApp), indicating that help-seeking evolves from informational needs into identity and belonging needs.

Mechanistically, self-diagnosis can be interpreted as an adaptive attempt to achieve cognitive clarity. Distress often produces uncertainty, heightened arousal and attentional narrowing conditions in which information seeking functions as uncertainty reduction and perceived control restoration [41]. In this model, diagnostic labels provide coherence: they transform ambiguous distress into a recognisable “category,” which can reduce isolation and validate feelings. Yet the KIIs suggest a common downside: diagnostic anchoring, where youth interpret diverse stressors through a single disorder narrative. This aligns with broader cognitive evidence that people under uncertainty may rely on simplified explanatory frames, strengthening confirmation bias and narrowing interpretive possibilities [42]. It also resonates with evidence that online narratives can shift symptom interpretation through availability heuristics what is repeatedly encountered becomes cognitively accessible and therefore subjectively "true" [43]. Thus, self-diagnosis may improve vocabulary for distress and encourage reflection, while simultaneously increasing risks of misattribution, over-pathologising normal stress, or delaying appropriate care.

The strong association between TikTok/Instagram pathways and diagnostic identity framing (72%) reflects a distinctive contemporary dynamic: labels do not only describe symptoms; they can become identity scripts. This is consistent with emerging research on TikTok and other short-form platforms demonstrating that mental health labels are often communicated through high-resonance narratives and checklist formats that encourage self-identification, despite substantial variation in information quality [44]. For Kenyan youth, the identity framing function is likely amplified by the social meaning of distress in contexts where vulnerability can be moralised or stigmatised. If offline norms discourage open disclosure, online identities may offer alternative moral communities spaces where distress is not judged but recognised. This explains why identity framing is strongest in feed-led entry routes where peer validation and social proof are embedded.

4.3. Affect Regulation as the Engine of Repeated Engagement

Table 2 demonstrates that affect regulation motives dominate online help-seeking. Reassurance seeking, belonging and narrative coherence were consistently rated highest, while professional referral motivation was low. This finding clarifies an important point: youth are not simply using the internet as a health library; they are using it as an emotion regulation tool. This corresponds with a large body of psychological theory and evidence indicating that emotion regulation is central to coping, and that individuals actively select strategies that reduce arousal and improve perceived stability during distress [41]. In digital contexts, searching and scrolling may function like rapid-access coping: it creates immediate relief, reassurance and containment, even if short-lived.

Figure 2 synthesises this mechanism as an affect regulation loop: distress triggers online engagement; online engagement yields relief and belonging; relief reinforces repeated engagement. This loop is consistent with reinforcement learning models in which short-term reward strengthens future behaviour. It also mirrors evidence from adolescent digital behaviour research showing that emotionally salient content and social feedback (likes/comments) can reinforce repeated checking and engagement [43, 45]. In the Kenyan context, where in-person counselling access remains uneven, reinforcement cycles may be especially potent: if online engagement is the most accessible "relief resource," it becomes a default coping mechanism.

The platform scan adds further detail: high-engagement posts frequently use symptom-checklist frames and emotionally triggering narratives ("signs you are traumatised"), which may intensify attentional capture. This aligns with research showing that emotional salience shapes what users remember and return to, increasing repeated exposure and reliance on the same interpretive frames [43]. The implication is not that youth digital engagement is inherently harmful; rather, it suggests that the same psychological drivers that make online help-seeking attractive (relief, belonging, reassurance) also make youth susceptible to cycles of rumination, symptom monitoring, and content dependency particularly when algorithmic systems repeatedly feed similar content.

4.4. Algorithm-shaped Symptom Attribution: When Platforms Become Interpretive Authorities

A distinctive contribution of this study is the empirical mapping of algorithm-shaped symptom attribution. Table 3 shows that a majority of youth experienced intensified exposure after interaction (71%), repeated diagnostic category appearance (69%), and reliance on social proof cues as credibility signals (74%). These findings reflect an emerging but increasingly important reality: algorithmic systems do not only "deliver content"; they shape interpretive environments, influencing which symptom narratives feel most plausible and which labels become salient.

In cognitive terms, repeated exposure increases familiarity, and familiarity increases perceived truthfulness (the illusory truth effect). When distress content repeatedly appears in a feed, youth may interpret it as evidence of relevance ("it keeps appearing so it must be true"), thereby strengthening diagnostic certainty. This mechanism aligns with wider evidence that adolescents interpret health content through a blend of heuristic and social cues rather than formal verification processes [46]. Social proof further magnifies the effect: if peers validate a label ("this is me"), the label gains legitimacy not through evidence but through community endorsement.

The KII evidence suggests that this process can promote confirmation bias and self-monitoring. Youth may begin scanning themselves for symptoms they repeatedly see, and ordinary stress experiences may become reinterpreted as chronic pathology. Contemporary work on youth digital lives shows that social platforms transform peer relations and feedback structures, intensifying social comparison and shaping identity work [45]. Within mental health content ecosystems, identity work can become diagnosis work: labels become "who I am" rather than "what I am experiencing." This is consistent with systematic synthesis of TikTok mental health use showing that content can improve awareness and relatability, while quality variability and oversimplified framing create risks of misleading guidance and inaccurate symptom attribution [44].

Algorithmic systems were not directly interrogated or reverse-engineered; platform influence was examined through self-reported exposure patterns and observable content clustering, consistent with ethical guidance for internet-mediated research.

4.5. Ethical Risks and Safeguarding Gaps: Predictable Ecosystem Harms

Table 4 shows high prevalence of misinformation (57%), privacy leakage (44%), unregulated pseudo-counselling (39%), and weak crisis referral integration (61%). These risks were not peripheral; they were routine exposures. This corresponds with global findings that online help-seeking is simultaneously beneficial and risky: young people gain anonymity and support but face credibility challenges, privacy vulnerability, and difficulty transitioning to offline care [39, 40]. The Kenyan context may amplify these risks due to fragmented regulatory frameworks for digital counselling and limited integration of formal referral pathways into mainstream platforms.

Privacy leakage in WhatsApp and peer spaces reflects a core paradox. Youth seek these spaces for safety and confidentiality, yet these platforms often lack enforceable confidentiality protections, making users dependent on social trust rather than technical safeguards. Privacy violations (screenshots, forwarding) can rapidly transform disclosure into harm, including cyberbullying and shame-based stigma. These harms can have long-term consequences, including reduced future help-seeking and increased withdrawal.

Unregulated pseudo-counselling and predatory exploitation risks reveal another structural vulnerability: direct messaging affords intimate support exchanges but also enables manipulation. Without clear boundary standards and verification cues, youth may struggle to distinguish supportive peers from exploitative actors. This aligns with ethical guidance for internet-mediated research and youth online safety, which emphasises that vulnerability increases when private spaces are unmoderated and safeguarding is weak [47, 48].

The weak crisis escalation/referral prompts (61%) is perhaps the most actionable governance gap. Evidence from social media mental health campaigns suggests that engagement alone does not guarantee effective help-seeking outcomes; platform dynamics shape whether content leads to behavioural escalation or passive consumption [49]. If crisis prompts and referral pathways are absent, high-risk users may remain trapped in peer reassurance loops rather than connected to professional support.

4.6. Toward Ecosystem Governance, Not Only "New Apps"

A key implication is that Kenya's youth digital psychosocial wellbeing cannot be addressed only by developing new digital interventions, although these remain valuable. Evidence from Kenya-based interventions demonstrates that structured psychosocial programs can reduce depressive and anxiety symptoms and are scalable in school contexts [50]. However, the current study shows that most youth are already living within mainstream platform ecosystems. Therefore, the primary strategy should be ecosystem governance: embed credibility cues, referral links, and safeguarding protocols into the platforms that structure everyday youth help-seeking.

This includes (i) strengthening verification and quality labelling for creators presenting mental health content; (ii) establishing minimum standards for online counselling boundaries and disclosures; (iii) creating group-level accountability mechanisms in peer spaces; and (iv) integrating youth-friendly helpline prompts into search results and high-risk algorithm clusters. Such approaches align with global recommendations for safer online environments and youth mental health risk prevention in the digital age [51, 52].

5. Conclusion

This study demonstrates that digital help-seeking among Kenyan youth functions as an informal, multi-platform psychosocial support ecosystem rather than a single intervention pathway. Youth typically begin with search-led self-triage and transition into feed-led narrative spaces, where diagnostic labels become socially validated identity frames. Online engagement is sustained primarily by affect regulation motives reassurance, belonging, and narrative coherence reinforced through short-term emotional relief and algorithmic clustering. Algorithm-shaped symptom attribution is widespread, with repeated exposure and social proof acting as credibility amplifiers that intensify diagnostic anchoring and self-monitoring. Ethical risks operate as predictable ecosystem-level vulnerabilities, with high exposure to misinformation, privacy leakage, pseudo-counselling, and weak crisis escalation/referral integration. Together, the results highlight the need for ecosystem governance and safeguarding embedded within mainstream platforms youth already use, rather than relying exclusively on new digital mental health applications.

6. Recommendations

To strengthen youth psychosocial safety and effectiveness of digital help-seeking pathways, Kenya should prioritise platform-integrated referral signposting, including helpline prompts and service navigation embedded within search outputs and high-risk content clusters. To address affect regulation-driven cycles, interventions should promote youth digital resilience tools (credible coping libraries, guided self-check prompts, and youth-friendly psychoeducation) that interrupt reassurance loops without removing supportive access. To reduce algorithm-shaped symptom misattribution and identity fixation, stakeholders should implement credibility enhancements such as verified creator tags, content quality labelling, and partnership models that elevate evidence-based psychoeducation while discouraging "diagnosis-by-content" narratives. Finally, to mitigate ethical risks and governance gaps, Kenya should develop minimum standards for online counselling boundaries and disclosures, strengthen moderation and admin accountability norms in peer spaces (especially WhatsApp groups), integrate privacy protection messaging into youth-facing platforms, and establish safeguarding protocols for minors including crisis escalation prompts and anti-exploitation protections in DM-based environments.

Abbreviations

ADHD	Attention-Deficit/Hyperactivity Disorder
AoIR	Association of Internet Researchers
BPS	British Psychological Society
DM	Direct Message
KII	Key Informant Interview
LMICs	Low- and Middle-Income Countries
NGO	Non-Governmental Organization
SSA	Sub-Saharan Africa
WHO	World Health Organization

Acknowledgments

The author acknowledges the Kenyan youth who contributed their perspectives and experiences that informed the conceptual and empirical grounding of this study. Appreciation is extended to mental health practitioners, educators, youth programme staff, and digital wellbeing stakeholders who participated as key informants and provided critical insights into emerging patterns of digital help-seeking, self-diagnosis, and online psychosocial support practices.

Author Contributions

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Data Availability Statement

The data is available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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