



Acceptance of Artificial-Intelligence Chatbots for Support with Depressive Symptoms: The Predictive Primacy of Perceived Usefulness Over Well-Being

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Received: August 01, 2026; Manuscript No: JGPH-26-3318; Editor Assigned: August 05, 2026; PreQc No: JGPH-26-3318 (PQ); Reviewed: August 13, 2026; Revised: August 14, 2026; Manuscript No: JGPH-26-3318 (R); Published: September 18, 2026

Citation: Pazer S (2026). Acceptance of Artificial-Intelligence Chatbots for Support with Depressive Symptoms: The Predictive Primacy of Perceived Usefulness Over Well-Being. J. Glob. Pub. Hea. Healthc. Innov. Vol.1 Iss.1, September (2026), pp:1-14.

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ABSTRACT

Artificial-intelligence (AI) chatbots are increasingly proposed as low-threshold instruments for supporting people with depressive symptoms, yet it remains unclear whether their acceptance is governed by users' psychological need or by instrumental appraisal. Drawing on the Technology Acceptance Model, the present study reports original empirical data from a cross-sectional online survey that examined whether the acceptance of AI chatbots for depressive support is predicted by perceived usefulness, by psychological well-being, and by prior therapy experience. A non-probabilistic, self-selected sample of 99 adults ($M = 36.56$ years, $SD = 10.36$) was recruited through topic-relevant communities on the social-media platform Reddit and completed three-item Likert scales assessing well-being, perceived usefulness, and acceptance. Perceived usefulness correlated strongly with acceptance, $r = .77$, $p < .001$, whereas well-being was unrelated to acceptance, $r = -.00$, $p = .989$. A multiple regression explained a substantial proportion of the variance in acceptance, $R^2 = .60$, adjusted $R^2 = .59$, $F(2, 96) = 72.45$, $p < .001$, with perceived usefulness emerging as the sole significant predictor, $\beta = .78$, $p < .001$, while well-being did not contribute, $\beta = .05$, $p = .55$. Acceptance did not differ between participants with and without prior therapy experience, $t(97) = 0.32$, $p = .748$. These findings indicate that the acceptance of AI chatbots for depressive support follows an instrumental rather than a need-based logic: it is driven almost entirely by perceived usefulness, whereas current well-being and prior therapy experience play no discernible role. Implications for the design and framing of digital mental-health tools are discussed.

Keywords: GST Compliance; Input Tax Credit (ITC); Tax Reform; Small and Medium Enterprises (SMEs); GSTR Reconciliation; Digital Transformation; Tax Knowledge; Transaction Complexity

INTRODUCTION

Depressive disorders rank among the most prevalent and burdensome conditions worldwide, affecting an estimated several hundred million people and constituting a leading contributor to years lived with disability [1]. Despite the availability of efficacious pharmacological and psychotherapeutic treatments, whose benefits have been documented across age groups and delivery format a persistent treatment gap separates the number of individuals who could benefit from care from the far smaller number who actually receive it [2,3]. Structural

barriers such as long waiting times, geographic scarcity of providers, and financial cost combine with attitudinal barriers such as stigma and low perceived need to keep many people with depressive symptoms outside the formal care system [4,5]. Against this backdrop, digital and low-threshold forms of support have attracted sustained scholarly and clinical attention as a means of extending the reach of mental-health provision, and the ambition of this field has broadened over time from the remote delivery of treatment to the wider promotion of psychological well-being [6].

The scale of the problem lends this treatment gap particular gravity. Depression is not only common but recurrent and frequently chronic, and its consequences extend from impaired daily functioning and diminished quality of life to elevated mortality [7]. The gap between need and care is widest precisely where resources are scarcest, but it is far from absent even in well-resourced settings, where waiting lists, cost, and stigma continue to deter many who might benefit from treatment [4,8]. It is within this space between the availability of effective care and its actual reach that low-threshold digital tools are positioned, and their promise is to lower the practical and psychological cost of taking a first step towards support.

The empirical case for digital provision is by now reasonably well established at the level of aggregate effects. Meta-analytic syntheses of internet-delivered cognitive-behavioural interventions have documented reliable reductions in depressive symptoms relative to control conditions and an individual-participant-data synthesis confirmed that even self-guided programmes outperform control conditions, albeit with smaller effects than guided formats [9,10,11]. Comparable conclusions have been drawn for smartphone-delivered interventions, which yield small-to-moderate improvements in depressive symptomatology across randomised trials [12,13]. Two qualifications temper this picture. First, the presence of human guidance consistently amplifies effects, so that fully automated formats tend to occupy the lower end of the efficacy distribution [14]. Second, attrition in digital interventions is high and systematic rather than incidental, to the point that dropout has been described as a defining structural feature of the field [15,16]. Efficacy under trial conditions therefore does not translate automatically into public-health benefit, and the question of who is willing to engage in the first place becomes correspondingly consequential.

Among these digital innovations, conversational agents driven by artificial intelligence (AI) have emerged as a particularly promising modality. AI chatbots are software systems that simulate human-like dialogue through natural-language processing and can deliver psychoeducation, structured cognitive-behavioural exercises, mood tracking, and empathic conversational support on demand and at scale [17,18,19]. Because they are available around the clock, require no appointment, and can be accessed anonymously from a personal device, such agents potentially circumvent several of the structural and attitudinal barriers that impede conventional help-seeking. Early controlled evaluations have suggested that dedicated therapeutic chatbots can produce modest but meaningful reductions in depressive and anxious symptoms real-world usage data indicate that more engaged users report greater symptomatic improvement and reviews of the field have documented rapid growth in both the number and sophistication of these tools [17,20-24,19]. At the same time, quantitative syntheses caution that the underlying evidence base remains small, methodologically

heterogeneous, and dominated by feasibility and pilot work [24,25].

