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Public sentiment toward traditional mental health providers and AI alternatives: a mixed-methods analysis of 2025 multilingual X discourse

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The integration of artificial intelligence (AI) into mental health care is not merely a technological shift but a societal response to perceived challenges within human-centric care delivery. This mixed-methods study critically examines this transition by analyzing high-engagement public discourse on X (formerly Twitter) from January 1 to September 1, 2025 (N = 496 posts, English/Spanish). The findings reveal a central paradox: while public discourse shows profound frustration with traditional providers—citing prohibitive costs and inefficacy (61%–65% negative sentiment)—its embrace of AI is deeply ambivalent. Users value AI primarily for its non-human qualities of accessibility, anonymity, and scalability (53%–58% positive sentiment), yet simultaneously critique it for its failure to replicate the quintessentially human trait of empathy. Spanish-language discourse further illuminates this, positioning AI's anonymity as a direct countermeasure to cultural stigma. Interpreting these findings through a critical application of the Unified Theory of Acceptance and Use of Technology (UTAUT), this paper argues that AI is not being adopted as a therapeutic equivalent, but as a pragmatic, if imperfect, tool to navigate the deficiencies in the "facilitating conditions" of traditional care. This dynamic, however, presents a significant risk: that AI becomes a technological patch for deep-seated systemic problems, potentially delaying fundamental healthcare reform. This study offers a novel, critical perspective on AI's role, urging a shift from designing AI that mimics empathy to creating hybrid systems that leverage AI's strengths ethically and transparently, without absolving the human system of its duty to care.

KEYWORDS
artificial intelligence, cultural comparison, mental health, mixed-methods, sentiment analysis, social media, technology acceptance, UTAUT

1 Introduction

The global mental health crisis is not a new phenomenon, but its character is undergoing a fundamental transformation. Decades of evidence have solidified the efficacy of human-led therapeutic interventions (American Psychological Association, 2023), yet the infrastructure designed to deliver this care is collapsing under the weight of its own inaccessibility. For millions, the "gold standard" of a human therapist is a theoretical ideal, obstructed by the stark realities of prohibitive costs, interminable waitlists, and pervasive social stigma (Kazdin and Rabbitt, 2013; WHO, 2022).

This is more than a gap in services; it is a crisis of faith in the human-centric model's ability to meet the scale of human need.

Into the gap created by these access challenges, artificial intelligence (AI) has emerged as an alternative modality that may reflect unmet needs within the population. AI-powered tools, from chatbots to large language models, promise a new paradigm: care that is immediate, anonymous, and infinitely scalable (Fitzpatrick et al., 2017). This study, however, argues that the public discourse surrounding AI is not about the technology itself, but about the human system it is poised to disrupt. The central thesis of this paper is that the public's embrace of mental health AI is defined by a critical paradox: users are turning to non-human solutions precisely because of systemic human failures, creating a dynamic where they simultaneously demand impossible-to-replicate human qualities (like empathy) from AI while valuing it most for its explicitly non-human attributes (anonymity and scalability).

This paradox reveals a deep-seated tension in our expectations of care. On one hand, the public's frustration with the existing system has lowered the barrier for accepting technological alternatives. On the other, the deeply personal and relational nature of mental health creates a high bar for what is considered acceptable, leading to intense scrutiny of AI's emotional and ethical shortcomings (Fiske et al., 2019). Understanding this tension is paramount. It has the power to shape the trajectory of mental healthcare for decades, determining whether AI becomes a genuine force for equity or a convenient excuse for further disinvestment in human-led care.

This mixed-methods study confronts this paradox directly by analyzing the raw, unfiltered discourse on the social media platform X. By examining 496 high-engagement posts from 2025 in both English and Spanish, we move beyond clinical trials and developer promises to a court of public opinion found in the expressed opinion in social media discourse on X. We ask not only *what* people think, but *why*. What are the narratives of hope and fear that define this moment? How do cultural factors, such as stigma in Spanish-speaking communities, moderate these views?

To interpret our findings, we employ a critical application of the Unified Theory of Acceptance and Use of Technology (UTAUT). Rather than simply mapping our themes onto its constructs, we use the framework to deconstruct the paradox itself. We analyze how deficiencies in "Facilitating Conditions" (cost, access) in the traditional system directly fuel AI adoption, while conflicts in "Performance Expectancy" (the desire for both scalability and empathy) reveal the public's deep ambivalence.

This study aims to make a significant, critical contribution to the field. It provides a novel, data-driven analysis of the central conflict in digital mental health and offers a theoretically grounded argument for a more intentional and ethical path forward. The findings are a call to action for policymakers, clinicians, and developers alike: to move beyond the simplistic human-vs.-machine debate and toward the creation of hybrid systems that are not only technologically advanced but also humanistically wise.

1.1 Research questions and objectives

This study is guided by the following research questions:

RQ1: what are the predominant positive and negative sentiments expressed on X toward traditional mental health providers (therapists, counselors, psychologists, psychiatrists) in 2025?

RQ2: what are the predominant positive and negative sentiments expressed on X toward the use of AI in mental health, and how do these sentiments compare to those directed at human providers?

RQ3: what are the key qualitative themes that characterize public discourse about human and AI-based mental healthcare, and do these themes differ significantly between English and Spanish-speaking users?

RQ4: how can the integrated findings, interpreted through the lens of technology acceptance theories, inform our understanding of AI's potential role within the broader mental health ecosystem?

To address these questions, the study pursues the following objectives:

1. To quantify and compare the polarity of sentiment (positive, negative, neutral) toward human providers and AI mental health tools using a large-scale dataset of X posts.
2. To identify and analyze the specific narratives, concerns, and praises that emerge from public conversations in both English and Spanish.
3. To explore cultural nuances, particularly the role of stigma, in shaping differential perceptions of traditional vs. AI-driven care.
4. To synthesize the quantitative and qualitative findings to propose evidence-based implications for the ethical development and integration of hybrid mental health models.

