

# AI Chatbots as Productivity and Wellbeing Tools: Mixed Methods Survey of Young Female Knowledge Workers

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## Article

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# Abstract

Workplace mental health challenges are disproportionately affecting young female knowledge workers, who report elevated levels of stress, anxiety, and emotional strain within high-pressure organisational cultures. Large language model (LLM)-based chatbots have the potential to support positive psychology in the workplace by supporting strengths-based thinking, cognitive reframing, and fostering purpose, gratitude, and optimism. This mixed-methods study investigates how women aged 25–34 are using LLM-based chatbots as digital coping tools within knowledge-intensive work environments. While 82% reported using LLMs for work-related tasks, 29% had used them for workplace mental health support. Participants described LLMs as reducing cognitive load and providing accessible, stigma-free spaces for reflection amid demanding schedules. However, concerns around trust, data privacy, and the absence of human empathy limited deeper engagement, with participants emphasising the need for gender-sensitive and psychologically informed design. Notably, general-purpose LLMs were used more frequently than dedicated mental health apps, suggesting the emergence of dual task–wellbeing roles for workplace AI systems. These findings position generative AI not merely as a productivity tool but as an emergent, informal wellbeing infrastructure, raising important implications for organisational responsibility, ethical AI governance, and the design of inclusive human–AI support systems for young working women.

## Introduction

Globally, approximately 15% of working-age adults live with a mental disorder such as depression or anxiety <sup>1</sup>. Mental health has therefore become a critical workplace concern, with its neglect not only exacerbating individual distress but also undermining organisational performance and straining wider socioeconomic systems. Work-related stress, anxiety and depression are associated with high levels of absenteeism and presenteeism, often escalating into long-term sickness absence and productivity loss. Within organisations, mental health in the workplace directly impacts employee engagement, creativity, and retention, making it central to sustainable organisational development <sup>2</sup>. Workplace mental health is a product of inter-related structural, social, and individual pressures, with organisational and operational demands indivisible from the personal lives of employees and societal support systems <sup>2</sup>. However, workplace mental health challenges are not evenly distributed. Research consistently identifies gender disparities in the data, with women reporting higher levels of stress, burnout, anxiety, and depression <sup>3,4</sup>. In the UK, young female workers aged 25–34 have been identified as being disproportionately vulnerable to workplace mental health distress <sup>5</sup>. The heightened risk of this cohort is associated with career progression pressures, gender- and age-based discrimination, and a persistent struggle to balance professional and personal responsibilities <sup>5–7</sup>. These vulnerabilities are believed to arise from multiple, overlapping pressures on this group. Gendered workplace dynamics, including imposter syndrome, difficulties in establishing authority, and subtle or overt discrimination, are known to exacerbate mental health risks <sup>8</sup>. Broader societal expectations around caregiving and career development further add to these pressures <sup>9</sup>. Together, these factors undermine mental wellbeing, diminish confidence, and

negatively shape career trajectories, underscoring the need for further research into the challenges faced by young female workers, and new strategies for reducing the stress burden of this cohort.

A range of non-digital workplace interventions have sought to address worker mental health, and workplace mental health strains. Individual-level supports include employee assistance programmes (EAPs), counselling, and stress management training, while organisational strategies involving the reconfiguration of work, introduction of flexible work policies, and implementation of anti-discrimination initiatives, have been enacted <sup>1</sup>. Although these improve mental wellbeing, persistent barriers remain, including a stigma around help-seeking, limited programme access and support outside working hours, confidentiality concerns, and low uptake among younger employees <sup>2</sup>. These limitations highlight the need for complementary, user-driven approaches that are accessible, relevant, and responsive to vulnerable cohorts.

Over the past decade, web- and smartphone-based digital mental health interventions (DMHIs) have gained prominence due to their scalability, accessibility, and potential for reducing stigma relative to face-to-face care <sup>10,11</sup>. Systematic literature reviews have found that digital interventions such as Cognitive Behavioural Therapy (CBT) and stress management improve the psychological wellbeing of employees and reduce stress in the workplace <sup>11–13</sup>. However, challenges still remain, including low adherence, limited personalisation, and privacy concerns <sup>14,15</sup>. These limitations suggest that further innovation is required to enhance relevance, trust, and sustained use within occupational settings.

At the same time, positive psychology has increasingly shaped organisational wellbeing research by shifting the focus from correcting deficits toward cultivating strengths such as resilience, creativity, emotional intelligence, flow, hope, and courage <sup>16–18</sup>. Integrating these strengths-based principles into digital mental health support offers the potential to enhance engagement and promote psychological flourishing alongside the reduction of distress.

Recent advances in large language models (LLMs) and the availability of services such as OpenAI ChatGPT <sup>19</sup>, Google Gemini <sup>20</sup>, and GitHub Copilot <sup>21</sup>, have opened new possibilities for both productivity- and positive psychology-based interventions. Prior studies suggest that these tools can assist with a range of task-related functions that also impinge upon worker stress, from organisation and prioritisation, to the reduction of cognitive load. This technology has not only shown potential for reducing workload-related stress, but its multi-purpose language, conversation and knowledge capabilities enable it to readily traverse domains, moving seamlessly from helping with technical tasks, to engaging in more personal, relational discussion <sup>22,23</sup>. Both work-related task stress and personal emotional duress weigh upon mental health in the workplace, often at the same time, with the distinction between the personal and professional an often arbitrary if practical one. The ability of LLM-based chatbots to address both domains seamlessly overcomes that arbitrariness, enabling users to move from addressing task overload, to the stress caused by that overload, to a general stress burden from a mix of the personal and professional. While general-purpose LLM-based chatbots are primarily used as

task-oriented productivity tools, their ability to traverse domains offer scope for a potential dual use supporting both productivity and mental health.

