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Exploring Lifestyle Pressures and Expectations Induced by Continuous Health Monitoring

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A B S T R A C T

This study aimed to explore the lived experiences of individuals using continuous health monitoring technologies, with a focus on how these tools shape lifestyle pressures, behavioral expectations, and psychological responses. A qualitative exploratory design was employed, utilizing semi-structured interviews with 24 adult participants residing in Hungary who had used wearable or app-based health monitoring tools for at least six months. Participants were selected through purposive sampling to ensure diversity in age, gender, and health status. Data were collected until theoretical saturation was reached. Interviews were transcribed verbatim and analyzed thematically using NVivo 12 Plus software. The analysis followed a three-phase coding process: open coding to generate initial concepts, axial coding to identify thematic relationships, and selective coding to consolidate core categories. Five central themes emerged from the data: (1) data-driven identity and self-worth, in which participants linked their personal value to metrics and digital achievements; (2) emotional consequences of health surveillance, including anxiety, guilt, and frustration tied to device feedback; (3) behavioral conformity and goal obsession, reflecting compulsive engagement with digital targets; (4) loss of autonomy and bodily intuition, where users reported diminished reliance on internal cues; and (5) social surveillance and self-regulation fatigue, marked by perceived peer judgment and performance pressure. These findings suggest that continuous monitoring, while intended to promote health, may also contribute to psychological burden and lifestyle rigidity. Continuous health monitoring technologies have the potential to enhance preventive care but may simultaneously induce emotional distress and behavioral dependency. To support well-being, future designs must integrate adaptive feedback, contextual sensitivity, and emotional support mechanisms to mitigate unintended psychosocial consequences.

Keywords: *continuous health monitoring; digital health; lifestyle pressure; wearable technology; qualitative study; self-tracking; psychological impact.*

1. Introduction

In recent years, continuous health monitoring technologies—such as wearable devices, mobile health (mHealth) applications, and remote sensor systems—have rapidly reshaped the way individuals manage and interact with their health data. Continuous health monitoring is often framed within the preventive paradigm of modern healthcare, with a strong emphasis on hypertension management, metabolic risk reduction, and cardiovascular optimization. Numerous studies have underscored the efficacy of these tools in promoting early detection of hypertension, tracking blood glucose, and encouraging physical activity adherence across various demographic groups (1-3). These systems are also lauded for improving communication between patients and healthcare providers, enhancing decision-making in both hospital and community-based settings (4, 5). In resource-limited contexts, digital monitoring applications have been effectively deployed to optimize hypertension control and reduce clinical burden through home-based surveillance and telehealth integration (6-8). However, while these studies have largely focused on biomedical outcomes and user adherence, there remains a growing concern about the psychological and social implications of these devices in everyday life.

Emerging research reveals that the use of continuous monitoring technologies is not always experienced as empowering. Instead, it can impose normative expectations regarding what constitutes “healthy behavior,” often quantified through step counts, calorie deficits, sleep scores, and heart rate variability (9-11). These metrics, though seemingly objective, may condition users to evaluate their self-worth through numerical targets and externally imposed feedback loops, creating a performance-driven lifestyle that emphasizes control over wellness. In a systematic review on self-monitoring among hypertensive patients, many reported experiencing frustration, stress, and guilt when failing to meet app-generated goals—particularly when those goals felt misaligned with their lived realities or physical capacities (10). Likewise, Du et al. found that users of lifestyle-monitoring apps often internalized algorithmic evaluations, leading to heightened anxiety and reduced intrinsic motivation (9).

This internalization process appears to be intensified by the gamification and social comparison features built into many mHealth platforms. Competitive leaderboards, streak tracking, and “achievement badges” can foster both motivation and psychological strain, depending on individual differences and contextual factors (3, 5). Rather than supporting autonomy, such mechanisms may promote hypervigilance, compulsive behavior, and social performance anxiety. Several studies also highlight that this feedback architecture disproportionately affects young adults and urban populations, where identity construction is increasingly tied to digital representations of health and productivity (12, 13). Among adolescents and university students, in particular, continuous tracking systems have been associated with disordered eating patterns, sleep disturbances, and a loss of bodily intuition (14, 15).

