Everyday Disruptions to Goals: Implications for Wellbeing Technology

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Abstract

Health technologies tools provide support for behavioral goals but largely assume that people live a stable life routine and continuously engage with their goal. Despite barriers to behavior being discussed in literature, they are largely not at the center of design, and researchers lack a systematic understanding of the prevalence and burdens of disruptions. To characterize individuals' disruptions to engaging in wellbeing goals, we surveyed 149 US adults. We identified eight types of disruptions, such as emotional/cognitive, physical/medical, financial and four resulting burdens (emotional, physical, logistical, and financial). The majority of participants experienced multiple disruptions, with over 40% of experiencing daily disruptions. Over half of participants experienced disruptions lasting over a month. We discuss how health and wellbeing technologies can support people's goals through adaptation based on disruptions' burden, temporality, relevance and scale of disruptions.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Disruptions, Personal Informatics, Wellbeing, Goal-setting, Barriers to behavior, Health

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1 Introduction

People's engagement with health behaviors is impacted by both everyday life stressors as well as significant life events that make it difficult to stick to routines [23, 71, 93], require re-adjusting their goals and routines [43], or lead to abandonment of their goals [22]. Recurrent demands from work or family lead to stopping exercise [102, 111]. Unexpected childcare duties lead to pausing mental health care [85]. Events, such as social gatherings, holidays, or travel, lead to temporary pauses in eating healthy [91, 96, 119]. People's engagement with health is constantly strained through small and large events, which poses the need to consider disruptions in the design of health and wellbeing technologies.

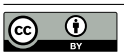
Over 100,000 health-related technologies promise to support people's health [10], but their adoption is low. Such apps provide a variety of functionalities, including tracking data, access to training and programs for fitness, diet, or mental health, as well as support for goal setting and information access. However, tools fall short at supporting people during disruptions. Pregnancy and injury lead people to stop using their physical activity trackers [33]. Life events and changes in circumstances lead to goal changes that tools cannot keep up with [29, 40]. When returning to a tool after a period of non-use, apps make people feel further disappointment by being reminded that they broke their usage streak [12, 121]. Designing technologies that help people recover from disruptive events can transform people's engagement with their health by increasing engagement with health behaviors and supporting more effective bounce-back from adverse events.

To design technologies that are supportive during or after disruption, we need a deeper understanding of such periods. While barriers to behaviors, such as exercise, diet, mental health care, and physical therapy, have been extensively studied in health research [27, 39, 60], in HCI, they often surface as secondary findings rather than the central focus of investigation. Evaluations of health technologies often highlight how life circumstances interfere with engagement. For example, injuries prevent exercise [4], travel and meetings, disrupting medication adherence [15], social situations undermine healthy eating [20], or environmental safety limits opportunities for exercise [99]. While studies reveal some barriers to engagement with health, HCI lacks a systematic understanding of the characteristics of events disruptive to wellbeing goals, such as how disruptions vary in type, frequency, and burden, and how such characteristics should inform the design of technologies that aim to support sustained goal pursuit.

In this study, we aim to characterize the range of disruptions that interfere with engaging in health and wellbeing goals, and characterize the temporality and burden of such disruptions to wellbeing goals. Our study answers the following research questions:

(1) What goal disruptions do people experience when managing wellbeing goals?
(2) What kinds of burden do goal disruptions produce for people? How frequently and for how long do the disruptions impact people's goals?

To understand people's experiences with disruptions that impact their engagement with wellbeing goals, we surveyed 149 US adults about: what wellbeing goals they had, the types of disruptions they



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experienced to their goals, and the burden those disruptions created. We found the following:

Participants experienced 8 different *types of disruptions*: physical/medical, emotional/cognitive, financial, social interactions, work, family/household, travel/recreation and environmental. *Impact of disruptions on goals:* A third of participants reported disruptions that impacted multiple of their goals. Some disruptions were associated with all types of goals, in particular emotional/cognitive disruptions and work disruptions. While others were only associated with goals that they were most closely related to (physical activity, nutrition, financial).

Burden of disruptions on goals: Participants described four *types of burden* on goals: emotional, logistical, physical, and financial. For half of participants, a disruption created multiple types of burden. All disruption types produced emotional and logistical burdens.

Duration of disruptions: About half of participants experienced day-long, week-long and persistent disruptions (lasted more than a month) to goals, though the type of disruptions were unevenly distributed. Day-long disruptions were typically emotional/cognitive disruptions, physical/medical, work, or social interactions. *Frequency of disruptions:* Disruptions were distributed evenly across daily, weekly, monthly, and less-than-six month recurrence. Emotional/cognitive disruptions were most often reported as recurring daily, and work disruptions were more frequently described as recurring weekly.

This research contributes to personal informatics and wellbeing research in HCI by providing an empirical characterization of disruptions to goals along with dimensions of relevance to goals: burden created, and temporality of impact on goals (duration and frequency). We discuss how wellbeing technologies can better account for disruptions through adaptation based on disruptions' burden, temporality, relevance and scale of disruptions.

2 Related Work

We synthesize literature from health, psychology, and sociology that characterizes disruptions in different systematic ways compared to HCI. We highlight how HCI research accounts for disruptions to health and point out the gaps to motivate why we need to account for disruptions that people experience to their health and wellbeing goals.

2.1 Disruptions to health goals

We refer to disruptions to health as situations or events that interfere with a person's life and derail their health goals. We borrow from health, psychology, and sociology literature that characterizes disruptions to health as: (1) the source of disruptive events, (2) from a temporal scale perspective, and (3) from the perspective of impact on health. These characteristics draw in part from a resilience lens of characterizing everyday stressors [5], but extrapolate with other literature discussing stressors [5, 7], and life events [45, 89, 115]. A characterization of disruptions allows us to discuss how HCI researchers might design technology to address disruptions in light of their different characteristics.

2.1.1 Source of situations that disrupt engagement in health. We refer to disruptions as originating from *daily stressors* or from *life events*. *Daily stressors* are events that interfere with a person's goals on a daily basis. Everyday stressors have been categorized according to their *content* [7] in over 54 classifications including interpersonal tensions, work such as demands, overload, job structure, home (e.g., pet events, neighborhood concerns), household and car repairs, events that happen to others but impact the individual (e.g., health, death), weather, and others. While some *life events* can be part of daily stressors, they have generally been characterized as larger changes [45, 49, 115]. Some of the most disruptive life events involve the death of a partner, divorce, or marriage [115]. Other life events, such as, changes in identity, such as gender transitions, or getting diagnosed with a health condition, also lead to large changes in a person's life [45]. Life events can also consist of moving, starting/losing a job, kids moving away from home, getting a loan, beginning school, or getting incarcerated.