Dedicated LLM-based mental health chatbots such as Youper, Wysa, and Woebot enable what is known as human-AI companionship, a type of support that complements rather than replaces human care <sup>24</sup>. Research shows that user engagement improves when AI demonstrates empathy, responsiveness, and relational continuity, fostering a sense of presence even in digital contexts <sup>25</sup>. Within this space, LLM-based chatbots hold promise for providing non-judgmental, always-available environments for processing emotions, lowering stigma-related barriers to help-seeking; and supporting emotional regulation <sup>23</sup>. When responsibly designed, AI companionship may contribute to therapeutic outcomes and promote broader societal goals, such as reducing stigma and fostering empathy toward mental illness <sup>26</sup>. However, these benefits require careful attention to ethical design, and safeguards against problematic use, including relational over-attachment or dependency, among other misuses <sup>27</sup>.

Despite these advances, research on LLM-based chatbots for workplace mental health purposes has largely overlooked young female workers, a group disproportionately affected by gender-specific stressors <sup>1,8</sup>. According to Mental Health UK's Burnout Report 2025, women aged 25–34 report the highest workplace stress, with 56% citing heavy workloads and 45% concerned about job security <sup>7</sup>. These pressures are particularly pronounced in professional occupations and large organisations, emphasising the need for tailored, gender-sensitive interventions.

LLM-based chatbots offer potential for a gender-sensitive, personalised support that addresses the unique stressors confronting young working women, including imposter syndrome, work-life balance, and professional development pressures <sup>23</sup>. Beyond mitigating distress, the conversational and adaptive capabilities of LLM chatbots may also support the application of positive psychology principles in workplace contexts by encouraging strengths-based reflection, reinforcing adaptive coping strategies, and promoting psychological resources such as resilience, confidence, and optimism.

This study addresses these gaps by examining how young female full-time workers in the UK aged 25–34 engage with LLM-based chatbots as a workplace mental health support. A mixed-methods survey was conducted to examine how participants use LLM-based chatbots. The survey canvassed the experience of this group when engaging the technology, and their views on its perceived benefits, barriers to its adoption, and design recommendations for its use as a workplace mental health support for young female workers. The findings highlight the need for gender-sensitive designs that maximise the benefits of the technology, such as accessibility, confidentiality and task support, while addressing barriers to its use, particularly trust-related concerns. Interestingly, participants reported using LLM-based chatbots more frequently than dedicated LLM-based mental health platforms, underscoring their potential in workplace contexts. These results suggest that LLM-based chatbots can function as complementary tools, supporting both productivity and emotional wellbeing alongside human-led mental health interventions.

## Results

We present the results of a mixed methods survey investigating how young female knowledge workers (n = 169) use and experience LLM-based chatbots in the workplace.

## Quantitative Survey Findings

### Perceptions of Workplace Mental Health Support

Participants viewed their workplaces as moderately supportive of mental health, with over half agreeing that their organisations encouraged open discussion (58.0%), implemented initiatives (53.3%), and provided managerial support (58.0%). However, comfort with data sharing revealed a gap between formal support and lived experience. Participants were more willing to share voluntary, work-related information, such as workload indicators (30.0%) and self-reported stress levels (29.5%), than clinical information (10.9%) or wearable device data (11.9%). This disparity highlights concerns about privacy, control, and data sensitivity, suggesting that engagement with LLM-based chatbots depends not only on organisational culture but also on the perceived intrusiveness of requested data.

### Use of Non-Digital Mental Health Interventions

Non-digital mental health interventions were widely utilised, with 81.1% of participants engaging in at least one. Physical activity (68.6%), mindfulness practices (34.9%), and in-person counselling (29.2%) were most common. These results indicate These findings show that young female workers proactively engage in multiple forms of self-care, balancing preventive approaches (e.g., mindfulness, exercise) with reactive measures (e.g., counselling) to maintain good mental health.

### Use of Digital Mental Health Interventions

DMHIs were also widely used, with 69.6% engaging with at least one tool. The most common DMHIs included mindfulness apps (41.4%), wearable tracking applications (37.3%), and LLM-based chatbots (25.4%), while employer-provided platforms were used by 7.1%, and dedicated chatbot-based mental health apps by only 5.3% (Table 1).

Participants primarily discovered DMHIs online (42.6%) or through recommendations (25.4%), reflecting self-directed engagement. Platforms were mostly smartphone-based (60.9%), followed by web-based (20.1%) and wearable technology (17.2%), with 51.4% using multiple devices. Primary purposes of use included stress reduction (53.3%), general wellbeing maintenance (42%), emotional support (34.9%), mindfulness (26.1%), crisis support (11.9%), mood tracking (11.8%), and coaching (8.3%).

Table 1  
Types of DMHIs used to support participant workplace mental health (n = 118 )

| DMHI Type                                                   | n  | %     |
|-------------------------------------------------------------|----|-------|
| Mindfulness apps (e.g., Headspace, Calm)                    | 70 | 41.4% |
| Wearable tracking apps (e.g., Fitbit, Apple Health)         | 63 | 37.3% |
| LLM-based chatbots (e.g., ChatGPT, Gemini, Copilot)         | 43 | 25.4% |
| Psychoeducational websites (e.g., NHS Every Mind Matters)   | 28 | 16.5% |
| Mood tracking apps (e.g., Daylio, Moodpath)                 | 16 | 9.5%  |
| Therapist-assisted platforms (e.g., BetterHelp)             | 13 | 7.7%  |
| Employer-provided DMH platforms (e.g., Unmind, SilverCloud) | 12 | 7.1%  |
| CBT-based tools (e.g., Sanvello, MoodKit)                   | 11 | 6.5%  |
| Chatbot-based mental health apps (e.g., Woebot, Wysa)       | 9  | 5.3%  |
| Coaching apps (e.g., Happify, Fabulous)                     | 4  | 2.4%  |
| Peer support platforms (e.g., 7 Cups, Togetherall)          | 1  | 0.6%  |
| Crisis support apps (e.g., Stay Alive, MY3)                 | 0  | 0%    |

## Use of LLM-Based Chatbots for Work Tasks Versus Workplace Mental Health

LLM-based chatbots were widely used for work-related tasks, with 82.8% reporting use, primarily for content generation (66.9%) and idea development (49.7%). Barriers to adoption included access restrictions, limited knowledge, perceived lack of need, ethical concerns, personal reservations, or data security.