These behavioral and emotional outcomes are further shaped by sociocultural and economic contexts. In low-income and marginalized populations, the adoption of self-monitoring tools can be mediated by limited digital literacy, fear of judgment, or a sense of disempowerment in the face of data-centric expectations (16). A recent study by Shamsuddin et al. in Kuala Lumpur’s urban poor communities emphasized that lifestyle-promoting tools must be complemented by community-based education and empowerment to avoid reinforcing health inequities (16). Similarly, the work of Sidarta et al. and Somantri et al. in Indonesia underscores that community-led health measurement initiatives are most effective when they account for local beliefs and psychosocial dynamics, rather than relying solely on technological intervention (15, 17). These findings suggest that the impact of continuous health monitoring is not merely individual, but deeply embedded in cultural, socioeconomic, and relational contexts.

From a developmental and aging perspective, continuous monitoring may serve distinct functions. In elderly populations, for instance, wearable monitoring tools have been associated with improved disease management and greater feelings of control; however, they also risk inducing stress due to perceived surveillance or technological burden (18, 19). Park et al. found that older users valued simplicity, emotional support, and personalized guidance over raw data presentation (18). Aydın and Aydin-Avci emphasized the importance of aligning digital interventions with users’ lifestyle realities, especially for managing chronic conditions in marginalized populations such as the elderly Romani community in Turkey (19). These insights reveal that while technological integration can enhance health promotion, it must be carefully tailored to the experiential and emotional landscapes of users across the lifespan.

The influence of continuous monitoring technologies extends beyond the physiological domain, contributing to an emergent culture of “datafied health,” where well-being is

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understood primarily through digital traces. As Khan et al. describe in their design-centered study, the future of hypertension care lies not only in precision technology but in human-centered frameworks that balance data with dignity and context (20). This balance is echoed in the work of Geerse et al., who argue for the co-design of care pathways that integrate user emotions, routines, and values into the tracking experience (21). Similarly, Tseng et al. and Atomi et al. emphasize that while cuffless monitoring and ECG-based estimates can improve real-time detection, their impact is ultimately shaped by how users interpret, react to, and internalize the data they receive (1, 22).

In light of these multidisciplinary insights, it becomes clear that the implications of continuous health monitoring extend far beyond usability and clinical efficiency. The integration of digital metrics into daily life shapes how individuals experience time, responsibility, and control over their health behaviors. While several studies advocate for integrating genetic, environmental, and lifestyle data for more personalized health promotion (23), it is equally important to understand how the perceived obligation to self-optimize may foster psychological vulnerability or reduce behavioral autonomy. Niu et al.'s research on genetic predisposition and lifestyle scoring highlights that predictive data may inadvertently reinforce deterministic thinking or unhealthy behavioral rigidity when not contextualized properly (23).

This study aims to build on the existing literature by exploring the subjective experiences of individuals engaging with continuous health monitoring technologies. Specifically, it investigates how such technologies create pressures, expectations, and psychological responses in users' daily lives. Using a qualitative design and drawing on the lived experiences of users in Hungary, this study seeks to answer: How do individuals experience and respond to the implicit and explicit pressures of continuous health monitoring systems?

2. Methods and Materials

2.1. Study Design and Participants

This study employed a qualitative exploratory design to examine individuals' lived experiences, perceived pressures, and behavioral expectations associated with continuous health monitoring technologies. The qualitative approach was selected due to its strength in capturing subjective meanings and complex emotional, social, and cognitive dimensions of human behavior. Purposeful sampling was used to recruit participants who had been actively using wearable health monitoring devices (e.g., fitness trackers, smartwatches, or mobile health applications) for at least six months. A total of 24 adult participants (aged 22–61) residing in various regions of Hungary were enrolled. Efforts were made to ensure diversity in gender, age, occupation, and health status to capture a wide range of perspectives. Recruitment was conducted through social media announcements and community health forums, followed by eligibility screening through an online questionnaire.