Situations that create disruptions can also be categorized based on different sources, from societal and community levels, social, and individual levels. Such sources are derived from barriers to engagement with health behavior. They can include family and community situations (such as a busy family schedule), as well as living and working conditions barriers (such as an unsafe neighborhood, long work hours) [39, 112]. Other disruptive situations can come from individual characteristics, such as feeling bored or low motivation [77]. Finally, societal events like economic changes can create stressors on people's lives that impact engagement with health goals.

2.1.2 Temporality of disruptions. Stressors and life events unfold at different scales. Certain events are characterized as daily hassles, or *acute stressors* [24], which consist of short-term exposures to stressors that last a short period of time, usually hours to days. Such events resolve within that time, causing changes that are quick to resolve or easy to return from by the end of the disruption. For example, a kid catching a cold can disrupt their parents' routines for a few days, but afterwards, routines resume. *Chronic stressors* are prolonged and challenging circumstances [24]. Lack of resources can be seen as a chronic stressor caused by socio-demographic background, and work demands can be seen as persistent stressors caused by organizations. The persistent nature of recurring stressors can make them more negatively impactful on people by creating mental strain and amplifying physical problems [22, 86].

Life events can have either an acute or a chronic stressor effect. Life events unfold over long periods of time, and they impact multiple aspects of a person's life [97]. They are typically associated with a range of multiple smaller-scale disruptions that are changing over time [97]. For example, the logistical impact of moving resolves over time (e.g., packing, moving, unpacking), but not having friends in a new city after a move can make an individual have persistent chronic loneliness for an indefinite amount of time.

2.1.3 Impact of disruptions on engagement with health. Disruptions negatively impact internal characteristics of the individual (thoughts, emotions, behaviors), or environmental characteristics (way the job is structured, caregiving routines, social interactions) in ways that negatively interfere with engagement with their health [86, 89]. The negative effects of disruptions can manifest as increased stress [86], worse food choices [43], and exercising less [3]. Although disruptions can be unexpected, they are relatively predictable at a population level and occur in most people's lives at

some point, with literature providing information about how they unfold [22]. Stressors often generate a physiological, cognitive, and affective response [24, 31]. They trigger emotional reactions, e.g., anxiety or frustration, or cognitive patterns like rumination [94]. People may need to cope through maladaptive behaviors (e.g., smoking, overeating) or adaptive ones (e.g., exercise, problem-solving) [31].

Disruptive events create burdens. Strains from everyday stressors such as commuting, housework, and interacting with others [58] create time constraints for engaging with health [71]. Caregiving and work responsibilities make it challenging for families to be physically active [100]. When life events happen, people need new routines [78, 84, 122]. Life events' consequences can be severe, having been found to precede onsets of a first lifetime episode of depression [79]. They are often associated with people engaging in social reconfiguration, including reconfiguring routines [89, 115]. Life events can create multiple types of disruption in a person's life, creating physical strains (e.g., medical events, pregnancy), logistical strains (e.g., losing a job, getting married), and social coordination strains (e.g., getting divorced, moving in with someone).

In summary, in order to characterize disruptions to health goals, we borrow from the daily stressors and life events literature. We use the characterization of stressors as depending on the source, temporality, and strain produced as a way to investigate disruptions to wellbeing goals. Although these dimensions were used to characterize daily stressors, they have not been used to systematically characterize dimensions of different types of disruptions. This ground offers a basis for how we seek to characterize the prevalence of disruptions to wellbeing goals, which can guide the design of technology.

2.2 Accounting for Disruptions in Design Processes

Health researchers and designers have studied and created technologies that account for disruptions in people's lives to varying extents. We describe the research that accounts for disruptions to health, and point out the gaps in how literature accounts for disruptions people experience when engaging in health behavior.

2.2.1 Studying and designing for life events and barriers. HCI researchers have examined people's technology practices during life events like becoming a parent [65, 66], being pregnant [72, 73], public crisis [95, 105], and managing a chronic condition [52, 53, 108]. In such cases, the primary focus has been on communication and coordination technologies, or on managing the disruption itself, rather than on how the disruption affects existing health goals. Investigations into the use of health technologies have surfaced that disruptions create barriers to achieving health goals. Major life events, such as changes in family circumstances [28, 107], medical events [28, 54], and societal events like a pandemic [45, 84, 95] can disrupt people's goals. Loss of a job can require a person to take on additional food preparation responsibilities [43]. Unexpected schedules and life changes frequently make it challenging for people to act consistently on their nutrition goals [76]. Holidays, public health crises, and travel disrupt people's exercise goals [82]. Caregiving and work responsibilities often limit parents' ability to participate in physical activity goals with their children [100]. Members from limited-resource communities face impediments, "socially produced barriers that make the behavior more challenging to perform", such as disruptive events, constrained access to resources, and burdening duties in pursuing their physical activity goals [101]. Barriers create difficulties in engaging in health goals, which can lead to lapses in use of technology and, in some cases, giving up on goals [29, 34, 35, 37].

A lot of the research above articulates needs for design in light of barriers and life events. However, most of these studies have studied specific events and how to navigate life events (e.g., pregnancy, being a new parent, chronic conditions). Few have taken an approach to understand a wide range of events that interfere with people's behavior, like studying life events interfering with healthy eating [43], or with gender transitions [44]. Such studies help us understand the breadth of disruptions or their impact that we should design for, and call for action for such systematic understanding.

In this study, we strive to understand the prevalence and range of disruptions to wellbeing goals that people encounter. This would enable us to better understand what disruption characteristics to account for as we design for disruptive events as a collection of circumstances that might occur, rather than isolated events.

2.2.2 Designing for disengagement and adaptability. HCI and digital health researchers have designed technologies, such as personal trackers [30, 32, 124] and digital interventions [92, 125] that support health and behavior change goals across behaviors related to physical activity [46, 113, 123], nutrition [9], mental wellbeing [62, 75], etc. To promote engagement with goals, these technologies are increasingly designed for adaptability and disengagement based on changing user context and needs.

