The International Journal Of Global Mental Health, Innovation, Policy, Action, Culture & Transformation
e-ISSN: 3107-8311

Motivated Non-Use in AI-Based Mental Health Interventions: A Structural Readiness Account of Engagement Failure

Nikesh Lagun, *Independent Researcher, Kathmandu, Nepal*

Affiliations: No institutional affiliation

Email: lagunnikesh2064@gmail.com

ORCID: 0009-0005-6372-4852

Abstract: Digital mental health interventions (DMHIs), including AI-enabled applications, chatbots, and digital cognitive behavioural therapy platforms, have expanded rapidly as scalable approaches to improving access to care. Despite demonstrated efficacy under controlled conditions, real-world impact remains constrained by persistent engagement failure and early discontinuation. Many users disengage shortly after adoption, even when they report valuing the intervention and intending to use it. Existing explanations of engagement failure primarily emphasize motivation, usability, or perceived usefulness; however, these frameworks provide limited insight into why motivated users often fail to initiate or re-initiate engagement. Drawing on a narrative review of the digital mental health literature, this paper argues that engagement breakdown frequently occurs at the level of action initiation rather than intention formation. A structural readiness account is proposed, grounded in activation dynamics and threshold-dependent ignition processes formalized in Lagun's Law within Cognitive Drive Architecture. From this perspective, non-use reflects a readiness mismatch between preserved intention and insufficient momentary activation, rather than a deficit of motivation or interest. The paper outlines implications for readiness-aware and ethically responsible AI design, highlights relevance for clinical interpretation and policy evaluation, and proposes empirically testable predictions for future research. By reframing engagement failure through activation-dependent threshold dynamics, this work advances a mechanistic foundation for understanding and improving engagement in AI-based mental health interventions.

Keywords: *Digital Mental Health, Artificial Intelligence, Engagement, Intention–Action Gap, Readiness, Human-Centered Design, Lagun's Law*

1. Background and Rationale

Digital mental health interventions (DMHIs), including smartphone applications, conversational agents, and AI-enhanced cognitive behavioural therapy platforms, have expanded rapidly as scalable tools intended to support psychological well-being and improve access to mental health care. These technologies are frequently positioned as solutions to longstanding barriers in traditional service delivery, such as limited clinician availability, high costs, and geographic constraints (Torous et al., 2021; World Health Organization [WHO], 2022). Advances in artificial intelligence have further accelerated their development, enabling increased personalization, automation, and reach across diverse populations. Yet despite their promise, sustained engagement remains a persistent and unresolved challenge.

Across narrative reviews and empirical investigations, engagement with DMHIs is characterized by substantial variability and high rates of early discontinuation. Eysenbach's articulation of the "law of attrition" identified dropout as a defining feature of eHealth interventions, and subsequent research confirms that this pattern persists in contemporary digital mental health tools (Eysenbach, 2005; Kelders et al., 2012). Real-world deployment data indicate that a large proportion of users disengage shortly after adoption. For example, approximately 70% of users discontinue mobile health applications within the first 100 days (Baumel et al., 2019), with similar trends observed in mental health-specific interventions (Fleming et al., 2018; Hollis et al., 2017). Even when clinical efficacy is demonstrated under controlled conditions, sustained engagement sufficient to produce benefit is often limited to a minority of users.

Importantly, disengagement does not always reflect rejection or dissatisfaction. Qualitative and mixed-methods studies consistently document a recurring phenomenon in which users recognize an intervention's potential value and express genuine intention to use it yet fail to initiate or re-initiate engagement (Fleming et al., 2018; Mohr et al., 2011). Users commonly report knowing that an application "could help" while simultaneously having trouble opening it or continuing beyond initial sessions. This pattern of motivated non-use presents a structural paradox: how can individuals who endorse the value of an intervention nevertheless fail to act?

Most existing explanations emphasize motivational strength, perceived usefulness, usability, or interface friction. While these factors undoubtedly influence engagement, they primarily address why individuals adopt or value an intervention. They provide comparatively limited insight into the structural conditions under which intention translates into executable behavior. As AI-based mental health tools become integrated into stepped care pathways and

public health systems (Proctor et al., 2011; Torous et al., 2021), understanding this intention–execution gap becomes increasingly urgent. Without a mechanistic account of initiation failure, improvements in algorithmic sophistication or persuasive design are unlikely to resolve real-world attrition.