Whether such tools ultimately fulfil their public-health promise, however, depends less on their technical efficacy than on whether prospective users are willing to adopt them. Acceptance is the pivotal precondition of any impact: a demonstrably effective tool that is rejected by its intended audience confers no benefit. This observation raises a fundamental and as yet insufficiently resolved question about the psychological logic of acceptance in the mental-health domain. On one reading, acceptance might be primarily need-driven. People experiencing greater distress or lower well-being might be expected to reach more readily for any accessible form of support, so that the willingness to adopt an AI chatbot would rise as psychological well-being falls. On an alternative reading, acceptance might be primarily instrumental. Here the decisive consideration would not be the depth of a person's distress but their appraisal of whether the tool is genuinely useful for the problem at hand, in line with the central tenet of technology-acceptance theory that perceived usefulness governs the intention to use a system [26,27].

These two accounts carry markedly different implications. If acceptance were need-driven, developers and health-care systems could assume that those who need chatbots most would be most inclined to use them, and outreach could be targeted at distress. If, by contrast, acceptance were instrumental, then the level of a person's distress would be largely immaterial to their willingness to adopt the tool, and efforts to increase uptake would need to concentrate on demonstrating and communicating concrete usefulness. A further consideration concerns prior experience with formal psychotherapy. It is plausible that individuals who have previously engaged in therapy hold more differentiated expectations of what psychological support entails and might therefore differ systematically in their acceptance of an automated alternative, whether more favourably, because they recognise its potential, or less favourably, because they measure it against a human standard.

Although the Technology Acceptance Model has been applied extensively to health technologies comparatively little quantitative work has directly pitted an instrumental account of chatbot acceptance against a need-based account within the same design, and fewer studies still have done so for the specific and sensitive case of support for depressive symptoms. Existing acceptability research on health chatbots has largely been descriptive, mapping attitudes and reservations rather than adjudicating between competing predictive models [28-31]. The present study addresses this gap by examining, in a single cross-sectional online survey, the relative contribution of perceived usefulness, psychological well-being, and prior therapy experience to the acceptance of AI chatbots for depressive support. The overarching research question is

therefore whether the acceptance of AI chatbots for support with depressive symptoms is driven primarily by an instrumental appraisal of usefulness or by a need arising from diminished well-being, and whether prior therapy experience shapes that acceptance. Answering this question is of both theoretical and practical importance, as it speaks to how digital mental-health tools should be designed, framed, and disseminated if they are to reach the people they are intended to serve.

A closer consideration of the mental-health context sharpens the theoretical stakes of this question. Unlike many consumer technologies, tools that address depressive symptoms operate in a domain characterised by ambivalence, vulnerability, and stigma, and the decision to engage with them is rarely a purely technical one [30,32]. Prospective users must weigh not only whether a tool works but also whether they are prepared to disclose sensitive experiences to an automated system, whether such a system can be trusted with intimate information, and whether turning to a machine for emotional support is congruent with their self-image. These considerations might be expected to loosen the grip of instrumental appraisal and to hand a larger role to the user's psychological state, so that the mental-health context would represent a hard test of the technology-acceptance logic rather than a straightforward extension of it. It is precisely because the domain is atypical that the outcome of a direct contest between instrumental and need-based accounts is genuinely uncertain and worth establishing empirically.

There is, moreover, a practical urgency to resolving the question. Public-health actors and technology developers are already investing considerable resources in conversational agents for mental health on the assumption that unmet need will translate into willingness to use [33,34]. Yet a recurrent and sobering finding in the digital-mental-health literature is that engagement with such tools is frequently low and attrition high, even among people with clear clinical need [15,16]. This disjunction between need and uptake is difficult to reconcile with a simple need-based model and hints that whatever drives initial acceptance may be only weakly tied to the severity of a person's distress. Understanding what actually predicts acceptance is therefore not an academic nicety but a prerequisite for designing tools and outreach strategies that convert potential into use.

Conceptually, the appeal of conversational agents for depression rests on a convergence of technological maturity and clinical need. Advances in natural-language processing have made it possible for software to sustain coherent, contextually responsive dialogue, and this capability has been harnessed to deliver structured psychological content in a conversational form that many users find approachable [35]. At the same time, the scalability of software offers a potential answer to the chronic under-supply of human providers, since a single

application can, in principle, serve very large numbers of users simultaneously and at negligible marginal cost [33]. Programmatic statements on the future of psychological-treatment research have likewise identified scalable delivery, alongside mechanistic understanding, as a central priority for the field [36]. These properties have prompted considerable optimism, but optimism about capability must be tempered by realism about adoption, and it is the psychology of adoption, rather than the engineering of capability, that the present study addresses.

The present research is best understood as a deliberately focused test of two competing explanations rather than a comprehensive model of chatbot adoption. By holding the design lean and pitting perceived usefulness directly against psychological well-being within a single sample, the study sacrifices breadth for the sake of an unambiguous comparison. This focus is a strength for the question at hand, because a sprawling model with many predictors would obscure the very contrast that motivates the investigation. The cost is that other determinants of acceptance, well documented in the wider literature, are held outside the frame and reserved for future work.

THEORETICAL BACKGROUND

The Technology Acceptance Model

The dominant theoretical framework for understanding the adoption of novel technologies is the Technology Acceptance Model (TAM), introduced by Davis (1989). Building on the theory of reasoned action and its successor, the theory of planned behaviour (Ajzen, 1991), the TAM proposes that the intention to use a technology, and thereby its actual use, is determined by two proximal beliefs: perceived usefulness, defined as the degree to which a person believes that using a particular system would enhance their performance or help them accomplish a goal, and perceived ease of use, defined as the degree to which they believe that using the system would be free of effort [37,38,26]. Of these, perceived usefulness has repeatedly proven to be the stronger and more consistent predictor of behavioural intention across a wide range of technologies and settings.

Subsequent theoretical development extended and consolidated the model. TAM2 introduced social-influence processes and cognitive-instrumental determinants such as job relevance, output quality, and result demonstrability, thereby specifying the sources from which perceptions of usefulness are formed [27]. TAM3 subsequently integrated these extensions with a parallel account of the determinants of perceived ease of use, yielding an explicit framework for intervening on acceptance rather than merely predicting it [40]. In parallel, the Unified Theory of Acceptance and Use of Technology synthesised eight competing acceptance models into a single framework in which performance expectancy, a construct closely aligned with perceived usefulness, was identified as the most

powerful determinant of behavioural intention, and its consumer-oriented extension retained this structure while adding hedonic motivation, price value, and habit [41,42]. Comparable emphasis is placed on relative advantage within diffusion-of-innovations theory, which likewise treats the perceived superiority of an innovation over the practice it replaces as the strongest and most reliable correlate of adoption [43]. The persistent primacy of usefulness-related constructs across these frameworks provides the conceptual foundation for the present investigation and motivates the expectation that, in the context of AI chatbots for depressive support, perceived usefulness will likewise be the dominant driver of acceptance.