Designing for disengagement and lapses: People pause or stop using personal trackers [33, 37, 57], and adaptive interventions [87] for many reasons, such as ineffective data tracking, burdensome tracking, privacy concerns, changing life circumstances, reduced motivation, and shifting goals and priorities. More recently, Bhattacharjee et al. note that workplace responsibilities, life responsibilities, and other events disrupted people's engagement with mental health interventions [13]. In their work, they call for a more comprehensive understanding of users' lives in order to design tools that support people's psychological needs without furthering their distress during periods of heightened stress.

Epstein et al. note, lapses in technology use do not always correspond to lapses in performing the target behavior [37]. Existing design strategies for resuming *technology use* do not differentiate between the reasons for disruption that caused the lapse and whether it had an effect on engagement with the goal. Technologies designed to promote resuming or re-engagement with the goal need to offer different types of support depending on the nature of the disruption, such as resuming after an unpredictable injury or illness versus a changed routine due to a new job. Our work takes the first step towards this gap by characterizing the disruptions that shape goal pursuit, enabling future work to relate it to types of disengagement and designing for re-engagement.

Designing for adaptability: Increasingly, personal informatics technologies and adaptive interventions are designed to support different types of adaptations based on an individual's changing circumstances [64, 83, 117]. Adaptive designs include support for

adjusting goals, such as setting flexible goals [81], setting backup or alternate goals [19, 80], setting margins for their goals [1, 55], and adjusting the difficulty of the goals based on progress [63, 81], or self-efficacy [8, 98].

Technologies also support adapting engagement behaviors with goals. For example, technology can adjust the frequency when users will engage in a behavior (e.g., exercise more, avoid smoking) [3, 47], where and with whom an individual might do an activity [3], and the amount of effort a behavioral activity requires [50]. Individualized support can help a person adapt what activities they will do to achieve their goals, such as what exercises to do, or what foods to eat, by taking their preferences into account [3, 4, 20, 41, 88]. They can personalize daily goals based on recent actions, such as meals [41], sedentary behavior and physical activity sessions [46]. Increasingly, adaptive technologies, such as just-in-time interventions, also leverage real-time sensed user context (such as time of day, weather, location, etc.) to tailor when to encourage people to engage in an activity [46]. Although adaptive designs are helpful in general, existing adaptive approaches offer limited guidance on how technologies should adapt in response to or during periods of disruptions. Current adaptive technologies primarily adjust goal parameters, such as the timing and duration of activity, but these types of adaptations may be insufficient for the disruptions people are experiencing (e.g., adjusting for an injury vs. late work hours). We need a deeper understanding of what adaptations are useful for different characteristics of disruptions, including unpredictable events (e.g., injury), planned but prolonged activities (e.g., major travel or house purchase), or short and recurring tasks (e.g., daily caregiving). In this study, we take the first step by characterizing disruptions that can inform how technologies may adapt.

To summarize, existing HCI research has discussed barriers to health behaviors, as a secondary outcome of research studies in health, but not as a central focus of understanding how technologies can be better designed to account for different types of disruptions. HCI research in personal informatics, just-in-time interventions for health, lapsing and re-engagement emphasize the need for understanding how technologies should respond and adapt to circumstances in a person's life; however, we lack a characterization of connecting the types of adaptations needed based on the characteristics of disruptions people experience. Our study aims to systematically characterize disruptive events by drawing on psychology and sociology's approaches to describe everyday stressors and life events, in particular drawing on dimensions characterizing source of disruption, temporality and strain (or burden) that disruptions pose on people's lives.

3 Methods

To characterize the types of disruptions people experience, we conducted a survey, which was classified as exempt by our institution's IRB. We analyzed the data using qualitative coding and descriptive statistics.

3.1 Survey Design

We conducted a survey to understand the type and prevalence of disruptions in people's daily lives when working on their personal health and wellbeing goals. The survey asked participants to share 1) two to five wellbeing goals, 2) up to five disruptive circumstances for each goal, 3) six questions regarding details of the disruptive circumstances and how they affected the goals, and 4) the demographics of the respondent (Appendix A includes survey instrument). The survey prompted the participant to share up to five wellbeing goals. Based on a broad, holistic definition of wellbeing (including physical, social, work, and financial wellbeing) [26, 116], we suggested that participants share goals that fit with their lived experiences [68]. We expected that a variety of goals might go beyond traditional physical and mental health goals. Additionally, recent studies [17, 29, 61] show that people often pursue multiple goals in parallel.

For each goal, we asked participants to recall up to five circumstances that interfered with or made it challenging for them to work on their goal. To reduce recall bias [110], we asked participants to recall disruptive circumstances within the last 48 hours. To reduce participant burden, we limited responses to five goals and five circumstances. Pilot testing showed that answering all questions for five goals and five circumstances took approximately 20 minutes per participant. For each circumstance, we also asked participants to describe, using free-form text, its impact on their wellbeing, impact on the goal, if the disruption created any additional tasks for them.

Participants selected from predefined options indicating how long the disruption lasted (or was expected to last) and how frequently they encountered each disruption. The survey did not collect individually identifiable information. In this paper, we report on the survey questions related to the disruptions, which are:

- List 1 to 5 circumstances that disrupted or interfered with your goal in the last 1-2 days.
- Describe how the circumstance affected your wellbeing?
- Describe any additional activities, actions, or tasks you had to do in response to the circumstance?
- For how long was your goal disrupted due to circumstance (if still disrupted, how long do you anticipate it being so)?
- How often do you experience a disruption to your goal related to circumstance?

Before deploying the final survey, we iterated on its design through several rounds of pilot testing with the authors and a small convenience sample. Feedback focused on improving the clarity of wording, organization, and flow of questions, and participants' ease of understanding and answering them. We also collected a small set of initial data through Prolific, which informed further iterations of the survey. As the design of the survey did not change, these responses were included for further data cleaning and analysis.