2.2. Data Collection

Data were collected through semi-structured, in-depth interviews conducted in Hungarian, either face-to-face or via secure video conferencing platforms, depending on participant preference and geographic location. An interview guide with open-ended questions was developed to facilitate discussion around participants' motivations for using monitoring tools, perceived expectations from self and others, lifestyle adjustments, emotional responses, and social comparisons. Sample prompts included: "How has tracking your health data affected your daily routines or decisions?", and "Have you felt pressure to meet specific goals set by your device or application?". Interviews ranged from 45 to 75 minutes and were audio-recorded with informed consent. Field notes were also taken to capture contextual and non-verbal cues. Data collection continued until theoretical saturation was achieved—that is, when no new themes or insights emerged from subsequent interviews.

2.3. Data Analysis

All interviews were transcribed verbatim and translated into English for analysis while preserving semantic integrity. NVivo 12 Plus software was employed to assist with data management and coding. A thematic analysis approach was applied, following Braun and Clarke's (2006) six-step framework: familiarization with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. Coding was both inductive and deductive—allowing for both the emergence

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of new insights and alignment with existing conceptual frameworks on digital health surveillance and lifestyle regulation. To ensure analytical rigor, two independent researchers coded a subset of transcripts, and discrepancies were resolved through consensus. Memos and reflexive journals were maintained to enhance credibility and transparency throughout the analytic process.

3. Findings and Results

A total of 24 participants (13 women and 11 men) took part in the study, all of whom were Hungarian residents between the ages of 22 and 61 (M = 38.4 years, SD = 9.6). The sample included individuals from diverse occupational backgrounds: 7 participants were employed in the health and fitness industry (e.g., trainers, physiotherapists), 6 worked in office-based professions (e.g., administrative staff, accountants), 5 were students, and the remaining 6 included retirees and self-employed individuals. In terms of educational background, 15 participants held a university degree, 6 had completed secondary education, and 3 had postgraduate qualifications. All participants had been using wearable health monitoring devices or apps for a minimum of six months, with 17 reporting daily use and 7 indicating usage several times a week. Additionally, 19 participants used wearable devices (e.g., smartwatches, fitness bands), while 5 relied exclusively on smartphone health apps. The duration of usage ranged from 6 months to 4 years, with a median duration of 18 months. This variation provided a broad spectrum of lived experiences relevant to the study objectives.

The initial phase of data analysis involved open coding, wherein interview transcripts were reviewed line-by-line to identify and label discrete concepts, experiences, feelings, and behaviors expressed by participants. This stage aimed to break down the data into manageable units of meaning by assigning descriptive codes that reflected participants' perceptions and responses to continuous health monitoring. Coding was conducted inductively, staying close to the participants' language, and was focused on recurring patterns, implicit expectations, lifestyle adjustments, psychological effects, and social implications. Each instance of a concept was coded, even if mentioned by only one participant, in order to preserve data richness. A total of 78 open codes were generated from the 24 interviews, representing diverse yet overlapping themes. The table below presents the open codes alongside interviewees who referenced them:

Table 1

Open Coding

Open Code	Participants (P#)	Representative Quote
Feeling obligated to meet daily step goals	P3, P6, P9, P14, P19, P21	"If I don't hit 10,000 steps, it feels like I failed the day."
Anxiety when missing health data	P1, P5, P8, P13, P17, P23	"When the tracker doesn't record my walk, I feel anxious, like it didn't count."
Increased guilt on inactive days	P2, P7, P12, P16, P18, P22	"I feel really guilty on rest days, even when I know I need them."
Comparing scores with friends	P4, P10, P11, P15, P20	"I always check how my stats compare to my gym friends. It's addictive."
External validation through app achievements	P6, P13, P19, P24	"Getting those badges makes me feel seen. Like someone is clapping for me."
Avoiding social events to maintain calorie balance	P3, P9, P11, P18	"Sometimes I skip dinners out just to keep my app numbers clean."
Pressure to present a "fit" digital identity	P5, P8, P12, P20	"I feel like my fitness app profile is who people think I am now."
Self-judgment based on weekly metrics	P1, P2, P14, P22	"If the weekly report is bad, I feel bad about myself too."
Daily weight tracking compulsion	P7, P10, P21	"I can't start my day without checking my weight—even if I know it's not healthy."
Constant sleep quality monitoring	P4, P13, P17, P23	"I wake up and check my sleep score before I even get out of bed."
Fear of being perceived as lazy	P6, P9, P15, P19	"I don't want others to think I'm slacking when they see my stats."
Motivation loss when progress plateaus	P3, P11, P16, P20	"When the graphs stop going up, I lose all motivation."
Feeling watched by the device	P1, P5, P8, P14	"It's like having a coach in my wrist, judging every move."
Setting unrealistic health goals	P2, P6, P10, P18	"The app suggests goals that are just not realistic for my life."
Over-prioritizing numbers over well-being	P4, P7, P13, P21	"Even if I'm tired or sick, I still push for the numbers."
Disrupted sleep due to device notifications	P5, P11, P22	"I wake up just to check alerts—it's ruining my rest."
Eating habits dictated by calorie trackers	P2, P8, P16, P24	"I eat based on what the app allows, not on how hungry I feel."

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Emotional dependency on performance charts	P3, P10, P14, P19	"If my performance graph dips, my mood goes down with it."
Avoiding exercise without digital tracking	P6, P9, P17, P20	"I won't bother working out if I forgot my watch—it has to be recorded."
Perceived social ranking based on fitness apps	P4, P7, P12, P15	"There's a leaderboard, and I care way too much about where I am on it."
Device addiction or overreliance	P1, P5, P18, P22	"I don't trust myself anymore—I need the app to tell me how I'm doing."
Distrust in body's natural signals	P2, P10, P13, P21	"I stopped listening to my body—I only listen to the numbers."
Self-surveillance fatigue	P3, P8, P17, P23	"I'm tired of tracking everything—I just want to be free."
Competing with strangers online	P6, P11, P20, P24	"I join these challenges with people I don't know just to prove something."
Feeling penalized by algorithmic feedback	P4, P9, P14, P16	"The app gave me a bad rating even though I tried my best."
Skipping rest days due to app reminders	P1, P5, P12, P19	"Even on Sundays, the app says 'you're behind'—so I go run."
Changing eating patterns for app approval	P2, P8, P13, P20	"I eat smaller portions just so the app gives me a green check."
Using trackers to justify self-worth	P3, P10, P14, P18	"If I meet my goals, I feel like a better person. If not, I feel worthless."
Conflict between pleasure and performance	P7, P11, P17, P21	"Sometimes I want to enjoy a meal but then feel I betrayed my fitness."
Device-induced stress spikes	P4, P6, P9, P15	"The notifications stress me out more than they help me."
Planning life around digital goals	P1, P5, P16, P22	"I plan my walks, meals, even sleep based on the app's demands."
Becoming data-obsessed	P3, P7, P10, P23	"I check the stats 10 times a day. It's become compulsive."
Ignoring physical limits due to goal pressure	P2, P6, P12, P19	"Even with knee pain, I pushed through because the app said I was behind."
Replacing intuition with digital advice	P4, P8, P13, P20	"I let the app tell me when to rest or eat—even if I feel different."
Ritualizing morning metrics check	P5, P11, P14, P24	"First thing every morning: check weight, check sleep, check steps."
Obsessing over minor fluctuations	P1, P7, P17, P21	"A 0.3kg change ruins my mood for the day."
Disconnecting from bodily awareness	P2, P9, P12, P18	"I don't really feel my body anymore—I just follow the screen."
Prioritizing device notifications over body cues	P3, P6, P15, P22	"Even if I feel tired, I go out because the app says I should move."
Shame after failing streaks	P4, P8, P13, P19	"I lost my 30-day streak and felt ashamed, like I disappointed someone."
Hiding behaviors from tracking devices	P5, P10, P14, P20	"Sometimes I leave my watch off when I eat badly—I don't want to record it."
Constant need for self-improvement	P1, P6, P9, P16	"It's never enough. There's always a higher goal waiting."
Turning everyday activity into performance	P3, P7, P11, P17	"Even walking the dog becomes a race for points."
Emotional ups and downs tied to daily scores	P2, P5, P13, P21	"Good scores lift my mood. Bad scores ruin my day."
Feeling judged by algorithms	P4, P8, P10, P19	"The app acts like it knows better than me—it's always judging."
Perceived surveillance by others via shared apps	P6, P12, P14, P23	"I feel like people are watching me through the app's friend list."
Relying on streaks for motivation	P3, P7, P11, P18	"I only keep going because I don't want to break the streak."
Losing spontaneity in physical activities	P1, P9, P13, P22	"I can't go for a walk without thinking of the numbers now."
Rewarding self only when metrics align	P2, P5, P14, P20	"I only allow myself a treat if the app says I've earned it."
Using multiple apps for cross-checking data	P6, P10, P16, P24	"One app isn't enough—I check several just to be sure I'm doing okay."
App influence on mood throughout day	P3, P8, P12, P17	"How I feel depends on what the app tells me in the morning."
Resentment toward the device over time	P1, P4, P11, P21	"Sometimes I hate the device—but I can't stop using it."
Diminished intrinsic motivation	P2, P6, P9, P19	"I used to enjoy exercise—now I only do it to fill the rings."