To address this gap, the present paper advances a structural readiness lens that focuses on activation dynamics and ignition thresholds governing action onset. Rather than treating engagement failure solely as a deficit of motivation or usability, this perspective conceptualizes non-use as a readiness mismatch between intention and the structural conditions required for action. Situated within a broader structural account of action initiation, this framework aims to clarify the mechanistic bottleneck underlying motivated non-use and to inform readiness-aware, ethically responsible AI design in digital mental health contexts.

2. Engagement Failure in Digital Mental Health Interventions: Current Evidence

A substantial body of research has examined engagement, adherence, and dropout in digital mental health interventions, consistently identifying non-use and early discontinuation as central constraints on their effectiveness. Across mobile applications, web-based programs, and AI-assisted tools, engagement typically follows a steep decline after initial uptake. Eysenbach's formulation of the "law of attrition" characterized dropout as a defining feature of digital interventions rather than an anomaly (Eysenbach, 2005), and subsequent research confirms that high attrition rates persist across mental health conditions, delivery formats, and populations (Kelders et al., 2012; Fleming et al., 2018).

Large-scale syntheses indicate that while initial adoption may be widespread, sustained engagement remains comparatively uncommon. Approximately 70% of users discontinue mobile health applications within the first 100 days (Baumel et al., 2019), with similar trends observed in mental health-specific platforms (Fleming et al., 2018; Hollis et al., 2017). Completion rates for digital interventions targeting depression and anxiety frequently fall below 50%, and real-world adherence is often substantially lower than that observed in controlled trials (Kelders et al., 2012). Notably, these patterns are documented even among interventions with demonstrated clinical efficacy, suggesting that disengagement cannot be attributed solely to ineffective therapeutic content.

In response, research has sought to identify determinants of engagement. Commonly examined factors include reminder systems, tailoring and personalization, perceived usefulness, ease of use, and the incorporation of human support (Venkatesh et al., 2003; Baumeister et al., 2014). Such features are associated with improved adoption and short-term

interaction frequency. Guided interventions generally outperform fully unguided ones, and personalized content can enhance perceived relevance (Kelders et al., 2012). These findings demonstrate that design and motivational variables meaningfully influence engagement trajectories.

However, despite these advances, a recurring empirical pattern remains insufficiently explained. Many users who report high perceived usefulness, positive attitudes, and explicit intention to engage nevertheless discontinue early or fail to initiate sustained interaction. Qualitative research repeatedly describes individuals who recognize that a digital intervention "makes sense" or "could help," yet struggle to begin or resume use (Borghouts et al., 2021; Yardley et al., 2016). Importantly, these initiation failures often occur prior to substantive exposure to therapeutic content, suggesting that barriers operate upstream of persuasion, learning, or skill acquisition.

Taken together, the literature reveals a convergence around three findings: (1) attrition is widespread and persistent; (2) motivational and usability variables predict adoption and short-term engagement; and (3) motivated non-use continues to occur even when these variables are favorable. What remains comparatively underdeveloped is a mechanistic account of how engagement is initiated and re-initiated now of action. Prevailing models are well-suited to explaining why individuals value or adopt an intervention, but they are largely agnostic regarding the structural conditions required for intention to translate into executable behavior.

This under-specification becomes particularly salient in real-world contexts characterized by fluctuating cognitive load, emotional distress, and competing demands. Without a model of initiation dynamics, engagement failure is often interpreted as a matter of choice, insufficient motivation, or interface friction. Yet the recurring pattern of motivated non-use suggests the presence of a structural bottleneck between intention and action. Addressing this gap requires attention not only to motivational determinants but to activation-level processes governing action onset, a dimension that has received comparatively limited explicit treatment within digital mental health research (Yardley et al., 2016; Nahum-Shani et al., 2018).

3. The Intention–Action Gap in Digital Mental Health Engagement

Much of the existing literature on engagement with digital mental health interventions emphasizes motivational, cognitive, or usability-based explanations for non-use. Prominent models of technology acceptance and behavior change assume that when users perceive an intervention as useful, easy to use, and aligned with their goals, engagement is likely to follow

(Davis, 1989; Venkatesh et al., 2003). Similarly, dominant health behavior frameworks position intention strength, outcome expectancy, and perceived behavioural control as primary determinants of action (Ajzen, 1991; Michie et al., 2011). These approaches have generated valuable insight into adoption and early engagement. However, they offer limited explanatory precision for a recurring empirical pattern in digital mental health: individuals frequently value an intervention and intend to use it yet fail to initiate or sustain engagement (Sheeran & Webb, 2016).

This discrepancy reflects the broader intention–action gap documented in behavioural science. Research on implementation intentions demonstrates that specifying when and how to act increases the likelihood of behavioural execution (Gollwitzer & Sheeran, 2006). Such work clarifies that intention alone is insufficient and that cue-linked planning strengthens action probability. Yet even implementation intention models primarily formalize cue–response coupling rather than the internal activation conditions required for execution. They assume that once a sufficiently specified intention is present and a relevant cue is encountered, behavior will follow with increased probability.

Digital mental health engagement presents cases that challenge this assumption. Users often form explicit plans to begin or resume use, encounter appropriate cues (e.g., reminders or scheduled sessions), and nevertheless fail to act. Initiation breakdown frequently occurs at two recurrent junctures: first use and re-entry following lapse. Importantly, these failures often precede substantive exposure to intervention content (Mohr et al., 2011; Yardley et al., 2016). This pattern suggests that barriers may operate not only at the level of intention formation or cue specification, but at the level of action activation itself.

Motivational explanations struggle to account for this phenomenon because they conflate wanting with acting. When non-use is interpreted as diminished desire or commitment, engagement failure is treated as a deficit of motivational strength. Yet qualitative accounts repeatedly document users who express genuine interest while having trouble initiating behavior (Mohr et al., 2011; Kelders et al., 2012). Similarly, usability-focused explanations emphasize friction reduction and interface optimization, which improve efficiency once interaction has begun but do not necessarily resolve initiation collapse. Both frameworks are strong predictors of adoption and interaction quality; neither explicitly models the structural conditions governing whether action can occur at a given moment.

The shared limitation is an under-specification of activation dynamics. Prevailing models typically assume continuity between intention strength and action probability: as motivation increases, behavior becomes more likely. However, initiation failure in motivated

users suggests the possibility of discontinuity — that behavior may depend on crossing a threshold of internal activation, below which action does not occur regardless of expressed intention. Such threshold-bound dynamics become especially relevant in contexts characterized by fluctuating cognitive load, emotional distress, competing demands, and fatigue (West & Brown, 2013). Under these conditions, even modest increases in internal friction may prevent action entirely.

Recent structural perspectives on effort and action initiation have begun to formalize this distinction. Within Cognitive Drive Architecture, for example, action is conceptualized as contingent upon internal configurations reaching an ignition threshold, rather than as a direct linear function of motivational strength (Lagun, 2025a; Lagun, 2025b). In this view, motivated inaction reflects suppressed activation rather than absent desire. Latent task load and unresolved intention burden may further elevate effective thresholds, rendering initiation improbable even when users endorse the value of the behavior (Lagun, 2025c). Importantly, the present argument does not require acceptance of any specific formal model; rather, CDA provides one structured articulation of threshold-dependent activation dynamics that illuminate the engagement paradox observed in digital mental health contexts.

Taken together, motivation- and usability-based explanations account for why users adopt and value digital interventions but leave a critical explanatory gap at the level of action onset. Addressing this gap requires shifting analytical focus from intention strength to the structural conditions under which intention becomes executable. This distinction provides the conceptual foundation for a readiness-oriented account of motivated non-use and prepares the ground for examining how activation-aware principles can inform AI-based mental health design.

4. A Structural Readiness Account of Engagement Failure

To clarify why motivated users may nevertheless fail to engage with AI-based mental health tools, this section advances a structural readiness account centered on the mechanics of action initiation. Rather than treating engagement solely as a function of desire, preference, or valuation, this account distinguishes between endorsing an intervention and possessing the momentary capacity to act on that endorsement. The central claim is that engagement requires not only motivation and usability, but a configuration of internal conditions sufficient to permit behavioural ignition.

Ignition is defined here as the transition from intention to observable action. In digital mental health contexts, ignition corresponds to concrete behaviors such as opening an

application, initiating an exercise, or resuming use after a lapse. Importantly, ignition is not reducible to interest, agreement, or positive attitude. A user may cognitively value an intervention and emotionally desire its benefits while remaining unable to initiate engagement. This distinction helps explain why disengagement frequently occurs prior to meaningful interaction with therapeutic content (Gollwitzer, 1999).

The structural readiness account proposes that ignition depends on crossing an activation threshold. This threshold represents the minimum effective activation state required for behavior to occur. Crucially, it is not equivalent to motivation strength. Instead, it reflects the joint influence of motivational drive, cognitive load, emotional state, background stress, unresolved task burden, and contextual constraints. When effective activation falls below threshold, behavior does not occur, even if intention remains intact. This introduces a discontinuity into the engagement process: below threshold, action probability collapses; above threshold, initiation becomes possible.

This threshold is dynamic rather than fixed. In real-world mental health contexts, cognitive fatigue, emotional distress, and competing demands can elevate the effective threshold required for action. Even small increases in internal friction may therefore be sufficient to prevent initiation when users are operating near this boundary (Baumeister & Vohs, 2007; West & Brown, 2013). Structural readiness refers to the broader configuration of internal and contextual variables that lowers this threshold or increases effective activation, thereby permitting ignition. Because these configurations fluctuate over time, readiness is inherently moment sensitive. Engagement capacity may vary across hours or days, even when explicit motivation remains stable.

Structural perspectives on effort and initiation have formalized similar threshold-dependent dynamics. Within Cognitive Drive Architecture, for example, motivated inaction is conceptualized as suppressed ignition rather than absent desire (Lagun, 2025a; Lagun, 2025b). In this framework, drive output depends on system parameters reaching an activation boundary, and latent task burden may further elevate effective thresholds under conditions of unresolved intention (Lagun, 2025c). While the present argument does not depend on the acceptance of any single formal model, CDA provides one structured articulation of how initiation collapse can occur despite preserved motivation.

This threshold-dependent framing yields a critical implication: increasing motivational messaging alone may not restore engagement if activation remains below threshold. Persuasive prompts, reminders, or value reinforcement may amplify intention strength without altering the structural conditions required for ignition. Under suppressed readiness states, such

interventions may therefore show diminishing returns. By contrast, reducing activation cost, lowering friction at the point of initiation, or alleviating background cognitive load may be more effective mechanisms for restoring engagement.

By foregrounding ignition, activation thresholds, and structural readiness, this account reframes engagement failure as a predictable outcome of misaligned internal configurations rather than a deficit of will or interest. It does not displace motivational or usability frameworks but complements them by specifying an additional layer at which breakdown can occur. In doing so, it establishes a conceptual foundation for activation-aware AI design capable of supporting initiation and re-engagement under fluctuating real-world conditions.

5. Practical Implications for Readiness-Aware AI Mental Health Design

A structural readiness perspective implies that engagement design must account for threshold-dependent initiation rather than assuming linear translation from motivation to action. If behavioural ignition depends on crossing a fluctuating activation boundary, then effective systems must either increase effective activation or lower the threshold required for initiation. Design strategies that focus solely on amplifying motivation may leave the structural bottleneck unchanged.

Principle 1: Detect Readiness Rather Than Demand Action

Many digital mental health tools operate on scheduled prompts that assume action capacity is constant across time. However, if ignition is threshold-dependent and moment-sensitive, calls to action delivered during low-readiness states will predictably fail, regardless of user intention (Nahum-Shani et al., 2018; Boucher & Raiker, 2024).

From a structural perspective, readiness detection functions as an attempt to estimate whether effective activation is currently sufficient to cross the threshold. Lightweight check-ins, contextual inference (e.g., time of day, recent activity), and user-controlled pacing allow systems to align demands with moments of higher activation feasibility. This approach does not attempt to increase motivation per se; rather, it seeks to avoid triggering initiation attempts when structural conditions are misaligned.

Principle 2: Lower the Ignition Cost of Engagement

When users operate near threshold, even minor increases in required effort can prevent action. Engagement research consistently demonstrates that higher complexity and greater initial task demand are associated with dropout (Eysenbach, 2005; Kelders et al., 2012). From a readiness standpoint, these features elevate the activation cost required to cross the threshold.

Lowering ignition cost directly reduces the threshold barrier. One-tap entry, short default interactions, "micro-start" options, and pre-structured tasks decrease the activation required to initiate engagement. These strategies do not substitute for therapeutic depth but function as structural enablers that permit behavior under low-capacity conditions. In threshold terms, they shift the boundary downward, increasing the probability that preserved intention translates into action.

Principle 3: Treat Re-Entry as a Separate Ignition Event

Engagement trajectories are rarely linear. Lapses are common, yet many systems implicitly assume continuity and require full recommitment upon return (Kidman et al., 2024). Under a threshold model, re-entry is not a continuation but a new ignition event, subject to the same activation constraints as first use.

Designing for re-entry, therefore, requires lowering the threshold now of return. Non-judgmental "welcome back" flows, clear resume points, and flexible progression reduce the activation cost of restarting. Qualitative findings suggest that users are more likely to re-engage when interruption is normalized and the return path is cognitively manageable (Rennick-Egglestone et al., 2016). Structurally, these features reduce the activation penalty associated with lapse.

Principle 4: Avoid Coercive Threshold Manipulation

A readiness-aware approach also has ethical implications. If action depends on crossing a fluctuating activation boundary, then attempts to forcibly push users across the threshold through pressure, guilt, or excessive nudging risk violating autonomy and potentially exacerbating distress (Burr et al., 2020; Mittelstadt et al., 2016).

Artificially amplifying activation through manipulative design may temporarily increase engagement metrics but does not resolve underlying readiness constraints. Ethical readiness-aware design instead aims to support voluntary threshold crossing by lowering unnecessary barriers and respecting momentary capacity. Framing non-use as a readiness mismatch reduces self-blame and aligns system behavior with principles of proportionality, transparency, and user agency.

Taken together, these principles translate the structural readiness account into design consequences. Rather than if increasing motivation will linearly increase engagement, readiness-aware systems recognize that behavior emerges when activation crosses a dynamic boundary. Design therefore operates on two primary levers: reducing the threshold required for initiation and aligning interaction timing with states of sufficient activation. By targeting the structural conditions under which action becomes possible, this approach complements

existing motivational and usability frameworks while directly addressing the initiation bottleneck documented across digital mental health contexts.

6. Clinical and Policy Relevance

Reframing engagement failure as a matter of structural readiness rather than motivation alone has implications extending beyond individual tool design. If behavioural initiation depends on crossing a fluctuating activation threshold, then non-use represents a below-threshold state rather than necessarily diminished intention or resistance. In clinical contexts, this distinction is consequential. Patients may endorse therapeutic rationales and express willingness to engage while lacking sufficient activation to initiate behavior under current conditions (Kazdin, 2017; Dimidjian et al., 2011). A readiness-oriented interpretation recognizes that action capacity fluctuates independently of insight or desire.

For clinicians integrating AI-supported interventions into care, this perspective supports more accurate and compassionate interpretations of disengagement. Early dropout need not be interpreted as noncompliance or lack of commitment, but may reflect temporary threshold elevation due to emotional distress, cognitive fatigue, or competing demands. Recognizing initiation as threshold-dependent reinforces the importance of clinical scaffolding, relational support, and flexible pacing when digital tools are incorporated into treatment pathways.

At the level of health systems and implementation policy, the structural readiness lens challenges prevailing evaluation assumptions. Many evaluation frameworks emphasize completion rates, continuous usage metrics, or aggregate engagement duration. Such metrics implicitly assume that engagement unfolds linearly and that sustained use is the primary indicator of value. However, a threshold-dependent model predicts episodic engagement, temporary below-threshold states, and re-ignition events rather than uninterrupted trajectories.

Implementation science has repeatedly demonstrated that interventions effective under trial conditions may falter at scale due to contextual and cognitive constraints that limit uptake (Proctor et al., 2011). Incorporating readiness-sensitive criteria, such as support for low-effort initiation, facilitation of re-entry after lapse, and tolerance for intermittent use, may therefore improve alignment between efficacy research and real-world effectiveness. Systems that enable repeated threshold crossing under variable conditions may prove more impactful than those optimized solely for sustained continuous engagement.

These considerations are especially relevant as AI mental health tools are embedded within stepped care models, public health systems, and employer-sponsored programs, where

engagement is largely self-initiated and occurs amid competing demands. Evaluating tools exclusively through completion metrics risks mischaracterizing flexible or episodic engagement as failure, even when such patterns reflect adaptive, readiness-sensitive use.

Equity considerations further underscore the importance of a structural lens. Activation thresholds are not distributed evenly across populations. Socioeconomic stress, unstable housing, chronic illness, caregiving burden, and persistent cognitive or emotional strain can elevate effective initiation thresholds independently of motivation (Marmot et al., 2020; Torous et al., 2021). Digital interventions that assume stable readiness may therefore disproportionately advantage individuals with greater temporal, cognitive, and emotional resources. By contrast, readiness-sensitive systems that lower ignition cost and accommodate fluctuation may reduce structural exclusion and better support populations facing elevated activation burdens.

Taken together, these clinical and policy implications suggest that engagement failure should not be treated solely as a user-level deficit or product-level flaw. Instead, it reflects the interaction between fluctuating activation thresholds and system design. Viewing non-use as a readiness mismatch rather than a deficiency provides a foundation for more ethical interpretation, more accurate evaluation, and more equitable integration of AI into mental health ecosystems.

7. Limitations and Future Research Directions

This paper is conceptual in nature and does not present new empirical data. Its primary contribution lies in synthesizing existing evidence on engagement failure in digital mental health interventions and proposing a structural readiness lens to clarify a persistent intention–action gap. The arguments advanced here should therefore be interpreted as theoretically integrative rather than empirically confirmatory. Although the reviewed literature substantiates the prevalence and practical significance of motivated non-use, the readiness-oriented account requires systematic empirical testing.

A central task for future research is the operationalization of activation failure. Current engagement metrics typically rely on aggregate indicators such as session counts, duration, or completion rates. These measures may obscure threshold-dependent initiation failures, moments in which users endorse an intention yet do not initiate behavior. Fine-grained temporal analyses examining behavior immediately following prompts, reminders, or planned engagement windows may help distinguish readiness-related barriers from motivational or usability-related factors. Ecological momentary assessment, passive sensing, and high-

resolution interaction logging offer promising methodological tools for identifying such initiation bottlenecks while minimizing additional user burden.

If the structural readiness account is correct, several differentiating predictions follow. First, reducing initiation demands (e.g., lowering ignition cost) should increase engagement even when reported motivation remains unchanged. Second, increasing motivational prompts alone should not reliably restore engagement under conditions of suppressed readiness. Third, re-entry following a lapse should function as a discrete ignition event rather than a simple continuation of prior engagement. Empirical work capable of testing these predictions would substantially clarify the explanatory contribution of the readiness framework relative to purely motivational models.

Experimental research comparing readiness-aware designs with conventional reminder- or persuasion-based approaches represents a particularly important direction. Controlled studies could examine whether designs that minimize initiation friction, normalize interruption, and support flexible re-entry yield more stable or equitable engagement patterns, especially among users reporting high but fluctuating motivation. Such work may also reveal whether engagement trajectories exhibit non-linear or threshold-like characteristics, as predicted by activation-based models.

Qualitative research will likewise be essential. In-depth interviews, diary studies, and experience-sampling approaches exploring the lived experience of wanting to engage but being unable to begin can illuminate the phenomenology of activation failure. These methods are especially important for populations experiencing heightened stress, comorbidity, or socioeconomic constraint, where effective activation thresholds may be elevated.

Finally, boundary conditions must be acknowledged. Readiness mismatch is unlikely to account for all forms of disengagement. In some contexts, disengagement may reflect genuine motivational collapse, symptom-driven avoidance, stigma, or dissatisfaction with intervention content. Future research should therefore examine how readiness dynamics interact with motivational, affective, and structural factors across different clinical and sociocultural contexts. Clarifying these interactions will be necessary for situating structural readiness as one component within a broader explanatory ecosystem rather than as a universal account.

Taken together, these directions highlight the need for multi-level investigation spanning behavioural measurement, experimental design, qualitative inquiry, and implementation research. Only through such systematic study can the structural readiness

account be refined, bounded, and empirically validated within real-world digital mental health systems.

8. Conclusion

Persistent engagement failure remains a central constraint on the real-world effectiveness of AI-based mental health interventions. Although motivation, usability, and perceived usefulness are important determinants of adoption and early engagement, the evidence reviewed here indicates that they do not fully explain why users who value an intervention nevertheless fail to initiate or sustain use. The structural readiness lens clarifies a critical but under-specified bottleneck at the level of activation, where intention may be present but action fails to ignite.

By distinguishing valuation from activation, this framework reframes motivated non-use not as a deficit of will, commitment, or insight, but as a readiness mismatch arising from fluctuating cognitive, emotional, and contextual constraints. Engagement failure, under this account, becomes a predictable outcome of threshold dynamics rather than an anomaly requiring motivational correction. This shift carries theoretical significance: it suggests that models of digital engagement must account not only for why users want to act, but for the conditions under which action becomes structurally possible.

Adopting a readiness-aware orientation encourages AI mental health systems that are sensitive to user state, that lower initiation demands, and that normalize interruption and re-entry without stigma. As AI technologies become more deeply embedded within mental health care delivery, integrating activation-sensitive principles offers a human-centered pathway for improving engagement while respecting autonomy, cognitive limits, and the lived realities of users. More broadly, foregrounding readiness expands the conceptual vocabulary of digital mental health research by positioning ignition, not intention, as the decisive inflection point between endorsement and behavior.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Baumeister, H., Reichler, L., Munzinger, M., & Lin, J. (2014). The impact of guidance on Internet-based mental health interventions — A systematic review. *Internet Interventions, 1*(4), 205–215. https://doi.org/10.1016/j.invent.2014.08.003

Baumeister, R. F., & Vohs, K. D. (2007). Self-regulation, ego depletion, and motivation. *Social and Personality Psychology Compass, 1*(1), 115–128. https://doi.org/10.1111/j.1751-9004.2007.00001.x

Baumel, A., Muench, F., Edan, S., & Kane, J. M. (2019). Objective User Engagement With Mental Health Apps: Systematic Search and Panel-Based Usage Analysis. *Journal of medical Internet research, 21*(9), e14567. https://doi.org/10.2196/14567

Borghouts, J., Eikey, E., Mark, G., De Leon, C., Schueller, S. M., Schneider, M., Stadnick, N., Zheng, K., Mukamel, D., & Sorkin, D. H. (2021). Barriers to and Facilitators of User Engagement With Digital Mental Health Interventions: Systematic Review. *Journal of medical Internet research, 23*(3), e24387. https://doi.org/10.2196/24387

Boucher, E. M., & Raiker, J. S. (2024). Engagement and retention in digital mental health interventions: a narrative review. *BMC Digital Health, 2(*1), 52. https://doi.org/10.1186/s44247-024-00105-9

Burr, C., Taddeo, M., & Floridi, L. (2020). The Ethics of Digital Well-Being: A Thematic Review. *Science and engineering ethics, 26*(4), 2313–2343. https://doi.org/10.1007/s11948-020-00175-8

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Dimidjian, S., Barrera, M., Jr, Martell, C., Muñoz, R. F., & Lewinsohn, P. M. (2011). The origins and current status of behavioral activation treatments for depression. *Annual review of clinical psychology, 7*, 1–38. https://doi.org/10.1146/annurev-clinpsy-032210-104535

Doherty, G., Coyle, D., & Matthews, M. (2010). Design and evaluation guidelines for mental health technologies. *Interacting with computers, 22(*4), 243-252. https://doi.org/10.1016/j.intcom.2010.02.006

Donkin, L., Christensen, H., Naismith, S. L., Neal, B., Hickie, I. B., & Glozier, N. (2011). A systematic review of the impact of adherence on the effectiveness of e-therapies. *Journal of medical Internet research, 13*(3), e52. https://doi.org/10.2196/jmir.1772

Eysenbach G. (2005). The law of attrition. *Journal of medical Internet research, 7*(1), e11. https://doi.org/10.2196/jmir.7.1.e11

Fleming, T., Bavin, L., Lucassen, M., Stasiak, K., Hopkins, S., & Merry, S. (2018). Beyond the Trial: Systematic Review of Real-World Uptake and Engagement With Digital Self-

Help Interventions for Depression, Low Mood, or Anxiety. *Journal of medical Internet research, 20(*6), e199. https://doi.org/10.2196/jmir.9275

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist, 54*(7), 493–503. https://doi.org/10.1037/0003-066X.54.7.493

Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: A meta-analysis of effects and processes. In M. P. Zanna (Ed.), Advances in experimental social psychology, Vol. 38, pp. 69–119). Elsevier Academic Press. https://doi.org/10.1016/S0065-2601(06)38002-1

Hollis, C., Falconer, C. J., Martin, J. L., Whittington, C., Stockton, S., Glazebrook, C., & Davies, E. B. (2017). Annual Research Review: Digital health interventions for children and young people with mental health problems - a systematic and meta-review. *Journal of child psychology and psychiatry, and allied disciplines, 58*(4), 474–503. https://doi.org/10.1111/jcpp.12663

Kazdin A. E. (2017). Addressing the treatment gap: A key challenge for extending evidence-based psychosocial interventions. *Behaviour research and therapy, 88,* 7–18. https://doi.org/10.1016/j.brat.2016.06.004

Kelders, S. M., Kok, R. N., Ossebaard, H. C., & Van Gemert-Pijnen, J. E. (2012). Persuasive system design does matter: a systematic review of adherence to web-based interventions. *Journal of medical Internet research, 14*(6), e152. https://doi.org/10.2196/jmir.2104

Kidman, P. G., Curtis, R. G., Watson, A., & Maher, C. A. (2024). When and Why Adults Abandon Lifestyle Behavior and Mental Health Mobile Apps: Scoping Review. *Journal of medical Internet research, 26*, e56897. https://doi.org/10.2196/56897

Lagun, Nikesh (2025a). Cognitive Thermostat Theory (CTT): The Control-Theoretic Ignition Engine of Cognitive Drive Architecture (CDA). figshare. Preprint. https://doi.org/10.6084/m9.figshare.30920054.v1

Lagun, N. (2025b). Lagun's law and the foundations of cognitive drive architecture: A first principles theory of effort and performance. *International Journal of Science and Research Archive.* https://doi.org/10.30574/ijsra.2025.15.2.1425

Lagun, N. (2025c). Latent Task Architecture: Modeling Cognitive Readiness Under Unresolved Intentions. *Research Square*. https://doi.org/10.21203/rs.3.rs-6896824/v1

Marmot, M., Allen, J., Goldblatt, P., Herd, E., & Morrison, J. (2021). Build back fairer. London: Institute of Health Equity, Available online:

https://www.health.org.uk/sites/default/files/upload/publications/2020/Build-back-fairer-the-COVID-19-Marmot-review.pdf (accessed on 4 January 2026).

Michie, S., van Stralen, M. M., & West, R. (2011). The behaviour change wheel: a new method for characterising and designing behaviour change interventions. Implementation science : IS, 6, 42. https://doi.org/10.1186/1748-5908-6-42

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, *3*(2). https://doi.org/10.1177/2053951716679679

Mohr, D. C., Burns, M. N., Schueller, S. M., Clarke, G., & Klinkman, M. (2013). Behavioral intervention technologies: evidence review and recommendations for future research in mental health. *General hospital psychiatry*, *35*(4), 332–338. https://doi.org/10.1016/j.genhosppsych.2013.03.008

Mohr, D. C., Cuijpers, P., & Lehman, K. (2011). Supportive accountability: a model for providing human support to enhance adherence to eHealth interventions. *Journal of medical Internet research*, *13*(1), e30. https://doi.org/10.2196/jmir.1602

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2018). Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. Annals of behavioral medicine : a publication of the *Society of Behavioral Medicine*, *52*(6), 446–462. https://doi.org/10.1007/s12160-016-9830-8

Norman, D. (2013). The Design of Everyday Things: Revised and Expanded Edition. Basic Books.

Proctor, E., Silmere, H., Raghavan, R., Hovmand, P., Aarons, G., Bunger, A., Griffey, R., & Hensley, M. (2011). Outcomes for implementation research: conceptual distinctions, measurement challenges, and research agenda. *Administration and policy in mental health*, *38*(2), 65–76. https://doi.org/10.1007/s10488-010-0319-7

Rennick-Egglestone, S., Knowles, S., Toms, G., Bee, P., Lovell, K., & Bower, P. (2016, May). Health Technologies' In the Wild' Experiences of Engagement with Computerised CBT. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (pp. 2124-2135). https://doi.org/10.1145/2858036.2858128

Sheeran, P., & Webb, T. L. (2016). The intention–behavior gap. *Social and Personality Psychology Compass*, 10(9), 503–518. https://doi.org/10.1111/spc3.12265

Torous, J., Bucci, S., Bell, I. H., Kessing, L. V., Faurholt-Jepsen, M., Whelan, P., Carvalho, A. F., Keshavan, M., Linardon, J., & Firth, J. (2021). The growing field of digital

psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality. World psychiatry : official journal of the World Psychiatric Association (WPA), 20(3), 318–335. https://doi.org/10.1002/wps.20883

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

West, R., & Brown, J. (2013). Theory of addiction (2nd ed.). Wiley Blackwell. https://doi.org/10.1002/9781118484890

World Health Organization. (2022). World mental health report: Transforming mental health for all. World Health Organization.

Yardley, L., Morrison, L., Bradbury, K., & Muller, I. (2015). The person-based approach to intervention development: application to digital health-related behavior change interventions. *Journal of medical Internet research*, *17*(1), e30. https://doi.org/10.2196/jmir.4055

Yardley, L., Spring, B. J., Riper, H., Morrison, L. G., Crane, D. H., Curtis, K., Merchant, G. C., Naughton, F., & Blandford, A. (2016). Understanding and Promoting Effective Engagement With Digital Behavior Change Interventions. *American journal of preventive medicine*, *51(*5), 833–842. https://doi.org/10.1016/j.amepre.2016.06.015

Abbreviations

AI: Artificial Intelligence

DMHI: Digital Mental Health Intervention

DMHIs: Digital Mental Health Interventions

Declarations

Competing interests: The author declares no conflicts of interest for this work.

Ethics approval and consent to participate: Not Applicable.

Funding: The authors received no financial support for the preparation of this manuscript.