3.2 Recruitment and Participants

Participants were recruited through Prolific, an online participant recruitment platform commonly used for academic research. We used Prolific's recruitment filters to limit participation to adults aged 18 years or older. Additional inclusion criteria required participants to: 1) speak and read English, 2) have access to a mobile, tablet, or desktop device, and 3) report having at least two wellbeing goals. We aimed to have a participant sample with some commonalities and differences. We restricted our sample to people who live in the US, which implies some level of commonalities in how they

Gender	Age	Race	Ethnicity	Employment Status
Woman: 66 (44.3%)	18-25: 26 (17.45%)	Caucasian/White: 74 (49.66%)	Hispanic: 24 (16.11%)	Full-time: 34 (22.82%)
Man: 66 (44.3%)	26-35: 34 (22.82%)	Asian: 19 (12.75%)	Non-hispanic: 120 (80.54%)	Part-time: 11 (7.38%)
Non-binary: 16 (10.74%)	36-45: 29 (19.46%)	African American/Black: 37 (24.83%)	Prefer not to say: 5 (3.36%)	Not in paid work: 5 (3.36%)
Gender Fluid: 1 (0.67%)	46-55: 22 (14.77%)	American Indian/Alaska Native: 6 (4.03%)		Unemployed: 8 (5.37%)
	56-65: 13 (8.72%)	Multiple races: 12 (8.05%)		Other: 3 (2.01%)
	66-75: 22 (14.77%)	Asian Hawaiian/Pacific Islander: 1 (0.67%)		No Response: 88 (59.06%)
	76+: 3 (2.01%)			

Table 1: Participant Demographics.

might have encounters with health management (e.g. the US has a specific infrastructure of health services, approach to health insurance coverage). However, we also expect a sample with a range of different experiences in managing goals. To achieve heterogeneity we recruited based on demographic characteristics of people who are part of the US census (that is people who live in the US). We sought a sample representative of the US demographics [14]. We followed gender ratios from the census, but to have non-binary gender representation, we oversampled for non-binary gender, as the U.S. Census population data includes sex only. To account for racial and ethnic diversity, made a concerted effort to include participants from a variety of racial and ethnic backgrounds, as well as age, trying to match US census representation. After they completed the survey, we paid participants $4 pro-rated based on the living wage rate of $16/hr. The completion time for the survey was on average 15 minutes.

We collected the data in batches, monitoring for completeness of survey responses, resulting in 158 responses in total. The first and second authors reviewed all responses to identify and exclude poor-quality data. We removed 10 responses containing poor quality answers (e.g., single words like "understand" or accidental replies such as "sorry, I misunderstood the question"). We deleted an additional response because the participant withdrew consent. This resulted in a final sample of 149 participants. Participants' ages ranged from 18 years to 76+ years (median = 40, SD = 16.99). Our sample included participants across several gender identities, with similar proportions identifying as women and men (44.3% each), and smaller groups identifying as non-binary and gender fluid. Nearly half of the sample identified as Caucasian/White (49.7%), with a substantial portion identifying as African American/Black (24.8%). The remaining participants (roughly 25%) identified across other racial groups, including Asian, multiracial, American Indian/Alaska Native, and Asian Hawaiian/Pacific Islander. In terms of ethnicity, 16.1% of participants identified as Hispanic. Participants also reported a mix of employment status, including full-time and part-time work, unemployment, and other non-paid roles, though a large proportion did not provide a response. Further demographic details are presented in Table 1.

3.3 Data Analysis

We analyzed the survey data using descriptive statistics, qualitative deductive, and inductive coding. We detail the analysis below.

Goal categories and *disruption categories* (open-ended responses): we primarily used a deductive coding approach based on prior theoretical work on categories of goals [18] and types of barriers and events [6, 45, 57]. We collected a total of 558 unique disruptions per participant. 10 participants did not provide a response for all of their disruptions. Within the disruption categories answers, the content surfaced information about *what the disruption is attributed to*, which we coded based on the World Health Organization (WHO) Committee on the Social Determinants of Health's conceptual framework (e.g., individual, inter-personal) [109, 114]. While these frameworks informed our coding during analysis, they did not shape the survey design itself.

Impact of disruption on wellbeing and *additional tasks created* (open-ended responses): the first author inductively created an additional code category- *type of burden produced*- which included codes such as emotional burden, physiological burden, etc. Five participants reported no burden, but rather a positive effect on mood.

We analyzed the *frequency* and *duration* of disruption using descriptive statistics. Duration and frequency were reported for each disruption as they interfere with a goal; therefore, some disruptions were reported multiple times, but for different goals, with potentially different durations and frequencies relative to the goal. Hence, this analysis includes repeated disruptions, totaling 653.

For coding open-ended responses, the first author created a preliminary codebook with definitions and examples. The first and second authors then individually coded the same 25 responses using the preliminary codebook. They met and iterated on the codebook to clarify code definitions, adding additional codes and examples for codes. For example, code "organizational" under the category "burden produced" was renamed to "logistical" with an updated definition. Using this final codebook (Appendix B), the first and second authors coded the remaining responses while meeting weekly with the last author to discuss new codes, resolve discrepancies, refine code definitions, and discuss edge cases. During the coding process, they added additional codes for capturing supplementary characteristics of each circumstance, including whether it recurred across another participant's goal, whether it was an event, and the socio-ecological factor it aligned with. To assess the reliability of our qualitative coding, we individually coded 155 randomly chosen responses from the full dataset. The inter-coder reliability (IRR) over the three main codes- goal category, disruption category, and burden produced codes was a Cohen's Kappa of 0.82. IRR was not calculated for supplementary codes, as they were used for qualitative thematic characterization of the main codes. The main codes were also analyzed using descriptive statistics.

4 Findings

Participants reported a number of situations and events, which we term disruptions, that made it challenging to pursue their goals. We categorized these disruptions into eight types (e.g., emotional/cognitive, work responsibilities, financial, social interaction). Many disruptions impacted multiple types of goals, and they were unevenly distributed across goal domains. Disruptions created four resulting burdens: emotional, physical, logistical, and financial, with emotional burdens being the most frequently reported. Disruptions varied in their temporality and differed in both duration, from a single day to over a month, and frequency, with some types showing distinct recurring patterns while others were more sporadic.

4.1 Context: Types of Goals, and Amount of Disruptions

4.1.1 Types of goals. 149 participants reported 426 personal wellbeing goals (Figure 1). Most participants 125 (83.9%) reported health goals (N=228, 53.5% goals), which were grouped in the categories of: Physical activity and fitness goals (N=68, 45.6% participants; N=71, 16.7% goals), nutrition and weight management goals (N=65, 43.6% participants; N=73, 17.1% goals), mental health and wellbeing goals (N=52, 34.9% participants; N=63, 14.8% goals). Few participants reported other goals: sleep goals (N=6, 4%), sobriety goals (N=5, 3.4%), preventative health care goals (N=5, 3.4%), and health condition management goals (N=3, 2%).