The axial coding phase involved reassembling the data fractured during open coding by identifying relationships and patterns among the codes. During this stage, open codes were grouped into conceptual categories based on shared meaning, causal relationships, and underlying phenomena. These categories, or axial codes, represent more abstract dimensions of participants' experiences. The process aimed to link conditions (causal and contextual), actions/interactions (strategies), and consequences, thus constructing a more integrated understanding of how continuous health monitoring shapes lifestyle pressures and psychological responses. A total of 21 axial codes emerged, each composed of related open codes that reflected a central phenomenon or mechanism.

Table 2

Axial Coding

Axial Code	Related Open Codes
Obligation to Perform	Feeling obligated to meet daily step goals; Skipping rest days; Constant need for self-improvement; Turning activity into performance
Guilt and Shame Dynamics	Increased guilt on inactive days; Shame after failing streaks; Self-judgment based on weekly metrics
Dependence on Quantified Feedback	Emotional dependency on performance charts; Becoming data-obsessed; Ritualizing morning metrics check

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Loss of Bodily Intuition	Distrust in body's natural signals; Disconnecting from bodily awareness; Replacing intuition with digital advice
External Validation Seeking	External validation through app achievements; Using trackers to justify self-worth; Perceived social ranking
Overregulation of Diet and Eating	Eating habits dictated by calorie trackers; Changing eating patterns for app approval; Rewarding self only when metrics align
Surveillance and Being Watched	Feeling watched by the device; Perceived surveillance by others via shared apps; Feeling judged by algorithms
Mood Contingent on Metrics	App influence on mood throughout day; Emotional ups and downs tied to daily scores; Obsessing over minor fluctuations
Comparison and Competition	Comparing scores with friends; Competing with strangers online; Relying on streaks for motivation
Intrusion into Social Life	Avoiding social events to maintain calorie balance; Losing spontaneity; Planning life around digital goals
Overreliance on Technology	Device addiction or overreliance; Using multiple apps for cross-checking data; Skipping exercise without tracking
Performance vs. Well-being Conflict	Conflict between pleasure and performance; Over-prioritizing numbers over well-being; Ignoring physical limits
Cognitive Fatigue and Burnout	Self-surveillance fatigue; Device-induced stress spikes; Resentment toward the device
Sleep Disruption and Anxiety	Constant sleep quality monitoring; Disrupted sleep due to notifications; Anxiety when missing health data
Algorithmic Punishment Feelings	Feeling penalized by algorithmic feedback; Setting unrealistic health goals; Shame after failing streaks
Behavioral Concealment and Resistance	Hiding behaviors from tracking devices; Resentment toward the device; Avoiding social events
Loss of Intrinsic Motivation	Diminished intrinsic motivation; External validation through app achievements; Relying on streaks
Technology-Controlled Lifestyle	Prioritizing device notifications; Planning life around goals; Letting the app dictate behavior
Identity Tied to Data	Pressure to present “fit” digital identity; Self-worth from achievements; Feeling judged by algorithms
Feedback-Driven Anxiety	Device-induced stress; Anxiety over missing data; Emotional reactions to low metrics
Pervasive Goal Orientation	Setting unrealistic goals; Constant need for improvement; Planning life around numeric achievements