For workplace mental health purposes, only 29% of participants reported using LLM-based chatbots. Benefits included task organisation, preparation for difficult interactions, stress management, and emotional reflection. Users emphasised practical value and timely, non-judgmental support that eased workload stress and reduced anxiety. Among non-users, barriers included limited awareness, preference for human support, concerns about AI accuracy and privacy, and restrictive organisational policies. These findings suggest low uptake does not reflect outright rejection of the technology.

Cross-tabulation revealed a significant association between use for work tasks and mental health. Among participants who used LLM-based chatbots for work, 34.3% also used them for mental health purposes, compared to 3.4% among non-users. Chi-square analysis confirmed significance,  $\chi^2(1, n = 169) = 11.097, p < .001$ , with continuity correction  $\chi^2 = 9.649, p = .002$ , and Fisher's Exact Test  $p < .001$ .

This indicates that adoption for work tasks substantially increases the likelihood of workplace mental health use.

## Perception of LLM-Based Chatbots

Participants expressed mixed attitudes. Overall comfort and trust were moderate but divided: 45.6% expressed discomfort, and 42% questioned reliability. Willingness to use chatbots for real-time mental state check-ins was cautious (34.3% willing; 52.6% reluctant), though 42.6% viewed them as complementary to human support.

Independent samples t-tests comparing users and non-users for mental health purposes revealed significant differences in comfort, trust, and perceived utility. Users reported greater comfort ( $t(105.85) = 9.74, p < .001$ , mean diff = 1.63 [95% CI 1.30, 1.96]), higher trust in accuracy ( $t(92.63) = 4.96, p < .001$ ), more willingness to engage in mental state check-ins ( $t(89.47) = 6.49, p < .001$ ), and stronger perceptions of complementarity with human support ( $t(87.52) = 6.26, p < .001$ ). Privacy concerns were similar across groups ( $t(85.07) = -0.88, p = .382$ ), indicating persistent caution regarding data handling. Engagement with LLM-based chatbots is thus closely linked to trust, comfort, and perceived utility. Trust was identified as a central factor shaping willingness to use LLM-based chatbots and perceptions of them as effective complements to human support<sup>28,29</sup>, while privacy concerns remained stable across groups.

## Qualitative Survey Findings

Thematic analysis of open-ended survey responses identified three overarching themes (Fig. 3): perceived barriers to adoption, perceived benefits of LLM-based chatbots, and voiced needs for gender-sensitive, personalised, and workplace-integrated support.

## Perceived Barriers to Adoption

Although participants recognised potential benefits, strong reservations emerged around reliability and safety. Concerns centred on privacy and confidentiality, lack of empathy, human connection, and risk of misinformation. While a small minority reported no concerns, most voiced scepticism regarding trustworthiness and authenticity.

## Privacy and Data Security

Privacy was described as one of the most significant barriers to adopting LLM-based chatbots as a workplace mental health support. Participants expressed concern about how their data might be stored, shared, or accessed, with these worries heightened in workplace contexts:

“What if there’s a leak or hack, what if a manager or colleague can see the conversation?” (P45)

Such responses highlight the importance of robust data security and transparent data handling where personal information is concerned, and the role these play in bolstering trust and facilitating the uptake of AI-driven mental health tools in professional settings.

## **Empathy and Human Connection**

Many participants doubted that LLM-based chatbots could replicate the relational depth and empathy of human support. Even when chatbots provided accurate information, participants felt that the emotional depth and personal insight offered by humans could not be matched. These reflections reinforced the perception that, while LLM-based chatbots may support practical needs, they cannot replace the emotional resonance and human connection essential for effective mental health support.

## **Reliability and Trust**

Reliability and trust were identified as key barriers to adoption. Participants questioned whether chatbot advice was grounded in professional or clinical expertise and worried about inaccurate or misleading guidance. Unverified responses were seen as potentially increasing stress, either by prompting poor decisions or requiring additional effort to fact-check information. Concerns about over-reliance were also prominent, with fears that dependence on LLM-based systems might discourage interpersonal help-seeking, increase isolation, and exacerbate mental health difficulties, particularly in light of high-profile cases involving unsafe AI-generated advice.

## **Perceived Benefits of LLM-Based Chatbots**

Participants described LLM-based chatbots as valuable complementary tools for supporting mental health, providing accessible, confidential, and timely guidance that aids practical decision-making. Instead of replacing human care, the technology was viewed as addressing gaps in everyday workplace stress management.

## **Accessibility and Confidential Support**

Participants emphasised the value of immediate, 24/7 access to support, which reduced the pressure of waiting for appointments or disclosing concerns to colleagues or managers. Rapid, objective responses were especially valued during acute stress, and the constant availability of support provided reassurance and peace of mind. Anonymity and perceived safety were seen as key benefits. However, perceptions of empathy were mixed: while some found chatbots supportive and validating, others viewed the absence of a human presence as a barrier to adoption.

## **Workload Management and Stress Reduction**

Workload pressures, including tight deadlines and competing demands, were frequently identified as major stressors. Participants used LLM-based chatbots to organise tasks, prioritise responsibilities, and solve problems during high-pressure periods—sometimes despite workplace restrictions:

“I did use ChatGPT secretly when the workload and pressure was very high and it helped me and created ease in my mind.” (P77)

Beyond task management, LLMs supported emotional regulation and workplace stability. During burnout or strain, chatbots helped users structure thoughts, communicate effectively, and maintain professionalism, serving as a buffer to process emotions and craft measured, compassionate responses.

## **Complementary Role to Human Support**

Participants emphasised that LLM-based chatbots provided both practical advice and emotional support, but as a complement to, rather than replacement for, human care. The workplace value lay in easing daily pressures and providing timely reassurance, helping users set realistic expectations, prioritise tasks. Many turned to LLM-based chatbots in moments of stress and anxiety to manage immediate concerns, finding reassurance in their availability and responsiveness.

