Wellness Watch or Worry Watch? Negative Psychological Impacts of Wearable Devices

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Psychological impacts stemming from the use of wearable devices are important to study because wearables are now widely adopted and promoted as tools for healthier living. While prior research has documented positive psychological impacts, far less attention has been given to the negative ones. In this work, we ask whether these negative psychological impacts are isolated anecdotes or reflect a systematic pattern, and whether the wearable computing research community adequately engages with them. First, in a large-scale study with a U.S. sample of 264 participants (149 wearable users, 115 non-users), we found that wearable users exhibited significantly higher obsessive–compulsive traits than non-users ($p < 0.05$). Moreover, based on free-text and Likert scale responses, approximately 1 in 4 wearable users reported negative psychological impacts from calorie tracking, smart notifications, and sleep tracking. All negative impacts could be broadly categorized into anxiety and worry, guilt and pressure, obsession and compulsion, false information and information overload, and negative self-image. To contextualize these findings, next we analyzed 782 papers published between 2024–2025 in 5 flagship wearable/mobile computing venues. We found that only 5 out of 123 wearable-related papers focused on negative psychological impacts as the core research direction. Our findings demonstrate a clear disconnect: the psychological toll of wearables is a common user experience, yet it remains largely unaddressed by the research community. We call for a broader focus on the responsible development of these technologies, one that treats the assessment of psychological impacts as a central component of wearable design and evaluation, similar to how accuracy, system aspects, privacy, and usability are considered.

CCS Concepts: • **Human-centered computing → Ubiquitous computing**; **Empirical studies in ubiquitous and mobile computing**; • **Applied computing** → *Health informatics.*

Additional Key Words and Phrases: wearable computing, mental health, negative psychological impacts, quantified self, obsessive-compulsive traits, user study, literature review, psychological harms

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1 INTRODUCTION

Wearable health and fitness devices such as smartwatches and activity trackers, are now part of everyday life [113, 128, 143]. Their rapid adoption reflects both consumer demand and research interest, with global shipments reaching hundreds of millions per year and at least one in five U.S. adults owning a device [119]. Wearables are widely promoted and studied as tools for healthier lifestyles [110]. Randomized trials and meta-analyses show that activity trackers can increase daily step counts, support modest weight loss, and improve markers of fitness [45]. They may also improve self-care and health perception and reduce psychological distress

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in some groups [27], leading clinicians to recommend sustained use for behavior change [45, 65]. Recent work further explores wearables for detecting or predicting psychological conditions such as stress, fatigue, and depression [72, 146].

Alongside these benefits, evidence also points to negative psychological impacts from wearable use [2, 4, 15, 78, 82, 83, 83, 86, 117]. We treat these impacts as psychological harm: outcomes that negatively affect emotional well-being such as distress, manipulation, or addiction [7, 81, 129]. Prior work links harms to core features, including health anxiety from arrhythmia notifications [117], "orthosomnia" from sleep scoring [15], and obsessive tracking and disordered eating concerns around continuous glucose monitors [4]. Yet evidence on prevalence and mechanisms remains limited: many studies focus on clinical populations or early adopters, rarely compare wearable users to non-users on mental health or personality traits, and seldom identify which wearable uses[1] are most associated with negative psychological impacts in the general population.

This gap in user-centric evidence is mirrored by a critical gap in our understanding of the research community's discourse and priorities. Existing secondary analyses of wearable technologies have largely focused on user adoption [46, 52], health efficacy [16, 17], or broader societal implications such as privacy [20, 95, 99, 147], with no comparable synthesis centered on negative psychological impacts. To identify potential blind spots, it is therefore important to examine agenda-setting venues that shape what constitutes valuable inquiry [97]. Venue-centric analyses have proven effective for revealing community-wide trends and gaps across domains including MobileHCI, CHI, ICWSM, IMWUT, and FAccT [62, 63, 103, 104, 126, 127, 150, 155]. Yet, to our knowledge, no such analysis has quantified attention to negative psychological impacts in the broader literature or in flagship mobile and wearable computing venues, potentially creating a disconnect between users' lived experiences and the priorities of the core technical community.

We address these gaps using two complementary lenses. First, a large-scale user study compares wearable users and non-users, and identifies wearable uses associated with negative psychological impacts. Second, a meta-analysis of flagship mobile and wearable computing venues quantifies how explicitly the literature engages with negative psychological impacts. Together, this reveals critical blindspot where user-reported harms and research attention diverge. To this end, we address three research questions (RQs):

RQ1: How do wearable users differ from non-users in demographics, mental health, and personality traits?
RQ2: Which wearable features are associated with negative psychological impacts, and what is their prevalence?
RQ3: To what extent do recent wearable-focused publications in flagship mobile and wearable computing venues address negative psychological impacts?

In answering these RQs, we make three main contributions:

Contribution 1: We conducted a large-scale study with 264 participants recruited from a U.S. adult sample quota-matched to U.S. census data on age, sex, and ethnicity. Within this sample, 149 participants reported active wearable use and 115 reported non-use. We examined how demographic characteristics, personality traits, and mental health measures differ between wearable users and non-users (Section 3). Demographic factors such as sex, ethnicity, and employment status showed no significant differences (Figure 2); wearable users were on average younger and showed higher obsessive–compulsive traits (OCI-R and OCD scores) than non-users (Bonferroni-corrected $p < 0.05$, Figure 3). Because the design is cross-sectional, this difference should be interpreted as an association that may reflect self-selection, differences in usage style, or unobserved confounds, rather than a causal effect (Section 3.2). This highlights the importance of considering user heterogeneity and psychological predispositions when evaluating wearable technologies and their potential downsides.

[1]Throughout this manuscript, we use the term "uses" to refer to different functionalities of wearables. Some of them are specific wearable features (i.e., step counter, activity tracking, stress monitoring, etc.), while other are a specific use cases (i.e., mindfulness or breathing exercises, casual or fashion use, etc.). The full list of 15 wearable uses considered in this study are given in Section 3.

Contribution 2: Among wearable users, 21 participants explicitly reported negative psychological impacts in Likert-scale questions, marking 36 instances of uses in total as negatively affecting their mental well-being within the past month (Section 3.3). While the most widely occurring uses, step counting and heart-rate monitoring (adopted by 82% and 75% of wearable users, respectively), were less often associated with negative experiences (Figure 4), calorie tracking and energy expenditure monitoring stood out as the uses most frequently linked to negative psychological impacts. Free-text responses revealed additional negative experiences beyond the structured selections (Section 3.3): 19 participants described negative psychological impacts despite not selecting specific uses as negatively affecting them in the Likert scales. Taken together, 40 participants, that is about 1 in 4 wearable users in our study, experienced negative psychological impacts, which could be clustered into five broad themes: anxiety and worry, guilt and pressure, obsession and compulsion, false information and information overload, and negative self-image. Overall, these results suggest that negative psychological impacts of wearables may not be marginal, but a common and often hidden part of the wearable device user experience.

Contribution 3: To contextualize the user study, we reviewed how flagship wearable and mobile computing venues (IMWUT, ISWC, MobiSys, MobiCom, SenSys) engage with negative psychological impacts of wearable technology (Section 4.2). Out of 782 papers published between 2024–2025, we identified 123 that explicitly involved wearables, yet only five of these (≈4%) made negative psychological impacts a central research objective. While around one-quarter briefly acknowledged issues such as stress, anxiety, or data overwhelm, these mentions were typically passing rather than substantive, and several categories of user-reported harms were largely absent from the discourse (Table 1). Together, these findings reveal a blind spot where technical progress outpaces systematic attention to psychological consequences, motivating a research agenda that treats psychological harms as a core dimension of wearable computing design and evaluation, alongside concerns such as privacy and ethics.

2 BACKGROUND AND RELATED WORK

Existing literature reveals a landscape where the tangible benefits of wearables are well-documented and celebrated, while the evidence for psychological harms remains fragmented and under-investigated at a population level. This points to two critical, complementary gaps. On the user side (Section 2.1), crucial questions about the prevalence of these harms, their feature-specific triggers, and the role of user traits in a general non-clinical population remain open. On the research community side (Section 2.2), there is a clear disconnect between the documented harms and the topics prioritized in flagship mobile and wearable computing venues.

2.1 The User Perspective: A Duality of Benefits and Harms

The literature paints a dualistic picture of the wearable user's experience. On one hand, a substantial body of work highlights tangible benefits to health and well-being (Section 2.1.1). On the other, a growing collection of clinical reports, user narratives, and small-scale studies points to a "dark side" characterized by unintended negative psychological impacts (Section 2.1.2).

2.1.1 The Bright Side: Documented Health and Well-being Benefits. Wearable technologies have diffused rapidly into everyday life. Market reports estimate that shipments of smartwatches, fitness bands, and smart rings exceed 150 million units each quarter, and at least 1 in 5 Americans owns a wearable [64]. The appeal of these devices lies in their ability to quantify behaviors such as step counts, heart rate, sleep, and calories burnt, providing immediate feedback and accountability. Research has repeatedly demonstrated tangible benefits. For instance, activity trackers motivate users to walk roughly 1,800 extra steps per day and improve perceptions of diet and mental health [43]. A survey of 237 wearable owners found that participants reported more positive than negative emotions while wearing their device, and that negative affect increased when prevented from wearing it, though users still valued the motivational benefits [118]. Beyond physical activity, wearables are increasingly used for heart-rate monitoring [100, 123], menstrual tracking [70, 88], sleep staging [14, 124], stress and fatigue monitoring [72, 92, 106, 130, 138], detecting bodily compulsions [125], and even continuous glucose monitoring [53, 60]. Furthermore, together with smartphone sensing, these technologies have been heavily researched for continuously inferring daily routines, social eating contexts, and overall mood and well-being [11, 13, 90, 93, 94]. These functions can empower users with chronic conditions by offering real-time awareness and supporting early detection of abnormalities. For example, cardiovascular patients may use wearable electrocardiogram features to detect atrial fibrillation episodes and share data with clinicians, while stress detection derive states from heart-rate variability or skin conductance to prompt interventions [51]. Accordingly, the technology community often presents wearables as precision-health tools that enhance autonomy and prevent disease. While this body of work highlights the clear benefits of wearable adoption, it also reflects a literature dominated by benefit-focused perspectives. Far less is known about unintended psychological costs, especially at population scale. This imbalance motivates closer examination of whether harms are systematically overlooked in favor of highlighting benefits.

2.1.2 The Dark Side: Emerging Evidence of Psychological Harms. Alongside their benefits, wearables can introduce a range of negative psychological impacts, as documented in both clinical research and popular media.