The most commonly reported goals (after the aggregate of health goals) were financial goals (N=82, 19.2%), for e.g., savings and investments, debt management, employment, planned expenses- by the second highest number of participants (N=64, 42.9%). Other popular goals that participants had were career and learning goals (N=47, 31.5% participants; N=51, 12.0% goals), relationship goals (N=31, 20.8%). Other goals reported by less than 10% of the participants were: recreation (N=14, 9.4%), cleaning/organization (N=11, 7.3%), and screentime management (N=4, 2.7%).

Although non-health goals might not appear strictly as wellbeing goals, participants stated them in accordance with our guidance, which was to include goals that impact wellbeing, including financial and social wellbeing.

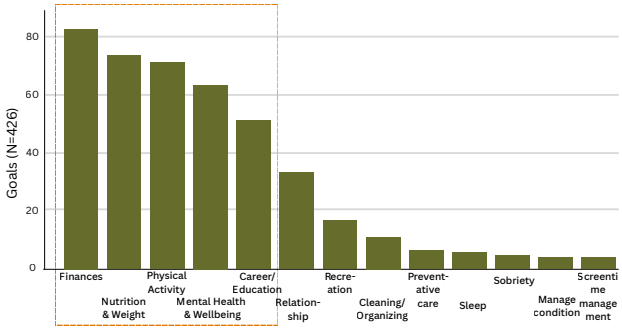


Figure 1: Goal counts (a participant could list multiple goals in the same category). Finances, physical activity, mental health/wellbeing, nutrition/weight management and career/education were top five reported wellbeing goals.

4.1.2 Disruptions affected most participants. Of the 149 participants, 146 participants (97.9%) reported at least 1 disruption affecting their goal within the last 2 days. Only 3 participants did not report any disruptions to any of their goals. These 146 participants reported 653 disruptions across all of their goals. Of the 653 disruptions, 95 were repeated reports, i.e, disruptions that a participant stated more than once, because they impacted more than one of their goals. After removing these repetitions, we identified 558 unique disruptions, which we describe further.

4.2 Circumstances Creating Disruptions

4.2.1 Types of Disruptions and Factors They Are Attributed to. We categorized disruptions to goals reported by participants into 8 types (Table 2): physical and medical, financial, emotional/ cognitive, social interactions, and work were the five most commonly reported. Disruption types varied based on the socio-ecological factors to which they were coded by. Physical/ medical disruptions, financial disruptions, and social interaction disruptions were commonly attributed to inter-personal factors. Emotional and cognitive disruptions were primarily attributed to individual-level factors and circumstances of the person, and not necessarily triggered by a particular event. Environmental disruptions and financial disruptions were commonly attributed to societal factors.

Physical and medical. Disruptions in the form of physical conditions, symptoms, or healthcare system barriers were reported by 49.7% (N=74) participants. They reported 100 (17.9%) disruptions in total (Fig. 2), which we categorized to be related to: pain (N=41,

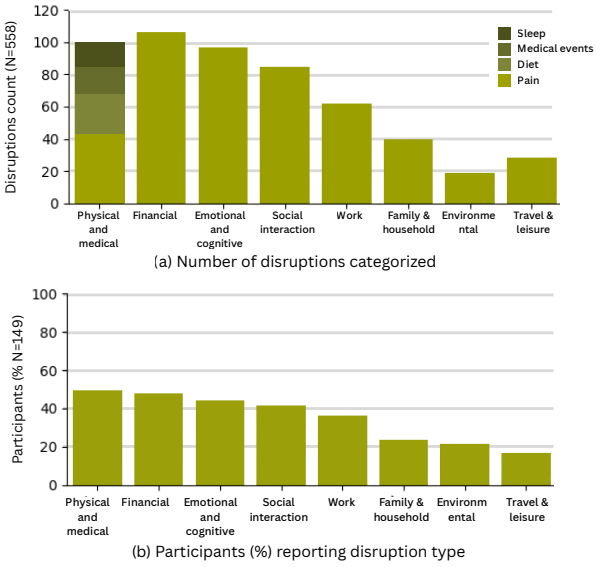


Figure 2: Physical/medical, financial, emotional/cognitive, social interactions, and work were the top five reported disruptions based on (a) disruptions reported (participants could report multiple disruptions of same type) and (b) percentage of participants who reported each type of disruption.

Disruption	Circumstance/event description	Examples
Physical and medical	Physical discomfort/ symptoms, illness, and medical care events, health behaviors (e.g. sleep, diet)	"arthritis related pain" (S138, S139), headaches, back pain (S05, S15, S24, S149), "knee surgery" (S105), "doctors not accepting new patients" (S38), "I was drinking too much water daily" (S137)
Financial	Financial insecurity/changes, habits, employment/labor issues	"Not making enough money" (S06, S19), "Rise in gas prices" (S28), " impulsive buying (S29)", "Jobs not accepting fresh grads" (S22)
Emotional/ cognitive	Feelings/ thoughts (e.g. forgetfulness, stress, anxiety, depression)	"in a depressive state" (S131), "high stress levels led to negative self-talk" (S44), "feeling it's pointless" (S34), "forgot to pack healthy lunch" (S07), "Lack of motivation" (S104), "too tired" (S107)
Social interactions	Unpleasant interactions, limited social connection, meetups	"Keep fighting with my boyfriend" (S104), "Going to cookouts with friends and family" (S53), "friend cancels plans" (S94), "living with partner who has a different diet and cooks often" (S90)
Work	Work or school-related (e.g., transitions, unexpected work, difficult schedule)	"Busy work schedule" (S32), "Unexpected work deadlines" (S44, S148), "start of school year" (S87, S116), "less clients" (S66)
Family/ household	Housold repairs, chores, caregiving duties	"Mom life" (S09), "without childcare" (S32), "busy running errands" (S113), "Car repairs" (S67, S97, S105, S126, S139), "Caring for disabled children" (S117)
Environmental	Spatial, digital and atmospheric environment	"noisy environment due to repairs" (S80), "Weather conditions" (S44), "Internet went out" (S88), "My blender burned out" (S39)
Travel/ leisure	Activities for recreation or travel	"I flew on an airplane for an 8 hour trip" (S05), "I watched deadpool & wolverine" (S39), "Spending too much time on my phone" (S142)

Table 2: Types of disruptions reported

7.3%), diet (N=26, 4.7%), medical (N=19, 3.4%), and sleep (N=14, 2.5%). Participants attributed disruptions to individual behavioral factors (e.g., *"waking up late"- S04)* or psychological factors (e.g., *"decided to rest"- S23*), while a few reported interpersonal factors (e.g., *"doctors not accepting new patients" - S38*).