For others, the interaction itself provided a sense of being heard and supported. Participants also highlighted the accessibility and efficiency of chatbots compared to traditional human services.

## **Gender-Sensitive Design for Young Women**

The most frequently highlighted theme here was the need for chatbots to reflect the workplace realities of young women, providing support that is both personalised and empathetic, and attentive to gender-specific challenges shaping daily professional experiences.

## **Recognition of Gender-Specific Challenges**

Participants stressed that DHMIs would be most effective if they felt personal, relatable, and empathetic to the pressures facing young female workers such as managing work–life demands, coping with stress and burnout, and navigating male-dominated workplaces. Several participants suggested that LLM-based chatbots should be trained to acknowledge and respond to these dynamics explicitly.

Beyond professional challenges, some participants noted the importance of recognising menstrual health and hormonal cycles in shaping emotional wellbeing. Tailoring chatbot content to account for both structural workplace inequalities and physiological factors was considered essential for credibility and meaningful impact.

## **Empathetic Interaction**

Participants emphasised the importance of warmth, empathy, and nuanced communication. They stressed the need for flexibility and sensitivity in chatbot interactions, particularly given the emotional vulnerability of users: This aligns with research showing that women may be more sensitive to emotional cues in both verbal and written communication<sup>30</sup>. It highlights that DMHIs should move beyond information delivery toward human-centred, emotionally attuned engagement.

## **Personalised Integration and Guidance**

Participants emphasised the importance of integrating AI into workplace systems, such as project timelines or workload tools, in ways that support employees without compromising privacy. Clear guidance and structured implementation were viewed as essential for meaningful adoption. Participants highlighted the need to clarify appropriate use, communicate system limitations, and provide links to formal support services to build confidence and engagement. LLM-based chatbots were seen as most effective when tailored to gender-specific workplace needs, combining empathetic communication with accessible features that address both professional demands and mental health support.

## Discussion

This study examined how young female workers in the United Kingdom engage with LLM-based chatbots for workplace mental health support, highlighting both gender-specific and transferable design implications. Participants reported repurposing general-purpose LLMs to manage stress, regulate emotions, and organise workloads, demonstrating user-driven adaptation beyond their initial productivity-oriented purpose. This dual use reflects the evolving role of AI in professional environments, where tools can simultaneously address practical tasks and mental wellbeing. Beyond task support, participants' use of LLM-based chatbots also demonstrated potential to foster positive psychology in the workplace by enhancing resilience, emotional regulation, reflective capacity, and strengths-based coping strategies—aligning with the introduction's emphasis on digital interventions that not only reduce distress but actively cultivate employee engagement and flourishing.

Analysis revealed two interrelated dimensions: gender-specific considerations and broader, transferable implications for workplace populations. Although the study focused on young women, many findings are applicable across demographics, particularly regarding the balance of trust, empathetic interaction, practical utility, and hybrid AI-human approaches, consistent with broader digital mental health research.

Young female workers actively seek mental health support even in organisations perceived as promoting wellbeing, highlighting the need for gender- and user-sensitive design. Specific stressors identified included imposter syndrome, workplace inequality, burnout, anxiety in hierarchical or male-dominated contexts, and biological influences such as hormonal cycles. LLM-based chatbots that acknowledge these lived experiences are more likely to be perceived as relevant, empathetic, and supportive, suggesting that systems incorporating gender-sensitive guidance may enhance engagement. Prior research indicates that DMHIs tailored to contextual and user-specific factors improve adherence and perceived utility<sup>31,32</sup>, aligning with Human-Centred Design (HCD) principles that emphasise alignment with social, psychological, and environmental contexts of users<sup>33</sup>.

Beyond functional assistance, participants valued empathetic and nuanced communication. Research suggests that women are particularly attuned to relational and emotional cues in both face-to-face and digital interactions<sup>34</sup>. Effective workplace chatbots must therefore extend beyond information provision to acknowledge emotional states, validate experiences, and offer reassurance. Empathy in AI-mediated support has been associated with stronger engagement and greater perceptions of legitimacy and

trustworthiness<sup>35</sup>. In workplace contexts, where psychological safety and perceived judgment are salient, empathetic communication may be critical for adoption <sup>35</sup>.

Participants further emphasised integrating chatbots into existing workplace systems, such as workload management tools, while maintaining strong privacy protections. Clear guidance, transparent communication of system limitations, and structured onboarding were seen as essential. These findings align with HCD and the Technology Acceptance Model (TAM), which highlight perceived usefulness and ease of use as central to adoption <sup>33,36</sup>. When tools are embedded into workflows and endorsed organisationally, they are more likely to be perceived as legitimate components of workplace wellbeing ecosystems.

Designing gender-sensitive LLM-based chatbots calls for empirically grounded frameworks that integrate contextual, psychosocial, and biological factors. For employers, integrating chatbots tailored to young women offers a practical avenue to enhance workplace wellbeing and demonstrate commitment to equity and inclusion. Effective deployment requires technological infrastructure, staff training, transparent governance, and alignment with human support systems. At a societal level, investing in empathetic and inclusive AI may help reduce gender-related disparities in mental health and workplace participation, fostering healthier and more equitable professional environments. Responsibly designed chatbots can extend beyond individual support to function as tools of organisational and social change.

Alongside gender-specific considerations, participants highlighted transferable challenges influencing adoption across diverse groups. Key barriers included concerns regarding privacy, limited empathy, and the reliability of information and advice. Prior research indicates that reliability fosters cognitive trust, empathy cultivates affective trust, and privacy ensures moral and legal trust. These 'trust factors' provide a multidimensional foundation for technology adoption in sensitive domains such as mental health <sup>37,38</sup>. The Unified Theory of Acceptance and Use of Technology (UTAUT, 2003), and its health technology extensions, consistently show that trust mediates behavioural intention and actual use. For LLM-based technology, reliance on trust is amplified by hallucinations, biases, and unpredictable outputs. Combined with privacy risks, users bear the burden of validating information <sup>39,40</sup>, highlighting the importance of trust for safe, ethical use.