Clinical and Research Findings. Prior evidence suggests that negative psychological impacts of wearables cluster into a few recurring categories and are often tied to specific features. Anxiety and fear have been documented in relation to cardiovascular monitoring: case reports describe atrial fibrillation patients receiving frequent alerts who performed hundreds of self-initiated electrocardiograms, experienced health anxiety, and repeatedly sought medical care [115]; in a population study, about 20% of wearable users with atrial fibrillation reported intense fear in response to irregular rhythm notifications [101]. Metrics and scoring systems can foster obsessive monitoring, including orthosomnia, where pursuit of ideal sleep scores leads users to distrust clinical evaluations and adopt maladaptive sleep behaviors [15], with prevalence estimates of 3–5% and links to perfectionistic tendencies [58]. Goal pursuit and gamified feedback can also produce guilt, shame, and pressure when targets are missed [12, 43]. Eating-related harms have been raised in the context of glucose and diet tracking: mental health professionals caution that continuous glucose monitors marketed for performance or weight loss may encourage fixation on fluctuations, restrictive dieting, and obsessive tracking [3, 4, 96, 142]. More broadly, researchers describe quantified-self dependence, where users feel incomplete without their device, experience guilt when unable to track, and show reduced intrinsic motivation [44, 85, 122]. These harms appear feature-specific: sleep-tracking scores can worsen sleep quality and fuel obsessive monitoring [2]; heart-rate and arrhythmia alerts can trigger fear and unnecessary care-seeking, especially with false positives [101, 115]; and glucose monitoring repurposed for dieting may exacerbate disordered eating behaviors [4]. Activity metrics such as step counts are often experienced as motivating, but rings and streaks can still create pressure [2, 43]. Personality traits may moderate these effects: individuals low in conscientiousness or openness are more likely to report negative emotions when feedback is poor or when unable to track [118]. Together, these findings suggest clinically meaningful harms, yet much of the evidence comes from case studies, small samples, or commentary, leaving open questions about prevalence, cross-feature comparisons, and which user characteristics amplify vulnerability.

User Narratives and Media Portrayals. Journalistic accounts and user narratives provide vivid illustrations of how these categories of harms can manifest in everyday life. Stories describe users who feel compelled to exercise at inappropriate times to avoid breaking a streak, or who wake during the night to check sleep scores, spiraling into worry when results are poor [2]. For instance, a recent BBC report details how the pressure to meet daily targets can lead to anxiety and an unhealthy relationship with exercise, with experts warning that for some, the data does more harm than good [71]. Dietitians and mental health advocates warn that calorie counters and glucose monitors can turn meals into mathematical exercises, provoking guilt and stress [4]. Charities such as Beat have cautioned that wearables may amplify health anxiety among people with a history of eating disorders [43]. Beyond this, there are numerous media articles on the negative impacts of wearable, from diverse angles [1, 5, 35, 66, 73]. These narratives underscore the heterogeneity of wearable experiences. While some users describe accountability and empowerment, others report guilt, shame, anxiety, and loss of autonomy. They highlight that harms often cluster around gamified uses, social comparison, privacy, data leakage, and an external locus of control. Still, anecdotal reports cannot answer how representative such experiences are. Our study addresses this limitation by systematically analyzing open-text responses from a large participant pool and mapping them to broader themes, providing evidence on whether such media portrayals are merely anecdotal or reflect a widespread phenomenon.

2.2 The Research Perspective: An Imbalance in Focus

The asymmetry between the coverage of positive and negative psychological impacts is not merely a feature of the user-focused literature; it reflects a deeper bias within the wearable computing research community itself, which is shaped by the culture and priorities of its flagship publication venues [97].

2.2.1 Limited Attention to Negative Psychological Impacts in Wearable Computing Research. Despite growing evidence of negative psychological impacts from user studies, it is unclear whether the wearable computing research community has adequately addressed them. A body of work now documents how wearables can induce anxiety and preoccupation, particularly in clinical populations [25, 116], and may trigger ruminative thinking in vulnerable individuals [6, 57]. Researchers have also identified phenomena such as "technostress" from feeling controlled by or needing validation from device data [112], technology anxiety among older adults [59, 137], and negative affect like guilt or frustration when unable to use a device [19, 118]. Recent work has also examined how users cope with negative incidents to continue wearable use, including strategies such as selective use, deactivating features, or self-deceptive behaviors [111]. Yet, publications in leading venues such as IMWUT, ISWC, MobiSys, MobiCom, and SenSys overwhelmingly emphasize benefits, with evaluations typically centering on accuracy, performance, or engagement rather than measured well-being [51]. While recent work has begun to expand the lens to broader harms such as context-induced harms [152] and critiques of detection-centric approaches [9], these perspectives do not always directly address everyday psychological harms. However, the depth and extent to which the wearable computing community has focused on negative psychological impacts, is unknown. This is important to know because a handful of commentaries have called for greater attention to negative psychological impacts [33, 64, 139].

2.2.2 Limited Attention to Negative Psychological Impacts in Prior Secondary Analysis of Wearable Research. Prior secondary analyses of wearable technology research can be categorized into three broader themes: reviews of user adoption and acceptance [46, 52], meta-analyses of health and behavioral efficacy [16, 17], and surveys on broader societal implications [20, 147]. Collectively, this body of work has identified key drivers of adoption such as perceived usefulness and social factors [36, 52]; confirmed the effectiveness of wearables for increasing physical activity [17]; and significant ethical concerns, including data privacy [26, 99] and the potential to exacerbate health inequalities [20, 98]. A subset of this literature has also begun to consider risks and unintended harms more broadly; for example, Xue et al. [148] provide a scoping review of intelligent wearables that summarizes uses and perceived risks, including social and psychological risks. Other work has documented unintended psychological harms [68, 132]. While these reviews provide an invaluable map of what is known, they do not analyze the wearable computing research community's own internal discourse and publication priorities. This is important because flagship mobile and wearable computing venues are not merely passive archives but powerful venues that actively shape the future of the field by signaling what constitutes valuable research. The research published and celebrated in these forums actively constructs the future of wearable computing. Therefore, to understand how the wearable computing community has addressed or overlooked topics like negative psychological impacts, our work provides a systematic analysis of the recent content published within these agenda-setting venues, offering a necessary meta-analysis of the community's own discourse.

2.3 Research Gap

In summary, existing literature reveals a landscape where the tangible benefits of wearables are well-documented, while the evidence for psychological harms, though growing, remains under-investigated. This points to two critical, complementary gaps. On the user side, much of the evidence for negative psychological impacts comes from clinical case reports, anecdotal accounts, or media reports. This leaves open crucial questions about the prevalence of these harms, their feature-specific triggers, and the role of user traits in a general (non-clinical) population. On the research community side, there is a clear disconnect between the documented harms and the topics prioritized in flagship mobile and wearable computing venues. These venues appear to favor technical advances and demonstrable health benefits, with potential harms rarely treated as core outcomes for evaluation. This raises the question of how often and how deeply, the wearable computing community acknowledges these impacts. Addressing both gaps is essential to align wearable research with a more balanced and human-centered understanding of both the benefits and the costs of wearable technologies.

3 USER STUDY AND FINDINGS

We conducted a cross-sectional study with 264 participants (149 wearable users, 115 non-users) recruited from a quota matched U.S. sample based on age, sex, and ethnicity. Participants completed demographic questions and validated instruments measuring anxiety, obsessive–compulsive traits, and personality. Wearable users reported feature-level use frequency and perceived mental well-being impacts across 15 common wearable uses, followed by an open-ended question to contextualize their ratings. Section 3.1 provides a description of this process. Thereafter, we provide experiments conducted to answer RQ1 and RQ2 in Section 3.2 and Section 3.3, respectively.

3.1 User Study

We employed a cross-sectional survey design administered on a custom-built web application, developed by us using SurveyJS, HTML, and Javascript. Participation was voluntary and informed consent was obtained at the outset. The questionnaire lasted approximately 10–15 minutes, was self-paced, and participants could withdraw at any point. To reduce fatigue and ensure fairness in task length, the survey employed a two-branch logic. Wearable users answered questions about their primary device, the duration of use, typical daily wear time, and detailed modules about 15 wearable uses. Non-wearable users instead completed parallel questions about health-tracking features available on their smartphones (for example Apple Health or Google Fit). All participants, regardless of branch, completed standardized mental health and personality scales (GAD-7, OCI-R, and Mini-IPIP), as well as demographic questions. This branching ensured that participants answered questions relevant to their experience while keeping survey length roughly equivalent across groups. This is a good practice to ensure participants are not encouraged to choose one over the others. Two pilot tests, first with five individuals, and then, with 10 additional individuals, were conducted to estimate completion time and refine item wording before deployment of the final survey. Responses from these pilots were not included in the answers analyzed in this manuscript.

Survey Questions. The questions asked from participants are summarized in Figure 1. Demographic questions asked participants to report age, sex, and ethnicity. Participants then completed validated instruments to assess anxiety, obsessive-compulsive tendencies, and personality traits, because these factors may relate to wearable tracking behaviors and help explain differences between users and non-users.

Generalized Anxiety Disorder–7 (GAD7) Questionnaire [133]. We used the GAD-7 to assess baseline anxiety symptoms and compare anxiety levels between wearable users and non-users, given prior reports linking wearable use with anxiety [33]. Participants rated how often they were bothered by seven anxiety symptoms over the

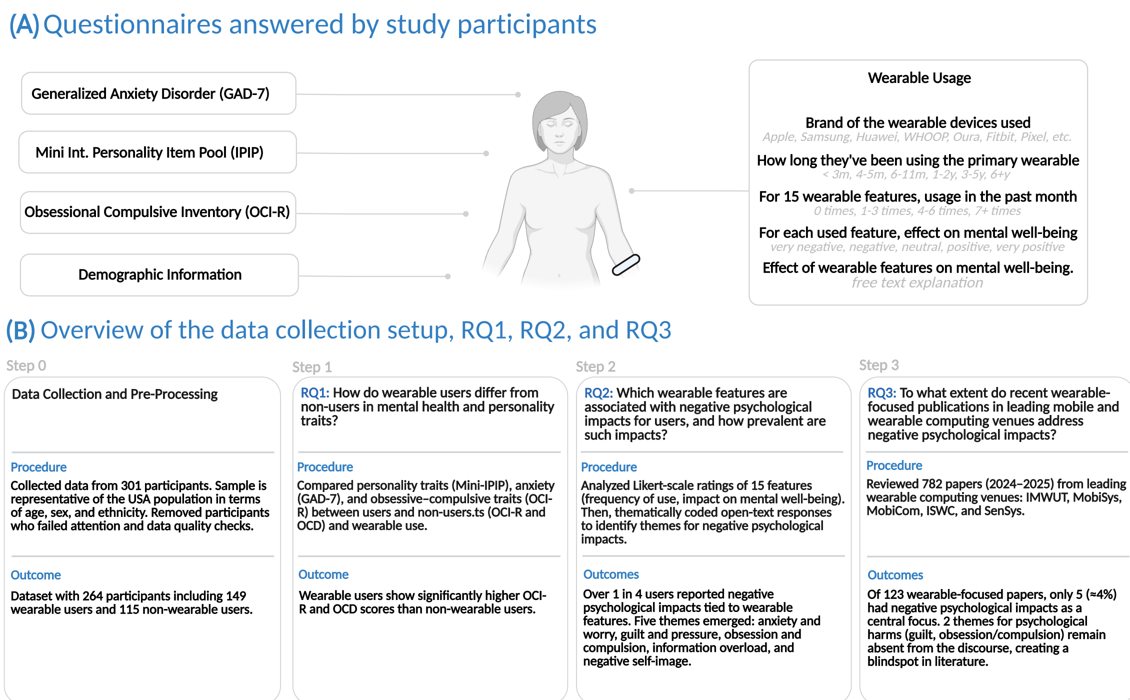

Fig. 1. Overview of the study. (A) Questionnaires administered to participants, including standardized instruments for anxiety (GAD-7), obsessive–compulsive traits (OCI-R), personality (Mini-IPIP), and demographics. Wearable users additionally reported 15 device uses (past-month usage frequency and perceived impact on mental well-being), device brand and duration of use, and provided free-text reflections. (B) Data collection and analysis workflow. Participants were recruited from a U.S. adult sample quota-matched to U.S. census data on age, sex, and ethnicity; after exclusions, the final sample comprised 264 participants (149 wearable users; 115 non-users). We address three research questions: RQ1, differences in mental health and personality traits between users and non-users; RQ2, prevalence and themes of negative psychological experiences users associate with wearable use; and RQ3, the extent to which flagship wearable computing venues explicitly engage with these impacts.

last two weeks on a 0 ("Not at all") to 3 ("Nearly every day") scale, producing a total score from 0–21 (higher indicates greater anxiety severity).