The final phase of the analysis, selective coding, involved integrating and refining the axial codes into core categories that represent the central themes of the participants' experiences. In this stage, the goal was to identify overarching constructs that organize the meaning structures embedded in the data, and explain how the axial codes relate to one another under broader psychosocial phenomena. This integration process required iterative comparisons and conceptual clustering of axial codes to reveal the essential narrative patterns shaping users' psychological and behavioral responses to continuous health monitoring. A total of five selective codes emerged, each encompassing multiple axial codes and capturing a core dimension of the lived experience under digital health surveillance.

Table 3

Selective Coding

Selective Code (Core Category)	Corresponding Axial Codes
Data-Driven Identity and Self-Worth	External Validation Seeking; Identity Tied to Data; Loss of Intrinsic Motivation
Emotional Consequences of Health Surveillance	Guilt and Shame Dynamics; Feedback-Driven Anxiety; Mood Contingent on Metrics; Sleep Disruption and Anxiety
Behavioral Conformity and Goal Obsession	Obligation to Perform; Pervasive Goal Orientation; Performance vs. Well-being Conflict; Dependence on Quantified Feedback
Loss of Autonomy and Bodily Intuition	Loss of Bodily Intuition; Overreliance on Technology; Technology-Controlled Lifestyle
Social Surveillance and Self-Regulation Fatigue	Surveillance and Being Watched; Comparison and Competition; Intrusion into Social Life; Behavioral Concealment and Resistance; Cognitive Fatigue and Burnout

The five selective codes represent the core narrative of how continuous health monitoring technology reshapes individuals' lifestyles and self-concepts. The first category, Data-Driven Identity and Self-Worth, reveals that users increasingly define their value through algorithmically measured achievements, leading to diminished internal motivation. Emotional Consequences of Health Surveillance highlights the psychological burdens associated with being constantly evaluated, especially in the form of guilt, anxiety, and mood fluctuations tied to metrics. In Behavioral Conformity and Goal Obsession, users adapt rigid patterns of activity driven by performance dashboards, even at the expense of well-being. Loss of Autonomy and Bodily Intuition captures a critical shift where natural bodily cues are overridden by digital instructions, reflecting a technologized form of self-regulation. Finally, Social Surveillance and Self-Regulation Fatigue demonstrates how users internalize perceived expectations from others and

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from the system itself, leading to exhaustion, concealment, and resistance. These five core themes offer a grounded understanding of the subtle, pervasive effects of continuous health monitoring on lifestyle pressures and personal agency.

4. Discussion and Conclusion

This qualitative study aimed to explore how continuous health monitoring technologies shape users' perceptions of lifestyle obligations, emotional regulation, and behavioral autonomy. The findings revealed five major themes: data-driven identity and self-worth, emotional consequences of health surveillance, behavioral conformity and goal obsession, loss of autonomy and bodily intuition, and social surveillance and self-regulation fatigue. Collectively, these themes illustrate that while continuous monitoring tools are intended to support health promotion and self-management, they may simultaneously impose subtle forms of psychological pressure and behavioral constraint, ultimately reshaping the user's relationship with their body, health goals, and digital identity.

The first theme, data-driven identity and self-worth, encapsulated the phenomenon of individuals evaluating their health—and, at times, their personal value—based on algorithmic feedback and quantified performance. This aligns with previous research noting that users often equate app-generated metrics with moral judgments about their discipline, healthiness, and productivity (9, 10). In our study, several participants reported feelings of pride or shame depending on how well they adhered to daily targets, with some admitting to modifying behaviors purely for the sake of maintaining a favorable digital image. Carlsson and Darwiche (5) observed a similar pattern among hypertensive patients who reported improved motivation with mobile health tools, but also an increased fear of failure when goals were not achieved. This suggests that continuous monitoring tools can foster both empowerment and dependency, with the latter becoming dominant when users internalize success as conditional upon algorithmic affirmation.

The second major theme, emotional consequences of health surveillance, reflected how feedback loops from wearable devices or health apps often induced anxiety, guilt, or frustration. These emotional responses were especially pronounced when participants failed to meet goals or felt their efforts were undervalued by the system. Du et al. (9) highlighted that users of self-monitoring systems for diabetes management frequently reported mood swings and discouragement due to inconsistent feedback or misaligned expectations. Similarly, Natale et al. (10) found that self-monitoring can lead to mental exhaustion, particularly in users who perceive tracking as a moral obligation rather than a voluntary tool. These findings reinforce the idea that the emotional burden of constant self-evaluation may outweigh the intended psychological benefits, especially in the absence of human support or contextual flexibility in goal-setting.

Behavioral conformity and goal obsession, the third emergent theme, involved users structuring their lives around the quantified goals imposed by devices, often at the expense of their personal intuition, pleasure, or flexibility. Participants reported compulsively walking, exercising, or restricting food intake to meet arbitrary app goals, even when physically unwell or mentally fatigued. This aligns with the work of Geerse et al. (21), who noted that the design of preventive care pathways—if overly focused on quantitative targets—can inadvertently promote a mechanical approach to health behavior. Similarly, Yang (11) argued that while chronic disease prevention requires consistent lifestyle modification, over-reliance on digital nudging may lead to behavioral rigidity and performance anxiety. Several participants in this study expressed that failing to maintain device-generated streaks resulted in self-criticism and compulsive compensatory behaviors, highlighting the potentially counterproductive consequences of goal-based tracking systems.

Closely linked to this was the fourth theme, loss of autonomy and bodily intuition. Many participants expressed that they no longer relied on physical cues (e.g., hunger, fatigue, stress) to guide behavior, and instead deferred to app-based metrics and reminders. This phenomenon has been previously documented by Thapa et al. (24), who noted that technologically mediated care systems often replace rather than complement users' intuitive understanding of health. In their pilot study on lifestyle-related disease prevention in Nepal, they emphasized that empowerment strategies should enhance rather than override bodily awareness. Similarly, Khan et al. (20) advocate for human-centered design in mHealth tools, suggesting that

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personalization and adaptive feedback are crucial to preserving user agency and trust. The findings of our study underscore that without such design considerations, users may come to view their own intuition as unreliable, ultimately leading to diminished confidence in self-regulation.

The final major theme, social surveillance and self-regulation fatigue, highlighted how participants often experienced a sense of being watched—not only by the device itself but also by peers, family members, or social networks linked to the app. This created a perceived social accountability that intensified stress and reduced authenticity in health-related behavior. Such experiences align with the observations of Rafaela Cavalheiro do Espírito et al. (12), who reported that adolescents monitored through 24-hour behavior tracking protocols showed elevated emotional reactivity and performative behavior patterns. Likewise, Park et al. (18) found that older adults using social features in lifestyle apps reported both motivation and anxiety stemming from perceived peer competition. These findings support the notion that continuous health monitoring can create a “digital panopticon,” where users modify behavior not for health gains but to avoid social judgment or digital exclusion.

Cultural and contextual factors also shaped participants' experiences with continuous monitoring. For example, some participants reported modifying their behavior to align with Westernized health ideals embedded in the app logic, even when these ideals conflicted with local dietary norms or work routines. Ngadiarti et al. (14) emphasized the importance of tailoring health interventions to community-level habits and knowledge, a recommendation echoed in Sidarta et al.'s work on hypertension screening programs in Indonesia (17). These findings point to the risk of cultural mismatch when universal app standards are imposed without accounting for localized practices and values.