Privacy was the most prominent barrier to uptake, centring on concerns about data storage, access, sharing, and potential misuse of confidential information. Although anonymity was recognised as facilitating disclosure, participants feared data breaches or unintended exposure to managers or colleagues, consistent with literature emphasising confidentiality as critical for DMHI adoption, particularly in workplace contexts where disclosure carries professional risk <sup>12</sup>. Participants expressed ambivalence: while more comfortable sharing sensitive information with LLM-based chatbots than with colleagues, they remained wary of how data might be used or governed. Nearly half reported discomfort sharing personal information, whereas comfort was higher for voluntary or work-related data, such as workload indicators (30.0%) and self-reported stress (29.5%). These findings highlight a central design tension: anonymity can reduce stigma and create a safe reflective space, yet insufficient organisational

transparency may erode trust. Robust safeguards, including transparent data policies, end-to-end encryption, and user control, are therefore essential for adoption, consistent with HCD principles emphasising clarity, accountability, and user empowerment<sup>33</sup>.

Another uptake barrier was the inability of LLM-based chatbots to replicate human empathy and relational depth. Although LLMs can simulate aspects of cognitive empathy by recognising emotions and offering supportive responses, participants emphasised that the technology cannot match the emotional understanding and interpersonal support by humans<sup>41</sup>. In particular, trust-based 'interhuman bonds' were highlighted as essential not only for effective mental health support, but also for the adoption of the technology<sup>42</sup>. This aligns with Bickmore and Picard's [2005] work on relational agents, showing that users value AI companions primarily when they demonstrate empathy, continuity, and sensitivity to emotional states<sup>37</sup>. Human-AI companionship can complement, but not replace, human support in mental health interventions.

LLM-based chatbots function effectively as both task and emotional supports. Participants highlighted their utility for immediate guidance, reflective space, and organisational assistance while recognising that complex emotional issues require human-led intervention. Integrating AI within programmes that include human support or redirection to specialists allows safe expansion of workplace mental health support without compromising relational depth.

Concerns about reliability and accuracy were another critical barrier conveyed by participants. Scepticism about the veracity of LLM-based chatbot outputs echoed literature on hallucinations and unverified outputs in AI-assisted mental health<sup>43</sup>. Notably, perceptions of reliability appeared to depend more on trust than on intrinsic privacy concerns, as no significant difference in privacy-related anxiety was observed between users and non-users for workplace mental health purposes. For non-users, barriers included limited awareness, perceived lack of need, and trust-related concerns. These findings suggest that low uptake does not reflect outright rejection, but rather highlights the importance of trust-building in realising LLM-based chatbots' potential for workplace mental health support. Unresolved reliability issues risk over-reliance, which could worsen mental health or produce harmful outcomes. Overall, the results emphasise the central role of trust in successful adoption<sup>28,42,44</sup>. Effective strategies could include transparent disclaimers, integration with evidence-based resources, and structured guidance on appropriate use. Addressing both factual reliability and perceived trustworthiness enhances confidence and reduces stress caused by inaccurate information or advice.

Adoption depends on user trust, usage guidance, and organisational culture. Researchers should explore mechanisms for privacy safeguards, empathetic design, and reliability checks. Employers play a key role in transparent governance, voluntary use policies, and clear boundaries to reduce fears of surveillance or misuse. Societal digital literacy initiatives clarifying AI's role in mental health can further support responsible adoption. Sustainable integration of LLM-based chatbots requires harmonising technical safeguards with ethical, organisational, and cultural practices that build and maintain trust.

Despite barriers, participants recognised substantial benefits. General-purpose LLMs (25.4%) were used far more than dedicated mental health chatbots (5.3%) or employer-provided platforms (7.1%), reflecting accessibility, familiarity, and cross-domain applicability. Participants using LLMs for work tasks were more likely to use them for mental health, creating dual-use efficiency and potential cost savings.

Round-the-clock, confidential, and non-judgmental support was highly valued, addressing barriers to workplace mental health engagement, including stigma, fear of judgement, and reliance on line managers for referrals <sup>45</sup>. By providing an always-on safe space for reflection and emotional processing, LLM-based chatbots reduce the cognitive and emotional burden of seeking help. Participants reported using chatbots surreptitiously during periods of high workload, noting the relief and confidence, highlighting the importance of low-pressure, stigma-free accessibility and align with research identifying these factors as key drivers of engagement <sup>46,47</sup>. Used this way, LLMs function as intermediate layers of care, encouraging proactive mental health management and supporting referral to human specialists when appropriate.

Participants also highlighted task organisation, prioritisation, and clarity in communication. Chatbots reduced stress and enhanced perceived control, aligning with research on cognitive load reduction and productivity <sup>48</sup>. Preparing for challenging conversations and distilling complex communications improved emotional regulation and professional effectiveness, consistent with Cognitive Load Theory <sup>49</sup>.

Participants emphasised that LLM-based chatbots should complement, not replace, human support. While AI provides immediate guidance, human practitioners are essential for nuanced emotional care and complex mental health needs. Notably, 42.6% of participants viewed chatbots as complementary to human support, aligning with research showing blended approaches combining DMHIs with human services enhance engagement <sup>14,42,50</sup>. This underscores the importance of hybrid workplace mental health models <sup>51</sup> that integrate AI tools with broader wellbeing strategies, balancing potential benefits with the risks of misuse or harm through human–AI interactions.

Implications extend to researchers, employers, and policymakers. Hybrid programmes should balance personalisation with transparency, provide boundaries to reduce surveillance fears, and triage users to specialists. Employers can leverage chatbots to expand confidential, immediate support while enhancing task management, communication, and productivity, but AI-only solutions should be avoided. At the societal level, LLM-based chatbots can reduce stigma and broaden access, with policy ensuring responsible and equitable use while preserving human expertise.