Obsessive–Compulsive Inventory–Revised (OCI-R) Questionnaire [47]. We used the OCI-R to quantify obsessive–compulsive tendencies that may relate to wearable tracking and feedback loops [8, 49]. Participants rated how much each experience bothered them in the past month on a 0 ("Not at all") to 4 ("Extremely") scale.

Mini-IPIP Scale [34]. We included the Mini-IPIP to measure baseline personality traits that may moderate technology engagement and health behaviors [76, 135]. Participants rated Big Five statements on a 1 ("Disagree strongly") to 5 ("Agree strongly") scale, yielding scores across the five dimensions. These questionnaires are validated instruments widely used in research.

Afterwards, wearable users completed a module to characterize their engagement with common device functionalities and to capture both feature-level use frequency and perceived impacts on mental well-being (Appendix C). They reported their primary consumer wearable device brand (e.g., Apple, Samsung, Fitbit, etc.), how long they had used a wearable (ranging from less than three months to more than five years), and their typical daily wear time. They then completed a matrix of 15 common wearable uses. For each feature (e.g., step counter, sleep tracking, heart-rate alerts, calorie tracking, stress monitoring, mindfulness exercises, social leaderboards, etc.), participants indicated frequency of use in the past month ("Never used/Not applicable", "0 times", "1–3 times per week", "4–6 times per week", or "7+ times per week"). They then rated the perceived impact of each feature on their mental well-being ("very negative", "negative", "neutral", "positive", or "very positive"). Finally, an open-text question asked: "Explain how one or more wearable features you rated (from very negative to very positive) influenced your mental wellbeing. Give specific examples, including the feature name, the situation, and how the feature affected you". The 15 wearable uses were selected based on a review of the most common and widely marketed functionalities available on leading consumer wearable devices as of 2025 (e.g., Apple Watch, Fitbit, Garmin, and Samsung Galaxy Watch), ensuring our survey captured the common uses wearable users interact with.

Participants. We recruited participants through Prolific[2], an established online research platform, with quotas to match the U.S. adult population in terms of age, sex, and ethnicity, to make the sample representative on those aspects. This was done using user recruitment features provided in the Prolific platform. A total of 301 individuals were recruited for the study. To ensure high-quality responses, data quality controls were applied in three stages. First, the survey included four embedded attention-check items (e.g., "To show you are paying attention, please select 'Nearly every day' for this item"). Participants who failed two or more of these checks were excluded ($n = 12$). Second, our custom website automatically recorded timestamps, enabling the detection of rushed responses. Based on pilot testing, participants who completed the entire survey in less than five minutes were excluded ($n = 6$). This left 283 valid responses. Third, because our focus was on active wearable use, we excluded 19 participants who reported wearing a device less than once per week during the past month. We did this because they do not cleanly fall into either active-use or non-use categories, and including them would introduce ambiguity in group comparisons. The final sample therefore comprised 264 participants: 149 wearable users (56.4%) and 115 non-users (43.6%). Among wearable users, 118 were classified as heavy users (wearing a device three or more days per week) and 41 as light users (wearing a device one to two days per week). Participants' ages ranged from 18 to 84 years (mean = 45.9), and the sample reflected broad gender and ethnic diversity consistent with U.S. census benchmarks, according to our checks. All participants were U.S. residents and reported fluency in English. The median completion time among participants for the final analytic dataset was 12 minutes.

Ethical Considerations. The study was reviewed and approved by the internal ethics board of a large multinational company (details withheld for double-blind review). Participants provided informed consent at the beginning of the survey and were informed of their rights, including the right to withdraw their answers. No personally identifying information (e.g., names, email addresses, IP addresses) was collected and Prolific platform IDs were used only for payment and not linked to responses. All data were stored in pseudonymized, aggregate form on secure servers. Participants received compensation at a fair rate of $12/hour pro-rated to the expected duration.

3.2 RQ1: How do wearable users differ from non-users in demographics, mental health, and personality traits?

Methods. To answer RQ1, we sought to determine whether wearable users differ systematically from non-users in mental health and personality traits, as prior research suggests that psychological predispositions may shape technology adoption and the likelihood of experiencing harms [18, 49, 157]. To do so, we analyzed three key validated questionnaires we asked participants: generalized anxiety (GAD-7), obsessive–compulsive traits (OCI-R

[2]https://www.prolific.com/

and its OCD subcomponent), and the personality dimensions (Mini-IPIP). To contextualize the results, we first compared demographic variables (age in Figure 2A, sex in Figure 2B, ethnicity in Figure 2C, and employment status in Figure 2D) across groups to establish whether any observed psychological differences might be confounded by baseline demographic imbalances. This step checked whether group-level differences were not simply attributable to demographic composition. We also did an analysis on device usage statistics, and provided in Appendix A.

Next, we examined generalized anxiety using GAD-7 scores, as anxiety has been frequently mentioned in anecdotal accounts of wearable-induced harms [115]. By comparing both continuous scores and categorical severity levels (minimal, mild, moderate, severe), we aimed to identify whether wearable adoption is linked to elevated anxiety risk at either the population or clinical severity level. We obtained the categories adhering to clinically defined thresholds [133], with minimal: 0 to 4, mild: 5 to 9, moderate: 10 to 14, and severe: 15 to 21. The results are presented in Figure 3A and Figure 3B. We then focused on obsessive–compulsive traits (OCI-R), given the strong theoretical connection between compulsive checking behaviors and the use of feedback-intensive technologies such as wearables [49]. Here, both the full scale and OCD-specific sub-component were analyzed, allowing us to test whether wearable users exhibit greater compulsive tendencies that might predispose them to maladaptive patterns of use. The results are presented in Figure 3C, Figure 3D, and Figure 3E.

Finally, we compared personality profiles using the Mini-IPIP. Personality traits, particularly Neuroticism and Conscientiousness, are known predictors of technology engagement and health behaviors [108, 156]. Examining group differences here allowed us to assess whether wearable users are psychologically predisposed toward or protected against certain negative experiences. The results are presented in Figure 3F. For continuous scale scores (GAD-7, OCI-R, and Mini-IPIP subscales), we used non-parametric Mann–Whitney U tests [89], as distributions deviated from normality. For categorical outcomes (e.g., GAD-7 severity bins, OCI-R severity categories), pairwise chi-square tests of independence [50] were applied to assess differences in proportions across groups, with Bonferroni correction [144] for the p-values. To complement p-values, we also calculated effect sizes as rank-biserial correlation (r_{rb}) for Mann–Whitney U tests [67] and Cramér's V (=ϕ for 2×2 tables) for chi-square tests [31]. This combination of descriptive and inferential analyses provided a assessment of whether wearable users differ from non-users in ways that may explain adoption patterns and vulnerability to psychological harms.

Findings. After applying our filtering criteria (Section 3), our final sample consisted of 264 participants, comprising 149 wearable users and 115 non-wearable users. We first examined the demographic composition of these two groups to identify any baseline differences (Figures 2A-2D). While the distribution of sex, ethnicity, and employment status were broadly similar across both groups, we observed a difference in age (Figure 2A). The mean age of wearable users was lower than that of non-wearable users, with the peak of the age distribution for wearable users appearing in the 25-35 range, compared to a slightly older peak for non-users (mean 44.3 for wearable users *vs.* 48.0 for non-wearable users; though the distributional difference is not statistically significant). This suggests that wearable adoption in our sample is more prevalent among younger adults, and this aligns with similar results presented in prior work [75, 98].

For general anxiety, as measured by the GAD-7, wearable users reported almost similar symptom severity compared to non-users (Figure 3A). A breakdown by clinical severity categories (Figure 3B) further clarified this finding. For instance, percentage of wearable users in the four categories minimal, mild, moderate, and severe was 58%, 25%, 12% and 5%, respectively. The percentages for non-wearable users was 57%, 23%, 13%, and 6%. Hence, the study participants falling into the severity categories did not differ significantly across the groups. Correspondingly, non-wearable users constituted a considerably larger proportion of the Minimal anxiety group, which primarily comes from the higher percentage of wearable users, compared to users who do not use them. Interestingly, for obsessive-compulsive traits measured by the OCI-R, the score distributions for both the full 18-item scale and the 15-item OCD component showed that wearable users had higher mean scores than non-users (Figures 3C and 3E). The difference between the distributions were statistically significant ($p<0.05$) for

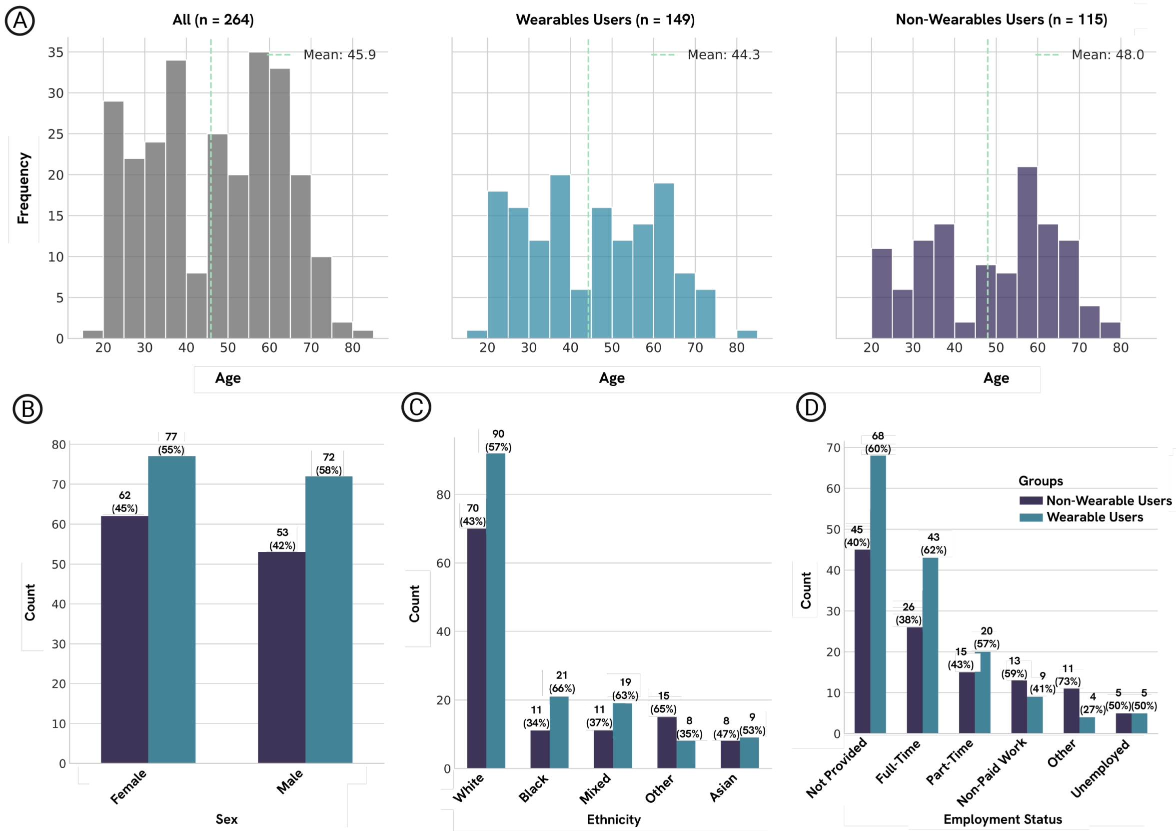

Fig. 2. Summary of demographic information for 264 participants (149 wearable users and 115 non-users): (A) Age distributions of all users (left), wearable users (middle), and users who do not use wearable devices (right). Wearable users have a lower mean age, compared to non-wearable users, though the difference is not statistically significant; (B) Sex distribution for wearable users and non-wearable users; (C) Ethnicity distribution for wearable users and non-wearable users; and (D) Employment status distribution for wearable users and non-wearable users. Wearable users are younger than non-users, highlighting the need to account for baseline demographics in understanding technology adoption.

both OCI-R and OCD. To the best of our knowledge, while prior work has used wearable devices for inferring and detecting OCD traits [49, 125, 141], the prevalence of differences between wearable users and non- wearable users for OCD symptoms, has not been discussed before. Further, when examining the clinical severity levels (Figure 3D), we found that wearable users were considerably more prevalent in the moderate (14% *vs.* 3%) and severe (3% *vs.* 0%) symptom categories. In contrast, non-wearable users were more likely to be categorized in the minimal (78% *vs.* 66%). These results suggest that, individuals with a greater tendency for obsessive-compulsive traits are more likely to be wearable users or vice versa.