Moreover, socio-economic status influenced participants’ perceptions of control and accessibility. For some, especially those managing chronic conditions, wearable technology was seen as a luxury or burden rather than a tool of empowerment. This reflects findings by Shamsuddin et al. (16), who identified natural health literacy and socio-economic barriers as critical variables influencing the efficacy of digital health tools. The study by Kudari and Annapurna (25) also reinforces this point by demonstrating that in populations with limited access to structured care, lifestyle interventions are only effective when paired with education and emotional support. In our study, users who lacked such supports were more likely to feel overwhelmed, disoriented, or resistant to device use over time.

Several participants also reported a gradual shift in how they understood health itself. Rather than associating well-being with internal states like energy, sleep quality, or emotional balance, they began to equate “being healthy” with numerical scores and achievement badges. This echoes the concerns of researchers like Maxmudjanovna et al. (13), who warn that over-mechanizing health assessment in youth populations may foster shallow or externally-driven health identities. Similarly, Fathurrizki et al. (7) caution that telehealth monitoring, while efficient, can unintentionally promote dependence on digital systems, thereby weakening intrinsic health literacy.

Taken together, these findings highlight the paradox of continuous health monitoring: while offering real-time feedback and promoting preventive practices, it also introduces emotional volatility, behavioral rigidity, and social pressure that may compromise long-term well-being. The study by Niu et al. (23) on genetic and lifestyle scoring illustrates this tension well: although scoring systems can help identify at-risk individuals, they may also produce fatalistic beliefs or compulsive behaviors if presented without nuanced interpretation. In this regard, educational interventions and culturally sensitive framing may be key to promoting healthy engagement with tracking technologies.

Lastly, this study echoes calls for redesigning health monitoring systems to account not only for physiological metrics but also for emotional and psychological outcomes. As Somantri et al. (15) and Atomi et al. (1) demonstrate, continuous monitoring systems must integrate education, interpersonal support, and flexibility in goal-setting to prevent the emergence of technostress and burnout. Aydın and Aydin-Avci (19) further support this approach, emphasizing that lifestyle interventions are only sustainable when they respect users' personal rhythms, cultural values, and existing health practices.

This study is not without limitations. First, the participant sample was geographically limited to Hungary, which may affect the generalizability of the findings to other cultural or

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healthcare settings. Second, although a diverse range of ages and occupational backgrounds were included, the study relied solely on self-reported experiences, which are subject to recall bias and emotional framing. Third, the study did not differentiate between types of tracking technologies or platforms, meaning that nuanced effects of specific app features or hardware interfaces were not fully explored. Finally, the study was qualitative in nature and thus not designed to measure the prevalence or intensity of the psychological patterns observed.

Future research could adopt a mixed-methods or longitudinal design to examine how patterns of dependence, emotional regulation, and lifestyle conformity evolve over time with prolonged exposure to continuous monitoring. Additionally, comparative studies between users in different cultural and socio-economic contexts could provide deeper insights into how environmental variables shape user experience. Future studies should also explore the design features of specific health platforms (e.g., gamification, social sharing, alert frequency) to assess which components are most likely to contribute to distress or burnout. Exploring the role of gender, digital literacy, and social identity could further enrich the analysis of how monitoring is internalized across user subgroups.

Practitioners, designers, and policymakers should strive to embed empathy, flexibility, and personalization into the development and implementation of continuous health monitoring technologies. Instead of enforcing uniform goals, applications should offer adaptive targets based on individual needs and circumstances. Designers should minimize punitive feedback mechanisms and promote supportive, non-judgmental prompts. Healthcare providers must be trained not only in interpreting health data but also in understanding how that data is experienced by users emotionally and psychologically. Finally, integrating user education, community support structures, and mental health screening into monitoring programs can mitigate unintended negative consequences and enhance holistic health outcomes.

Authors' Contributions

All authors equally contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study placed a high emphasis on ethical considerations. Informed consent obtained from all participants, ensuring they are fully aware of the nature of the study and their role in it. Confidentiality strictly maintained, with data anonymized to protect individual privacy. The study adhered to the ethical guidelines for research with human subjects as outlined in the Declaration of Helsinki.

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