Financial. Financial disruptions were reported by 47.7% (N=71) participants. They reported 106 (19%) financial disruptions (Fig. 2), including circumstances and events such as insufficient salary or increased expenditure on recurring financial obligations, unexpected expenses, excessive spending habits, and challenges in finding employment (Table 2). Participants (e.g., S17, S77, S118) attributed a variety of financial disruptions.

Emotional and cognitive. Negative emotional and cognitive experiences were reported by 44.3% (N=66) participants. They shared 97 (17.4%) disruptions that made it challenging for them to engage in their goals (Fig. 2). Participants did not attribute their negative emotional state to a specific event, but rather to individual psychological factors (e.g., *"didn't feel good"- S5*) or biological factors (e.g., *"Less energy as over 40 years old now"- S74*).

Social interaction. Social interactions were reported as disruptions to goals by 41.6% (N=62) participants. They reported 85 (15.2%) circumstances (Fig. 2) and events such as: disagreements with a partner or family member (e.g., S23, S55, S104, S137), hurtful remarks by family, friends, or colleagues (e.g., S04, S07, S141), and challenging living situation (S01, S133). A majority of the social disruptions shared by participants were attributed to interpersonal factors. However, 2 participants (S13, S35) reported social interaction disruptions that stemmed from socio-economic level factors such as negative news in the media.

Work (non-social). Workplace disruptions (non-social) were reported by 36.2% (N=54) participants. They shared 62 (11.4%) workplace or school-related circumstances and events (Fig. 2), such as unexpected workload (e.g., S07, S27, S33, S44, S45, S71) and unplanned or longer meetings. Others (S17, S34, S61, S66, S87, S116) described transitions and changes, such as starting a new job, the start or end of a school term, and staff layoffs.

Family and household. These disruptions were reported by 23.5% (N=35) participants (Fig. 2). They described 40 disruptions (7.2%) due to caregiving for children or family members (S113), household responsibilities such as cleaning (S32) or chores (*"Car needed urgent repairs"- S13*).

Environmental. Changes in the immediate spatial environment were reported by 21.5% (N=32) participants (Fig. 2). They reported 40 disruptions (7.2%) such as loud noises (S49, S80), mechanical failures (*"blender burned out"- S39*), larger environment such as weather changes, and digital environment such as losing utilities (*"website has been glitchy." - S96*).

Travel and recreation disruptions. These disruptions were reported by 16.8% (N=25) participants. They shared 28 disruptions (5%) (Fig. 2) due to trips (*"Traveling with family" - S105*) and screen-time activities (*"Surfing the web more than usual" - S11*).

4.2.2 Which disruptions impact what goals. We find that different types of disruptions impacted different types of goals. About a third of participants 56 (37.6%) reported a disruption that interfered with multiple of their goals. A significant number of disruptions interfered with multiple goals (N=95 of 558). Some disruptions were associated with all types of goals: emotional/ cognitive disruptions and work disruptions. Most other disruptions were associated with multiple types of goals: travel, household, and social interaction

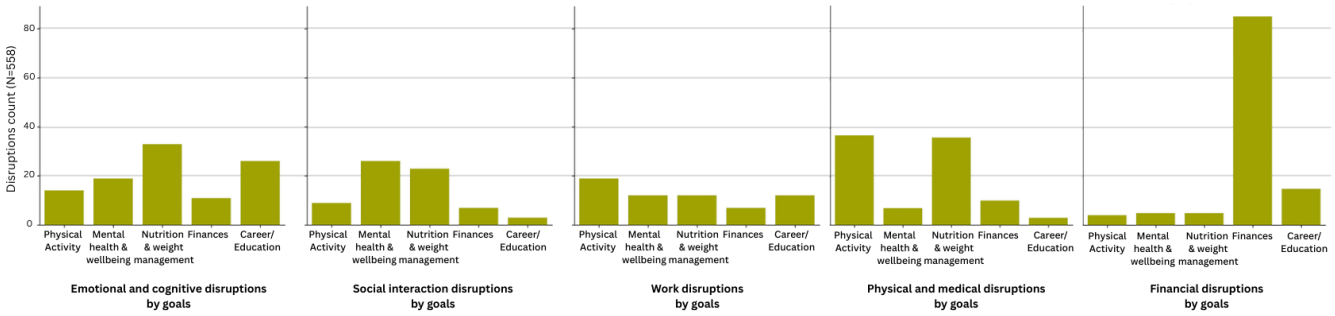


Figure 3: Number of disruptions affecting the top five goal categories for each common disruption type (of 558 unique disruptions).

disruptions. Some disruptions were associated just with goals that were most closely related: physical activity, nutrition/ weight management, and financial disruptions.

Emotional and cognitive disruptions can affect all goals. Across participants, we found that emotional and cognitive disruptions were associated with engagement with all of the 5 commonly reported goals (Fig. 3). Out of the 558 unique disruptions, the most common were related to goals of nutrition/weight (N=33 disruptions), mental health/wellbeing (N=19 disruptions), physical activity (N=14 disruptions), finance (N=11 disruptions), and career/education (N=26 disruptions). Low or lack of motivation disrupted mental wellbeing goals, such as practicing spirituality (S36, S120, S133, S142) and physical activity goals (S4, S34, S41, S44, S72).

Work disruptions can affect all goals. Many participants (S05, S27, S32, S39, S44, S83, S86, S93, S110, S126) described workplace responsibilities such as difficult work schedules and long/late night work hours disrupting their physical activity or nutrition/weight management goals, as they either had to skip a meal or didn't have sufficient time to cook meals. Workplace demands also disrupted mental health/wellbeing goals. Participants (S04, S14, S27, S44, S82, S83, S88, S93, S109, S116, S139) described how long hours and unexpected deadlines left them feeling exhausted or without the time and focus needed for restorative activities such as meditation, journaling, prayer, or therapy. Work responsibilities also interfered with participants' education/career goals, limiting the time and energy they could devote to studying, skill-building, or pursuing new career opportunities.