Finally, we compared the five personality traits between the two groups using the Mini-IPIP questionnaire (Figure 3F). The most prominent difference was observed in the Neuroticism trait. The wearable users scored lower on Neuroticism than their non-user counterparts (p>0.05). For the other four traits, Extraversion, Agreeableness, Conscientiousness, and Openness, no statistically significant differences were found, and wearable users had higher scores, compared to non-users. This finding suggests that while the groups share similar personality

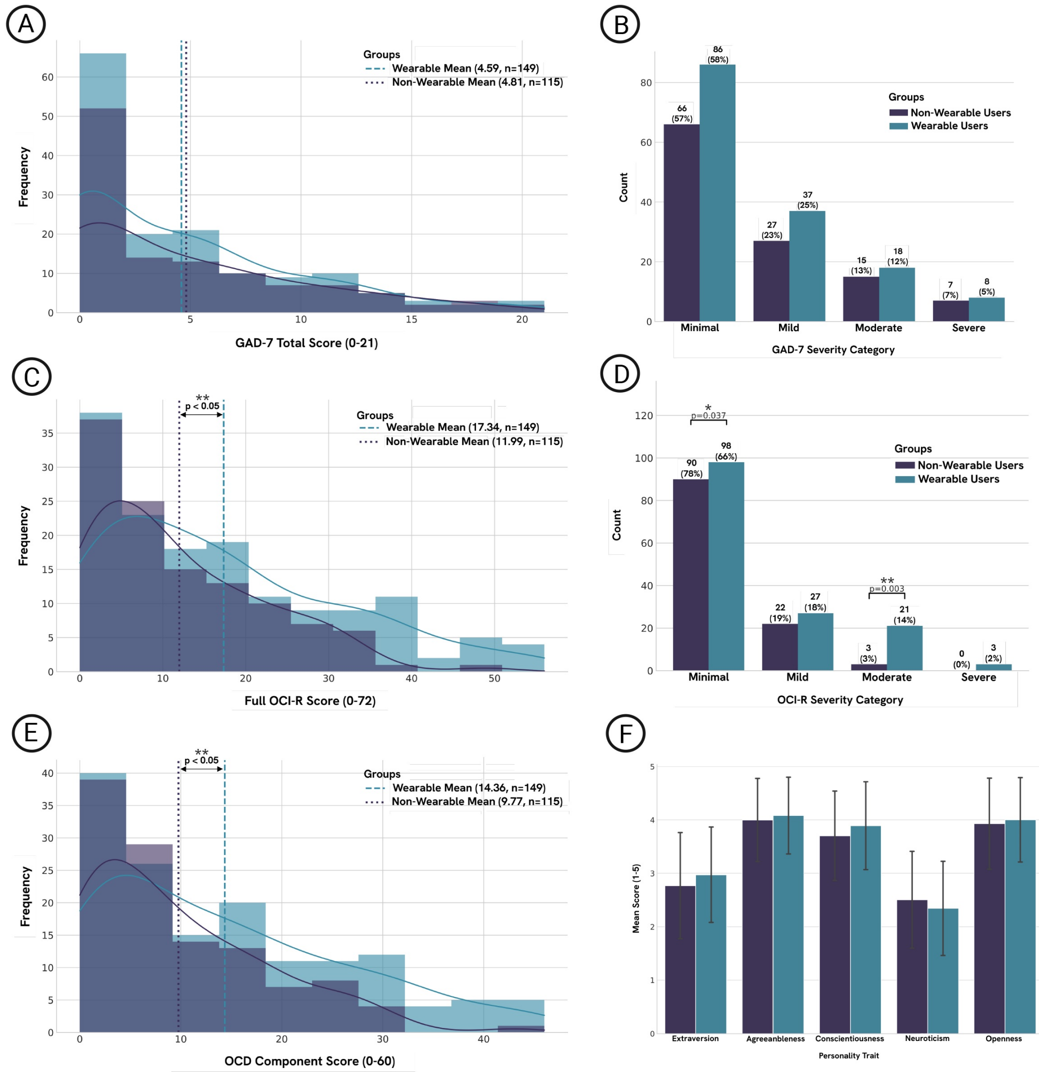

Fig. 3. Validated instruments administered to 149 wearable users and 115 non-users. (A) GAD-7 score distributions; (B) GAD-7 severity categories; (C) OCI-R score distributions; (D) OCI-R severity categories; (E) OCI-R OCD component score distributions; and (F) mean Mini-IPIP trait scores (error bars denote variability). Brackets indicate between-group tests with Bonferroni-corrected p-values. Effect sizes are reported as rank-biserial correlation (r_{rb}) for Mann–Whitney U tests and Cramér's V (=ϕ for 2×2 tables) for chi-square tests; asterisks denote effect-size magnitude (not significance): * small (≥ 0.10), ** medium (≥ 0.30), and *** large (≥ 0.50), in line with [28]. Wearable users exhibit higher obsessive–compulsive traits on OCI-R measures than non-users (Bonferroni-corrected $p < 0.05$, the difference is statistically significant), while GAD-7 and Mini-IPIP show no statistically significant between-group differences.

profiles in other respects, a lower level of neuroticism (a trait characterized by emotional instability and a tendency to experience negative emotions) is a distinguishing characteristic of wearable users in this study population. However, prior work has conflicting findings regarding the role of neuroticism in technology adoption [10, 21, 79].

3.3 RQ2: Which wearable uses do users report as contributing to negative psychological impacts, and how prevalent are these experiences?

As discussed in Section 2, prior work has shown that wearables can produce negative psychological impacts, but it remains unclear which uses are most implicated and how often these experiences occur. Identifying feature-level patterns is crucial, since different functionalities (e.g., step counting versus calorie tracking) may be associated to very different psychological risks despite similar adoption rates. Hence, to address RQ2, we investigated which specific wearable uses are most frequently associated with negative psychological impacts.

Methods. We analyzed responses from wearable users along two complementary dimensions. First, we examined structured Likert-scale ratings where participants reported both the frequency of use and the perceived mental health impact of 15 common wearable uses (e.g., step counts, sleep tracking, calorie tracking, heart-rate alerts, inactivity reminders). Frequency data allowed us to assess which uses were most widely adopted; this adoption rate was calculated by counting users who reported using a feature '1-3 times a week' or more (Figure 4A). Impact ratings enabled us to identify uses disproportionately linked to negative psychological impacts by tallying the number of times each feature was explicitly marked as 'negative' or 'very negative' to their mental health (Figure 4B).

For the bubble plot visualization (Figure 4C), we computed two scores for each feature. A Wearable Usage Score (plotted on the X-axis) was derived by mapping categorical frequencies (e.g., 'never' to 0, '1-3 times/week' to 2, '4-6 times/week' to 5, '7+ times/week' to 7) and averaging these numerical scores across wearable uses. Similarly, a Psychological Impact Score was derived by mapping impact ratings (e.g., 'very negative' to -2, 'negative' to -1, 'neutral' to 0, 'positive' to 1, 'very positive' to 2) and averaging them. To highlight divergences between usage and impact, this score was then min-max normalized and inverted, creating the Psychological Impact Score (plotted on the Y-axis) where 1.0 corresponds to the most negative mean rating and 0.0 to the most positive, out of the wearable uses. The bubble size in this plot represents the number of users who provided a valid rating for each feature. The results are presented in Section 3.3.

Second, we analyzed open-ended text in which participants described positive and negative psychological experiences with wearables. These responses were thematically coded by two people, to identify recurring categories. In the first round of coding, 13 broader categories were identified, and in the second round, after accounting similarities of the categories, they were binned into 5 broad themes. This qualitative analysis provided richer insight into the lived experiences behind the structured responses and enabled us to capture harms that participants may have experienced but did not formally rate as negative. The results are presented in Section 3.3. To this end, by combining structured ratings with thematic analysis of free-text reflections, we aimed to develop a comprehensive account of which wearable uses users perceive as psychologically harmful, how frequently such harms are reported, and in what forms they manifest.

Findings Based on Likert Scale Responses. Overall, there were 21 wearable users who marked at least one wearable feature to have an association with their psychology negatively. Altogether, they marked 36 uses to be having a negative psychological impact on them. As shown in Figure 4A, the analysis of feature adoption revealed that step count tracking (82%), heart-rate monitoring (75%), and activity type and level tracking (72%) were the most widely used wearable use among participants. Other uses such as sleep tracking (56%), calorie tracking (53%), and stress monitoring (40%) were also popular, highlighting that the majority of participants engaged with wearables for both physical activity and broader health and wellness monitoring. This high adoption suggests that