This study has limitations, including a self-selected sample skewed toward larger, office-based organisations, limiting generalisability to smaller or fully remote workplaces. Self-reported measures may be affected by social desirability or recall biases, and low usage of LLM-based chatbots constrained subgroup analyses. Rapid LLM evolution and unmeasured cultural or organisational factors may also affect relevance. Future research should use longitudinal, mixed-methods designs, larger and more diverse samples, and experimental comparisons of AI-supported, human-only, and blended interventions.

Co-design with young female workers, attention to organisational integration, privacy, and trust, and expansion to varied settings can improve adoption, efficacy, and generalisability.

In conclusion, general-purpose LLM-based chatbots show substantial potential as complementary workplace mental health tools for young female workers. Participants repurposed them for emotional support, stress management, and resilience. Adoption depends on trust, privacy, reliability, empathy, and context-aware deployment. Risks including misinformation, relational dependency, and misuse highlight the need for careful design, triage to human specialists, and organisational support. Realising their full potential requires coordinated engagement from researchers, employers, and policymakers to ensure responsible, sustainable, and evidence-based integration into workplace wellbeing initiatives.

## Methods

This section outlines the methodological approach used to investigate the ways in which young female workers experience and perceive the use of LLM-based chatbots for workplace mental health support. It describes the ethical considerations, subject scope and guiding research questions, before detailing the research design, participant recruitment process, survey materials, and analytical procedures of the study. The section concludes with an overview of both quantitative and qualitative data analysis strategies. Collectively, this methodology evidences the commitment of the study to rigour and ethical integrity, while affording space for exploring the possibilities and challenges suggested by this emerging area of digital mental health research.

### Ethical Considerations

This study was reviewed and approved by the UCLIC Research Ethics Committee (Approval ID Number: UCLIC\_2023\_004\_Ayobi). All methods were conducted in accordance with relevant guidelines and regulations, as well as the ethical principles outlined in the Declaration of Helsinki. Prior to participation, individuals were provided with a Participant Information Sheet and gave informed consent, both in compliance with the General Data Protection Regulation (GDPR, 2016) and the UK Data Protection Act (2018). Informed consent was obtained from all participants before their involvement in the study. Participants were fully informed about the purpose and procedures of the study and provided their consent electronically. Participation was entirely voluntary. All collected data were anonymised and treated confidentially, and no personal identifiers (such as identity card numbers, mobile phone numbers, or names) were collected. This study employed a mixed-methods survey design and did not involve any clinical trials involving human interventions.

## Research Scope and Research Questions

Building on existing literature, three insights shaped the focus of this study. First, LLM-based chatbots are multi-purpose tools capable of supporting both productivity and mental health simultaneously. Second, their adoption and effectiveness depend less on technological considerations and more on

factors such as trust, accuracy, empathy, ethics, and organisational integration. Third, young female workers represent a demographic for whom tailored, gender-sensitive interventions are especially critical given the well-evidenced duress this group faces in professional contexts.

The present study extends this literature by exploring the role of LLM-based chatbots as intermediate layers of support that can assist with task management, the complex demands of professional communication, and task-related stress reduction, while also complementing human-led interventions for emotional states and mental health conditions impinging upon performance and productivity. It also highlights the need for user-centred design, gender-sensitive personalisation, and organisational support and facilitation to maximise adoption and effectiveness.

The study was guided by the following research questions:

1. How do young female workers use and experience LLM-based chatbots as a workplace mental health support?
2. What benefits and challenges do they experience when using LLM-based chatbots to support workplace mental health?
3. What does this understanding imply for the design of future workplace mental health technologies?

## Research Approach

This study employed a mixed-methods online survey to capture both quantitative and qualitative measures of engagement with and perceptions of DMHIs, including LLM-based chatbots. Qualitative data eliciting insight into usage experience, perceived usage benefits, perceived usage barriers, and preferred system or tool features were collected to help buttress weaker areas of research. As Creswell and Creswell (2017) note, complex, context-dependent processes such as the adoption of technology for mental health purposes benefit from exploring numerical data (quantitative research) and in-depth narratives (qualitative research) <sup>52</sup>.

The rationale for the research design was threefold. First, mental health in professional contexts is often stigmatised, making anonymous digital surveys a suitable medium for disclosure <sup>44</sup>. Second, young women aged 25–34 are considered ‘digital natives’, having grown up with digital technologies <sup>53</sup>, and are therefore more comfortable with online tools that encourage candid participation. Third, prior research suggests that women prefer digital-mediated communication rather than direct, face-to-face interaction <sup>54</sup>.

## Participants

Participants were recruited in August 2023 via Prolific <sup>55</sup>, a reputable online crowdsourcing platform recognised as a high-quality, efficient medium through which to conduct behavioural and mental health

research. These considerations are vital when nuanced, demographic-specific recruitment and data integrity are central to the research process<sup>56</sup>. Prior to full-scale distribution, seven pilot studies of 45 participants were conducted to determine average completion times; refine question wording; and optimise technical operation.

Inclusion criteria were as follows:

1. Age 25–34 years (inclusive)
2. Self-identified as female
3. Employed full-time
4. Having residence in the UK

Participants received monetary compensation ranging from £1.00 to £1.50 for their time. Of 200 participants who completed the survey, 31 were excluded based on the following predefined criteria: duplicate responses; irrelevant answers to open-ended questions; responses that were overly brief or non-informative, completion times below five minutes; male gender identification; and non-targeted age group.

The resulting sample included 169 female workers aged 25–34, representing diverse industries. The largest sectors included human health and social care (16.6%), education (16.6%), and professional, scientific, and technical activities (10.1%). Occupation types skewed towards skilled, non-manual roles: professional (39.6%), associate professional (28.4%), and managerial (14.2%), with sales and customer service accounting for 12.4%. Participants were primarily employed in the private (50.9%) and public (41.4%) sectors, with smaller proportions in non-profit (5.3%) and freelance/self-employed roles (2.4%). Working arrangements included hybrid (49.1%), on-site (36.1%), and fully remote (14.8%). Almost half of participants (45.0%) were employed by large organisations with over 1,000 employees.