The enduring influence of the Technology Acceptance Model stems in part from its parsimony and in part from its empirical robustness. Across three decades of research spanning workplace software, e-commerce, e-learning, and health technologies, the two core beliefs have repeatedly accounted for a large share of the variance in usage intentions, and reviews have confirmed the reliability of these relationships. Extensions of the model have added antecedents such as social influence, facilitating conditions, hedonic motivation, and trust, yet even as the surrounding nomological network has grown more elaborate, the usefulness intention pathway has retained its status as the most stable and forceful relationship in the framework. This durability is the reason the present study places perceived usefulness at the center of its predictive model and treats it as the benchmark against which the competing need-based account is evaluated.

The model has nonetheless attracted substantive criticism, and it is worth registering these objections rather than adopting the framework uncritically. Reviews have noted that TAM typically explains a moderate proportion of the variance in self-reported system use and that its explanatory power declines when actual rather than intended use is the criterion [44]. More fundamentally, the model has been charged with an overly deterministic and individualistic conception of adoption that neglects the social, affective, and habitual processes surrounding technology use, and with resting on an intention behaviour link that is weaker than the framework presupposes [45]. Applications of the model in health care have yielded a similarly mixed picture, with reviews concluding that TAM performs reasonably as a descriptive framework but requires domain-specific adaptation to accommodate the particular concerns of patients and clinicians [29,30]. These critiques do not undermine the usefulness intention relationship itself, which remains the most consistently replicated element of the model, but they do recommend caution in generalising from intention to behaviour and in assuming that a framework developed for organisational information systems transfers unaltered to a domain defined by distress and disclosure.

Conversational Agents in Mental Health Care

The technology whose acceptance is at issue here occupies a distinctive position within digital mental health. Conversational agents differ from conventional self-help applications in that they present psychological content through simulated dialogue rather than through static modules, and this dialogic form is widely assumed to reduce the psychological distance between user and tool. Systematic reviews of conversational agents in health care have documented that the majority of deployed systems remain comparatively simple in architecture, relying on finite-state or rule-based dialogue rather than open-ended language generation, and that rigorous evaluations have been relatively scarce in relation to the volume of deployment. Within mental health specifically, scoping work has mapped considerable heterogeneity in the features, target conditions, and theoretical grounding of available agents [22].

The efficacy evidence, though encouraging, is preliminary. A randomised trial of a cognitive-behavioural chatbot found reductions in depressive symptoms among young adults over a two-week period relative to an information-only control, and a further trial of an agent delivering integrated psychological content reported comparable reductions in depression and anxiety among students [17,20]. Naturalistic data from a widely used empathy-oriented agent indicated that users with higher levels of engagement showed greater symptomatic improvement, although the observational design precludes causal attribution [21]. Mixed-method and quantitative syntheses concur that conversational agents can produce improvements in depressive symptoms while cautioning that the number of controlled trials is small, follow-up periods short, and risk of bias frequently substantial [24,25].

Alongside efficacy, a distinct literature has examined the risks and ethical implications of automated psychological support. Analyses of embodied and disembodied agents in psychiatry and psychotherapy have raised concerns about therapeutic responsibility, the management of crisis situations, and the appropriate limits of automated empathy [23,46]. Empirical safety work has shown that general-purpose conversational assistants respond inconsistently and at times hazardously to medical and mental-health queries, underscoring that conversational fluency is not equivalent to clinical adequacy [47]. Reviews of the psychiatric chatbot landscape have similarly emphasised that enthusiasm for the modality has outpaced the evidence supporting its safe deployment [19]. These considerations are relevant to acceptance because prospective users may reasonably weigh such risks in forming their judgements, and because acceptance research that ignores them risks treating adoption as an unqualified good.

Finally, the acceptability of health chatbots has been studied directly, if less systematically than their efficacy.

Mixed-methods work has found broadly ambivalent attitudes, with anonymity, immediacy, and convenience cited as motivations and concerns about accuracy, privacy, and the inability of automated systems to handle complex or emotionally charged material cited as deterrents [32]. An experimental survey found that acceptability was systematically moderated by the character of the health issue at stake: chatbots were rated as more acceptable for stigmatised concerns and as markedly less acceptable for concerns perceived as severe [31]. Since depression is both stigmatised and, in many presentations, severe, these two moderators pull in opposite directions, which is a further reason why the acceptance of chatbots for depressive support cannot simply be extrapolated from findings on health chatbots in general.

Perceived Usefulness and Behavioral Intention

Perceived usefulness occupies a central position in acceptance theory because it captures the instrumental value that a prospective user attaches to a technology. When a person judges that a system will help them attain an outcome they care about, the intention to use it tends to follow almost regardless of other considerations [26,41]. In the health domain, this instrumental appraisal has been shown to predict the acceptance of a broad array of digital interventions, from electronic health records to mobile self-management applications, and reviews of the health-informatics literature identify perceived usefulness as the construct most consistently associated with intention across heterogeneous technologies and user groups [29,30]. For an AI chatbot offering support with depressive symptoms, perceived usefulness would encompass beliefs that the tool can provide helpful information, assist in managing one's mood, or offer meaningful support in difficult moments. To the extent that acceptance is an instrumental judgement, such beliefs should translate directly and strongly into willingness to adopt, and perceived usefulness should account for a large share of the variance in acceptance.

It is worth underscoring why perceived usefulness, rather than any objective property of the technology, is the operative variable. Acceptance is a psychological phenomenon, and what moves a person to adopt a tool is their subjective belief about its value, not the value it may possess in the abstract. Two individuals confronted with the identical chatbot may arrive at opposite adoption decisions because they construe its usefulness differently, and it is this construal, not the underlying software, that acceptance research seeks to explain. In the context of depressive support, perceived usefulness accordingly captures a person's belief that the tool can do something of genuine consequence for them: alleviate low mood, provide a listening presence at difficult hours, or supply strategies for coping. Should acceptance prove to be governed by this belief, the lever for change would lie in shaping perceptions of usefulness rather than in selecting users by their level of need.