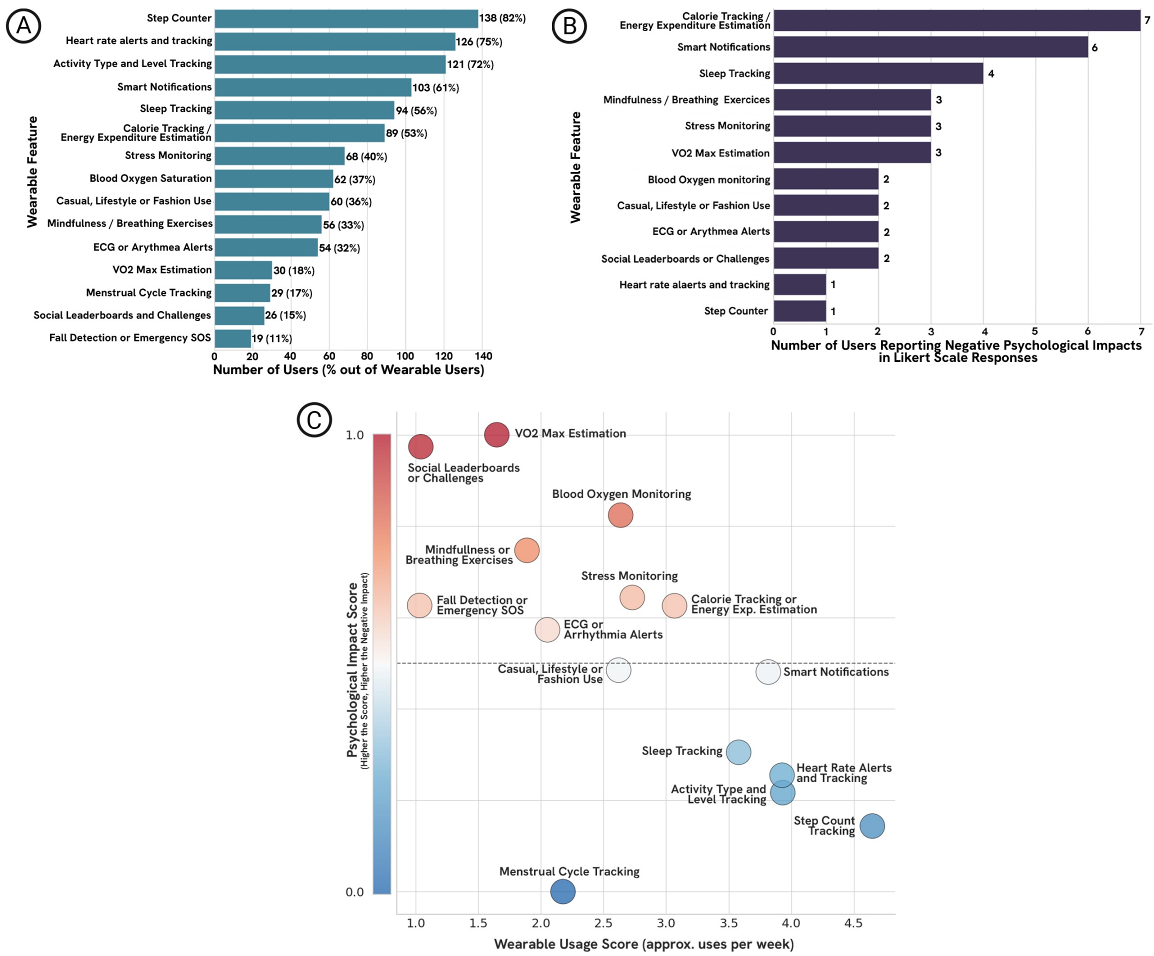

Fig. 4. The frequency of specific wearable uses and their negative psychological impacts among 149 wearable users: (A) Wearable uses (y-axis) plotted against the number of wearable owners who reported using each use (x-axis); (B) Wearable uses (y-axis) plotted against the number of wearable owners who reported experiencing a negative impact from each use (x-axis). This shows that the most widely adopted uses are not always those that show the highest number of negative impacts. (C) The wearable usage score, approximated based on mean frequency of each use among wearable owners (x-axis) plotted against the psychological impact score, calculated as the average of scores reported in the Likert-scale question. Higher the score, higher the negative psychological impact. The results show that the least frequently used features tend to be those with the most negative psychological impact.

reported psychological impacts may be related to repeated engagement with these uses. Further, when examining which uses participants explicitly rated as having a negative impact on them, calorie tracking/energy expenditure stood out as the most frequently cited source, followed by smart notifications and sleep tracking (Figure 4B). Interestingly, uses with the highest adoption (e.g., step counting and heart-rate tracking) were not necessarily those most strongly linked to psychological harm, suggesting that negative experiences are concentrated around specific kinds of functionality, particularly those tied to calorie tracking and constant digital prompts. Moreover, the bubble plot in of wearable usage score versus psychological impact score further clarifies these dynamics when taken together (Figure 4C). Wearable uses like social leaderboards or challenges and VO2 max estimation, had the highest psychological impact (meaning more negative impact), while also showing low mean usage. Further, calorie tracking/energy expenditure estimation, which had the highest number of negative psychological impact ratings (Figure 4B), had a moderate mean impact score (due to users also marking it as positively impacting them), for both usage and psychological impact. Together, these findings suggest that as a research community, we should pay particular attention to how wearables present social leader boards, how features such as VO2 max estimation and blood oxygen saturation are executed and presented, and manage notification intensity, as these uses appear to disproportionately linked to high negative psychological impact compared to others.

Findings Based on Free-Text Answers. Negative psychological impacts were reported across a wide spectrum of uses, even in the free-text responses provided by participants. We found 19 additional wearable users who did not mark any wearable feature negatively, providing free-text responses on negative psychological impacts they have had using different wearable uses. Based on our coding process (Section 3.3), across responses, five broad themes emerged. Appendix B provides a summary of these themes, with illustrative quotes from wearable users: *(i) Anxiety and worry.* Several participants reported that ambiguous or sensitive health feedback triggered anxiety. For instance, one participant explained: *"ECG warning generated anxiety because of false positives"* (66 yo, Female). She also described on stress from metrics such as blood oxygen monitoring by stating: *"overchecking caused stress as a result of blood oxygen monitoring"* (66 yo, Female). Similar concerns were raised about sleep scores and even mindfulness reminders, which occasionally added pressure rather than relief; *(ii) Guilt and pressure.* Activity reminders, calorie tracking, and goal-driven uses frequently elicited guilt or feelings of inadequacy when goals were missed. As one participant put it: *"Tracking calories makes me feel guilty"* (41 yo, Female). Another echoed this sentiment regarding reminders: *"I was pressurised and had a guilt feeling instead of being motivated"* (29 yo, Female). These responses reveal how wearables designed to encourage activity can instead become a source of judgment and pressure; *(iii) Obsession and compulsion.* For those with a history of disordered eating or perfectionism, calorie tracking and energy expenditure data contributed to unhealthy fixation. One user reflected: *"The calorie tracking was very negative because I developed an eating disorder while using it and I became obsessed"* (27 yo, Female). Similarly, sleep tracking encouraged hyper-vigilance, as captured by another user: *"Instead of listening to my body, I became obsessed with the sleep data, leading to performance anxiety around sleep itself"* (42 yo, Male); *(iv) False information and information overload.* Smart notifications were often described as intrusive, with one participant noting: *"I get overwhelmed by the smart notifications sometimes. It feels like I am constantly trapped into technology"* (26 yo, Female). Others highlighted the harm of social comparison, as one user commented: *"The competition takes away the focus on myself and mental health"* (56 yo, Female). Moreover, menstrual-cycle tracking and calorie estimation were also criticized for inaccuracies that undermined trust; *(v) Negative self-image.* Metrics such as VO_2-max, step counts, and calorie data sometimes left users feeling inadequate, lazy, or discouraged. A participant explained: *"VO_2-max estimation said I was lower than expected, which made me feel bad about how much I exercise"* (36 yo, Male). Another reflected on the demotivating effects of step counts: *"When I see my step count not be so high…I get hard on myself and feel like I didn't try hard enough"* (39 yo, Female). Such responses show how data, even when accurate, can foster negative self-perceptions about themselves.

Overall, these responses show that negative psychological impacts of wearables are multifaceted and often personalized. They depend not only on the technology's accuracy and sensitivity but also on the user's health status, prior experiences, and expectations. Taken together, our findings demonstrate that negative psychological experiences with wearables are not rare or idiosyncratic. In total, 40 participants (21 who explicitly selected negative Likert-scale ratings and an additional 19 who described harms in free-text answers) discussed psychological downsides of wearable use. This corresponds to roughly 1 in 4 users in our study (40 out of 149), a strikingly high proportion given the predominantly positive framing of wearable technologies in prior literature and marketing.

That so many participants volunteered or endorsed negative effects highlights the need for wearable design to move beyond simply maximizing engagement or accuracy, and instead actively mitigate risks of anxiety, guilt, compulsion, information overload, and harmful impacts on self-image. Addressing these concerns is essential if wearables are to promote long-term wellbeing rather than inadvertently undermining it.

4 LITERATURE REVIEW AND FINDINGS

In this section, we first provide the motivation behind the literature review (Section 4.1). Then, we provide the methodology for answering RQ3 and the findings (Section 4.2).

4.1 Motivation for the Literature Review

To answer RQ3, we systematically reviewed recent publications to determine if the wearable computing community's flagship venues are meaningfully addressing the negative psychological impacts of the technologies they introduce. While anecdotal and clinical evidence points to the five themes we identified in the user study, it remains unclear if these concerns have been discussed in the field's core research discourse. As venues, we selected IMWUT, ISWC, MobiSys, MobiCom, and SenSys. These represent the flagship venues of the wearable and mobile computing community, where innovations in sensing, interaction design, and system development are most often introduced. IMWUT (Ubicomp) and ISWC have historically been the primary publication outlets for human-centered wearable research. MobiSys, MobiCom, and SenSys are premier systems venues that showcase cutting-edge work on mobile sensing platforms and embedded systems, including wearables. Together, these venues capture the state of the art in both human-centered and systems-oriented wearable research, making them the appropriate lens for understanding how the community frames the benefits and risks of wearable devices.

4.2 RQ3: To what extent do recent wearable-focused publications in flagship mobile and wearable computing venues address negative psychological impacts?

Methods. We collected 782 papers published between 2024 and 2025 in five flagship wearable and mobile computing venues (IMWUT, ISWC, MobiSys, MobiCom, and SenSys). Manual screening of titles and abstracts identified 123 papers explicitly engaging with wearable devices, which formed the basis of our in-depth analysis.

To assess how the literature engages with user-reported psychological harms, we developed a coding schema with two paper-level dimensions: (i) whether the paper's primary objective is to understand, measure, or mitigate negative psychological impacts of wearable use; and (ii) whether the paper acknowledges any of the five negative psychological impact themes identified in our user study (binary presence/absence for each theme). We operationalized these dimensions in a code book with definitions and decision rules (e.g., distinguishing harms as a central research objective from harms noted only as limitations or background) and piloted the code book on an initial set of papers before full coding. Each paper received a label for primary objective and theme presence/absence, supported by extracted evidence (verbatim quotes or passages) used for verification. We used a frontier-scale large language model (Gemini 2.5 Pro) to support structured extraction of candidate harm-related text, candidate themes, and verbatim supporting excerpts into a constrained JSON format. Consistent with prior LLM-assisted hybrid annotation work in HCI and social computing [91, 120, 121], any paper flagged as engaging with a harm theme was verified by the research team by locating the extracted evidence in the PDF and confirming that (a) the quote was faithful and (b) the assigned theme label was warranted.

To validate reliability, two independent annotators manually coded a random 20% subset (24/123 papers) using the codebook and assessed agreement for the primary objective label and theme presence/absence. There were no disagreements in this subset, yielding 100% agreement on the paper-level labels. Theme labels matched manual judgments for 23/24 papers; the remaining case involved a borderline mention that we resolved via adjudication and carried forward into the full-corpus verification process. We further strengthened validity using OpenAI's

GPT-5.2 Thinking as an LLM-as-a-judge [54]. GPT-5.2 was prompted to apply the same rubric to determine which papers qualify as explicit focus without access to Gemini's prior labels or extracted evidence. For the explicit focus selection used in Table 1, GPT-5.2 produced 100% agreement with Gemini 2.5 Pro. For brief mentions, the two models occasionally surfaced different supporting excerpts, which triggered targeted manual validation and adjudication for all papers flagged by either model. When evidence was ambiguous, we re-checked the original PDFs and required an explicit, verifiable excerpt to retain a label of brief mention; otherwise, the paper was downgraded from brief mention to none. The final counts reported reflect these post-adjudication results.

Finally, we summarized each paper's engagement with negative psychological aspects into three levels: *none* (no mention of harms), *brief mention* (harms acknowledged but not a primary focus), and *explicit focus* (harms are a central research goal). This classification quantifies both the prevalence and depth of engagement with negative psychological impacts. We also grouped frequently recurring non-theme concerns (e.g., privacy anxiety) from the extracted evidence to characterize which types of harms the community most often foregrounds.