This sample provides a representative cross-section of young female workers in the UK, encompassing a range of organisational contexts, job roles, and workplace arrangements, and affording a meaningful exploration of mental health experiences and technology adoption behaviours.

## Survey Materials

### *Survey Design.*

An online survey format was selected for both practical and methodological reasons. This approach enables efficient recruitment across multiple sectors, simplifying logistics and facilitating timely data collection. Importantly, the online format enhanced participant anonymity, a factor known to be critical when addressing sensitive topics such as mental health, reducing social desirability bias<sup>57</sup>. Meanwhile, the use of open-ended questions within a context of anonymity and convenience encourages participants to articulate nuanced experiences naturally and expansively, complementing quantitative

insight in order to better understand the participant's experience of engaging LLM-based tools for mental health purposes, and draw out design implications.

### *Question Design.*

Survey development was informed by prior research on workplace mental health, the use of DMHIs broadly, and the use of LLM-based chatbots specifically<sup>5,31,37,38,58</sup>. Survey items were designed to capture both behavioural engagement and attitudinal drivers of adoption. To complement these structured measures, open-ended questions were included following Braun and Clarke's (2006) qualitative framework, enabling participants to share lived experiences and expectations beyond the constraints of numerical scales.

The first part of survey consisted of 20 structured questions, organised into five domains:

1. Demographics: age; gender; industry; job role; organisation type and size; and working arrangement.
2. Perception of workplace mental health supports: managerial support; workplace culture; and employer initiatives.
3. Use of non-DMHIs: experiences and types of non-digital mental health interventions (e.g., physical activity, in-person counselling, mindfulness, and peer support).
4. Use of DMHIs: experiences; types of digital mental health interventions and digital devices (e.g., smartphone applications, wearable devices, or web-based resources); source of discovery; current usage, usage frequency and usage intentions; and willingness to share mental health-related data with employers.
5. Use and perception of LLM-based chatbots: experience using for work and workplace mental health purposes; perception of comfort, trust, willingness to use as a workplace mental health support, privacy concerns, and complementarity with human support; and desired functionality.

This was followed by five open-ended exploratory questions: (1) the lived experience of participant workplace mental health challenges; (2) prior experience with DMHIs; (3) the perceived benefits of LLM-based chatbots as a workplace mental health support; (4) the perceived barriers to LLM-based chatbot adoption; and (5) suggestions for feature development to better support the mental wellbeing of young female workers in the workplace.

## **Procedure**

Participants were provided with an anonymous link to a survey hosted on Qualtrics<sup>59</sup>, a secure and widely used platform in social and health research. On accessing the survey, participants were asked to review the information sheet and consent form, marking a confirmation checkbox accordingly, thereby confirming that informed consent was obtained from all participants and/or their legal guardian(s), before completing six sections: (1) demographic questions; (2) items on perception of workplace mental health supports; (3) use of non-DMHIs; (4) use of DMHIs; (5) use and perception of LLM-based chatbots;

and (6) open-ended questions. After completion, participants were thanked and directed to a confirmation page.

## Data Analysis

### Quantitative Analysis.

Quantitative data were analysed using SPSS <sup>60</sup>. Descriptive statistics were first employed to summarise overall trends, including participant demographics, engagement with both non-DMHIs and DMHIs, and the use and perception of LLM-based chatbots for work and workplace mental health. Inferential analyses were subsequently conducted, including independent-samples t-tests and cross-tabulations, to compare groups (i.e., work task users vs. work task non-users) based on their use of LLM-based chatbots in these contexts. These comparisons sought to identify factors influencing adoption, such as comfort, trust, perceived utility, and privacy concerns. Taken together, the descriptive and inferential analyses provided a comprehensive view of workplace mental health technology engagement, offering key insights into the usage of and attitude towards DMHIs, including LLM-based chatbots.

### Qualitative Analysis.

Qualitative responses were analysed using Braun and Clarke's approach to reflexive thematic analysis <sup>61</sup>, an inductive approach that enables researchers to identify patterns and develop themes from the data, rather than themes being suggested or overlooked by pre-existing frameworks. Reflexive thematic analysis is deemed particularly suitable for exploratory, nascent areas of research, aligning well with a study that not only focuses on the use of a new technology (LLM-based chatbots), but the experience of a select demographic (young female workers) engaging that new technology within a specific context (the workplace) for a defined purpose (as a workplace mental health support). This approach allows for the identification of recurring patterns while remaining sensitive to individual variation, contextual nuance, and new or unexpected information. Coding was conducted at both the semantic and latent levels, capturing explicit descriptions and underlying assumptions regarding technology use, workplace mental health experiences, and interaction preferences.

The process involved iterative data familiarisation, initial coding using NVivo <sup>62</sup>, and the subsequent grouping of codes into broader themes. These themes were then reviewed for internal coherence and external distinction, defined in relation to the research questions and refined to ensure clarity and relevance.

## Declarations

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This research did not receive funding.

# Author Contribution

Bokyoung Um wrote the main manuscript text. Amid Ayobi supervised the project. All authors reviewed and edited the manuscript.

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# Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