A qualification concerns the criterion to which perceived usefulness is linked. Acceptance, as measured here and in most survey-based acceptance research, is an intention-like construct rather than observed behaviour, and the relationship between intentions and subsequent action is substantial but far from perfect. Meta-analytic work indicates that intentions account for roughly a quarter to a third of the variance in later behaviour, and that even sizeable experimentally induced changes in intention produce considerably smaller changes in behaviour [48,49]. The implication for the present study is twofold. A strong association between perceived usefulness and acceptance would establish the psychological logic of the adoption judgement without thereby establishing that usefulness translates into sustained use, and the well-documented attrition of digital mental-health tools is a reminder that the gap between willingness and behaviour is particularly consequential in this field [15,16].

Psychological Well-Being and Help-Seeking

An alternative to the instrumental account locates the impetus for adoption in the user's own psychological state. Models of help-seeking behaviour commonly posit that the recognition of a problem and the experience of distress constitute the first step towards seeking assistance [4,50]. From this perspective, diminished psychological well-being might function as a motivational engine for uptake: individuals experiencing low well-being would feel a more pressing need for support and might therefore be more receptive to any accessible avenue of help, including an AI chatbot. Psychological well-being itself is a multifaceted construct encompassing affective and evaluative components of how people experience their lives, which the eudaimonic tradition supplements with dimensions such as autonomy, purpose, and personal growth and which self-determination theory grounds in the satisfaction of basic psychological needs [51-54]. Its relation to the uptake of digital support tools is theoretically ambiguous. Lower well-being could heighten receptivity through need, yet distress can equally erode the motivation, energy, and self-efficacy required to engage with a new technology potentially attenuating or even reversing any need-driven effect. Whether well-being is in fact associated with the acceptance of AI chatbots for depressive support is thus an open empirical question rather than a foregone conclusion [55].

A conceptual point deserves emphasis here. Well-being and symptomatology are related but not interchangeable, and the mental-health continuum model explicitly distinguishes the absence of illness from the presence of positive functioning, allowing for states of languishing without disorder and of flourishing despite disorder [56]. A measure of current well-being therefore indexes a person's present experiential state rather than their diagnostic status or their history of psychological difficulty, a distinction that matters when interpreting a null result. Instruments developed in this tradition, such as brief

indices of subjective well-being, are widely used both as outcome measures and as screening tools precisely because they track the affective-evaluative dimension that patients themselves regard as salient [57].

The tension between the need-based and the demotivation possibilities mirrors a broader debate about the relationship between symptom severity and treatment engagement. Some evidence indicates that greater distress predicts more active help-seeking, consistent with a need-driven view, whereas other evidence documents that the very symptoms of depression, including anhedonia, hopelessness, and reduced motivation, can impede the initiation and maintenance of any effortful coping behaviour. Barrier research complicates the picture further: in large-scale survey work the most frequently endorsed reason for not seeking treatment among people with clinically significant symptoms is a low perceived need for care rather than an inability to access it, while stigma exerts a small-to-moderate deterrent effect on help-seeking that operates largely independently of symptom severity [5,8,33]. If these dynamics predominate, low well-being might not translate into greater acceptance of a chatbot and could even work against it. The direction and even the existence of a well-being effect on acceptance are therefore not deducible from theory alone, which is why the present study frames the need-based hypothesis as a falsifiable claim to be tested rather than an assumption to be built into the analysis.

Prior Therapy Experience

A further individual-difference variable of plausible relevance is prior experience with formal psychotherapy. Individuals who have previously undergone therapy have first-hand knowledge of what psychological support involves and may hold correspondingly elaborated expectations of any tool that purports to provide it. Such experience could foster acceptance if it renders the idea of structured psychological support familiar and non-threatening, or it could dampen acceptance if former clients evaluate an automated agent against the benchmark of a human therapeutic relationship and find it wanting. Because these opposing possibilities are equally defensible on theoretical grounds, prior therapy experience is examined here as a group-defining variable whose association with acceptance is treated as an open question.

The comparison standard invoked by the second possibility is not arbitrary. The working alliance between client and therapist is among the most robust correlates of psychotherapeutic outcome, with meta-analytic estimates converging on a modest but highly consistent association across treatment modalities and disorders [58,59]. People who have experienced this relationship might reasonably doubt that a software agent can supply its equivalent. Against this expectation stands a substantial body of human computer-interaction research suggesting that relational responses to machines are more readily elicited

than intuition would predict. Users apply social rules and expectations to computers largely without deliberation, automated relational agents have been shown to establish measurable working alliances in health-behaviour interventions, and self-disclosure to a conversational agent can yield emotional and relational benefits comparable to those of disclosure to a person [60-63]. There is even evidence that the belief of interacting with a machine rather than a human can increase willingness to disclose sensitive material, presumably because the perceived risk of social evaluation is reduced [64]. Prior therapy experience might therefore cut either way, sensitising former clients to what automation cannot provide or, conversely, lowering their threshold for engaging with a structured psychological offer in any form.

Prior therapy experience also functions as a rough proxy for a history of engagement with the mental-health system and, by extension, for a degree of mental-health literacy, which is itself associated with help-seeking [50]. Whether this history predisposes people towards or against an automated alternative cannot be settled a priori, and the literature offers grounds for both expectations. Examining it empirically alongside the appraisal and need variables allows the study to determine whether biographical background exerts any influence on acceptance once the more proximal determinants are considered.

Hypotheses

On the basis of the foregoing considerations, three hypotheses were formulated. Consistent with the central proposition of the Technology Acceptance Model, the first hypothesis (H1) states that perceived usefulness positively predicts the acceptance of AI chatbots for support with depressive symptoms. Reflecting the need-based account of help-seeking, the second hypothesis (H2) states that lower psychological well-being is associated with higher acceptance, indicating need-driven uptake. The third hypothesis (H3) states that prior therapy experience is associated with acceptance, with the direction of the association left open. Together these hypotheses allow the instrumental and the need-based accounts of acceptance to be tested against one another within a single design.