Findings. Our user-centered inquiry in Section 3.3 identified five core negative psychological themes associated with wearable technology: anxiety and worry, guilt and pressure, obsession and compulsion, false information and information overload, and negative self-image. This section now systematically maps the recent top-tier wearable and mobile computing literature against these themes. Our objective is to quantify the gap between the research community's stated priorities and the lived, psychological harms experienced by users, thereby identifying critical blind spots for future work.

Prevalent Research Focus: A Disconnect from Core Psychological Harms. Our extensive review reveals a consistent disconnect. The community's research agenda does not align with the core psychological harms users report. Instead, the field's attention is overwhelmingly directed toward two other areas: (1) externally observable social challenges, and (2) technically tractable systems-level problems. A significant body of work focuses on externally-facing issues such as social discomfort and privacy. Researchers address the stigma of public wearable use or the fear of data leakage [149]. For example, the "unvoiced" wearable interface is motivated by mitigating the significant negative psychological impacts of conventional VUIs such as social discomfort and privacy issues. This focus is echoed in studies of voice assistants where social discomfort and privacy issues significantly influence users' perceptions and willingness to adopt the technology [134]. Privacy related anxiety is a common theme [22, 39, 56, 105], even covered by recent reviews [99]. Consequently, a substantial body of work centers on mitigating these risks through technical solutions like preventing eavesdropping or inference attacks [24, 154]. This focus persists because these problems are *tractable*: they are externally visible, easier to articulate, and solvable through novel interaction designs [149] or attack mitigation [29]. This creates a feedback loop that reinforces the importance of tractable problems while systematically sidelining less visible, internal psychological harms, or other similar problems. Further, it is interesting that privacy was not mentioned as a factor associated with negative psychological impacts to wearable users, during our user study.

Another well-covered research area concerns physical, ergonomic, and usability issues [55, 61, 151]. The form factor and material quality of wearable devices can lead to physical problems, a concern frequently flagged by researchers. For instance, studies on low-cost trackers [74] identify user reports of poor hardware quality such as watch bands that break easily, and even physical harm, including "burns, rashes, bumps, and bruises". User frustration with device limitations, particularly data or inference inaccuracy, is also a recognized issue [56, 105, 136]. However, an analysis of how these issues are framed reveals a different kind of problem. For instance, in [74], users often excuse these technical flaws and inaccuracies due to the low price, with one person stating, "at this price...its amazing!" even while questioning the data's reliability. The paper's core critique is that this focus on "affordability" is misleading. The problem with these low-quality devices is not simply that they might be abandoned; it's that their poor longevity and the frequent need to "replace the watches entirely, or discard the watch" create a significant and recurring financial burden. In this paradigm, the user's negative experience is often dismissed due to the low price, obscuring the fact that the devices may "not actually be cost effective" and disproportionately burden the very low-SES users they are intended to help.

Explicitly Focusing on Negative Psychological Impacts. Against this backdrop, only a small subset of studies directly focus on the psychological burdens users report. Of the 123 wearable publications, we identified only 5 papers (≈4.06%) that made one of our five themes a central research objective. The study by Lin et al. [82] directly investigated negative psychological outcomes from menstrual health tracking. They found that exposure to intimate health data could have negative consequences on how they regard their body image, particularly when users perceived their data as abnormal. This led to being burdened with worry and stress, and feeling anxious and concerned about a possible medical issue. The authors' recommendations explicitly aim to combat body-related anxiety and stigmatization. In another study, Lin et al. [83] directly address information overload, finding that the sensemaking process for complex health data is a significant source of psychological distress. The study notes that participants often felt overwhelmed by the data's volume and complexity, which led to disengagement and anxiety. Ley-Flores et al. [78] explicitly centers on negative self-image, framing negative body perceptions as the primary barrier to physical activity. Their co-design work explores how technology can transform body perceptions/sensations like feeling tired or heavy, treating the internal psychological experience as the central problem to solve. Ponnada et al. [107] directly tackle information overload by designing to mitigate the user burden associated with frequent self-reporting. Their μEMA system is explicitly evaluated on its ability to reduce cognitive and interruption burden, finding it was less burdensome than EMA ($p < 0.001$). This work operationalized psychological load as a primary metric. Finally, Yang et al. [149] focus on the anxiety and worry due to smartwatch privacy leaks. They frame the risk of data exposure as a significant psychological burden leading to anxiety for the smartwatch user and potential embarrassment. Their system is designed specifically to alleviate this psychological distress. The scarcity of such research is revealing. These five papers share a common trait: they employ methods outside the field's norm. They use studies focused on mental state [82], comparative evaluations with psychological constructs like user burden as primary metrics [107], and subjective measures of stress as critical outcomes [149]. To investigate these internal states, researchers must adopt qualitative depth, longitudinal observation, and direct psychological measurement, approaches more complex than standard system performance or model accuracy evaluations.

Incidental Mentions of Negative Psychological Impacts. Beyond these five focused studies, we found a pattern of widespread but surface-level awareness. Approximately one-quarter of the papers (38 of 123) contained at least a passing mention of issues like anxiety or worry or cognitive/information overload. These acknowledgments, however, were almost universally relegated to secondary points in discussion or limitations sections. More explicitly, 28 papers (≈24%) discussed to anxiety and worry, while 27 (≈23%) discussed themes related to false information and information overload. Some studies used tools like NASA-TLX to measure cognitive burden [23, 84] and others uses System Usability scale (SUS) to examine usability [151]. Beyond these, however, most mentions are brief and lack analysis. "False information" as a term appears only rarely, as an potential misdiagnosis in a health context [153], while it was differently formulated as inaccuracy of models or data. Critically, the other themes from our user study are almost entirely absent from the literature. We found no publications that substantively discuss users feeling guilty for not meeting goals or pressured by their devices. The concept of obsessive or compulsive overuse was never explicitly mentioned. The only indirect hint was a study noting participants worked to maintain step-count "streaks", but the authors did not frame this as a negative emotional outcome. This reveals a collective blind spot in the community. The location of these mentions is as significant as their content. By relegating "data overwhelm" to limitations or future work, authors perform a rhetorical maneuver: they demonstrate awareness while defining the problem as outside their scope. This practice creates a

Table 1. Coverage of the 5 user-reported negative psychological impact themes across 123 wearable-focused papers from flagship venues (2024–2025). The table categorizes the literature based on whether papers explicitly focused on the harm as a primary research goal or only briefly mentioned it, mapped across the 5 themes. This reveals a profound disconnect between users' lived experiences and the research agenda: while issues like cognitive overload and privacy anxiety receive brief mentions, major user-reported psychological harms due to wearable use, like guilt, pressure, and obsessive compulsion are rarely studied by the community.

Negative Psychological Impact Theme	**Papers with Explicit Focus** (as a primary research goal)	**Papers with Brief Mentions** (mentioned anywhere in the paper)
Anxiety and Worry (Stress, general anxiety about data/use)	3 papers explicitly studying or mitigating user anxiety/stress [82, 83, 149].	28 papers mention user anxiety or stress in some context, but not as a primary focus (e.g., noting stress from device alerts or failures). Many papers focused on anxiety regarding privacy.
Guilt and Pressure (Feeling pressured or guilty about device use or goals)	0 papers.	0 papers. No occurrences of themes around guilt and pressure.
Obsession and Compulsion (Device overuse or compulsive checking)	0 papers.	0 papers. No occurrences of themes like obsessive use, addiction, or compulsion were found.
False Information and Information Overload (Misleading data, information overload)	2 papers focusing on reducing cognitive overload in device interactions [83, 107].	27 papers briefly acknowledge overload or high cognitive load. A few (4) also note trust issues with data accuracy, in passing.
Negative Self-Image (Impact on self-esteem or body image)	2 papers explicitly examined negative self-image issues [78, 82].	3 papers.

systemic pattern of "acknowledged but deferred" problems. The community recognizes these issues exist but perpetually pushes their investigation into the future. The complete absence of themes like guilt and obsession reveals a disciplinary habit of acknowledging only some harms, while failing to accept responsibility for making any of them a central research priority.

Thematic Overview of the Research Gap. Our analysis concludes with a clear finding: a profound disconnect exists between the negative psychological impacts users experienced, and the problems the wearable computing community chooses to solve. Table 1 provides a quantitative summary of this gap, illustrating how the majority of user-reported psychological impacts are missing from the research agenda: anxiety and overload receive attention; guilt and pressure and compulsive behavior receive none at all. Even under anxiety, most studies focus on anxiety due to privacy concerns. This misalignment is not a simple oversight. It also represents an urgent call to action. The community must broaden its research agendas beyond technically tractable problems. It must embrace the methodological complexity required to design for holistic psychological well-being of the users it claims to serve, moving towards responsible development of wearable technologies.

5 DISCUSSION

Our findings reveal a considerable, yet largely overlooked aspect of the wearable technology landscape. While these devices are celebrated for their health benefits, they carry psychological harms that affect a substantial portion of users, approximately 1 in 4 in our study. This discussion section first provides a summary of results for each research question (Section 5.1), explores the implications of these findings for theory and practice (Section 5.2) and outlines the limitations of our work to guide future research (Section 5.3).

5.1 Summary of Results

Given below are the summary of results of our study, in response to the three research questions.

RQ1: Generally, wearable users were younger than non-users. We also found that wearable users and non-users reported similar distributions for generalized anxiety scores (GAD-7) and personality traits. However, wearable users scored significantly higher on obsessive-compulsive traits (OCI-R) compared to non-users.

RQ2: We found that negative psychological impacts are common, reported by approximately 1 in 4 of our wearable users (38 out of 149). While the most adopted uses were step counting (82%) and heart-rate monitoring (75%), the uses most frequently associated with negative psychological impacts were calorie tracking, smart notifications, and sleep tracking. These negative psychological impacts could be broadly categorized into five main themes: (1) anxiety and worry, (2) guilt and pressure, (3) obsession and compulsion, (4) false information and information overload, and (5) negative self-image.

RQ3: Our literature review of 123 relevant papers from five flagship venues (2024–2025) revealed a considerable disconnect between users' lived experiences and the research community's focus. The literature predominantly addresses external issues such as privacy anxiety and social acceptability. In contrast, the five psychological themes we identified were rarely the primary objective of a study. Only 5 of 123 papers (≈4.06%) had one of these themes as a central focus. Critically, themes of guilt and pressure and obsession and compulsion, which were prominent in our user study, were found to be absent from the academic discourse in wearable computing.

5.2 Implications

Theoretical Implications. This research challenges the techno-solutionist narrative in wearable computing that frames wearables as neutral tools for empowerment and behavior change. Our finding that wearable users exhibit significantly higher obsessive-compulsive traits than non-users complicates this view and raises a chicken-and-egg question: are people with pre-existing compulsive tendencies more drawn to wearables, or do continuous tracking and feedback loops foster or exacerbate these tendencies? While our cross-sectional design cannot determine causality, the results suggest a feedback loop in which psychological predispositions and device uses may amplify one another, a dynamic that is often under-specified in theories of technology use.