Many disruptions impacted multiple goals. Most disruptions were associated with multiple types of goals: travel, household, social interactions disruptions (Fig. 3). For example, social disruptions were reported more for mental health/wellbeing goals (N=26 of 558 disruptions) and nutrition/weight management goals (N=23 of 558 disruptions). 6 participants (e.g., S46, S69) reported travel and recreation disruptions interfering with their financial, physical activity, or nutrition/ weight management goals. 12 participants (e.g., S01, S06, S109) shared that financial disruptions interfered with their financial goals as well as goals like health, recreation, education/learning, and relationships. For example, S06 had a low paycheck, which disrupted their relationship goal of saving for their daughter, and their education goal of learning new job skills.

Some disruptions were associated only with their most closely related goals. Out of the 558 disruptions, physical/medical disruptions primarily affected closely aligned goals (Fig. 3): physical activity goals (N=37 disruptions) and nutrition/weight management goals (N=36 disruptions) . Financial disruptions overwhelmingly impacted finances (N=86 disruptions).

4.3 Disruptions Created Multiple Types of Burden

Disruptions varied in burden type they created and the scale of that burden. 139 participants reported 558 disruptions. For half of the participants (N=75, 50.3%), a single disruption produced multiple types of burdens. The types of burdens created by disruptions were: emotional (the need for emotion regulation), logistical (tasks

Burden type	Description of the burden created	Examples of burdens as described in disruptive circumstances
Emotional	Negative mood, requiring emotional regulation.	"I was pissed" (S58), "frustrated, it made me feel broken'" (S24), "emotionally stressed" (S6), "made me want to stop trying" (S7), "worrying about money" (S122)
Logistical	Additional tasks (e.g., learning new tasks, adjusting routines).	"ice down the bruise for three days" (S58), "find programs that can help pay for the bills" (S130), " troubleshooting... contacting customer support" (S80)
Physical	Impaired physical functioning, temporary pain, exhaustion.	"restricted my movement" (S32), "Made me be drowsy all day" (S75), "physical exhaustion" (S6), "constant pain" (S105)
Financial	New expenses or money shortage.	"I couldn't always afford to eat or pay all my bills" (S62), "I had to sink all my month's extra income into health issues" (S135)

Table 3: Types of burdens based on disruptive circumstances reported by participants.

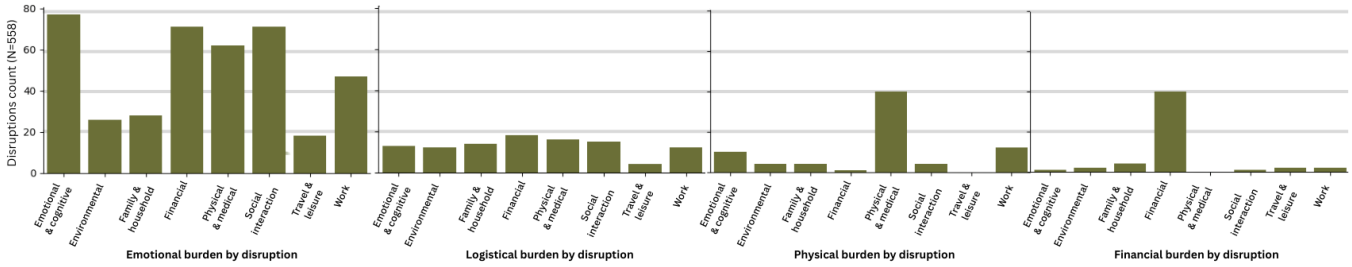


Figure 4: Number of disruptions by disruption type for each burden type (Emotional, Logistical, Physical, and Financial). Emotional burdens were most common in terms of the number of disruptions reported.

such as seeking information or adjusting routines), physical (reduced physical functioning), and financial (new expenses) (Table 3). While all disruption types produced emotional and logistical burdens, physical burden was most commonly associated with physical/medical disruptions, work-related disruptions, and emotional/cognitive disruptions. Financial burden was primarily linked to financial disruptions (Fig. 4).

4.3.1 Emotional burden reported by a majority of participants, associated with all disruptions. Emotional burden was reported by a majority of participants 128 (85.9%): it affected moods negatively, requiring participants to regulate their emotions. The burden constituted a large part of all disruptions (71.7% of 558 disruptions).

Participants reported emotional burden stemming from all categories of disruptions (Fig. 4): emotional/cognitive disruptions (N=77 disruptions, 13.8%), social disruptions (N=71 disruptions, 12.7%), health disruptions (N=62, 8.4%), financial disruptions (N=71, 12.7%), work responsibilities disruptions (N=47, 8.4%), family and household disruptions (N=28, 5%), environmental disruptions (N=26, 4.7%), and travel and leisure disruptions (N=18, 3.2%) . The emotional burden distribution by goals matches the distribution of the disruptions participants experienced. Examples of burdens include feelings of frustration and guilt, discouragement and hurt, hopelessness and overwhelm.

4.3.2 Logistical burden reported by a third of participants, associated with all disruptions. Disruptions created additional tasks that participants needed to do (Fig. 4), mostly in the form of needing to resolve the burdens that came up with the disruption. Logistical burden was reported by 55 (36.9%) participants. They reported 104 (18.6%) such disruptions. Most types of disruptions caused logistical burdens, with 7% to 9% of participants reporting logistical burdens from most disruptions. In addition to mitigating the disruptions, participants sometimes reported doing additional tasks: information seeking and changing routine, like having to search for additional sources of income (S140), new health tasks (e.g., doctor appointments) (S53), or changing eating routine around family events (S102).

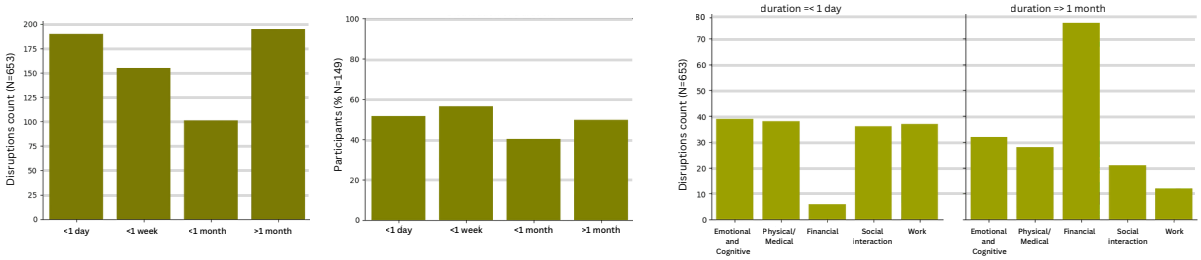
4.3.3 Physical burden reported by a third of participants, associated with medical, work, emotional disruptions. Disruptions affected a third of participants' (N=54, 36.6%) physical functioning, such as causing pain, physical exhaustion, mobility limitations, and bodily responses to stress and anxiety. Participants reported 75 (13.4%) such disruptions (Fig. 4). Not surprisingly, more of such burdens came from physical/medical disruptions (N=40 disruptions, 7.2%). But some physical burdens, like physical tiredness, also came from work (N=12 disruptions, 2.2%) and emotional/cognitive (N=10 disruptions, 1.8%) disruptions.