2 Literature review

2.1 The crisis in traditional mental healthcare access

The foundation of modern mental healthcare rests on the expertise of human providers who offer diagnosis, psychotherapy, and pharmacological treatment. The effectiveness of these interventions is well-documented (Cuijpers et al., 2020). However, the system designed to deliver this care is fundamentally misaligned with public need. The "access crisis" is a multifaceted problem rooted in economic, structural, and social barriers.

Economically, the cost of mental healthcare is a primary deterrent (Insel, 2008). In the United States, for example, an out-of-pocket therapy session can range from $100 to over $250, and many therapists do not accept insurance, creating a barrier for low- and middle-income individuals. Structurally, a global shortage of mental health professionals results in long waitlists, with individuals often waiting months for an initial appointment, a delay that can be critical in times of acute distress (World Health Organization, 2022). This shortage is particularly severe in rural and low-income areas, creating "mental health deserts."

Socially, stigma remains a powerful barrier. Despite growing public awareness, seeking help for mental illness is often perceived as a sign of weakness or personal failing, a view that is particularly potent in certain cultural contexts. Research on Latin communities, for instance, highlights the influence of *machismo* and *marianismo* (traditional gender roles) and strong familial norms, which can discourage individuals from seeking professional help outside the family unit (Caplan, 2019; Mascayano et al., 2016). From a sociological perspective, these patterns reflect what Plummer (2001, 2019) describes as the interplay between intimate troubles and public issues—personal mental health struggles become constrained by broader social structures of stigma, shame, and cultural narrative. This cultural stigma amplifies the appeal of anonymous and private alternatives. Public discourse on social media often reflects these frustrations, with studies of Reddit and Twitter revealing widespread user complaints about the high cost, inaccessibility, and perceived inefficacy of traditional therapy (Gaur et al., 2018; Budenz et al., 2020).

2.2 The emergence of AI as a mental health alternative

AI-driven tools have emerged as a direct response to the gaps in traditional care. Early iterations, such as rule-based chatbots, have evolved into sophisticated conversational agents powered by advanced NLP and machine learning. These technologies can be broadly categorized into several types:

Therapeutic Chatbots (e.g., Woebot, Wysa): these are designed to deliver elements of structured therapies, most commonly CBT, through guided conversations. They help users identify negative thought patterns, complete mood journals, and learn coping skills. Randomized controlled trials have shown that chatbots like Woebot can significantly reduce symptoms of depression and anxiety (Fitzpatrick et al., 2017).

Symptom Checkers and Triage Tools: these AI systems help users understand their symptoms and guide them to the appropriate level of care, potentially reducing the burden on human providers by acting as a first line of support.

AI for Diagnosis and Treatment Personalization: researchers are exploring the use of machine learning to analyze data from various sources (e.g., speech patterns, text messages, electronic health records) to predict mental health crises, assist in diagnosis, and recommend personalized treatment plans.

The primary appeal of these tools lies in their ability to overcome traditional barriers. They are often low-cost or free, available 24/7, and provide a level of anonymity that can reduce the stigma associated with seeking help (Vaidyam et al., 2019). However, their rapid development has outpaced ethical and regulatory oversight. Concerns abound regarding their lack of genuine empathy, the risk of misinterpreting serious conditions, and the potential for creating dependency (Fiske et al., 2019). Furthermore, the vast amounts of sensitive data they collect raise critical questions about privacy, security, and the potential for algorithmic bias to perpetuate existing health disparities (Luxton, 2014).

2.3 Public sentiment analysis using social media

To gauge public perception of this evolving landscape, researchers have increasingly turned to social media sentiment analysis. Platforms like X offer vast, organically generated datasets that provide real-time insights into public attitudes. Methodologically, sentiment analysis can range from simple lexicon-based approaches (counting positive and negative words) to advanced machine learning models like BERT, which can understand context and nuance (Kummervold et al., 2021).

Previous studies have successfully used these methods to monitor public mental health. For example, De Choudhury et al. (2021) demonstrated that linguistic markers on Twitter could predict depression with high accuracy. Others have analyzed discourse to understand public attitudes toward specific conditions like ADHD or bipolar disorder (Coppersmith et al., 2015; Budenz et al., 2020). However, most existing research suffers from two key limitations: a monolingual focus (predominantly English) and a lack of direct comparison between traditional and AI-based care (D'Alfonso, 2020). This study addresses both limitations by analyzing English and Spanish discourse and by explicitly framing the analysis as a comparison of public sentiment as viewed through high-engagement public discourse on X toward human vs. AI providers.

2.4 Theoretical framework: technology acceptance in digital mental health

To understand the drivers of visible discourse on X toward AI in mental healthcare, this study is grounded in established theories of technology adoption. The Technology Acceptance Model (TAM) and its successor, the Unified Theory of Acceptance and Use of Technology (UTAUT), provide robust frameworks for interpreting why users accept or reject new technologies.

Developed by Davis (1989), TAM posits that a user's intention to adopt a technology is primarily determined by two core beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to "the degree to which a person believes that using a particular system would enhance his or her job performance," while PEOU is "the degree to which a person believes that using a particular system would be free of effort." In the context of mental health, PU can be interpreted as the public's belief that an AI tool can genuinely help them manage their mental wellbeing, while PEOU relates to how accessible, intuitive, and user-friendly these tools are. TAM has been widely applied in health informatics, though some scholars note its focus on PU and PEOU may be insufficient for the complexities of healthcare (Holden and Karsh, 2010).

To address these complexities, Venkatesh et al. (2003) developed the UTAUT, which integrates constructs from TAM and seven other prominent models. UTAUT proposes four key determinants of behavioral intention and use behavior:

1. Performance Expectancy: similar to PU, this is the belief that the technology will help an individual attain gains in performance or wellbeing.
2. Effort Expectancy: similar to PEOU, this is the degree of ease associated with the use of the system.

3. Social Influence: the extent to which an individual perceives that important others (e.g., family, friends, doctors) believe they should use the new system.
4. Facilitating Conditions: an individual's perception of the organizational and technical infrastructure available to support the use of the system (e.g., cost, accessibility, data security).

UTAUT has demonstrated greater explanatory power than TAM in healthcare settings, accounting for a larger variance in user intentions. For mental health AI, these constructs are highly relevant. "Social Influence" can relate to the stigma or encouragement surrounding the use of AI for mental health, while "Facilitating Conditions" can involve factors like cost, internet access, and data privacy regulations.

Furthermore, research applying these models to healthcare has identified additional critical factors, such as trust, anxiety, and perceived security (Gagnon et al., 2012). Trust is particularly paramount in mental healthcare, where users share sensitive personal information and rely on the system for guidance. Therefore, this study will use the core constructs of UTAUT—complemented by the crucial element of trust—to frame its analysis of public sentiment on X. By mapping qualitative themes onto these theoretical constructs, the study moves beyond simple description to offer a structured explanation of the factors driving public acceptance of AI in mental health.

Framework Positioning: in this study, UTAUT is employed as a *heuristic lens* for organizing and interpreting thematic findings rather than as a comprehensive explanatory or predictive model. We recognize that UTAUT was developed for technology adoption in organizational contexts and may not fully capture the complexity of mental health help-seeking, which is also shaped by illness-specific factors, therapeutic alliance expectations, and stigma dynamics not explicitly modeled in UTAUT (Clement et al., 2015; Corrigan et al., 2014). Accordingly, we complement UTAUT with attention to trust (Gagnon et al., 2012) and integrate insights from stigma theory (Corrigan and Watson, 2002) where the data warrant. This eclectic approach sacrifices some theoretical parsimony in favor of empirical responsiveness.

3 Methods

3.1 Research design

This study employed a convergent parallel mixed-methods design, as described by Guetterman et al. (2015). In this approach, quantitative and qualitative data are collected and analyzed concurrently but separately. The results are then merged and integrated during the interpretation phase. This design is particularly well-suited for exploring complex social phenomena like high-engagement public discourse, as it allows for both the broad, generalizable trends identified through quantitative analysis and the deep, contextual understanding provided by qualitative analysis. By triangulating the findings from these two streams, the design enhances the validity and richness of the overall conclusions (Fetters et al., 2013).

3.2 Participants and data collection

The "participants" in this study were anonymous X users who posted publicly available content. The dataset comprised 496 unique X posts collected from January 1, 2025, to September 4, 2025. The sample was balanced by language (248 English, 248 Spanish) and further stratified by category (approximately 124 posts each for human providers and AI in both languages).

Data was collected via X's Enterprise API, accessed through a paid commercial license. This method was chosen to ensure comprehensive and reliable data retrieval, though the authors acknowledge that the shift from free academic access to a paid tier model for X's API may present challenges for future replication of this study.

A multi-stage search strategy was used to gather relevant posts. This included both keyword-based and semantic searches.

Inclusion Criteria: posts had to be in English or Spanish, mention either traditional mental health providers or AI in a mental health context, contain words indicating sentiment (e.g., "helpful," "useless," "bueno," "dañino"), and have a minimum of five favorites (min_faves:5) to filter for posts with a degree of public engagement and reduce noise from bot accounts.

Sampling Frame Considerations: the use of an engagement threshold (min_faves:5) introduces a documented sampling bias toward high-visibility, potentially polarizing content. Research on social media discourse demonstrates that emotionally intense content—particularly negative content—receives disproportionate engagement due to platform algorithms optimizing for interaction (Brady et al., 2017; Crockett, 2017). Consequently, this sample represents *amplified public discourse* rather than a probability sample of attitudes in the general population. The findings should be interpreted as characterizing the *visible, engaged discourse* on X rather than population-level sentiment. This methodological choice was made deliberately to capture discourse with demonstrated social resonance, but readers should note this limitation when generalizing findings.

Exclusion Criteria: retweets were excluded to ensure data independence. Posts identified as spam, advertisements, or clearly irrelevant to the topic were manually removed during the data cleaning phase.

Search Queries:

English Keywords: (therapist OR counselor OR psychologist OR psychiatrist) AND (good OR bad OR helpful OR harmful OR effective OR ineffective OR useful OR useless OR beneficial OR detrimental) lang:en since:2025-01-01 until:2025-09-01 min_faves:5

Spanish Keywords: (terapeuta OR consejero OR psicólogo OR psiquiatra) AND (bueno OR malo OR útil OR dañino OR efectivo OR ineficaz OR beneficioso OR perjudicial) lang:es since:2025-01-01 until:2025-09-01 min_faves:5

AI-related Keywords: queries were adapted to include terms like ("AI therapy" OR chatbot) AND (mental health) with the same sentiment indicators.

AI-related Keywords (Spanish): ("terapia IA" OR "terapeuta IA" OR "chatbot" OR "chatbot de salud mental" OR "bot de terapia" OR "inteligencia artificial" AND "salud mental") lang:es since:2025-01-01 until:2025-09-01 min_faves:5

Semantic Searches: broader queries such as "views on mental health providers AI therapy 2025" were used to capture posts that might not contain the exact keywords.

After an initial collection of over 600 posts, deduplication (removing posts with identical or near-identical text) resulted in the final dataset of 496 unique posts. All collected data was anonymized in accordance with American Psychological Association (2020) ethical guidelines; usernames, timestamps, and any other potentially identifying information were removed.

3.3 Data analysis

3.3.1 Quantitative analysis

A custom sentiment classifier was developed in Python to analyze the quantitative data. A lexicon-based approach was selected for three methodological reasons. First, transparency: unlike "black-box" transformer models, lexicon-based methods allow full inspection of scoring decisions, which is critical for mixed-methods integration where qualitative analysis must be reconciled with quantitative patterns (Thelwall et al., 2010). Second, bilingual adaptability: while pre-trained models such as BERT perform well in English, their performance degrades significantly in multilingual contexts without extensive fine-tuning (Grambow et al., 2020). Given resource constraints and the need for equivalent classification procedures across languages, a carefully constructed bilingual lexicon offered greater methodological symmetry. Third, domain specificity: mental health discourse contains domain-specific language that general-purpose sentiment models may misclassify (e.g., clinical terms that appear negative but are neutral in context). The lexicon approach allowed for domain-appropriate weighting.

We acknowledge that lexicon-based methods have documented limitations, particularly in detecting sarcasm, irony, and context-dependent meaning (Ribeiro et al., 2016). To mitigate these limitations, two strategies were employed: (a) modifier detection algorithms that adjusted polarity based on negation and intensification, and (b) a mixed-methods design wherein qualitative analysis provided contextual validation of quantitative patterns. Additionally, the high inter-rater reliability ($\kappa = 0.85$) between the classifier and human coders on a 25% subsample suggests acceptable validity within this dataset. The classifier operated as follows:

- **Weighted Bilingual Lexicon**: a lexicon of positive and negative words was created for both English and Spanish. Words were assigned weights based on their intensity (e.g., "good" = 1.0, "excellent" = 1.5; "bad" = −1.0, "disastrous" = −1.5).
- **Modifier Detection**: the algorithm accounted for common linguistic modifiers. Intensifiers (e.g., "very," "muy") multiplied a word's weight by 1.5, while negations (e.g., "not," "no") reversed its polarity.
- **Polarity Score Calculation**: for each post, a compound polarity score was calculated using the formula: $Polarity = \Sigma(Word\ Weights \times Intensifier \times Negation)/Total\ Sentiment\ Words$
- **Categorization**: posts were categorized based on their polarity score: positive (>0.15), Negative (<-0.15), or Neutral (−0.15 to 0.15).

To ensure the classifier's reliability, two independent coders manually rated a randomly selected 25% subsample ($n = 124$) of the posts. The inter-rater reliability was high, with a Cohen's kappa coefficient of 0.85.

Statistical analyses were performed using SPSS. Chi-square tests were used to determine if there were significant differences in sentiment proportions between categories (human vs. AI) and languages. An analysis of variance (ANOVA) was conducted to compare average polarity scores across subcategories (e.g., therapists vs. psychiatrists). Finally, Pearson's correlation coefficient (r) was calculated to assess the relationship between sentiment polarity and engagement metrics (average likes).

3.3.2 Qualitative analysis

A qualitative thematic analysis was conducted to explore the nuances of public discourse. Following the methodology of Braun and Clarke (2006), this process involved six phases:

- **Familiarization**: the research team read and re-read a subsample of 200 high-engagement posts (those with >75 likes/reposts) to immerse themselves in the data.
- **Initial Coding**: initial codes were generated by identifying interesting features of the data relevant to the research questions (e.g., "cost barrier," "AI lacks empathy").
- **Theme Generation**: codes were collated into potential themes, and all relevant data extracts were gathered under these themes.
- **Theme Review**: the themes were reviewed and refined, ensuring they were coherent, distinct, and accurately represented the dataset. This involved splitting, combining, or discarding themes.
- **Theme Definition and Naming**: a detailed analysis of each theme was conducted to define its scope and essence, and a concise, descriptive name was assigned.
- **Report Production**: the final analysis was written, weaving together the thematic narrative with compelling, representative post excerpts (paraphrased for anonymity).

To ensure rigor, three coders were involved in the qualitative analysis. An intercoder reliability check on a 20% subsample of the qualitative data yielded a high Cohen's kappa of 0.87, indicating strong agreement on the coding framework. Special attention was paid to identifying subthemes that highlighted cultural nuances, particularly in the Spanish-language data.

3.4 Integration of findings

In the final stage, the quantitative and qualitative findings were integrated. A joint display table was created to juxtapose the sentiment proportions from the quantitative analysis with the corresponding qualitative themes. This allowed for a direct comparison of the "what" (the statistical trends) and the "why" (the underlying narratives). Meta-inferences were drawn by examining points of convergence (where quantitative and qualitative data told the same story) and divergence (where they presented a more complex, seemingly contradictory picture) to develop a holistic and nuanced interpretation of the findings (Guetterman et al., 2015).

4 Results

4.1 Quantitative findings

The analysis of 496 X posts revealed statistically significant differences in the *directional polarity* of discourse toward traditional human providers vs. AI-based mental health tools. As with all sentiment analysis, these findings represent *approximate indicators* of sentiment tendency within high-engagement X discourse rather than precise measurements of attitude valence. The patterns should be interpreted in conjunction with the qualitative findings that provide contextual depth. Overall, human providers were discussed with a predominantly negative sentiment, while AI tools garnered a more positive, albeit ambivalent, reception.

Table 1 provides a detailed breakdown of sentiment proportions, average polarity scores, and average engagement (likes) across categories and languages.

Key statistical insights:

- **Overall Sentiment Difference**: a Chi-square test of independence revealed a highly significant difference in sentiment distribution between human providers and AI tools ($\chi^2(2, N = 496) = 28.4$, $p < 0.001$). Human providers received significantly more negative sentiment (63% overall) than AI tools (35.5% overall).
- **Subcategory Differences**: an ANOVA showed a significant difference in average polarity scores among the provider subcategories ($F_{(3,492)} = 14.2$, $p < 0.001$). *Post-hoc* tests indicated that psychologists/psychiatrists were viewed significantly more negatively than therapists/counselors in both languages ($p < 0.05$).
- **Language Differences**: while both English and Spanish posts were predominantly negative toward human providers, the negativity was slightly higher in Spanish (65% vs. 61%). Conversely, positive sentiment toward AI was higher in Spanish than in English (58% vs. 53%).
- **Engagement and Negativity**: a strong positive correlation was found between negative sentiment and user engagement (Pearson's $r = 0.65$, $p < 0.01$). Posts expressing criticism or frustration with the mental health system received significantly more likes and reposts, suggesting that negative experiences are more likely to be amplified on the platform.

Temporal Trends:

Analysis of sentiment over the 9-month period revealed dynamic shifts in public opinion, often corresponding with real-world events.

As illustrated in Figure 1, negativity toward human providers peaked in June 2025, Monthly polarity scores for the full study period are detailed in Table 2. As illustrated in Figure 1, negativity toward human providers peaked in June 2025, coinciding with several widely circulated news reports about provider burnout and workforce shortages. In contrast, positive sentiment toward AI surged in August 2025, which correlated with the launch of two new popular mental health apps. However, this optimism was tempered by a noticeable dip in September following media coverage of a data breach at a prominent digital health company.

4.2 Qualitative findings

The thematic analysis of 200 high-engagement posts identified six primary themes—three related to human providers and three to AI—that provide rich context to the quantitative results.

Themes for Human Providers:

- **Systemic Barriers: "The System is Broken" (40% of posts)** This was the most dominant theme, encompassing frustrations with the structural and financial obstacles to care.

Subtheme: Prohibitive Cost: users frequently described mental healthcare as a luxury. Paraphrased excerpts include: *"Trying to find a therapist who takes my insurance is a second full-time job"* [English, post:18] and *"Psychologists are only for the rich. The rest of us just have to suffer"* [Spanish, post:115].

Subtheme: Inaccessibility and Wait Times: many posts detailed the struggle of finding available providers, especially in rural areas or for specialized care. *"Called 15 therapists today. Not a single one is accepting new patients. What am I supposed to do?"* [English, post:33]. *"They give you an appointment for a psychiatrist in six months. By then it could be too late"* [Spanish, post:142].

- **Inefficacy and Harm: "More Harm Than Good" (33% of posts)** A significant portion of the discourse centered on negative experiences with providers, questioning their effectiveness and, in some cases, accusing them of causing harm.

Subtheme: Over-medicalization and "Pill-Pushing": this was a major point of criticism directed at psychiatrists. *"You wait 3 months to see a psychiatrist, talk for 10 minutes, and walk out with a prescription you don't understand. They don't listen"* [English, post:47]. *"Psychiatrists just want to drug you. They don't care about the root of the problem"* [Spanish, post:159].

Subtheme: Lack of Connection and Invalidation: users described feeling misunderstood or invalidated by therapists. *"Paid $150 for a therapist to tell me to 'just try journaling.' It felt*

TABLE 1 Sentiment proportions, polarity scores, and engagement by category and language.

Category	N	Positive (%)	Negative (%)	Neutral (%)	Avg. polarity	Engagement (Avg. likes)
English human providers						
Therapists/Counselors	124	28	57	15	−0.24	420
Psychologists/Psychiatrists	124	22	65	13	−0.36	580
Total	248	25	61	14	−0.30	500
Spanish human providers						
Therapists/Counselors	124	23	62	15	−0.31	390
Psychologists/Psychiatrists	124	19	68	13	−0.40	530
Total	248	21	65	14	−0.35	460
English AI mental health	248	53	38	9	0.08	280
Spanish AI mental health	248	58	33	9	0.16	240
Overall	**496**	**39**	**49**	**12**	**−0.10**	**370**

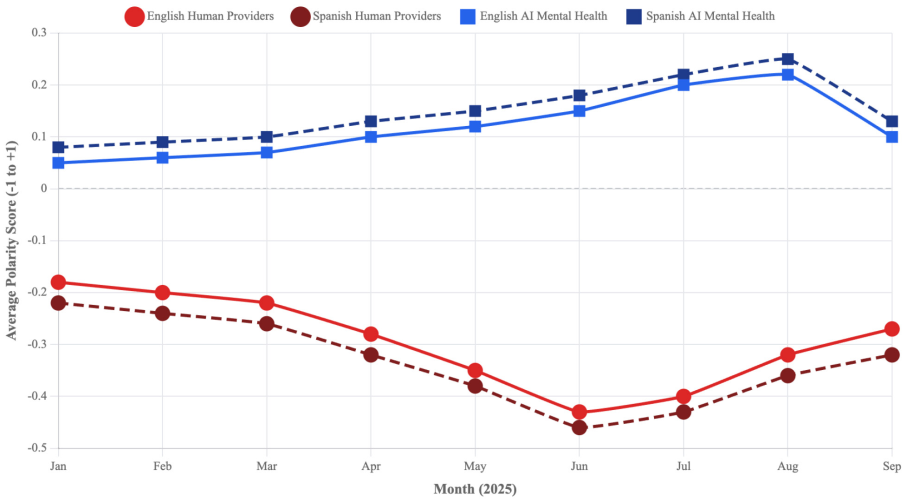

FIGURE 1
Temporal sentiment trends for human mental health providers and AI mental health systems from January to September 2025. Monthly average polarity scores (−1 to +1) derived from sentiment analysis of 496 X (formerly Twitter) posts (248 English, 248 Spanish). Human providers show persistent negativity peaking in June (−0.43 English, −0.46 Spanish) coinciding with burnout-related discourse, with recovery to −0.27 and −0.32 respectively by September. AI mental health systems demonstrate positive sentiment trends peaking in August (0.22 English, 0.25 Spanish) corresponding to application launches, declining to 0.10 and 0.13 respectively in September following risk-related coverage. Spanish-language posts consistently show more extreme sentiment patterns in both directions. Data points represent monthly averages from weighted lexicon-based sentiment classifier ($\kappa = 0.85$). Solid lines represent English-language posts; dashed lines represent Spanish-language posts. Horizontal reference line at $y = 0$ distinguishes positive from negative sentiment.

> *so dismissive"* [English, post:59]. *"Some psychologists project their own issues onto you. A bad therapist can do more damage than no therapist at all"* [English, post:81].

- **The Lifeline: "My Therapist Saved My Life" (17% of posts)** Despite the overwhelming negativity, a substantial number of posts expressed deep gratitude for effective providers, framing therapy as a transformative and life-saving experience.

Subtheme: Empathy and Connection: these posts highlighted the power of a strong therapeutic alliance. *"It took me three tries, but I finally found a therapist who truly gets me. That connection is everything"* [English, post:50].

Subtheme: Essential for Complex Cases: users acknowledged that for serious mental illness, there is no substitute for professional human care. *"For my severe OCD, a good psychologist was the only thing that worked. An app could never"* [Spanish, post:168].

TABLE 2 Monthly polarity scores (January–September 2025).

Month	English human providers	Spanish human providers	English AI mental health	Spanish AI mental health
January	−0.18	−0.22	0.05	0.08
February	−0.20	−0.24	0.06	0.09
March	−0.22	−0.26	0.07	0.10
April	−0.28	−0.32	0.10	0.13
May	−0.35	−0.38	0.12	0.15
June	−0.43	−0.46	0.15	0.18
July	−0.40	−0.43	0.20	0.22
August	−0.32	−0.36	0.22	0.25
September	−0.27	−0.32	0.10	0.13

Themes for AI in Mental Health:

- **The Accessibility Revolution: "Help is Finally Here" (44% of posts)** This theme captured the optimism surrounding AI's potential to democratize mental healthcare by overcoming the barriers associated with traditional care.

> **Subtheme: 24/7 Availability and Immediacy**: the ability to access support at any time was a frequently praised feature. *"Having an AI chatbot to talk to at 3 AM when my anxiety is spiraling is a game-changer"* [English, post:6].
>
> **Subtheme: Anonymity and Stigma Avoidance**: this was a particularly strong subtheme in Spanish-language posts. *"I can use an AI therapy app without my family knowing and judging me. It's a safe space"* [Spanish, post:178]. *"AI is free, anonymous, and doesn't look at you with pity"* [English, post:21].

- **The Empathy Gap: "A Soulless Algorithm" (31% of posts)** This theme encompassed the deep-seated skepticism and fear regarding AI's inability to replicate human connection and understanding.

> **Subtheme: Lack of Nuance and Genuine Empathy**: users expressed that AI responses felt generic, scripted, and emotionally hollow. *"The AI chatbot said 'I understand that must be difficult' in the exact same way it did yesterday. It doesn't understand anything"* [English, post:8].
>
> **Subtheme: Risk of Dependency and Escalation**: concerns were raised about the potential for users to become overly reliant on AI or for the technology to fail in a crisis. *"Relying on an AI for mental health feels like a dangerous abyss. What happens when you're in a real crisis and it gives you a canned response?"* [English, post:93]. *"I've seen threads where AI advice made someone's psychosis worse. This is not a game"* [Spanish, post:193].

- **The Hybrid Future: "The Best of Both Worlds" (16% of posts)** A forward-looking theme emerged where users envisioned an integrated model of care that leverages the strengths of both AI and human providers.

> **Subtheme: AI as a Triage and Support Tool**: users proposed that AI could serve as a "first step" or supplementary tool. *"The ideal system: AI for daily check-ins and coping exercises, and a human therapist for the deep, complex stuff"* [English, post:27].
>
> **Subtheme: AI to Empower Human Providers**: some posts suggested AI could help therapists by automating notes or providing data insights, freeing them up to focus on the patient. *"AI could handle the paperwork and let my therapist focus on me. That would be a win-win"* [English, post:105].

4.3 Integrated findings

Integrating the quantitative and qualitative data provides a holistic picture of public sentiment. A joint display (Table 3) maps the statistical findings to the corresponding qualitative themes.

Meta-Inferences:

- **Negativity toward Human Providers is Systemic, Not Personal**: the integrated data suggests that public frustration is aimed less at individual providers and more at a broken system they are forced to operate within. The "Lifeline" theme shows that effective human care is highly valued, but the "Systemic Barriers" theme indicates it is perceived as unattainable for many.
- **AI's Appeal is Primarily Pragmatic:** the public's positive sentiment toward AI is driven by its ability to address the practical deficiencies of the traditional system—namely, prohibitive cost, limited access, and lack of immediacy. This is not an endorsement of AI as a therapeutically equivalent modality but rather as a functional solution to systemic barriers.
- **Ambivalence toward AI Reflects a Core Conflict**: the divergence in the AI data reveals a central conflict in the public mind. Users are drawn to the convenience of AI but are deeply concerned about its lack of humanity. This suggests that acceptance is conditional and that trust has not yet been fully established.
- **Culture is a Powerful Moderator**: the more positive reception of AI in the Spanish-language data underscores the importance of cultural context. Where social stigma is a stronger barrier to traditional care, the anonymity offered by AI becomes a more powerful driver of acceptance.

TABLE 3 Joint display of integrated quantitative and qualitative findings.

Category	Quantitative finding (% Pos/Neg/Neu)	Dominant qualitative themes	Convergence/divergence
English human providers	25/61/14	"Systemic Barriers" (cost, access), "Inefficacy/Harm" (invalidation, over-medicalization)	Convergence: the high negative polarity (61%) directly aligns with the dominant qualitative themes of "Systemic Barriers" and "Inefficacy/Harm."
Spanish human providers	21/65/14	Same themes plus cultural stigma as powerful subtheme	Convergence: The even higher negativity (65%) is explained by the addition of cultural stigma as a powerful subtheme within "Systemic Barriers," making traditional care even less accessible or desirable.
English AI mental health	53/38/9	"Accessibility Revolution" vs. "The Empathy Gap"	Divergence: the overall positive polarity (53%) converges with the "Accessibility Revolution" theme. However, it diverges sharply with the significant minority theme of "The Empathy Gap" (38% negative), indicating a state of cautious optimism mixed with significant apprehension.
Spanish AI mental health	58/33/9	Stronger "Accessibility Revolution" (especially anonymity/stigma avoidance)	Stronger Convergence: the higher positive polarity (58%) strongly converges with the "Accessibility Revolution" theme, specifically the subtheme of "Anonymity and Stigma Avoidance," which was more pronounced in the Spanish data. The divergence with risk concerns is still present but less pronounced than in English.

5 Discussion

This study's mixed-methods analysis of multilingual X discourse provides a nuanced and timely snapshot of public sentiment at the intersection of mental health and artificial intelligence. The findings not only quantify the public's growing frustration with the traditional mental healthcare system but also illuminate the complex and ambivalent reception of AI as a potential alternative. By interpreting these findings through the theoretical lens of the Unified Theory of Acceptance and Use of Technology (UTAUT), we can move beyond a simple description of sentiment to a deeper understanding of the factors driving technology acceptance in this sensitive domain.

5.1 Interpreting the findings through the UTAUT framework

The UTAUT framework, with its constructs of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, provides a powerful structure for interpreting the results.

Facilitating Conditions: The Core of the Crisis and AI's Primary Appeal A notable pattern in this analysis is the prominence of discourse related to "Facilitating Conditions." The overwhelmingly negative sentiment toward human providers is rooted in the public's perception of poor facilitating conditions: prohibitive costs, long wait times, and a lack of available providers. These are the systemic barriers that prevent access to care.

Conversely, AI's positive sentiment is almost entirely driven by its perceived ability to offer superior facilitating conditions. The qualitative themes of "24/7 Availability," "Low/No Cost," and "Immediacy" directly map onto this UTAUT construct. In essence, the public sees AI not necessarily as a better form of therapy, but as a more accessible one. AI is positioned as a solution to the logistical failures of the traditional system, a "gap-filler" that can provide some level of support when the ideal (a human therapist) is unattainable.

Performance Expectancy: The Value of Humanity and the Limits of AI "Performance Expectancy" refers to the belief that a system will be effective. Here, the findings are more complex. The "Lifeline" theme, where users describe therapists as having saved their lives, indicates a very high performance expectancy for *effective* human care. However, the "Inefficacy and Harm" theme suggests that the perceptions expressed in X discourse for the *average* or *accessible* human provider is low, marred by experiences of invalidation and over-medicalization.

For AI, performance expectancy is ambivalent. While some users find AI tools helpful for managing daily anxiety or learning basic CBT skills, the dominant "Empathy Gap" theme reveals a low performance expectancy for AI's ability to handle complex emotional issues. The public largely does not believe an algorithm can perform the core functions of therapy: genuine empathy, nuanced understanding, and building a therapeutic alliance. This suggests that while AI may be accepted for low-stakes support, it has not yet earned the public's trust for deep therapeutic work.

Effort Expectancy: The Simplicity of AI "Effort Expectancy," or perceived ease of use, is another area where AI holds a distinct advantage. Accessing an AI chatbot via a smartphone is perceived as a low-effort activity compared to the high-effort process of finding, vetting, and scheduling appointments with a human therapist. This low barrier to entry is a significant driver of AI's appeal, particularly for younger, tech-savvy demographics.

Social Influence: The Decisive Role of Stigma "Social Influence" manifests most clearly in the cultural differences observed between the English and Spanish data. In the Spanish-language posts, the subtheme of familial and social judgment against seeking traditional therapy was a powerful negative social influence. This makes the anonymity of AI a key feature, as it allows users to bypass this negative social pressure. In this context, AI functions not merely as a tool but as a private sanctuary—a stigma-free space where help-seeking can occur without social judgment. Importantly, this role as a sanctuary reflects AI's value as an *accessible* alternative, not its equivalence or superiority as a *therapeutic* modality. Users value AI for its discretion, not necessarily for its clinical efficacy. This finding empirically supports previous research by Caplan (2019) and Mascayano et al. (2016) and Ren et al. (2022) and demonstrates that social influence can be a powerful moderator in technology acceptance, pushing users toward solutions that offer discretion.

Trust: The Unresolved Barrier for AI While not an original UTAUT construct, trust emerged as a critical cross-cutting theme. The "Lifeline" theme is built on a foundation of trust in a human provider. Conversely, the "Empathy Gap" and "Risk of Dependency" themes for AI are fundamentally about a lack of trust (Westerlund et al., 2012). Users do not trust AI to keep their data safe (as evidenced by the sentiment dip after news of a data breach), they do not trust it to handle a crisis appropriately, and they do not trust it to understand them as a human would. Building this trust is arguably the single greatest challenge for the future of AI in mental health.

Limitations of the UTAUT Framework: while UTAUT provides useful organizational categories, several observations in this study fit uneasily within its constructs. The profound emotional salience of the "Lifeline" theme—users describing therapists as having saved their lives—involves relational and existential dimensions that "Performance Expectancy" only partially captures. Similarly, the cultural stigma dynamics observed in Spanish-language data extend beyond "Social Influence" as typically operationalized, involving shame, familial honor, and religious dimensions that warrant engagement with stigma-specific theoretical frameworks (Corrigan and Watson, 2002). Future research might benefit from integrating UTAUT with therapeutic alliance theory (Bordin, 1979) and modified labeling approaches (Link et al., 1989) to develop more comprehensive models of mental health technology acceptance.

5.2 Implications of the findings

The findings of this study have significant implications for theory, practice, and future research.

Theoretical Implications: this study extends the application of the UTAUT model to the domain of AI in mental health, demonstrating its utility in explaining public sentiment derived from social media data. It highlights the outsized importance of "Facilitating Conditions" in healthcare contexts where access is a primary crisis. Furthermore, it underscores the need to integrate "Trust" as a core construct when applying technology acceptance models to healthcare, particularly in a field as sensitive as mental health. The findings also show how cultural factors like stigma can act as powerful moderators of "Social Influence," a crucial consideration for developing globally relevant theories of technology adoption.

Practical Implications:

- **For Policymakers and Healthcare Systems**: the discourse patterns identified in this study suggest significant public concern regarding access barriers, which warrants urgent policy action. Efforts must be redoubled to reduce costs, expand insurance coverage for mental health, and increase the pipeline of human providers. The findings also support the regulated integration of AI as a public health tool. AI could be used for triage, to provide low-intensity CBT interventions for mild to moderate conditions, and to offer immediate support for those on long waitlists. A "stepped-care" model, where users start with AI and are escalated to human care as needed, could be a viable path forward.
- **For AI Developers:** the "Empathy Gap" is not merely a technical problem; it is a design and perhaps ultimately a philosophical problem. Developers must move beyond creating tools that simply mimic empathy and focus on building tools that are transparent about their limitations. However, emerging research in artificial consciousness (AC) suggests that the boundaries of machine cognition and affective experience may be more fluid than previously assumed (Dehaene et al., 2017; Reggia, 2013). While current AI systems operate through pattern recognition rather than phenomenological experience, ongoing developments in AC research raise the possibility that future systems may possess capacities extending beyond behavioral mimicry. Should such developments materialize, the "Empathy Gap" identified in this study may require fundamental reconceptualization (De Choudhury et al., 2021). In the interim, developers should design systems that are honest about current limitations while remaining architecturally open to integration of more sophisticated affective capacities as the science evolves (Miner et al., 2016). User trust can be enhanced through clear communication about data privacy, security protocols, and the circumstances under which a user should seek human help. The "Hybrid Future" theme suggests a strong public appetite for tools designed to *complement*, not replace, human therapists.
- **For Clinicians**: clinicians should be prepared to discuss the use of mental health apps and AI with their patients, who are likely already using them. Rather than viewing AI as a competitor, providers can leverage it as a tool to support therapy, for example, by using apps for mood tracking or between-session skill practice. Professional training on the ethics and efficacy of digital mental health tools is becoming essential.

5.3 Limitations of the study

Despite its strengths, this study has several limitations. First, X users are not representative of the general population; they tend to be younger, more educated, and more politically vocal. The findings therefore reflect the views of a specific demographic and may not be fully generalizable.

Second, the dataset, while substantial, is a snapshot in time. Public sentiment toward AI is evolving rapidly, and a longitudinal study would be needed to track these changes over a longer period.

Third, the lexicon-based sentiment analysis, while reliable and transparent, may not capture more complex linguistic forms like sarcasm, irony, or nuance as effectively as more advanced transformer-based models like BERT (Gohil et al., 2018). However, the mixed-methods design helps to mitigate this by providing rich qualitative context. Finally, while the study included Spanish to add a cross-cultural dimension, it did not capture the vast diversity within the English- and Spanish-speaking worlds, nor did it include other languages.

6 Conclusion and future directions

This research provides a comprehensive, data-driven analysis of the current state of expressed opinion in social media discourse on human vs. AI-based mental healthcare. The patterns in high-visibility X discourse are consistent: among engaged social media users, the traditional system is perceived as failing on access and affordability, creating a gap that AI is beginning to fill. AI is not seen as a replacement for the irreplaceable value of human connection but as a pragmatic, accessible, and often necessary "first-best" option in a world where the "gold standard" of care is out of reach for many. The public's cautious optimism is, however, tempered by significant and valid concerns about trust, empathy, and safety.

The path forward is not a binary choice between humans and machines, but a thoughtful integration of both. The "Hybrid Future" envisioned by users in this study points toward a new ecosystem of care where AI handles initial support, triage, and skill-building, freeing up human clinicians to focus on the complex, nuanced, and deeply relational work that only they can do.

Future research should build on these findings in several key areas. Longitudinal studies are needed to track the evolution of public sentiment as AI technology matures and becomes more integrated into healthcare. Expanding the multilingual analysis to include languages like Mandarin, Hindi, and Arabic would provide a more global perspective. Randomized controlled trials are essential to rigorously evaluate the efficacy of these hybrid models in real-world clinical settings. Finally, qualitative research, including interviews and focus groups, could provide an even deeper understanding of the user experience and the specific factors that build or erode trust in mental health AI.

In conclusion, the discourse on X serves as a powerful barometer of a system in transition. It reflects a public that is both frustrated with the present and cautiously hopeful about the future. By listening to these voices, we can guide the development and integration of AI in a way that is not only technologically innovative but also ethically grounded, human-centered, and truly accessible to all.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

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