Our five themes of negative psychological impact contribute a user-grounded taxonomy of psychological harm that extends beyond prominent prior concerns (e.g., orthosomnia or privacy anxiety) to more everyday burdens. The prevalence of guilt and pressure, in particular, points to an experience of algorithmic judgment, where users interpret device-set goals and feedback as a standard for personal adequacy. This aligns with Lupton's sociological framework [87], which argues that self-tracking devices often function as moralizing agents that enforce ideals of self-responsibility, ultimately producing guilt when digital goals are unmet. Hence, this suggests HCI theories should account not only for technology as an informative tool, but also for how feedback can be internalized as self-evaluation. For example, dominant adoption frameworks such as the Technology Acceptance Model (TAM) and UTAUT explain use primarily through perceived usefulness, ease of use, and social influence [32, 140]. These models are not designed to explain why users may continue engaging with wearables while experiencing guilt, pressure, or compulsive checking, nor how system feedback becomes internalized as self-judgment. Likewise, influential HCI frameworks for behavior change and self-tracking, including persuasive technology and persuasive systems design [48, 102], largely treat goals, reminders, and feedback as mechanisms for intended outcomes, with limited conceptual vocabulary for when these same mechanisms become moralizing, coercive, or harmful. Personal informatics models describe iterative cycles and breakdowns in everyday tracking [40, 41, 80, 114], but they often frame negative experiences as frictions that lead to adjustment or abandonment, rather than as sustained psychological burdens that can co-exist with continued use. Finally, our literature review points to a blind spot in the wearable computing research community. The near absence of attention to themes like guilt and pressure and obsession and compulsion in top-tier venues suggests that the field's definition of harms has been narrow, often centered on privacy breaches or usability issues. We argue that psychological well-being should be treated as a first-order evaluation outcome, on par with accuracy, battery life, and engagement.

This gap is particularly clear, when contrasted with the trajectory of related HCI communities. Venues such as CHI, CSCW, and MobileHCI have increasingly engaged with Responsible AI (RAI) broadly, including harm taxonomies that explicitly include psychological distress, manipulation, and addiction as risks to mitigate [7, 81]. Our analysis suggests flagship mobile and wearable venues have not yet adopted a similarly holistic framing. While privacy and security are addressed [99], they are often treated as isolated challenges rather than as part of a broader responsibility for user well-being. Given that roughly 1 in 4 users reports at least one negative psychological impact from wearable use, and that entire categories of user-reported harm remain largely absent from research discourse, a shift toward this broader lens is overdue. A Responsible AI perspective would push the community to move beyond system performance and engagement, to treat psychological consequences as central, measurable outcomes that must be designed for, evaluated, and mitigated.

Practical Implications. Our findings have direct implications for the research community, designers, users, and clinicians, each of whom can help reduce psychological harms. The most immediate implication is for the wearable computing research community. A practical step forward is to broaden what counts as success: beyond accuracy, engagement, and battery life, researchers should treat psychological well-being as a first-order evaluation outcome. Concretely, this means incorporating validated instruments for anxiety, guilt, compulsion, and negative self-image into user studies, and treating harm reduction as a core research objective rather than a post-hoc limitation.

For designers and developers, our results challenge the common assumption that more data and more engagement are always better. Many high-engagement features that have a relation with negative psychological impacts in our findings include gamified loops, constant notifications, and immediate, granular statistics. Designers can mitigate these risks through concrete trade-offs. To reduce obsession and compulsion associated with constant access to metrics (e.g., checking sleep scores immediately upon waking), a practical approach is to introduce *compassionate friction*: present an initial qualitative summary (e.g., "It seems you had a restful night") and require intentional action to view granular scores, creating a small buffer that supports mindful engagement over compulsive checking. To reduce guilt and pressure linked to rigid, device-set goals and evaluative feedback (e.g., rings and streaks), interfaces can shift from prescriptive targets to reflective insights. Rather than framing a missed goal as failure, the system can contextualize low-activity days as compatible with recovery and well-being (e.g., "You've had a less active day. Rest is part of recovery"). To reduce anxiety and worry triggered by ambiguous alerts (e.g., false-positive ECG or SpO_2 warnings), designers should aim for "calm" and contextualized data: alerts should explain what the reading means, its common causes and uncertainty, and a clear next step (e.g., "This can be caused by... Try measuring again in a few minutes"). Recent work on contextualizing passive sensor data with large language models points in this direction [69].

For wearable users, our findings underscore the value of mindful engagement. Recognizing that anxiety, guilt, or compulsion can be tied to specific device uses can help users make informed choices: disabling certain notifications, hiding anxiety-provoking metrics, adjusting goals, or taking short "data holidays" to reconnect with internal cues rather than relying exclusively on device feedback.

For clinicians and mental health professionals, our findings serve as a practical alert: wearable use can amplify anxiety, obsessive thoughts, or disordered eating, and the elevated obsessive-compulsive traits among wearable users reinforces this risk. Clinicians can incorporate brief screening questions into intake and follow-up (e.g., "Do you use a fitness tracker? How do its notifications and goals make you feel?") to help patients identify whether tracking is supporting wellness or maintaining distress. Beyond screening, our results motivate a stepped, harm-reduction approach. When distress appears closely tied to a specific wearable function (e.g., sleep scoring, calorie targets, frequent alerts), a pragmatic first step is to reduce exposure by adjusting settings (e.g., disabling notifications, hiding evaluative scores, turning off weight/calorie goals), consistent with documented coping strategies where users selectively disengage from problematic features after negative incidents [111]. If symptoms persist or tracking becomes part of symptom maintenance (e.g., compulsive checking in orthosomnia), a time-limited pause from tracking may help interrupt the feedback loop and refocus on symptom-based goals, aligned with clinical accounts of orthosomnia and with personal informatics work describing "lapses" and temporary breaks as common, functional practices [15, 42, 80]. Prior personal informatics work further shows that lapses are a common stage of tracking and that guilt and frustration can shape which feedback styles feel supportive during re-engagement [40]. In higher-risk contexts (e.g., eating-disorder symptoms or body-image concerns), discontinuing calorie- and weight-focused tracking altogether may be warranted, given evidence that calorie counting and fitness tracking tools are associated with eating-disorder symptomatology and can trigger or exacerbate disordered behaviors [37, 77, 131].

5.3 Limitations and Future Work

This study has several limitations that motivate future research. First, our literature analysis covered only five flagship wearable and mobile computing venues over a two-year period (IMWUT, ISWC, MobiSys, MobiCom, and SenSys), which may miss relevant work on psychological harms. Broader top-tier HCI venues such as CHI may discuss negative impacts in ways not reflected in our venue set [30, 38, 109]. We focused on agenda-setting venues that most directly shape wearable computing norms and evaluation practices, but we also conducted a supplementary analysis of CHI papers from 2024 and 2025 (Appendix D). From 2307 papers, we identified 46 wearable-related papers; using the same coding approach, we found no papers with an explicit focus on our five harm themes and only two papers with brief mentions (Table 4). A broader cross-venue comparison remains important future work. Second, our survey sample, while broadly representative, was recruited from an online platform and may still reflect sampling biases. Third, our user study used a focused set of validated instruments to assess anxiety, compulsive tendencies, and personality. While deliberate, this set is not exhaustive: our qualitative findings highlight themes such as negative self-image and guilt that could be captured more directly with additional validated scales (e.g., regarding body image, perfectionism, or disordered eating tendencies). Finally, our cross-sectional design prevents causal claims about wearable use and psychological traits.

Because our measures reflect a single snapshot anchored to the past month, negative ratings may include transient annoyance or situational stressors rather than sustained harms. At the same time, longer-term impacts may be under-reported if participants had already adapted (e.g., disabling features, changing routines, or discontinuing use). Our prevalence estimates therefore reflect reports within the survey window, and our use-level patterns are self-reported associations that may change over time. Longitudinal and repeated-measures designs are needed to distinguish short-lived irritations from persistent harms and to capture trajectories of adaptation and coping. Further, all psychological outcomes in RQ2 are self-reported and may be influenced by recall effects, attribution biases, or differences in item interpretation. Triangulation with complementary data (e.g., device interaction logs, wearable- and phone-sensed behavioral signals, or longitudinal follow-ups) would strengthen claims about persistence and severity and help separate momentary reactions from enduring impacts. Finally, our venue meta-analysis relies on an LLM-assisted coding pipeline and may miss some relevant discussions, especially when harms are described implicitly. We therefore interpret our estimates as conservative lower bounds on explicit engagement. We mitigated this risk with a quote-anchored, paper-level rubric, a 20% manual reliability check (100% agreement), and an independent LLM-as-a-judge pipeline, as mentioned in Section 4.2.

Building on these limitations, several directions are especially important. First, future work should move beyond correlation to study causality through longitudinal designs that track individuals from before adoption through months or years of use, clarifying whether certain traits predict adoption or intensify with use. Second, the community should design and test features intended to mitigate psychological harm, ideally with users and clinicians such as interfaces that soften feedback during high-stress periods, mechanisms that encourage breaks from tracking, and goal-setting that prioritizes self-compassion over rigid targets. Third, our survey also captured smartphone-based health tracking (outside the scope of this paper); direct comparisons between wrist-worn, always-on tracking and intentional, app-based engagement are needed. Fourth, replication in more diverse demographic, cultural, and clinical populations remains essential, including adolescents and people with diagnosed mental health conditions who may be particularly vulnerable, and samples beyond the United States. Finally, future work should develop and validate more nuanced measures of psychological impact that go beyond engagement to capture constructs such as data-induced anxiety, goal-related guilt, and compulsive checking behaviors, enabling more consistent evaluation of both benefits and harms.

6 CONCLUSION

This paper provides evidence that the negative psychological impacts of wearable device use are not anecdotal, but a common user experience, reported by roughly one in four wearable users in our study. The negative impacts users suggested are ranging from anxiety and guilt to obsession. Our findings also establish a critical disconnect: the very harms users report most frequently are the ones least acknowledged by the wearable computing research community, which has demonstrated a significant blind spot, particularly concerning the emotional burdens of guilt and compulsive use. We call on the research community to move beyond a narrow focus on technical accuracy and behavioral benefits and to embrace psychological well-being as a central pillar of design and evaluation of wearable technologies. By acknowledging and actively mitigating these unquantified costs, we can begin to create wearable technologies that holistically support a healthier life.

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A DEVICE USE STATISTICS

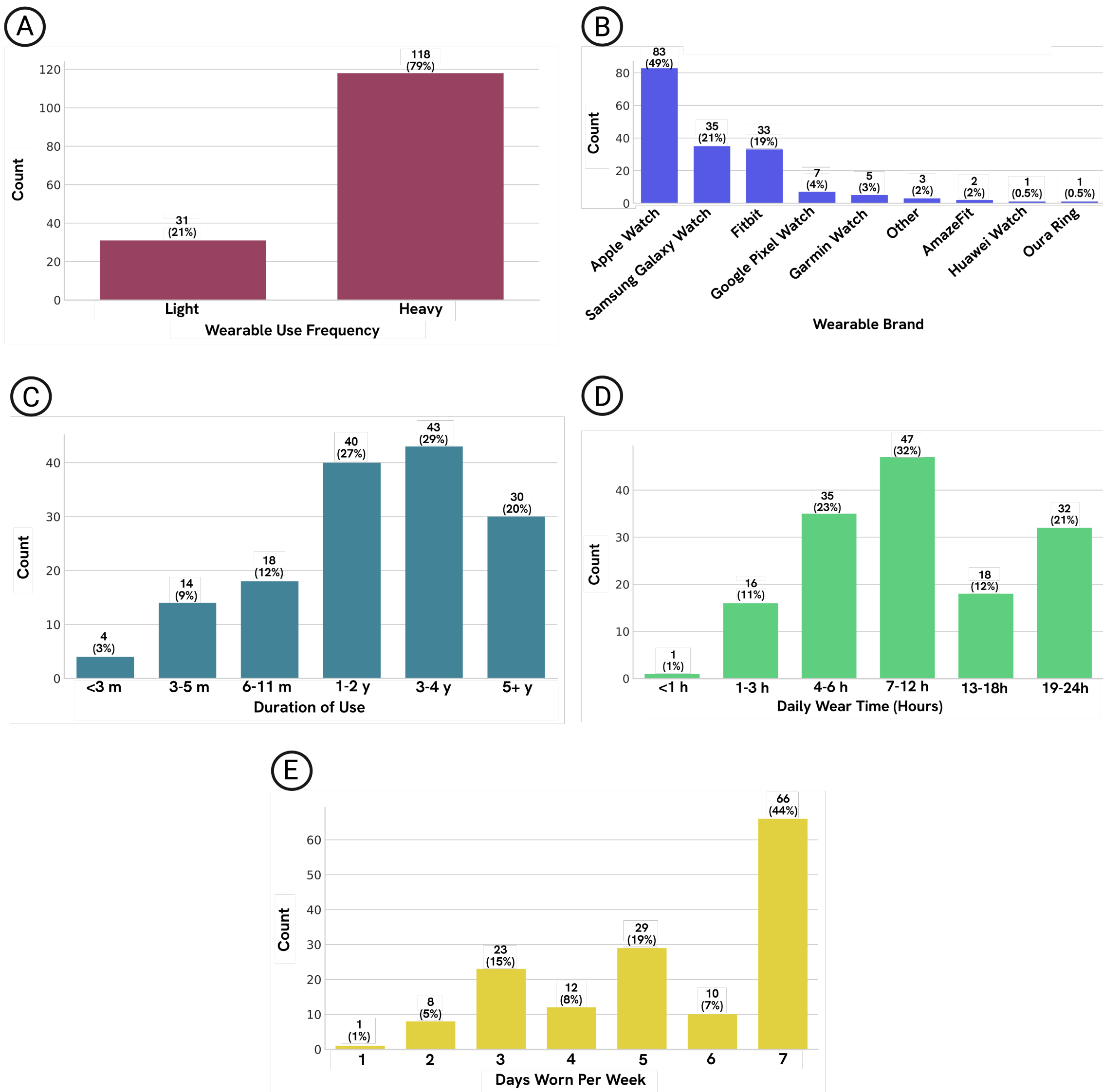

Fig. 5. Self-reported wearable device usage patterns among the 149 wearable users: (A) The count of users (y-axis) plotted against their self-reported wearable use frequency (x-axis), categorized as 'Light' or 'Heavy'; (B) The count of users (y-axis) plotted against the wearable brand they own (x-axis); (C) The count of users (y-axis) plotted against the total duration of use (x-axis); (D) The count of users (y-axis) plotted against their average daily wear time in hours (x-axis); (E) The count of users (y-axis) plotted against the number of days per week the device is worn (x-axis). Overall, the data indicates that the majority of participants are highly engaged heavy users who wear their devices continuously throughout the week, underscoring that the reported psychological impacts stem from chronic, daily integration of these technologies.

B FIVE THEMES OF NEGATIVE PSYCHOLOGICAL IMPACTS

Table 2. Summary of the 5 core themes of negative psychological impacts derived from the free-text responses of wearable users. Negative impacts are often deeply personalized and feature-specific, demonstrating how rigid system goals and evaluative metrics can transform fitness tools into sources of algorithmic judgment and psychological distress.

Theme	**Feature(s)**	**Illustrative Quotes**
Anxiety and Worry	ECG/arrhythmia alerts; Heart-rate alerts; SpO_2 monitoring; Stress monitoring; Sleep tracking; Smart notifications; Mindfulness/breathing reminders	*"ECG warning generated anxiety because of false positives"* (66 yo, Female); *"Overchecking caused stress as a result of blood oxygen monitoring"* (66 yo, Female); *"The heartrate monitor sometimes triggers my anxiety if my heart rate gets over like 200BP"* (25 yo, Male); *"Seeing a 'poor' sleep score created immediate anxiety and set a negative tone"* (42 yo, Male); *"Stress monitoring readings sometimes felt unnecessary and could cause worry if results looked unusual"* (34 yo, Male); *"Other times the mindfulness feature does irritate me and stresses me out even more"* (30 yo, Female)
Guilt and Pressure	Calorie tracking; Step counter; Activity reminders; Activity rings; Smart notifications	*"Tracking calories makes me feel guilty"* (41 yo, Female); *"I was pressurised and had a guilt feeling instead of being motivated"* (29 yo, Female); *"Sometimes when I am seeing my step count not be so high… it can be really discouraging"* (45 yo, Female); *"Constant notifications from fitness goals made me feel guilty or pressured on rest days"* (38 yo, Male); *"When I don't close the activity rings, I feel disappointed in myself"* (36 yo, Female)
Obsession and Compulsion	Calorie tracking; Sleep tracking	*"The calorie tracking was very negative because I developed an eating disorder while using it and I became obsessed"* (27 yo, Female); *"Calorie counts can cause me to start obsessing over calories burned"* (32 yo, Female); *"If it became a primary focus, calorie data could foster an unhealthy obsession with numbers"* (40 yo, Male); *"I became obsessed with the sleep data, leading to performance anxiety around sleep itself"* (42 yo, Male)
False Information and Information Overload	Smart notifications; Social leaderboards/challenges; Menstrual-cycle tracking; Calorie tracking	*"I get overwhelmed by the smart notifications sometimes. It feels like I am constantly trapped into technology"* (26 yo, Female); *"Smart notifications felt redundant and useless, just a nuisance overall"* (31 yo, Male); *"The competition takes away the focus on myself and mental health"* (56 yo, Female); *"Social leaderboards sometimes stressed me, as I felt pressured to compete"* (34 yo, Male); *"Menstrual Tracking… no tracking device or program has been accurate"* (40 yo, Female); *"The calorie checker may give inconsistencies and false results"* (33 yo, Male)
Negative Self-Image	Sleep tracking; Calorie tracking; VO_2-max estimation; Step counter	*"I consider my sleep tracking to be negative because I'm a chronic insomniac… It just depresses me a bit, about my self"* (54 yo, Female); *"As someone with a history of disordered eating… calorie counts can have a negative impact"* (32 yo, Female); *"VO_2-max estimation said I was lower than expected, which made me feel bad about how much I exercise"* (36 yo, Male); *"Step count showed me how lazy and not mobile I was… at first it made me feel bad"* (44 yo, Female); *"When I see my step count not be so high… I get hard on myself and feel like I didn't try hard enough"* (39 yo, Female)

C QUESTIONNAIRE

Table 3. Overview of the questionnaire administered to participants to evaluate wearable usage and its psychological impacts. The table details the specific survey constructs, including the 15 individual wearable features assessed, matrix-style response options for usage frequency and Likert-scale impact ratings, and open-ended text prompts for contextualizing mental wellbeing impacts. This structured survey design captures both the quantitative prevalence of specific feature adoption and the nuanced qualitative ways in which these features alter users' mental states.

ID	Question Text	Response Options
Wearable Usage	In a typical week during the past month, how often did you wear a smartwatch, wearable, or fitness band? *Description: Examples include Apple Watch, Samsung Galaxy Watch, Fitbit, Garmin, Google Pixel Watch, Huawei, AmazFit, Oura, Polar, Whoop, etc...*	(Single-choice) • 3 days per week or more • 1–2 days per week • Fewer than that per week • I do not use wearables
Wearable Brand	Primary wearable brand	(Multiple-choice) • Apple Watch • Samsung Galaxy Watch • Fitbit • Garmin • Google Pixel Watch • Huawei • AmazFit • Oura • Polar • Whoop • Other (Please specify)
Wearing History	How long have you used any wearable?	(Single-choice) • <3 mo • 3–5 mo • 6–11 mo • 1–2 y • 3–4 y • 5+ y

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Table 3 – continued from previous page

Short Title	**Question Text**	**Response Options**
Daily Wear Duration	Typical daily wear time	(Single-choice) • <1 h • 1–3 h • 4–6 h • 7–12 h • 13–18 h • 19–24 h
Wear Days	Days per week worn	(Single-choice) • 1 • 2 • 3 • 4 • 5 • 6 • 7
Wearable Feature Frequency	In a typical week during the past month, how often did you use each wearable feature? *Description: Hint: If you never used a feature or not heard about a feature, select 'Not applicable / Never used'. If you did not use the feature during the weeks of the past month, but have used it previously, select '0 times'.*	Response provided in a matrix **Scale (Columns):** • Not applicable / Never used • 0 times • 1–3 times per week • 4–6 times per week • 7 or more times per week **Items (Rows):** • Step count tracking • Activity type and level tracking • Heart-rate alerts and tracking • ECG or arrhythmia alerts • Sleep tracking • Stress monitoring • Blood-oxygen (SpO2) monitoring • VO2 max estimation • Menstrual cycle tracking • Calorie tracking or energy expenditure • Fall detection or Emergency SOS • Mindfulness or breathing exercises • Social leaderboards or challenges • Smart notifications • Casual, lifestyle or fashion use

Continued on next page

Table 3 – continued from previous page

Short Title	**Question Text**	**Response Options**
Psychological Impact	Overall, how would you describe each wearable feature's impact on your mental well-being?	Response provided in a matrix **Scale (Columns):** • Very Negative • Negative • Neutral • Positive • Very Positive **Items (Rows):** *(Same items as 'Wearable Feature Frequency')*
Impact Explanation	Explain (atleast 200 characters) how one or more wearable features you rated (from very negative to very positive) influenced your mental wellbeing. *Description: Give specific examples, including the feature name, the situation, and how the feature affected you*	(Open-text) Min. 200 characters.

D ANALYSIS OF CHI PAPERS FROM THE LAST TWO YEARS

Table 4. Analysis of the 5 negative psychological impact themes across 46 consumer health-tracking wearable papers published at CHI (2024–2025). This table maps whether papers included explicit focuses or brief mentions of the 5 themes. Consistent with the flagship mobile and wearable computing venues, the broader HCI literature exhibits a blind spot, yielding zero papers primarily focused on these core psychological harms and only passing mentions of cognitive burden.

Negative Psychological Impact Theme	**Papers with Explicit Focus** (as a primary research goal)	**Papers with Brief Mentions** (mentioned anywhere in the paper)
Anxiety and Worry (Stress, general anxiety about data/use)	**0 papers.**	**2 papers [138, 145].** Brief mentions are primarily privacy-related anxiety/stress or patient anxiety in health-monitoring contexts.
Guilt and Pressure (Feeling pressured or guilty about device use or goals)	**0 papers.**	**0 papers.**
Obsession and Compulsion (Device overuse or compulsive checking)	**0 papers.**	**0 papers.**
False Information and Information Overload (Misleading data, information overload)	**0 papers.**	**1 paper [145].** One paper briefly notes cognitive load / fatigue burdens; however, the burden discussed pertains to clinician-facing or bystander-facing alerts rather than wearer self-evaluative harms.
Negative Self-Image (Impact on self-esteem or body image)	**0 papers.**	**0 papers.**

We conducted a supplementary analysis of CHI 2024 and CHI 2025 to assess whether broad HCI venues engage with the same user-reported negative psychological themes. We first extracted wearable-related CHI papers (N=46) from the full CHI proceedings of the last two years (N=2307) using our wearable paper filtering procedure. To match the scope of this paper, we then restricted to consumer-grade wearables (e.g., smartwatch/fitness tracker/ring use for activity, sleep, stress, or cardiovascular tracking), excluding out-of-scope wearable categories (e.g., AR glasses, fabrication sensors, EEG devices, etc.). We applied the same quote-anchored coding protocol and theme mapping as in RQ3. As shown in Table 4, we find no CHI papers with an explicit focus on our five harm themes, and only two papers containing brief mentions related to Anxiety and Worry and False Information / Information Overload.