4.3.4 Financial burden impacted a quarter of participants, associated with financial disruptions. Disruptions impacted about a quarter of participants (N=43, 28.9%) by creating financial burden predominantly in the form of new expenses. Participants reported 52 (9.3%) disruptions that produced financial burden (Fig. 4), such as not having money to pay medical bills, food, or using savings. Not surprisingly, much of financial burden came from financial disruptions (N=40 disruptions, 7.2%).

4.4 Temporality: Duration and Frequency of Disruptions

4.4.1 Duration of disruptions. About half of the participants experienced either persistent or day-long and week-long disruptions. Day-long disruptions were typically emotional/cognitive, physical/medical, work, or social interaction disruptions. In contrast, persistent disruptions, most commonly financial, often interfered with goals for longer than a month and sometimes more than a year. Physical/medical and social interaction disruptions also showed duration-based distinctions: shorter disruptions tended to stem from acute or event-based issues, whereas longer disruptions were more often linked to ongoing or chronic situations.

Persistent disruptions impacted half of participants for more than a month, were primarily financial. 49.7% (N=74) participants reported disruptions interfering with their goals for longer than a month to a year (N=55 disruptions, 36.9%), and longer than a year (N=36 disruptions, 24.2%) . Participants reported almost a third of disruptions as being persistent disruptions (N=195, 29.9%). Persistent disruptions were often financial disruptions (N=76 of 195 persistent disruptions) or emotional/cognitive (N=32 of 195 persistent disruptions). Because of their prolonged duration, participants perceived these disruptions as interfering with their goals on a daily basis. For example, S121 shared that due to their long-term health disruption of "chronic illness", they struggled with their financial goals on a daily basis: *"Daily struggles with tasks that others take for granted. Preventing me from doing the things that I need or want to do, or responding to new challenges."*.



(a) Disruptions by duration (b) Participants (%) reporting different duration (c) Disruptions by disruption type for <1 day vs >1 month

Figure 5: (a) Number of disruptions by duration; (b) Participants % who reported disruption of different durations; (c) Number of disruptions by type of disruption for <1 day vs >1 month.

Week-long and month-long disruptions were relatively evenly distributed across common disruption types. Week-long disruptions impacted almost half of participants with month-long disruptions impacting 40.3% (N=60) participants. 56.4% (N=84) participants reported disruptions interfering with their goals between a day to a week. Examples included minor accidents and health procedures (S40, S99), work stress (S27), weather (S27, S24).

Disruptions lasting up to a day impacted half of the participants. 51.7% (N=77) participants reported disruptions that lasted just under a day. They reported 190 (29.1%) circumstances and events categorized by duration as follows: under an hour (N=39, 6%), more than an hour to half a day (N=79, 12.1%), over half a day to a day (N=72, 11%). Disruptions lasting up to a day generally involved a range of everyday situations, including emotional/cognitive, physical, work and social interactions, roughly evenly distributed (35-40 disruptions) (Fig. 5.b). These disruptions were very rarely financial. Short situations (under an hour) were often characterized by disagreements with others (S28, S23). Disruptions lasting a day were characterized by many through tiredness (S109,5, S7, S13, S15, S34, S36, S4), and work (S7, S27, S32, S44). Other circumstances, like leisure activities or scheduling conflicts, were also reported.

The nature of disruptions of the same type but varying length. *Week-long physical and medical disruptions were different from those lasting over a week to a month.* Participants reported different types of health and medical disruptions depending on the duration. Activities lasting less than a week were characterized more through short-term sickness or symptoms like: short illness (S148, S46), pain (S15, S126,S122), poor sleep (S135, S142), lapses in diet (S98, S137). Whereas disruptions lasting a week to a month were characterized more through more medical issues like chronic pain (S149) or recovery from medical procedures (S51, S57).

Day-long social disruptions were different from those week-long. Social interaction disruptions that lasted less than a day or between a day and a week commonly stemmed from everyday social events, like meeting friends, or having a family visit (S102, S46, S49, S82)). However, when people referred to disruptions lasting more than a week to a month, they brought up disruptions like lacking social support and people letting them down (S2, S25, S92).

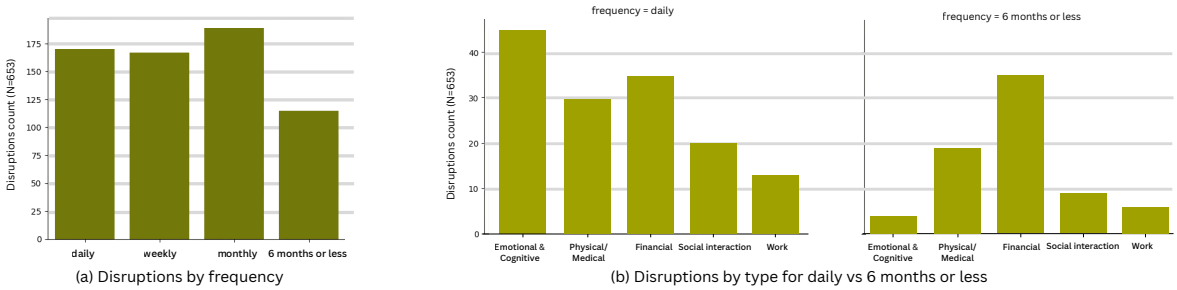
Characteristics of emotional/cognitive disruptions and workplace disruptions remained consistent across durations. Participants reported similar types of emotional/cognitive barriers, or work disruptions, regardless of their duration from less than a day, to those lasting more than a month. Examples include: unmotivated (S102), bad mental state (S133), low drive (S25). