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From physiological mechanisms to digital innovation: An integrated framework for AI-driven personalised mental health management, workplace wellbeing and business models

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Abstract
The global burden of mental ill health has been rising at an unprecedented rate, while the availability of digital and artificial-intelligence (AI) technologies has opened a revolutionary opportunity for mental-health service delivery. Existing research, however, remains fragmented along two largely separate tracks: workplace mental health at the organisational level and individual psychological healing at the personal level, AI applications are assessed primarily for technical feasibility rather than privacy protection, algorithmic bias and ethical governance, and the business models, outcome evaluation and professional-referral mechanisms of digital mental-health products have not been adequately aligned with scientific evidence. It is found in this study that, by systematically integrating stress science, positive psychology, workplace wellbeing, AI technology and evidence-based psychological healing, a complete knowledge system and practical model of personalised mental-health management can be constructed. Stress responses are governed by the autonomic nervous system and the hypothalamic–pituitary–adrenal (HPA) axis, heart-rate variability (HRV) serves as a key physiological marker of stress and the flexibility of brain–body integration, cognitive reappraisal is a more adaptive emotion-regulation strategy than expressive suppression, and resilience can be enhanced through blended cognitive-behavioural and mindfulness interventions. The Job Demands–Resources model and perceived-organisational-support theory provide the theoretical foundation for institutional workplace mental-health promotion, whereas natural-language processing, AI emotion recognition, generative AI and personalised recommendation constitute the technical engine of digital services, subject to stringent privacy, bias and governance safeguards. An integrated AI-personalised mindfulness practice workflow and four complementary business models (B2C subscription, B2B enterprise provision, B2B2C healing-service platform and clinical integration) are proposed. It is argued throughout that AI functions as an auxiliary instrument rather than a substitute for professional care, and that human–AI collaboration, professional referral boundaries and evidence-based validation constitute the prerequisites for sustainable development.

Keywords: Artificial intelligence, mental health, workplace wellbeing, mindfulness, emotion regulation, digital mental health, health-data governance

Introduction

The severity of global mental-health problems has been climbing at an unprecedented rate. The World Health Organization has observed that depression has become one of the leading causes of disability worldwide, and the prevalence of anxiety disorders, depression and stress-related conditions has continued to rise over the past two decades; the COVID-19 pandemic further intensified the worldwide deterioration in mental health. In the workplace domain, the impact of mental-health problems has been particularly far-reaching. Stress, anxiety and depression are regarded as major causes of lost working days, and the absenteeism, presenteeism and medical expenditure arising from mental-health problems constitute a substantial economic burden for employers. At the same time, the rapid development of digital technology and artificial intelligence has brought about a revolutionary opportunity for mental-health services. Digital mental-health tools, including smartphone applications, wearable devices, chatbots and virtual reality, are characterised by scalability, low access thresholds and personalisation, and they are capable of overcoming the human-resource, geographical and stigma-related constraints of conventional psychotherapy by providing mental-health support at any time and in any place (Torous *et al*., 2021) [21]. Meta-analytic evidence indicates that smartphone-based mental-health interventions produce significant and moderate improvements in depressive symptoms (Firth *et al*., 2017) [4], and that cognitive-behavioural therapy delivered through a conversational agent (chatbot) has been shown to reduce depressive symptoms effectively among young adults (Fitzpatrick *et al*., 2017) [5]. On the other hand, mindfulness-centred psychological healing methods have accumulated a rich body of scientific evidence over the past three decades. Structured interventions such as Mindfulness-Based Stress Reduction (MBSR) have been demonstrated to reduce stress, anxiety and depressive symptoms effectively (Goyal *et al*., 2014; Khoury *et al*., 2015) [6, 11], and mindfulness training has been shown to improve cognitive functions such as attention and working memory (Mrazek *et al*., 2013) [18]. Music interventions likewise demonstrate significant stress-relief effects (de Witte *et al*., 2020) [3], and these mind–body therapies are now being combined with digital technology to form a rapidly growing digital healing industry. Despite the rapid development of technologies and services, three gaps remain in the current field of mental-health management. First, workplace mental health (the organisational level) and individual psychological healing (the personal level) have largely developed independently of one another, and an integrative framework is lacking. Second, AI applications

have concentrated on technical feasibility, whereas discussion of privacy protection for mental-health data, algorithmic bias and ethical governance has been comparatively insufficient. Third, the business models, outcome evaluation and professional-referral mechanisms of digital mental-health products and healing services have not yet been adequately aligned with scientific evidence. Against this background, the present study aims to integrate systematically stress science, positive psychology, workplace wellbeing, AI technology and psychological healing, and to construct a complete knowledge system and practical model of personalised mental-health management.

Stress Response, the Autonomic Nervous System and Emotion Regulation

1. Stress Response and the Autonomic Nervous System

Stress may be defined as the physiological and psychological response produced when the human body confronts internal and external challenges; its core purpose is to mobilise bodily resources in order to cope with threat. This process is regulated jointly by the Autonomic Nervous System (ANS) and the hypothalamic–pituitary–adrenal (HPA) axis. The ANS comprises two major branches: the sympathetic branch and the parasympathetic branch. The sympathetic branch is activated under stressful conditions, accelerating the heartbeat, raising blood pressure, dilating the bronchi and secreting adrenaline, thereby initiating the "fight-or-flight" response. The parasympathetic branch, by contrast, predominates under conditions of safety and relaxation; through the vagus nerve it promotes a slower heartbeat, digestive functioning and bodily repair, sustaining the homeostatic "rest-and-digest" function. A healthy stress response should exhibit a dynamic "activation–recovery" balance: on encountering stress, the sympathetic branch is rapidly activated to meet the challenge, and once the stressor subsides the parasympathetic branch takes over immediately, returning the physiological system to homeostasis. The stresses of the modern workplace, however, are predominantly long-term, chronic psychosocial stressors such as excessive workload, role conflict, time pressure and organisational change. Prolonged exposure to such stressors may cause the ANS to lose its balance, giving rise to excessive sympathetic activation and reduced parasympathetic tone; this "autonomic dysregulation" has been shown to be closely associated with cardiovascular disease, metabolic disease and psychological disorders. Based on meta-analytic evidence drawn from more than 600,000 participants across 27 cohort studies, occupational stressors such as workload and long working hours exhibit a moderate and significant association with the risk of coronary heart disease and stroke, with excess risks of approximately 10% to 40% among those exposed (Kivimäki & Kawachi, 2015) [12].

2. Physiological Basis and Application of Heart-Rate Variability

Heart-Rate Variability (HRV) denotes the minute temporal differences between successive heartbeats; it reflects the dynamic regulatory capacity of the ANS over the heart and is at present one of the most widely applied physiological indicators of stress. HRV does not measure stress directly; rather, it reflects the regulatory elasticity of an individual's neurocardiac system. High HRV indicates good parasympathetic activity and a resilient physiological system capable of responding effectively to environmental change, whereas low HRV reflects sympathetic predominance and physiological rigidity, and is associated with stress load, inflammatory states and disease risk. In a meta-analysis integrating neuroimaging studies, Thayer *et al*. (2012) [20] proposed the Neurovisceral Integration Model, according to which HRV is closely related to activity in brain regions such as the prefrontal cortex and the amygdala. High HRV reflects stronger "top-down" regulation by the prefrontal cortex over subcortical threat-response systems such as the amygdala, indicating superior executive control and emotion-regulation capacity; conversely, low HRV is associated with excessive activation of the threat-response system. This model positions HRV as a key window indicator of stress and health: HRV is not merely a measure of autonomic function but also a proxy variable for the degree of vertical brain–body integration.

The clinical and applied value of HRV has been extensively validated. In the domain of workplace health, HRV may serve as an objective monitoring indicator of occupational stress and fatigue, and, when combined with wearable devices, continuous non-invasive stress tracking can be conducted. In the field of mind–body medicine, HRV biofeedback training — which strengthens homeostatic baroreflex functioning through slow breathing (approximately six breaths per minute) and real-time physiological feedback — has been shown to improve a variety of stress-related conditions; its mechanisms include strengthening the baroreflex gain, enhancing the regulatory influence of vagal afferent signals on the prefrontal cortex, and promoting ANS balance (Lehrer & Gevirtz, 2014) [15]. This technique provides an important physiological foundation for AI-enabled personalised stress management: as wearable devices measure HRV continuously and AI algorithms analyse an individual's HRV baseline and response patterns, stress states can be predicted, the degree of recovery evaluated, and personalised relaxation interventions recommended accordingly.

3. Cognition and Emotion Regulation

Emotion regulation may be defined as the processes through which an individual influences the generation, experience and expression of his or her own emotions; it constitutes a core capacity for mental health. The process model of emotion regulation advanced by Gross (2015) [8] classifies emotion-regulation strategies into five categories according to the point at which they act within the emotion-generation process: situation selection, situation modification, attentional deployment, cognitive change and response modulation. Cognitive reappraisal, belonging to cognitive change, adjusts emotional response by altering the interpretation of a situation; expressive suppression, belonging to response modulation, adjusts emotion by inhibiting overt emotional behaviour.

A large body of empirical research demonstrates that the health effects of different emotion-regulation strategies differ markedly. The meta-analysis by Webb *et al*. (2012) [22], which incorporated 306 experimental comparisons, found that cognitive-change strategies yielded moderate to good emotion-adjustment effects ($d+ = 0.36$), that the distraction strategy within attentional deployment was effective ($d+ = 0.27$), and that, although expressive suppression reduced overt behaviour, it failed to reduce the subjective experience of emotion and might even increase

physiological arousal and impair memory. Over the longer term, individuals who habitually employ cognitive reappraisal enjoy better mental health, whereas habitual suppressors face a higher risk of psychopathology. Deficits in emotion-regulation capacity have been shown to be associated with depression, borderline personality disorder, substance-use disorders and eating disorders, among other psychopathological conditions. Within the workplace context, emotion-regulation capacity constitutes an important personal resource for coping with occupational stress. Employees with high emotion-regulation capacity are better able to handle emotional labour, interpersonal conflict and setbacks at work, thereby reducing the risk of emotional exhaustion and burnout. Emotion-regulation capacity can also be enhanced through training: cognitive-behavioural therapy, mindfulness training and group emotion-regulation interventions have all been shown to strengthen emotion-regulation capacity and improve mental health. This finding supplies an important design basis for AI mental-health interventions — AI systems may identify a user's emotion-regulation pattern through textual analysis and provide targeted cognitive-reappraisal exercises or behavioural-strategy recommendations.

4. Psychological Resilience

Psychological resilience denotes the dynamic capacity of an individual to adapt effectively and recover normal functioning in the face of adversity, trauma, threat or significant stress. Resilience is not a fixed personality trait but a malleable capacity that can be enhanced through training and intervention; its constituent elements include cognitive flexibility, emotion regulation, social-support networks, a sense of meaning and self-efficacy. In a systematic review and meta-analysis incorporating 11 randomised controlled trials, Joyce *et al.* (2018) [10] found that resilience interventions produced a moderate positive effect (effect size 0.44), with the blended intervention combining cognitive-behavioural therapy and mindfulness training achieving the strongest effect (effect size 0.51). These results indicate that resilience training has moved from concept to empirical evidence and may serve as an effective intervention strategy for workplace mental-health promotion. It should be noted that the effects of resilience interventions vary across populations and contexts; single-session workshops yield limited effects, whereas sustained, multimodal training programmes are more effective. Within the workplace context, individual resilience and organisational resilience complement one another: individual resilience enables employees to maintain functioning under stress, whereas organisational resilience, through sound management systems, a supportive culture and the provision of resources, reduces employees' exposure to excessive stress. An ideal mental-health management strategy should address both: on the one hand, enhancing individual coping capacity through resilience training, and on the other hand reducing the stressors themselves through job design and organisational change.

Positive Psychology and Workplace Wellbeing

1. Positive Psychology and Job Wellbeing

Positive Psychology, advocated by Seligman and colleagues at the turn of the century, maintains that psychology should not confine itself to the repair of psychopathology but should also investigate human strengths, virtues and the conditions of flourishing. Within the workplace context, positive psychology gave rise to research fields such as positive organisational behaviour and workplace wellbeing, extending employee mental health from the negative definition of "absence of disease" to the positive concept of "positive functioning and flourishing". Job wellbeing comprises subjective wellbeing (life satisfaction and positive affect), psychological wellbeing (autonomy, competence, relatedness, meaning and growth) and work engagement (vigour, dedication and absorption). A large body of research confirms that job wellbeing is not merely a personal welfare issue for employees but is closely related to job performance, creativity, retention intention and physical health. Positive emotions broaden an individual's cognitive and behavioural resources (the broaden-and-build theory), facilitating problem-solving and interpersonal cooperation and thereby forming a virtuous spiral.

2. Work–Life Balance

Work–life balance refers to a satisfactory state of resource allocation and psychological experience between an individual's work role and non-work roles (family, leisure, social participation). Greenhaus *et al.* (2003) [7] observed that work–family balance consists of three components: time balance, involvement balance and satisfaction balance; when an individual invests unevenly between the two roles (for example, devoting far more time to work than to family), quality of life declines significantly. Work–life conflict (mutual interference between the demands of work and family roles) has been shown to be positively correlated with burnout, psychological distress and turnover intention; conversely, work–family enrichment (where the resources of one role enhance performance in the other) is positively associated with wellbeing. New challenges confront work–life balance in the modern workplace. The proliferation of digital technology has increasingly blurred the boundary between work and life; the expectation of "always being on call" makes psychological detachment difficult, so that employees cannot recover from work during non-working hours, and accumulated fatigue and stress result over time. Consequently, organisational strategies that promote work–life balance — including flexible working hours, remote work, boundary-management policies and recovery support — have become an important component of workplace mental-health management.

3. Workplace-Stress Theory and Organisational Support

Among theoretical frameworks of workplace stress, the Job Demands–Resources (JD-R) model is the most comprehensive. The JD-R theory proposed by Bakker and Demerouti (2017) [1] maintains that all job characteristics may be divided into two broad categories: job demands and job resources. Job demands (such as workload, time pressure and emotional demands) require sustained physical and psychological effort; excessively high demands initiate a "health-impairment process" leading to exhaustion and health problems. Job resources (such as autonomy, social support, performance feedback and skill variety) initiate a "motivational process" that promotes engagement and growth. More importantly, job resources exert a buffering effect, moderating the negative impact of job demands on health; when demands are high yet resources are sufficient, employees not only avoid burnout but may instead

demonstrate high engagement. Organisational support constitutes a core element of job resources. Perceived Organizational Support (POS) refers to an employee's global belief as to whether the organisation values his or her contribution and cares about his or her wellbeing. The meta-analysis by Kurtessis *et al*. (2017) [14], integrating 558 studies, confirmed that POS is positively correlated with leadership quality, human-resource practices and working conditions, and predicts employees' organisational commitment, job satisfaction, performance and wellbeing, while negatively predicting turnover intention and withdrawal behaviour. The mechanism of POS rests on social-exchange theory: when employees perceive organisational support and care, a sense of obligation to repay the organisation and an emotional bond are generated, leading in turn to work engagement. JD-R theory and POS research provide clear design guidance for institutional workplace mental health: effective mental-health management should not only address psychological distress that has already arisen (downstream intervention) but should also, through job design, management quality and organisational culture, proactively construct a supportive working environment (upstream prevention), reduce exposure to stressors and provide sufficient resource buffering.

4. Workplace Health Promotion Programmes

Workplace Health Promotion (WHP) denotes the series of systematic measures adopted by enterprises to enhance employee health and wellbeing; its scope has expanded from traditional physical health (health checks, physical fitness, healthy diet) to mental-health promotion. A complete mental-health-promotion framework should include three levels of intervention. The first level is primary prevention, which reduces the incidence of mental-health problems through job design, stress-management training and mental-health literacy education. The second level is secondary prevention, which, through stress screening and early identification, detects high-risk employees at an early stage and provides early intervention. The third level is tertiary prevention, which, through professional treatment, recovery support and return-to-work programmes, assists individuals already suffering from psychological disorders in restoring functioning. The economic benefits of workplace health promotion have been extensively validated. Productivity losses attributable to mental-health problems — including absenteeism and presenteeism — are often far higher than direct medical costs and constitute a considerable economic burden for enterprises. Investment in employee mental-health promotion is therefore regarded as a strategy with a positive return on investment: every unit of resource invested in workplace mental health yields a multiple return in productivity gains and medical-cost savings. This economic argument, combined with the ethical argument (the enterprise's social responsibility for employee wellbeing), has become the principal driving force behind the advancement of workplace mental-health institutions.

Employee Assistance Programmes and the Workplace Mental-Health System

1. The EAP Market and Service Models

The Employee Assistance Program (EAP) is a professional mental-health support service provided by enterprises to employees. It originated in occupational alcohol programmes in the United States in the mid-twentieth century and subsequently expanded progressively to cover counselling, stress management, family problems, legal and financial assistance and a diverse range of further domains. The core services of the modern EAP include short-term counselling (typically focused sessions of approximately 30 to 60 minutes each), psychological assessment and screening, crisis intervention, professional referral, managerial consultation (assisting supervisors in handling employee problems) and health-promotion activities. Several important trends may be observed in the development of the EAP market. First, the delivery model has shifted from in-house provision by enterprises to outsourcing by external professional agencies; external EAP suppliers, relying on economies of scale and specialised division of labour, provide more cost-effective services. Second, the service format has expanded from traditional face-to-face counselling to multiple channels including telephone counselling, online counselling and application-based services, thereby improving accessibility and convenience. Third, the positioning of EAP is shifting from "problem handling" toward "comprehensive wellbeing", integrating mental health, physical health, financial health and social welfare to form a one-stop employee-support service. The EAP market has continued to expand as enterprise mental-health awareness rises. In Taiwan, large enterprises and multinational companies have generally adopted EAP, whereas the adoption rate among small and medium-sized enterprises remains comparatively low, leaving considerable room for market growth. EAP pricing models commonly charge per employee per month, or adopt a fee-for-service model; some suppliers also offer flexible hybrid schemes.

2. Operational Management of Mental-Health Services

The operational management of mental-health services involves multiple dimensions, including service design, quality control, data governance and continuous improvement. In terms of service design, EAP and mental-health services must establish clear service scope and usage procedures: how employees access the service (self-booking, supervisor referral, proactive EAP outreach), the duration and maximum number of sessions per case, and the circumstances under which referral to external professional agencies is required, all require explicit operational standards. Quality control constitutes the core challenge in the operation of mental-health services. Service quality involves the qualifications and training of professionals, the evidence base of intervention methods, the standardisation of service processes and the measurement of outcomes. In practice, EAP suppliers must establish clinical-supervision mechanisms, conduct regular service audits, track user satisfaction and improvement outcomes, and drive continuous optimisation of service content through data. Outcome measurement must balance subjective indicators (satisfaction, perceived improvement) with objective indicators (changes in symptom-scale scores, attendance and productivity metrics). Data governance carries special importance in mental-health services. Mental-health data constitute highly sensitive personal data, and their collection, storage, use and sharing must comply with personal-information regulations and professional ethical norms. Service operators must establish stringent

data-security measures (encryption, access control, de-identification), explicit informed-consent procedures and incident-response mechanisms for data breaches. In addition, operational management must attend to equitable access, preventing concentration of service resources among particular population groups that would produce health inequality.

3. The Professional-Referral Mechanism

Professional referral constitutes an important hub of the mental-health service system. The severity spectrum of mental-health problems is extremely broad, ranging from everyday stress adaptation and mild emotional distress to severe psychological disorders and suicide risk; cases of differing severity require different levels of intervention. The design of the referral mechanism aims to ensure that cases are directed to an appropriate level of service, preventing mild cases from excessively occupying scarce professional resources while simultaneously ensuring that high-risk cases receive timely professional medical intervention. The core of the referral mechanism is risk-stratified assessment. In the initial session, the EAP counsellor must, through structured assessment instruments (such as the PHQ-9 depression scale and the GAD-7 anxiety scale) and clinical judgement, evaluate symptom severity, degree of functional impairment and suicide risk, and determine the handling pathway accordingly: low-risk cases receive short-term counselling or self-help resources from the EAP; moderate-risk cases are referred to psychotherapy or psychiatric outpatient clinics; and high-risk cases (such as those with strong suicidal ideation) trigger crisis-intervention and emergency-referral procedures. An effective referral mechanism must also include post-referral follow-up feedback, confirming that cases actually receive the required services and, where appropriate, providing information feedback to the referring unit under conditions of case consent and confidentiality.

4. Outcome Evaluation of Mental-Health Services

Outcome evaluation of mental-health services is essential for demonstrating service value, driving quality improvement and supporting resource allocation. The evaluation framework should comprise three levels: outcome evaluation, which measures the actual impact of the service on case mental health, such as symptom improvement, functional recovery and enhanced quality of life; process evaluation, which measures the quality of service delivery, such as accessibility, utilisation rate, attrition and satisfaction; and cost-effectiveness evaluation, which measures the economic relationship between service input and output, such as the cost per unit of health improvement and the reduction in productivity loss. Several methodological challenges confront outcome evaluation. First, there are difficulties in implementing randomised controlled trials in real settings: ethical and practical constraints in enterprise environments make strict random allocation difficult to achieve, and most evaluations therefore adopt quasi-experimental or pre–post comparison designs. Second, there are considerations of evaluation timing: the effects of mental-health improvement may require several months to emerge, and short-term evaluation may underestimate service effectiveness. Third, there is the choice of measurement instruments: different instruments vary in sensitivity to change, and appropriate outcome indicators must be selected according to service objectives. Notwithstanding these challenges, systematic outcome evaluation remains a necessary condition for the professionalisation and sustainable development of mental-health services.

AI Mental-Health Technology and Ethical Governance

1. Natural-Language Processing and Analysis of Health Text Data

Natural-Language Processing (NLP) enables computers to understand and analyse human language, opening an entirely new data source and analytical method for the mental-health domain. Mental-health status is strongly reflected in patterns of language use: the linguistic features of depressed individuals include a higher frequency of first-person singular pronouns, more negative-emotion vocabulary, fewer social-engagement words and a more rigid language style. By analysing these linguistic features through machine learning, NLP systems may infer mental-health status from text produced by individuals (such as social-media posts, diaries and open questionnaire items). Social media and big data offer an unprecedented opportunity for mental-health surveillance. Conway and O'Connor (2016) [2] observed that combining social-media big data with NLP technology enables population-level mental-health monitoring, such as analysing emotional trends in a particular region or community, providing early detection of outbreaks of mental-health problems, and evaluating the effectiveness of public-health interventions. Such methods offer the advantages of immediacy, low cost and broad coverage, supplementing the temporal and scale limitations of conventional survey methods. In personalised mental-health services, the application of NLP is more direct: chatbots, through NLP, understand users' textual input and provide cognitive-behavioural-orientation conversational support (Fitzpatrick *et al.*, 2017) [5]; psychological assessment tools, through NLP, analyse responses to open-ended questions to assist symptom evaluation; and diary and self-expression applications, through NLP, feed back users' emotional patterns and thinking styles to promote self-awareness. It should be noted, however, that the accuracy of NLP mental-health analysis depends heavily on the quality and representativeness of training data; cross-cultural, cross-language and cross-register linguistic differences (formal writing versus colloquial posts) may significantly affect model performance, and this technical limitation must be handled with care in application.

2. Applications and Limitations of AI Emotion Recognition

AI Emotion Recognition technology aims to infer an individual's emotional state automatically through the analysis of facial expressions, speech, physiological signals or text. Among these, facial-expression recognition based on visual information is the most mature branch of research: conventional methods combine manually designed features (such as local binary patterns and optical flow) with classifiers, whereas deep-learning methods employ convolutional neural networks (CNNs) for end-to-end expression-feature learning and combine long short-term memory networks (LSTMs) to process the temporal dynamics across consecutive frames (Ko, 2018). Such technology has achieved fairly high recognition accuracy

under controlled laboratory conditions and has been applied to workplace-fatigue monitoring, customer-service quality assessment and human–machine interaction design. Nevertheless, several limitations must be faced when AI emotion recognition is applied in the mental-health domain. First is the issue of ecological validity: expressions performed or induced in the laboratory differ markedly from subtle emotional expressions in real life, and recognition accuracy declines substantially in-the-wild. Second is the complexity of emotion: genuine emotions frequently blend several basic emotions and are highly dependent on situational context, so that facial expression alone cannot fully capture them. Third are cultural and individual differences: the meaning of expression varies across cultures, and neurodiversity (for example, the expression patterns of autistic-spectrum individuals) may likewise be misclassified by the system. Fourth are ethical risks: emotion recognition involves inference about an individual's internal state, and in workplace-monitoring settings without adequate informed consent it may infringe employee privacy and provoke a trust crisis. Accordingly, AI emotion recognition should be positioned within mental-health services as an "auxiliary indicator" rather than a "diagnostic instrument": inferred outputs must be cross-validated against multimodal information (speech, physiology, behaviour) and subjected to final judgement by professionals, and AI inference must not be equated directly with clinical fact.

3. Privacy, Bias and Ethics of Mental-Health Data

Ethical governance of mental-health data constitutes the cornerstone of AI mental-health service development. Mental-health data carry high sensitivity and stigma risk; once breached, they may inflict serious harm on an individual's employment, insurance and social relationships. The processing of mental-health data must therefore follow strict principles: data minimisation (collecting only the minimum dataset necessary to achieve the service purpose), purpose limitation (data used solely for the consented purpose), security safeguards (encryption, access control, anonymisation), and user informed consent and autonomous control. Algorithmic bias constitutes another major ethical challenge for AI mental-health services. Owing to insufficient representativeness of training data, machine-learning models may produce systematic misclassification or disparities in service quality for particular groups (such as women, ethnic minorities, low-socioeconomic-status individuals and non-English speakers). For example, an emotion-analysis model trained on English social-media data may perform significantly worse on non-English text; a psychological-risk prediction model trained on a specific demographic may, when applied to other populations, generate excessive or inappropriate risk labels. Sources of bias include data bias (training data failing to reflect the true population), annotation bias (subjective judgement of human annotators) and algorithmic bias (the structural amplification of existing bias by the model); these must be mitigated through diversified data collection, bias auditing and fairness evaluation. An ethical-governance framework should encompass accountability (who is responsible for AI decisions), transparency (explainability of algorithmic logic) and human oversight (AI recommendations subjected to professional review). In addition, boundary management of AI mental-health services is critical: AI systems should clearly state their capability limits and, on detecting high-risk signals (such as suicidal ideation), should refer cases in good time to human professional services, avoiding the dangerous misperception that "AI replaces the professional".

4. Design of an AI-Assisted Workplace-Stress Self-Check

Building on the technical foundations and ethical principles outlined above, this subsection designs a four-stage AI-assisted workplace-stress self-check service workflow as a front-end instrument for enterprise employee mental-health management.

Stage 1: Multimodal stress-data collection: Through an enterprise-provided application or wearable device, employees' stress-related data are collected passively, including HRV and resting heart rate (measured continuously by the wearable), sleep-quality indicators, activity volume and working-hour patterns; these are supplemented by actively entered psychological scales (such as the Perceived Stress Scale, PSS, and a burnout scale), emotional diaries and a stress-source questionnaire. The design priority of this stage is minimising the usage burden: automatic sensing predominates, active input plays a supporting role, and clear informed-consent procedures explain the purposes of data use and protective measures.

Stage 2: Personalised stress-state analysis: The AI system integrates the multimodal data, establishes an individual employee's stress baseline (taking account of differences in age, sex and personal historical data), and detects abnormal changes in stress state in real time — for example, HRV falling significantly below the personal baseline, continuous deterioration in sleep quality, or a rising proportion of negative-emotion text. The system also conducts stress-source analysis, identifying principal stress triggers through textual data (diaries, questionnaires) and work-context data (workload, meeting density).

Stage 3: Stratified risk assessment and feedback: According to stress indicators and the risk-assessment model, employees are classified into three levels: green light (stress manageable), yellow light (elevated stress, intervention recommended) and red light (high stress or high-risk signal, professional assistance recommended). Green-light employees receive immediate positive feedback and preventive advice; yellow-light employees receive personalised stress-management recommendations, including relaxation exercises, breathing training, exercise suggestions and work-adjustment prompts; red-light employees trigger a care mechanism, under which contact with the EAP or psychological professional services is recommended and a human specialist conducts follow-up.

Stage 4: Intervention-outcome tracking and privacy protection: The system continuously tracks changes in stress indicators after intervention, evaluates intervention effectiveness and dynamically adjusts recommendations. On privacy protection, enterprise managers may view only de-identified aggregate statistics (such as department-level stress trends); individual employees' stress data are accessible only to the employee and his or her authorised

mental-health professionals, ensuring that the self-check service does not degenerate into a performance-monitoring tool. This design balances the benefits of AI technology against the ethical boundaries of mental health and constitutes a key demonstration of the digitalisation of workplace mental health.

Mindfulness, Meditation and Mind–Body Healing

1. Mindfulness, Meditation and Attentional Regulation

Mindfulness refers to the capacity to focus attention, non-judgementally and with awareness, on present-moment experience. Derived from Eastern meditative traditions and systematised by Kabat-Zinn and colleagues into structured programmes such as MBSR, mindfulness has become one of the most thoroughly researched intervention methods in the field of psychological healing. Its core mechanism lies in attentional regulation: stability and control of attention are trained through focused practices (such as observing the breath and body scanning), while acceptance and a decentring attitude toward inner experience are cultivated through open-awareness practices. The randomised controlled study by Mrazek *et al*. (2013) [18] showed that merely two weeks of mindfulness training significantly improved working-memory capacity and GRE reading-comprehension performance while reducing the frequency of mind wandering, with improvements most pronounced among participants who were easily distracted before training. This result reveals the direct benefits of mindfulness training for attention and executive function, providing an empirical basis for applying mindfulness in workplace contexts requiring high concentration.

At the level of clinical benefit, the systematic review and meta-analysis by Goyal *et al*. (2014) [6], incorporating 47 randomised controlled trials, found that mindfulness-meditation programmes produced moderate improvements in anxiety (effect size 0.38), depression (0.30) and pain (0.33), with effects sustained for three to six months. The meta-analysis by Khoury *et al*. (2015) [11], targeting healthy populations, likewise showed that MBSR produced a large effect size for stress (Hedges' g = 0.55) and moderate improvements in anxiety, depression and quality of life. This evidence supports the extension of mindfulness interventions from clinical patients to mental-health promotion applications among the general population.

2. Stress, Emotion and the Physiological Mechanisms of Relaxation

Mind–body relaxation is a core strategy for stress management and emotion regulation; its physiological mechanism involves activation of the parasympathetic nervous system and reversal of the stress physiological response. The relaxation response, first described by Benson and colleagues, denotes a physiological state elicited through specific techniques (such as diaphragmatic breathing, repeated prayer or meditation), characterised by a reduced metabolic rate, slower heartbeat, lower blood pressure and diminished muscle tension. Long-term practice of the relaxation response may reduce the secretion of the stress hormone cortisol, regulate inflammatory response and strengthen immune function. At the neural-mechanism level, relaxation techniques activate vagal afferent signals, promote prefrontal regulation over threat-response systems such as the amygdala, and restore ANS balance (Thayer *et al*., 2012) [20]. Slow diaphragmatic breathing (approximately six breaths per minute), through the resonant effect of the baroreflex and respiratory sinus arrhythmia, substantially raises HRV; this mechanism is precisely the physiological basis of HRV biofeedback training (Lehrer & Gevirtz, 2014) [15]. Thus, relaxation techniques such as breathing practice, progressive muscle relaxation, guided imagery and meditation are, in essence, learnable physiological-regulation strategies that restore the homeostatic flexibility of the mind–body system.

3. Applications of Music, Sound and the Relaxation Experience

Music and sound are among humanity's oldest emotion-regulation tools, and their applied value in the mental-health domain has received systematic empirical support. The systematic review and two meta-analyses by de Witte *et al*. (2020) [3], incorporating 104 randomised controlled trials, 327 effect sizes and 9,617 participants, found that music interventions produced significant relief in both physiological stress indicators (d = 0.380) and psychological stress indicators (d = 0.545), with a larger effect on heart rate (d = 0.456) than on blood-pressure and hormonal indicators. This evidence indicates that music listening and music therapy are effective stress-management interventions whose effects cover both physiological and psychological levels. The mechanisms of music-based stress relief operate through several pathways. The physiological pathway: music regulates the ANS, promoting parasympathetic activation and lowering heart rate and blood pressure. The psychological pathway: music diverts attention, induces positive emotion and provides a channel for emotional expression. The neural pathway: music activates the reward system (such as dopamine release), regulates emotional processing in the limbic system, and influences physiological rhythms through rhythmic entrainment. At the application level, music interventions may be divided into "music medicine" (listening to pre-recorded music) and "music therapy" (personalised intervention led by a professional music therapist); both are widely applied in clinical settings. Sound healing is a healing service format that has risen rapidly in recent years, encompassing tools such as singing bowls, tuning forks, gongs, white noise and natural sounds; its claim rests on promoting mind–body relaxation through the vibrational frequency of sound. The scientific evidence base for such services, however, remains comparatively weak, with most studies still at a preliminary stage. Service providers should carefully distinguish between "evidence-supported music interventions" and "sound therapies awaiting evidence validation" and avoid exaggerated claims.

4. Application Limitations of Neurofeedback and Neurotechnology

Neurofeedback constitutes an important application of neurotechnology in the psychological-healing domain: by measuring brain-wave activity in real time (typically through electroencephalography, EEG) and feeding it back to the user through visual or auditory signals, it guides users to learn self-regulation of particular brain-wave patterns. Common training protocols include raising SMR or beta waves to enhance concentration, raising alpha waves to promote relaxation, and alpha/theta training to promote deep relaxation and creativity. The comprehensive review by

Marzbani *et al*. (2016) [17] observed that neurofeedback has been applied as adjunctive treatment for attention-deficit/hyperactivity disorder, anxiety, depression, insomnia and epilepsy, as well as for the enhancement of athletic and musical performance. The scientific evidence base of neurofeedback nevertheless remains subject to significant controversy. Marzbani *et al*. (2016) [17] explicitly note that, although many studies report positive effects, current scientific evidence is insufficient to support a conclusion of universal efficacy; its limitations include: small sample sizes in most studies, poorly controlled comparison-group designs, difficulty in distinguishing effects from placebo, lengthy and costly training schedules, and an unproven long-term maintenance of effects. In addition, its mechanism of action remains incompletely clarified, and the absence of standardised training protocols and outcome-evaluation indicators makes comparison across studies difficult. At the application level, neurofeedback and other neurotechnologies (such as wearable EEG headbands and transcranial direct-current stimulation) are progressively entering the consumer market, marketed under the banners of "brain training" and "neuro-optimisation". The claims of such consumer-grade products must be treated with caution: a signal-quality gap exists between consumer-grade and medical-grade devices, and their training effects lack high-quality clinical validation; consumers should understand such products as "health-promotion tools" rather than "medical treatment tools". Ethical governance of neurotechnology must develop in parallel, covering privacy protection of neural data, the fairness and autonomy of neural enhancement, and the avoidance of over-medicalisation and technological mythmaking.

The Digital Mental-Health Product and Healing-Service Industry

1. Subscription Model and Product Design of Mindfulness Applications

Mindfulness and meditation applications are the fastest-growing product category in the digital mental-health market; leading products represented by Calm and Headspace have established commercial scale of several million subscribed users. The core business model of such products is subscription: users download the application free of charge and experience limited free content, unlocking complete meditation courses, sleep stories and music content through monthly or annual subscriptions. The advantages of the subscription model lie in predictable recurring revenue, high customer lifetime value and sustained user relationships; its challenge lies in the need to continuously produce high-quality new content in order to maintain renewal rates. The product design of mindfulness applications must balance scientific effectiveness with user experience. The randomised controlled trial by Huberty *et al*. (2019) [9], targeting university students and employing the Calm app for ten minutes daily over eight consecutive weeks, showed that perceived stress was significantly reduced and mindfulness and self-compassion enhanced, with effect sizes ranging from moderate to large (0.59 to 1.24), and that effects persisted after intervention completion. This result supports the feasibility and effectiveness of delivering mindfulness interventions through applications while also identifying key elements of product design: structured course content, habit-formation mechanisms for daily practice, a clean and friendly interface, and appropriately designed reminders. Effective mindfulness-application product design should include the following elements: personalised guided content (adjusted according to user experience level and objectives); a progressive course structure (from basic breathing exercises to advanced awareness practices); real-time feedback and progress tracking (to reinforce motivation and self-efficacy); community and social-support functions (to increase belonging and persistence); and scientific and professional content oversight (to ensure intervention quality and safety).

2. Meditation Studios, Music-Therapy Workshops and Healing-Service Management

Alongside the rapid growth of digital products, physical healing services are likewise flourishing, including meditation studios, music-therapy workshops, yoga centres and integrated mind–body–spirit venues. The value of such physical services lies in providing immersive experience, on-site guidance by professionals and the warmth of community interaction, which digital products cannot fully replace. The service formats of meditation studios include group meditation courses, mindfulness workshops, silent retreat camps and one-to-one meditation instruction; music-therapy workshops provide singing-bowl sessions, gong baths, sound meditation and personalised music-therapy cases. The operation and management of physical healing services must address several key issues. First is professional human resources: the training and certification systems for meditation teachers and music therapists are still at an early developmental stage, service quality varies considerably, and the establishment of professional certification and continuing-education mechanisms is a necessary condition for industry maturation. Second is service safety management: meditation and relaxation practice are safe for most people, yet particular risks exist for specific groups (such as those with severe mental illness, epilepsy or acute stress trauma), and service providers must possess risk-assessment and referral capability. Third is the business model: physical healing spaces carry relatively high operating costs and must develop diversified revenue sources, such as per-session fees, course passes, monthly membership, enterprise private booking and cross-industry collaboration.

3. Outcome Evaluation of Digital Mental-Health Products

Outcome evaluation of digital mental-health products constitutes a key challenge for industry development. A very large number of mental-health applications currently exist on the market, yet most lack rigorous outcome validation, and evidence-based products account for only a minority. Torous *et al*. (2021) [21] observe that, although the evidence base of digital psychiatry is growing rapidly, most studies remain at an early stage and more rigorous randomised controlled trials, real-world studies and implementation-science interventions are required. The outcome-evaluation framework must encompass multiple dimensions. First is clinical effectiveness: through randomised controlled trials or quasi-experimental designs, the product's impact on mental-health indicators (symptoms, wellbeing, functioning) is measured. Second is engagement and retention: usage frequency, duration and attrition patterns are analysed to understand actual usage behaviour. Third is user experience: satisfaction, usability

and acceptability are assessed. Fourth is safety: adverse events and risk signals (such as the identification and handling of suicide risk) are monitored. Fifth is cost-effectiveness: the economic value of product intervention is evaluated. It is worth noting that a close association exists between engagement and clinical effectiveness, and most digital mental-health products face the challenge of "easy to download, difficult to retain". The meta-analysis by Firth *et al*. (2017) [4] showed that smartphone mental-health interventions produced a moderate effect on depressive symptoms, but that the effect diminished significantly when compared against active-control groups (g = 0.22), suggesting that product effects may be moderated by expectancy effects and engagement. Outcome evaluation should therefore track both "intervention dose" (actual usage) and "intervention effect", and engagement optimisation should be regarded as a core objective of product design.

4. Generative-AI Music and Personalised Meditation Content

The rapid development of Generative AI has opened entirely new possibilities for the personalised production of mental-health content. Large Language Models (LLMs) can dynamically generate personalised meditation-guidance scripts, mindfulness-practice instructions and emotional-diary responses according to user needs; generative music models can generate personalised relaxation music and ambient soundscapes in real time according to preferred style, rhythm and emotional state. Such technology moves mental-health content from "static pre-recorded content" toward "dynamic personalised content", enabling closer alignment with an individual user's cultural background, linguistic habits and present state. Generative AI offers multiple advantages in mental-health content application. First is scalability: AI can produce multilingual, multi-style content at low cost, overcoming the production-capacity constraints of human recording. Second is personalisation: AI can adjust content style and difficulty in real time according to user preferences and feedback. Third is contextualisation: AI can dynamically select the most suitable intervention content in combination with the user's immediate state (such as stress indicators, time and location).

Nevertheless, generative-AI mental-health content must confront important quality and ethical challenges. First is content-quality oversight: generative models may produce inaccurate, inappropriate or even harmful mental-health advice, and stringent content-review and human-supervision mechanisms must be established. Second is the difference in the therapeutic relationship: AI-generated guidance lacks the emotional presence and individualised attention of a human guide, and its healing effect may differ from human guidance. Third is data privacy: personalised content generation requires the collection of large volumes of personal mental-health data, and data protection and user informed consent must be ensured. Fourth is the risk of over-dependence: users may over-rely on AI content and delay seeking professional assistance. Accordingly, generative AI in the mental-health domain should be positioned as an "auxiliary instrument for professional services", complementing rather than replacing human professional care.

5. AI User Segmentation and Content Recommendation

Personalisation is the key to improving effectiveness and retention in digital mental-health services, and AI user segmentation and content recommendation are precisely the core technologies for realising personalisation. User segmentation analyses users' behavioural data, psychological characteristics and intervention responses through machine learning, classifying users into groups: for example, by intervention preference into "structured-course" and "free-practice" users; by stress source into "work-stress", "interpersonal-stress" and "mind–body-symptom" types; and by participation pattern into "high-frequency-short-session", "regular" and "flexible" users. The purpose of segmentation is to provide the best-matched content and intervention strategy for each group. On this basis, content-recommendation systems dynamically recommend the most suitable meditation courses, music content and practice frequency to each user. Recommendation algorithms must simultaneously consider multiple objectives: the match between content and user needs (stress type, objectives, and symptoms); the suitability of content difficulty to user experience; the compatibility of content style with user preferences; and the feasibility of intervention frequency relative to the user's life rhythm. Reinforcement-learning methods are particularly suited to such dynamic recommendation contexts: the system continuously adjusts its recommendation strategy according to real-time user feedback (engagement, satisfaction, effectiveness indicators), striking an optimal balance between challenge and achievement to maximise long-term participation and health benefit. The effectiveness of personalisation has received preliminary empirical support: relative to generic static content, personalised recommendation significantly improves user engagement and retention. Personalisation, however, must attend to the risk of the "filter bubble": over-personalised recommendation may limit users' exposure to diverse content, and recommendation algorithms may amplify existing selection bias. Personalised recommendation systems should therefore retain a mechanism for content-diversity exploration and optimise for mental-health outcomes rather than engagement alone.

An Integrated Model of AI-Personalised Mental-Health Services

1. Establishing an AI-Personalised Mindfulness-Practice Workflow

Integrating the scientific foundations and technical capabilities outlined above, this subsection designs a complete AI-personalised mindfulness-practice workflow, providing an experience approximating that of a personal meditation teacher from initial assessment through long-term practice management.

Stage 1: Initial assessment and personal-profile construction: On first use, the system conducts a multidimensional initial assessment, including: stress state (scales and HRV baseline), degree of emotional distress, sleep quality, mindfulness experience and practice preferences, daily routine and available time, and health objectives (stress reduction, improved sleep, enhanced concentration, emotion regulation, etc.). Integrating the assessment results, the system constructs the user's personal

mental-health profile as the basis for content recommendation and practice planning.

Stage 2: Personalised practice-programme generation: According to the personal profile, the system automatically generates a personalised mindfulness-practice programme, including: weekly practice frequency and per-session duration (flexibly adjusted to daily routine); a combination of practice types (breath awareness, body scanning, open awareness, loving-kindness meditation, mindful walking, configured according to objectives and preferences); course difficulty and progression (arranged progressively by experience level); and supporting content (relaxation music, sleep guidance, emotional-diary prompts, etc.).

Stage 3: AI-guided practice and real-time adaptation: During each practice, the AI system provides voice guidance (human-recorded or generative-AI-produced) and, combining physiological data (HRV, heart rate from the wearable) with behavioural data (interruptions, feedback during practice), adjusts the guidance rhythm in real time. After practice, the system guides the user through a brief experience record as input to personalised feedback. The system also dynamically adjusts the day's practice recommendation according to daily stress state: shorter stress-relief practice on high-stress days, sleep-guidance on sleep-deprived days, and alertness-enhancing practice on workdays demanding high concentration.

Stage 4: Outcome tracking and dynamic optimization: The system periodically analyses changes in the user's practice data and mental-health indicators, evaluates the actual effectiveness of the practice programme, and dynamically adjusts content composition and difficulty. The AI model continuously learns from user feedback and physiological responses, so that recommendations become increasingly aligned with personal needs. Milestone and achievement mechanisms are established to reinforce the motivation for sustained practice. For high-risk users (such as those with persistently deteriorating emotional indicators), the system recommends referral to human professional services in good time, ensuring service safety.

The core value of this workflow lies in combining the professional knowledge of mindfulness intervention (content structure, progress design, safety oversight) with the personalisation capacity of AI (data analysis, dynamic recommendation, real-time adaptation), so that ordinary users may obtain a high-quality personalised mindfulness-practice experience without a one-to-one meditation teacher.

2. An Integrated Business Model

Based on the service workflow and industry analysis above, AI-personalised mental-health services may develop diversified business models targeting different customer groups and market positions.

Model 1: B2C personal subscription service: A mental-health application subscription for general consumers, combining AI stress self-check, personalised mindfulness practice, an AI emotional diary and relaxation music. Revenue derives from subscription fees and value-added services (such as human online counselling). The core challenges of this model are retention rate and paid conversion; the key to success lies in providing perceptible health benefits and an excellent user experience.

Model 2: B2B enterprise mental-health programme: An integrated employee mental-health service provided to enterprises, comprising: an AI workplace-stress self-check system, a personalised mindfulness-practice application, EAP-integrated referral services and managerial mental-health training. Enterprises pay an annual fee by headcount. This model combines the "scalability of digital tools" with the "depth of professional services" and provides enterprises with de-identified aggregate stress-trend reports as a basis for health-management decision-making, forming a win-win commercial relationship.

Model 3: B2B2C healing-service ecosystem platform: Digital solutions are provided to physical healing establishments such as meditation studios, music-therapy workshops and yoga centres: membership-management systems, online course platforms, an AI personalisation-recommendation engine and outcome-evaluation tools. Physical establishments thereby extend their service reach and improve membership-management efficiency, while the platform earns revenue through system-licensing fees and transaction commissions.

Model 4: Integration with the healthcare system: Collaboration with hospital psychiatry departments, counselling clinics and health-check centres provides digital mental-health assessment and intervention tools as an extension of clinical services. AI tools handle standardised screening, tracking and self-help intervention, while professionals concentrate on diagnosis and treatment of complex cases, forming a division-of-labour "AI + professional" model that simultaneously raises service capacity and accessibility.Regardless of model, the critical success factors include: service effectiveness supported by scientific evidence; rigorous data-privacy and ethical governance; professional quality oversight; sustained content innovation and personalisation capacity; and clear professional-referral boundaries.

Conclusions

This study systematically examines the two core domains of mental-health management — workplace mental health and psychological healing — and, combining AI technology with an industry perspective, constructs an integrated model of personalised mental-health services. The principal findings are summarised as follows. First, in stress science, the stress response is governed by the ANS and the HPA axis; long-term chronic stress produces autonomic dysregulation and increases the risk of cardiovascular disease and psychological disorder (Kivimäki & Kawachi, 2015) [12]. HRV is a key physiological indicator of stress and health, reflecting the regulatory flexibility of brain–body integration (Thayer *et al*., 2012) [20], and HRV biofeedback training can effectively improve stress-related conditions (Lehrer & Gevirtz, 2014) [15]. Second, in emotion regulation and psychological resilience, the health effects of emotion-regulation strategies differ markedly, with cognitive reappraisal superior to expressive suppression (Webb *et al*., 2012; Gross, 2015) [8, 22]. Resilience can be

enhanced through training, with the blended intervention combining cognitive-behavioural therapy and mindfulness achieving the best effect (Joyce *et al*., 2018) [10]. Third, in workplace wellbeing, the JD-R model and organisational-support theory provide the theoretical foundation for institutional workplace mental health (Bakker & Demerouti, 2017; Kurtessis *et al*., 2017) [1, 14], and work–life balance is closely related to employee wellbeing (Greenhaus *et al*., 2003) [7]. EAP and workplace-health-promotion institutions have moved from problem handling toward comprehensive wellbeing, with professional referral and outcome evaluation constituting the keys to professionalisation. Fourth, in AI mental-health technology, NLP textual analysis can infer mental-health status from language use, and social-media big data offers a new pathway for population-level mental-health monitoring (Conway & O'Connor, 2016) [2]. Although AI emotion recognition is fairly mature, it carries limitations of ecological validity, cultural difference and ethical risk (Ko, 2018). Privacy, bias and ethical governance of mental-health data constitute the cornerstone of AI application, and human oversight and professional-referral boundaries are indispensable. Fifth, in psychological-healing science, mindfulness interventions demonstrate moderate-to-strong evidence-based effects on stress, anxiety and depression (Goyal *et al*., 2014; Khoury *et al*., 2015) [6, 11] and improve cognitive functions such as attention and working memory (Mrazek *et al*., 2013) [18]. Music interventions significantly relieve both physiological and psychological stress (de Witte *et al*., 2020) [3]. Neurotechnologies such as neurofeedback possess application potential, yet their scientific evidence base requires strengthening (Marzbani *et al*., 2016) [17]. Sixth, in the digital mental-health industry, the subscription model of mindfulness applications has established a scaled commercial foundation, and evidence confirms the effectiveness of its intervention (Huberty *et al*., 2019) [9]. Chatbots and smartphone interventions can effectively reduce depressive and anxious symptoms (Fitzpatrick *et al*., 2017; Firth *et al*., 2017) [4, 5], and the overall evidence base of digital psychiatry is growing rapidly (Torous *et al*., 2021) [21]. Generative AI and personalisation-recommendation technology open a new chapter in the personalised production of mental-health content, but rigorous quality oversight and ethical governance are required (Lu, 2026)..

A three-tier workplace mental-health system should be established: upstream, reducing stressors through job design and management quality; midstream, providing early intervention through mental-health screening and EAP; downstream, establishing professional-referral and recovery-support mechanisms. When introducing AI-assisted stress self-check tools, de-identified aggregate data must be used as the basis for management, and the tool must be prevented from degenerating into performance monitoring in order to preserve employee trust (OpenAI, 2026). Digital mental-health products should be grounded in scientific evidence, with rigorous outcome-evaluation mechanisms established and exaggerated claims avoided. Personalised content recommendation should optimise for mental-health outcomes rather than engagement alone. Human review and supervision mechanisms should be established for generative-AI content to ensure quality and safety. Physical healing services should promote professional certification and safety-management systems and establish clear referral boundaries with the professional mental-health system. Mental-health promotion should be incorporated into the core agenda of public-health and labour policy, and workplace mental-health standards and guidance should be advanced. An evaluation and certification mechanism for digital mental-health products should be established to guide healthy industry development. Privacy protection and ethical norms for mental-health data should be strengthened to ensure the fairness and accountability of AI mental-health services. Investment should be directed toward expanding service capacity and improving accessibility in order to narrow the mental-health-care gap. A regular mindfulness-practice and stress-management habit should be established, and physiological indicators such as HRV should be used as self-awareness tools without blind reliance on data. When choosing digital mental-health products, evidence-based, professionally overseen products should be preferred. When emotional distress persists or worsens, professional assistance should be sought promptly; digital tools are auxiliary to, not substitutes for, professional medical care.

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