These three hypotheses are not merely additive but stand in a relation of theoretical rivalry. Hypotheses 1 and 2 instantiate the instrumental and the need-based accounts respectively, and the design permits their simultaneous evaluation because perceived usefulness and well-being are entered together as predictors of the same outcome. Should perceived usefulness dominate while well-being proves inert, the instrumental account would be favoured; should well-being carry independent predictive weight, the need-based account would gain support. Hypothesis 3 supplements this contest by asking whether a stable individual characteristic, prior therapy experience, conditions acceptance over and above these appraisals. In this way the study is structured to yield a clear verdict on

which logic best describes the acceptance of AI chatbots for depressive support.

METHOD

Study Design

The study employed a cross-sectional, correlational design realised through a single-wave online survey. All constructs were measured concurrently by self-report, and no experimental manipulation was introduced. This design was chosen because the research question concerns the pattern of associations among acceptance and its putative determinants in the general adult population rather than any causal intervention effect. The study was conducted in accordance with the ethical principles for research involving human participants set out in the Declaration of Helsinki [65].

Sample and Procedure

Participants were recruited through an anonymous online questionnaire distributed within topic-relevant communities on the social-media platform Reddit, that is, through subreddits whose themes were relevant to the study content. Recruitment therefore yielded a non-probabilistic, self-selected online sample rather than a representative one. Interested users followed a link to the survey, read a page of study information, and provided consent before completing the instrument; participation was voluntary and uncompensated, and respondents could withdraw at any point simply by closing the browser. The final sample comprised 99 adults ranging in age from 18 to 60 years ($M = 36.56$, $SD = 10.36$). With respect to gender, 58 participants identified as women (58.6%), 40 as men (40.4%), and 1 as diverse (1.0%). A majority of the sample reported prior experience with psychotherapy, with 70 participants (70.7%) indicating such experience and 29 (29.3%) indicating none.

Recruitment through interest-based online communities was chosen deliberately, as it affords rapid and cost-efficient access to adults who are engaged with digital media and who may be plausibly receptive to reflecting on digital mental-health tools. Methodological evaluations of this recruitment channel indicate that it enables fast and inexpensive access to topically defined populations and yields data of a quality comparable to established crowdsourcing platforms, while also noting that Reddit samples tend to skew towards younger, Western, and digitally literate respondents [66,67]. More generally, web-based samples have been shown to be more diverse than the student samples that dominate psychological research and not to be unduly compromised by non-serious responding [68]. These same features nonetheless entail that the sample cannot be regarded as representative of the general population or of people with depressive symptoms specifically, a limitation revisited in the Discussion. No identifying information was collected, responses were

stored in anonymised form, and the survey imposed no eligibility criteria beyond adult age and the capacity to complete an online questionnaire.

Measures

Three multi-item scales, each comprising three items answered on a five-point Likert format ranging from 1 (*does not apply at all*) to 5 (*applies completely*), were used to assess the focal constructs; a scale score was computed for each participant as the mean of the three constituent items. Psychological well-being was measured with three items capturing the affective and evaluative quality of participants' recent experience (e.g., "Overall, I have felt content in recent weeks"); internal consistency was good, Cronbach's $\alpha = .86$. Perceived usefulness was measured with three items assessing the extent to which respondents believed that an AI chatbot could be helpful for dealing with depressive symptoms (e.g., "An AI chatbot could help me cope with low mood"); internal consistency was acceptable, $\alpha = .76$. Acceptance of AI chatbots for depressive support was measured with three items assessing willingness to use such a tool (e.g., "I could imagine using an AI chatbot for support with depressive symptoms"); internal consistency was high, $\alpha = .89$. Prior therapy experience was assessed with a single dichotomous item asking whether the respondent had ever been in psychotherapy (yes/no).

The item content of the perceived-usefulness and acceptance scales was adapted from the standard operationalisations of perceived usefulness and behavioural intention in the technology-acceptance tradition, and the well-being items followed the affective-evaluative logic common to brief subjective well-being indices [18,26,41,57]. It should be emphasised that the well-being scale is not a diagnostic instrument and that no standardised depression measure such as the PHQ-9 was administered; the study therefore speaks to well-being as a continuous experiential state rather than to clinical depression as a diagnostic category [69].

The decision to employ compact three-item scales reflected a balance between measurement adequacy and respondent burden in an online context in which excessive length is a known driver of attrition [15]. Evidence from measurement research indicates that the advantage of longer scales is not universal and diminishes for constructs that are concrete and singular in meaning which describes the present constructs reasonably well [70]. Item wording for each scale was designed to sample the core meaning of the construct rather than its peripheral facets, and the observed reliabilities indicated that the items within each scale cohered well. Scale scores were formed as unweighted means so that each score remained on the original one-to-five metric and could be interpreted directly against the scale midpoint of three. Higher scores accordingly denoted greater well-being, greater perceived usefulness, and greater acceptance respectively.

Statistical Analysis

All analyses were conducted in R version 4.3.1, with the significance threshold set at $\alpha = .05$ for two-tailed tests. The analytic strategy proceeded in four steps. First, descriptive statistics and Cronbach's alpha coefficients were computed for all scales. Second, zero-order Pearson correlations were estimated among well-being, perceived usefulness, and acceptance. Third, a multiple linear regression was fitted with acceptance as the dependent variable and perceived usefulness and well-being as simultaneous predictors, yielding standardised coefficients and the proportion of explained variance. Fourth, an independent-samples *t* test compared acceptance between participants with and without prior therapy experience. Standardised regression coefficients and correlation coefficients served as effect-size indices, interpreted in line with conventional benchmarks, and the analytic procedures followed standard treatments of regression diagnostics and assumption checking [71-73].

Cronbach's alpha was reported for comparability with the wider literature, with the caveat that it assumes essential tau-equivalence and is best understood as a lower bound on reliability rather than as a direct estimate of it [74-76]. Given the small number of items per scale and their high inter-item correlations, the reported coefficients are unlikely to overstate reliability materially, but they should not be read as evidence of unidimensionality.

