

MindPulse: Using AI and Wearables to Promote Mental Wellbeing and Reduce Digital Health Inequality

Population group: students, shift workers, carers and people with chronic illness

Population Health and Digital Health

(LCHS7009)

Component 2

Digital health promotion poster

(Poster)
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BACKGROUND

Mental ill-health is a major public-health issue: more than one billion people worldwide live with a mental health condition, and access to services is unequal. Scalable early intervention is necessary because formal-care coverage remains much lower in low-income settings than in higher-income countries. Previous support includes counselling, helplines, CBT, iCBT and digital tools such as Wysa, Woebot and Headspace. (WHO, 2025; Patel et al., 2018; Linardon et al., 2019; Fitzpatrick et al., 2017; Inkster et al., 2018; O'Daffer et al., 2022).

MindPulse is a proposed intervention using smartwatch/smartphone signals, optional mood check-ins and brief just-in-time support to detect deterioration early. Compared with Wysa/Woebot (chatbot CBT) and Headspace (guided mindfulness), its innovation is combining passive sensing, personalised baselines, equity audit and consent-based escalation. (Onnela and Rauch, 2016; Nahum-Shani et al., 2018; Torous et al., 2018).

Mental health service coverage remains deeply unequal

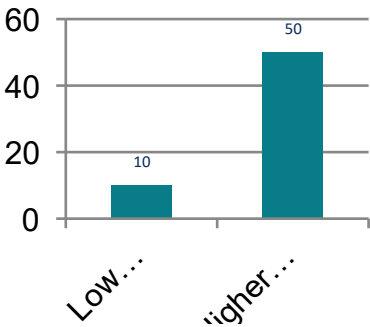


Figure 1. Thresholds reported by WHO; bars use boundary values, not exact country estimates.



ADDRESSING DIGITAL HEALTH INEQUALITY

- ✓ Device-loan or subsidised wearable schemes to reduce cost barriers (Patel et al., 2018; McNamee et al., 2016)
- ✓ Multilingual and plain-language design with community onboarding (Patel et al., 2018)
- ✓ Accessibility settings plus low-data/offline use for poor connectivity (Patel et al., 2018)
- ✓ Culturally sensitive co-design with carers, students and shift workers (Craig et al., 2008; Torous et al., 2018)
- ✓ Non-digital alternatives and clinician referral for risk escalation (NICE, 2022; NHS England, 2026)
- ✓ Equity audits by age, disability, ethnicity, income and work pattern; track false-alert rates by subgroup (Obermeyer et al., 2019)

HEALTH PROMOTION VALUES AND PRINCIPLES

Health promotion focuses on empowerment, equity, participation, prevention and enabling people to have control over health. MindPulse supports these values through opt-in use, explicit consent, user control over data sharing and co-designed features for underserved groups. It focuses on upstream prevention, self-efficacy, emotional literacy and timely action—not crisis care alone. (WHO, 1986; Patel et al., 2018; Michie et al., 2011; NICE, 2022; NHS England, 2026).

Implementation must adapt to population context: exam cycles in students, irregular sleep in shift workers, time poverty in carers and symptom burden in chronic illness. Success requires alternatives for people without wearables, low digital confidence or privacy concerns. (Patel et al., 2018; Torous et al., 2018; Huckvale et al., 2019; Obermeyer et al., 2019).

Empowerment

user choice

Equity

loan scheme

Participation

co-design

Prevention

early support



KEY FEATURES OF MINDPULSE

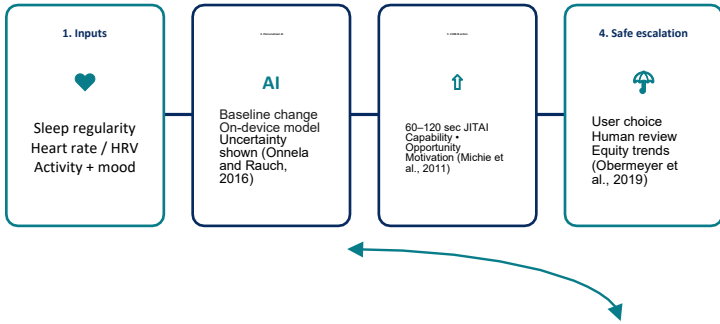
- ✓ Passive sensing of sleep, activity and HRV with user opt-in (Onnela and Rauch, 2016)
- ✓ Optional mood check-ins + monthly PHQ-9/GAD-7 (Kroenke et al., 2001; Spitzer et al., 2006)
- ✓ Personalised AI baseline with uncertainty shown (Onnela and Rauch, 2016; Huckvale et al., 2019)
- ✓ 60–120 second micro-actions matched to COM-B/JITAI (Michie et al., 2011; Nahum-Shani et al., 2018)
- ✓ Explainable risk summary + consent-based escalation to human support (NICE, 2022; NHS England, 2026)

BEHAVIOURAL CHANGE THEORY: COM-B

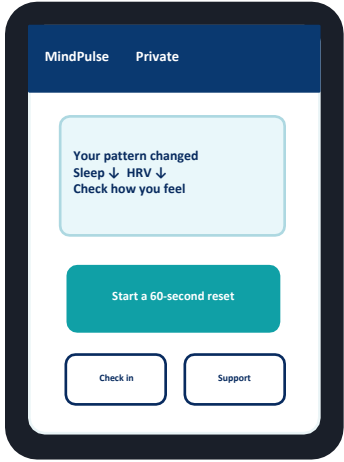
According to COM-B, behaviour results from Capability, Opportunity and Motivation. MindPulse uses wearable signals (sleep regularity, HR/HRV, activity) plus optional mood checks to deliver just-in-time adaptive interventions. Short breathing, sleep-planning and cognitive reframing exercises build capability; private access and signposting support opportunity; personalised feedback supports motivation. (Michie et al., 2011; Onnela and Rauch, 2016; Nahum-Shani et al., 2018).

Critical limitation: passive signals are proxies, so the app should present uncertainty, avoid diagnosis, allow opt-out and route sustained/high-risk patterns to human review. False positives, false reassurance, disengagement and cultural mismatch are key risks. (Onnela and Rauch, 2016; Torous et al., 2018; NICE, 2022).

MindPulse pathway: passive signals → proportionate support



Continuous learning only from consented outcomes, user feedback and equity audits (Huckvale et al., 2019; NICE, 2022)



EXPECTED OUTCOME



Adopting COM-B should increase coping capacity, early-support engagement and the speed of action after symptom change. Expected outcomes include improved self-monitoring, earlier help-seeking, reduced escalation of distress, and improved sleep, mood and functioning. (Michie et al., 2011; Nahum-Shani et al., 2018).

Measurable success indicators: PHQ-9/GAD-7 mean change and ≥5-point improvement, engagement/retention rates, alert precision/false-alert rate, crisis referrals, subgroup equity gaps, cost per engaged user and QALY where possible. (Kroenke et al., 2001; Spitzer et al., 2006; NICE, 2022; McNamee et al., 2016). Conflicting evidence: digital tools can help, but effects vary, attrition is high, and many commercial apps lack independent trials; therefore, MindPulse needs feasibility testing followed by an independent RCT and equity evaluation. (Linardon et al., 2019; Moshe et al., 2021; O'Daffer et al., 2022; Torous et al., 2018).



CONCLUSION

MindPulse has policy, education and research implications. Evidence should align with NICE and NHS DTAC-style standards; policymakers need robust governance and funding to reduce exclusion. Practitioners need digital mental-health literacy and training on ethical AI use. Research should progress from co-design/feasibility to independent trials evaluating outcomes, harm, cost-effectiveness and subgroup equity. (NICE, 2022; NHS England, 2026; Craig et al., 2008).

Ethical safeguards must address privacy leakage, data ownership, retention, bias, explainability and transparent algorithm updates. Scalability depends on low-cost deployment, interoperability and sustainable public procurement, not only app uptake. (Huckvale et al., 2019; Obermeyer et al., 2019; Mittelstadt et al., 2016; McNamee et al., 2016).

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