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## Figures

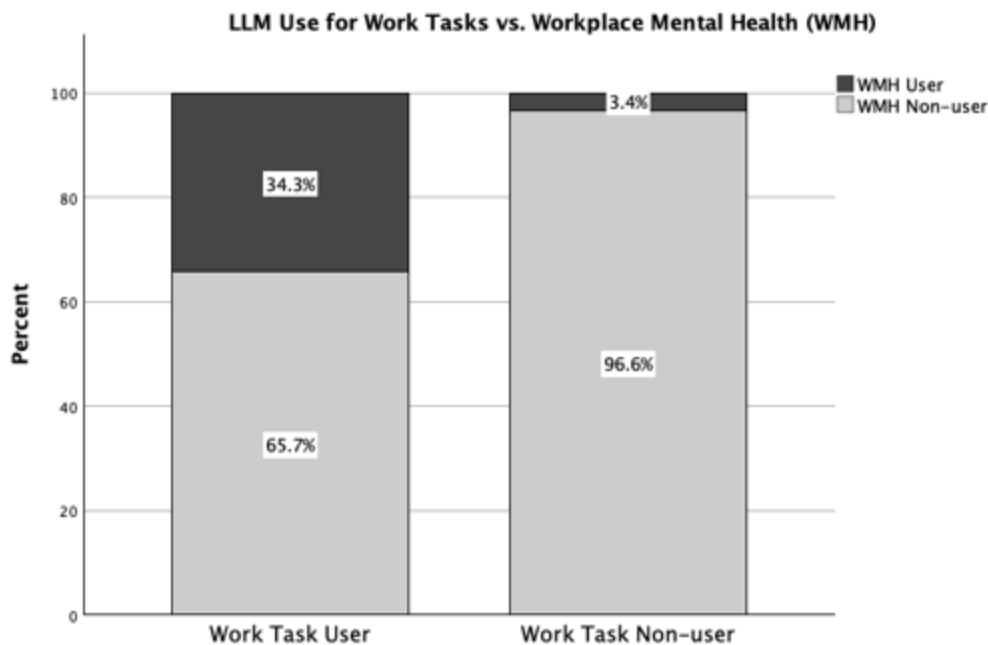


**Figure 1**

Distribution of LLM usage across work tasks and workplace mental health contexts (n = 169).

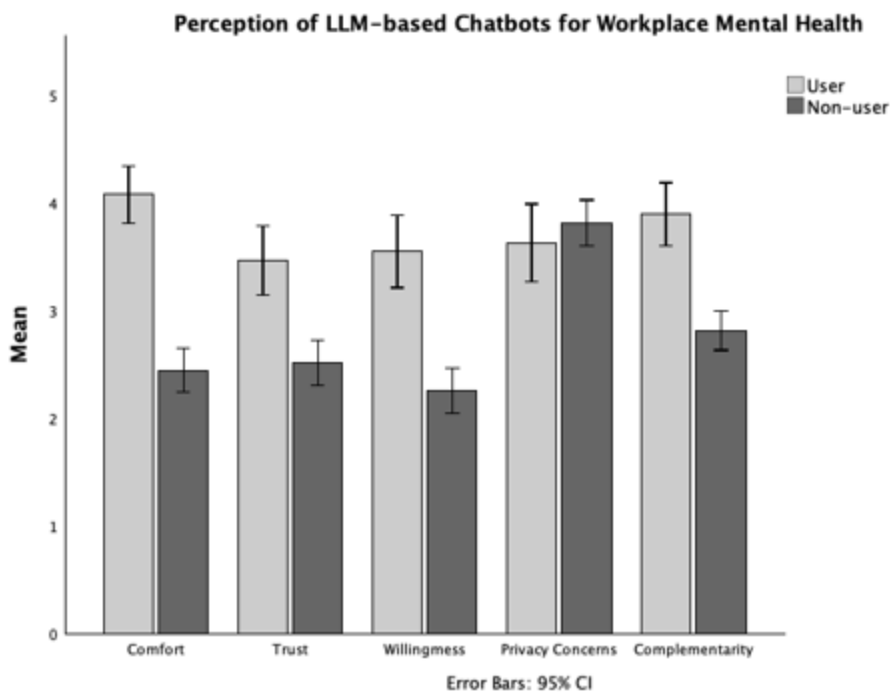


**Figure 2**

Mean ratings for comfort, trust, willingness to use, data privacy concerns, and perceptions of LLM-based chatbots as complementary to human support, comparing workplace mental health users and non-users (\*\*\*)  $p < 0.001$ , Error Bars: 95% CI).

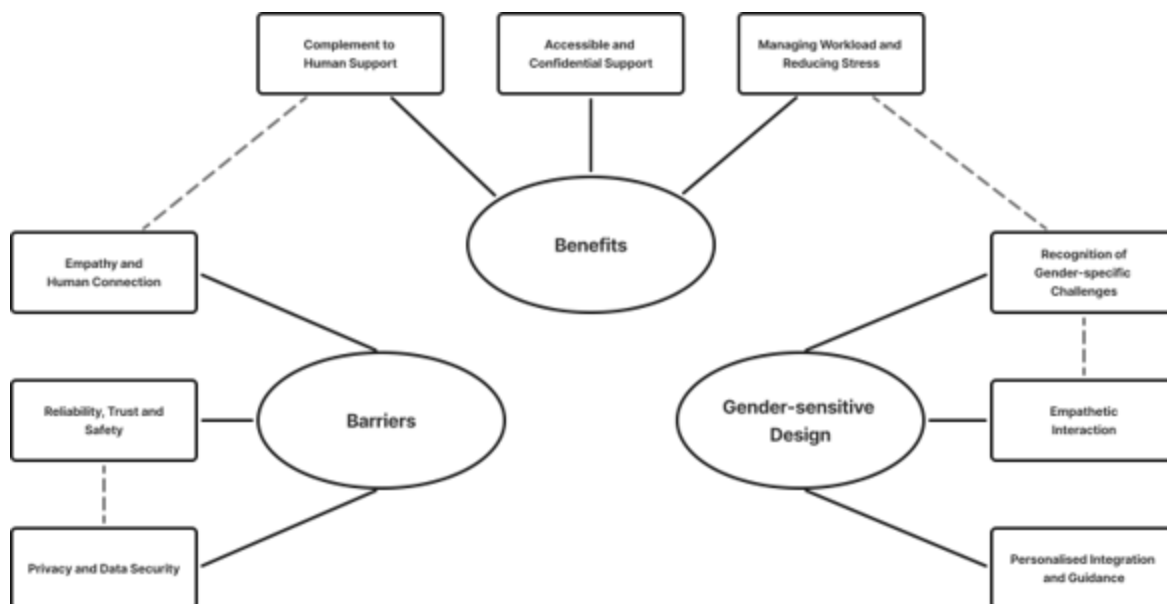


**Figure 3**

Thematic map from reflexive thematic analysis showing three core themes and nine sub-themes.