Because the sample size was determined by the recruitment window rather than by an a priori power calculation, a sensitivity analysis was conducted to establish which effects the design could detect (Faul et al., 2007). With $N = 99$, two predictors, $\alpha = .05$ (two-tailed), and power of .80, the smallest detectable effect in the regression model corresponds to $f^2 = .10$, that is, an effect between conventional small and medium benchmarks; the

smallest detectable zero-order correlation is approximately $r = .28$, and the smallest detectable group difference in the *t* test, given the unequal group sizes of 70 and 29, is approximately $d = 0.62$. The design was therefore well powered to detect effects of medium magnitude but not small ones, which bears directly on the interpretation of the null findings reported below.

Prior to hypothesis testing, the distributions of the study variables were inspected and the assumptions underlying the parametric procedures, including approximate normality of residuals, linearity, and homoscedasticity, were examined and judged tenable. The two predictors in the regression were only weakly interrelated, so multicollinearity was not a concern for the estimation or interpretation of the coefficients. Missing data were negligible, and analyses were conducted on the complete sample of 99 respondents.

RESULTS

Descriptive Findings and Reliabilities

Descriptive statistics and internal-consistency estimates for the three scales are reported in Table 1. On the five-point response metric, well-being was rated below the scale midpoint ($M = 2.61$, $SD = 0.85$), indicating a sample reporting relatively modest levels of well-being. Perceived usefulness was rated slightly above the midpoint ($M = 3.09$, $SD = 0.73$), and acceptance of AI chatbots for depressive support fell below the midpoint ($M = 2.67$, $SD = 0.91$), reflecting a broadly ambivalent-to-cautious overall stance. All three scales exhibited satisfactory to high internal consistency, with Cronbach's alpha ranging from .76 for perceived usefulness to .89 for acceptance, supporting the reliability of the composite scores used in the subsequent analyses.

Scale	Items n	M	SD	α
Well-Being	3	2.61	0.85	0.86
Perceived Usefulness	3	3.09	0.73	0.76
Acceptance	3	2.67	0.91	0.89

Table 1: Descriptive Statistics and Internal Consistency of the Study Scales

Note. $N = 99$. All scales were scored as the mean of three items on a five-point Likert format ranging from 1 to 5. α = Cronbach's alpha.

Two features of these descriptive results warrant note before the inferential analyses. First, the below-midpoint mean for well-being confirms that the sample was not one of uniformly flourishing respondents but included a meaningful spread of lower well-being, which is a precondition for detecting any need-based effect on acceptance should one exist. Second, the below-midpoint mean for acceptance, coupled with a substantial standard deviation, indicates genuine variability in willingness to

use AI chatbots, ranging from clear reluctance to clear openness. The variables under study were therefore sufficiently dispersed to support meaningful correlational and regression analysis. The overall level of acceptance observed here, hovering somewhat below the neutral point, is broadly consistent with the ambivalence reported in previous acceptability surveys of health chatbots [31,32].

Correlational Findings

The zero-order correlations among the study variables are presented in Table 2. Consistent with an instrumental account of acceptance, perceived usefulness was strongly and positively associated with acceptance, $r = .77$, $p < .001$, indicating that respondents who regarded AI chatbots as more useful were substantially more willing to use them.

By contrast, psychological well-being was essentially uncorrelated with acceptance, $r = -.00$, $p = .989$, offering no support for the proposition that lower well-being drives uptake. Well-being was also unrelated to perceived

usefulness, $r = -.07$, $p = .500$. The correlational pattern thus already foreshadows the central result: acceptance tracks the appraisal of usefulness but is independent of current well-being.

Variable	1	2	3
1. Well-Being	—		
2. Perceived Usefulness	-.07	—	
3. Acceptance	0	.77**	—

Table 2: Pearson Correlations Among Well-Being, Perceived Usefulness, and Acceptance

Note. $N = 99$. ** $p < .01$.

Regression Predicting Acceptance

To evaluate the joint and unique contributions of perceived usefulness and well-being to acceptance, a multiple linear regression was estimated with acceptance as the dependent variable; results are summarised in Table 3. The model accounted for a substantial portion of the variance in acceptance, $R^2 = .60$, adjusted $R^2 = .59$, and

was highly significant, $F(2, 96) = 72.45$, $p < .001$. Within the model, perceived usefulness was the sole significant predictor and exerted a strong positive effect, $\beta = .78$, 95% CI [.66, .89], $p < .001$. Well-being, by contrast, did not contribute meaningfully to the prediction of acceptance, $\beta = .05$, 95% CI [-.09, .18], $p = .55$. Hypothesis 1 was therefore strongly supported: perceived usefulness positively and robustly predicted acceptance. Hypothesis 2 was not supported; well-being was unrelated to acceptance and, contrary to the need-based prediction, showed no tendency for lower well-being to accompany higher acceptance.

Predictor	β	p	95% CI
Perceived Usefulness	0.78	< .001	[.66, .89]
Well-Being	0.05	0.55	[-.09, .18]

Table 3: Multiple Regression Predicting Acceptance from Perceived Usefulness and Well-Being

Note. $N = 99$. Dependent variable = Acceptance. β = standardised regression coefficient; CI = confidence interval for β . Model $R^2 = .60$, adjusted $R^2 = .59$, $F(2, 96) = 72.45$, $p < .001$.

The magnitude of these effects merits emphasis. A standardised coefficient of .78 for perceived usefulness denotes an exceptionally strong association by the conventions commonly applied in the behavioural sciences, and the proportion of variance explained, sixty percent, is large for a two-predictor model of an attitudinal outcome [71]. That this explanatory power derived almost wholly from a single predictor, with the second contributing essentially nothing, underscores the extent to which acceptance in this sample was a function of instrumental appraisal alone. The regression thus does not merely confirm the bivariate correlation but demonstrates that well-being adds no incremental prediction once usefulness is taken into account. It should be noted that the confidence interval for the well-being coefficient, spanning [-.09, .18], excludes effects of even modest magnitude in either direction, so the null result is informative rather than merely inconclusive within the limits established by the sensitivity analysis reported above.

Group Comparison by Therapy Experience

Finally, an independent-samples t test examined whether acceptance differed as a function of prior therapy experience. Participants with prior therapy experience

reported acceptance levels ($M = 2.69$) that were virtually indistinguishable from those reported by participants without such experience ($M = 2.62$), and the difference was not statistically significant, $t(97) = 0.32$, $p = .748$. Hypothesis 3 was therefore not supported: prior therapy experience bore no discernible relation to the acceptance of AI chatbots for depressive support. Taken together, the results converge on a single conclusion, namely that acceptance is predicted almost exclusively by perceived usefulness, whereas neither psychological well-being nor prior therapy experience plays any appreciable role.

DISCUSSION

Summary and Theoretical Integration

The present study set out to determine whether the acceptance of AI chatbots for support with depressive symptoms is governed by an instrumental appraisal of usefulness or by a need arising from diminished psychological well-being, and whether prior therapy experience shapes that acceptance. The findings speak with unusual clarity. Perceived usefulness was strongly related to acceptance at the bivariate level and remained an equally strong predictor in the multiple regression, where it accounted, together with well-being, for sixty percent of the variance in acceptance while being the only significant contributor. Psychological well-being, by contrast, was essentially uncorrelated with acceptance and added nothing to the regression, and prior therapy experience did not differentiate acceptance levels at all. Of the three hypotheses, only the first, derived directly from the

Technology Acceptance Model, received support; the need-based hypothesis and the therapy-experience hypothesis were both disconfirmed.

These results carry a coherent theoretical message. The acceptance of AI chatbots for depressive support appears to follow an instrumental rather than a need-based logic. What predicts whether a person is willing to use such a tool is not how badly they are feeling but whether they judge the tool to be useful. This pattern aligns closely with the central proposition of the Technology Acceptance Model, in which perceived usefulness is the dominant determinant of behavioural intention and with reviews of technology acceptance in health care that identify usefulness as the most consistently significant predictor across settings [26,27,29,30,41]. It extends that proposition into the sensitive and under-examined domain of automated mental-health support. The null association with well-being is theoretically instructive in its own right, for it suggests that models of help-seeking that treat distress as the primary motor of uptake may not transfer straightforwardly to the adoption of digital tools, where the cognitive appraisal of instrumental value evidently eclipses the motivational pull of need [4]. It is consistent, however, with barrier research showing that perceived need for care, rather than distress as such, is the more proximal determinant of help-seeking decisions [5]. The irrelevance of prior therapy experience further reinforces the picture of acceptance as a present-focused, appraisal-driven judgement rather than one anchored in personal history.

It is instructive to consider why the instrumental logic should prevail so decisively even in a domain marked by vulnerability and stigma, where one might have anticipated a stronger role for psychological need. One interpretation is that the appraisal of usefulness already absorbs much of what a need-based account attributes to distress: a person who believes a chatbot could genuinely help is, by that very belief, oriented towards their own difficulties, and the additional information carried by a separate measure of well-being may be slight. Another interpretation is that the decision to adopt a novel and still-unfamiliar technology is dominated by cognitive evaluation of the tool itself, with affective state receding into the background at the point of the adoption judgement. A third possibility draws on the distinction between well-being and symptomatology: a general index of recent affective-evaluative experience may simply be too distal from the specific concern that a depression-focused chatbot addresses to exert predictive force, whereas a measure of perceived need or symptom-specific burden might behave differently [56]. Whichever reading is correct, the practical upshot is the same: usefulness, not need, is where the explanatory action lies.

The findings also stand in an interesting relation to the acceptability literature on health chatbots more broadly. Experimental work has shown that acceptability rises for stigmatised health issues and falls for severe ones, and depression sits awkwardly at the intersection of these two

moderators [31]. The moderate overall acceptance observed here, slightly below the neutral point, may reflect precisely this cross-pressure: the anonymity of an automated interlocutor is attractive for a stigmatised concern, while the perceived seriousness of depression argues against entrusting it to software. That perceived usefulness nonetheless dominated the prediction suggests that these contextual considerations operate through, rather than alongside, the usefulness appraisal, being absorbed into the judgement of whether the tool can help with this particular problem. Qualitative findings on the motivations and reservations that users articulate with respect to health chatbots are consonant with such an account, in that both the attractions and the objections respondents raise are framed largely in terms of what the technology can and cannot do [32].

Viewed in the light of the wider evidence base, the results also help to make sense of the persistent gap between clinical need and actual engagement with digital mental-health tools. If uptake were governed by need, the sizeable population of distressed individuals should furnish a correspondingly large body of engaged users, yet this is not what is observed in practice [15,16]. An instrumental account resolves the paradox: distress alone does not generate use, and unless prospective users come to perceive a tool as genuinely useful, their need will not convert into adoption. On this reading, the low engagement that has troubled the field is not a puzzle but an expected consequence of tools whose usefulness has not been made apparent to those they aim to serve. This interpretation should be advanced with the caveat that acceptance is an intention-like construct and that the intention-behaviour relationship is itself imperfect, so the present data can explain the formation of willingness but not its subsequent translation into sustained use [48,49].

Practical Implications

The practical implications follow directly from the primacy of perceived usefulness. If willingness to adopt an AI chatbot depends chiefly on whether prospective users believe it to be useful, then the most effective lever for increasing uptake is to establish and communicate that usefulness in concrete, credible terms. Developers should prioritise demonstrable functionality and transparent evidence of benefit, and those disseminating such tools should frame them in terms of the specific, tangible ways in which they can help rather than in terms of the severity of the problems they address. The finding that acceptance is unrelated to well-being cautions against an outreach strategy that targets only the most distressed, since distress is not what predicts openness to the tool; a broad framing emphasising usefulness is likely to be more effective than one that presupposes acute need. The absence of any difference by prior therapy experience is similarly reassuring, indicating that both therapy-experienced and therapy-naïve users can be addressed with a common message centred on usefulness.

A second implication concerns the design of the tools themselves. Because acceptance hinges on perceived rather than actual usefulness, developers face a twofold task: they must build agents that are genuinely capable of helping and they must ensure that this capability is legible to users from the earliest moments of contact. The determinants of usefulness perceptions identified in the acceptance literature, notably result demonstrability and output quality, offer concrete design targets in this respect [27,40]. Features that make benefit tangible and immediate, such as transparent explanations of what the tool does, early demonstrations of concrete assistance, and clear signposting of the situations in which it can help, are likely to translate technical competence into the perception of usefulness that actually predicts adoption. Conversely, tools whose value is opaque or slow to materialise risk being abandoned regardless of their underlying quality, a pattern consistent with the low engagement frequently reported for digital mental-health applications [15,16].

A third implication is a cautionary one, and it follows from the same finding that grounds the first two. If acceptance can be raised by shaping perceptions of usefulness, then acceptance can in principle be raised beyond what the underlying tool warrants. The gap between perceived and actual capability is precisely where the ethical risks of automated psychological support are concentrated, given documented inconsistencies in how conversational systems handle clinically sensitive material and the unresolved questions of responsibility and crisis management that attend automated care [23,46,47]. The design imperative is therefore not to maximise perceived usefulness as such but to align it with demonstrated benefit, and to make the limits of the tool as legible as its capabilities. Clear signposting to human services for concerns exceeding the scope of the agent is a minimal requirement, particularly given evidence that acceptability declines sharply as perceived severity rises [31]. Rapid expansion of digital provision, accelerated in recent years by the pressures on conventional services makes the alignment of perception and capability more rather than less urgent [35].

LIMITATIONS

Several limitations qualify these conclusions. First, the cross-sectional design permits no causal inference; although the theoretical framing treats perceived usefulness as a determinant of acceptance, the concurrent measurement of both constructs means that the direction of influence cannot be established from these data. A reciprocal or even reversed relationship is conceivable, in which a general openness to automated support colours the appraisal of usefulness rather than following from it.

Second, the sample was a self-selected, non-probabilistic group recruited through Reddit communities, which limits the generalisability of the findings to the broader population of people with depressive symptoms; users of a

particular social-media platform who volunteer for a survey on this topic may differ systematically from non-users in ways relevant to technology acceptance, and such samples are known to over-represent younger and more digitally literate respondents [67]. Given that digital literacy is itself plausibly associated with the appraisal of digital tools, the strength of the usefulness-acceptance relationship may be conditioned by this feature of the sample.

Third, all constructs were assessed by self-report within a single instrument, which raises the possibility of common-method bias inflating the observed associations, particularly the strong link between perceived usefulness and acceptance [77]. No procedural or statistical remedy for this bias, such as the inclusion of a theoretically unrelated marker variable [78], was implemented, and the magnitude of the observed association should be interpreted with this in mind. Conceptual overlap between the two constructs is a related concern: items asking whether a chatbot could help and items asking whether one would use it may tap adjacent regions of the same underlying attitude, so that part of the observed association reflects measurement proximity rather than a substantive predictive relationship.

Fourth, each construct was measured with a brief three-item scale; although internal consistencies were satisfactory, such short scales may not capture the full breadth of the constructs and may underrepresent their conceptual complexity, and the reported alpha coefficients rest on assumptions that were not formally tested [75,76].

Fifth, psychological well-being was operationalised narrowly through three affective-evaluative items and did not encompass the full multidimensional structure of well-being nor was clinical depressive symptomatology assessed with a validated instrument such as the PHQ-9 [53,56,69]. The null finding for well-being should therefore be interpreted with reference to this circumscribed measurement rather than as evidence against any conceivable role of psychological state, and in particular it does not exclude an association between diagnosed depression and acceptance.

Sixth, the sensitivity analysis reported above indicates that the design was powered to detect effects of medium but not small magnitude, so genuinely small associations between well-being and acceptance, or genuinely small group differences by therapy experience, would have escaped detection. The confidence intervals reported for these null effects nonetheless constrain their plausible magnitude.

Finally, the study did not assess perceived ease of use, trust, privacy concerns, or other established acceptance antecedents, leaving the model deliberately parsimonious but incomplete, and the criterion was intention-like rather than behavioural, with all the interpretive caution that this implies [48,49].

Outlook

Future research could address these limitations along several fronts. Longitudinal and experimental designs that manipulate or track perceived usefulness over time would allow the causal status of usefulness to be tested directly and would clarify whether appraisals of usefulness precede and shape actual adoption behaviour. Probability-based or otherwise more representative sampling would establish whether the instrumental logic documented here generalises beyond self-selected social-media users, and multimethod designs incorporating behavioural indicators of use, including log data on engagement and retention, would guard against common-method bias and bridge the gap between stated willingness and observed behaviour. Broader and more differentiated measurement of well-being, including its eudaimonic as well as its hedonic facets, together with the inclusion of additional acceptance antecedents such as perceived ease of use, trust, and privacy concerns, would situate the present findings within a fuller nomological network [53,54]. Finally, replication across clinical and non-clinical populations would indicate whether the primacy of usefulness holds among people with diagnosed depressive disorders as robustly as it does in a general online sample. These desiderata are not peculiar to the present study but reflect recognised structural weaknesses of digital-mental-health research, among them a reliance on short evaluation windows, insufficient attention to real-world engagement, and a mismatch between the pace of technological change and that of conventional trial methodology [79].

Beyond these methodological refinements, the findings invite conceptual work on the boundary conditions of the instrumental account. It remains to be seen whether the primacy of usefulness documented here is specific to the pre-adoption stage, at which people form intentions without direct experience of the tool, or whether it persists once users have interacted with a chatbot and can appraise its value on the basis of lived experience. It is conceivable that psychological state assumes greater importance at later stages, shaping sustained engagement even where it does not shape initial acceptance, and that relational variables of the kind studied in psychotherapy research come to the fore once an interaction history exists [58,62,63]. Mapping how the determinants of use evolve across the adoption trajectory would enrich both the theory of technology acceptance and the practical design of digital mental-health support. A further question concerns the generalisability of these findings across generations of the technology itself: the conversational agents on which most of the existing evidence rests were comparatively constrained systems, and whether the acceptance calculus is altered by markedly more fluent systems is an empirical matter that the present data cannot settle [18].

In conclusion, the acceptance of AI chatbots for support with depressive symptoms is driven almost entirely by perceived usefulness, while psychological well-being and

prior therapy experience are unrelated to it. Acceptance in this domain thus reflects an instrumental appraisal of what a tool can do rather than a need arising from how a person feels. For the design, framing, and dissemination of digital mental-health support, the message is clear: to be accepted, an AI chatbot must above all be, and be seen to be, useful.

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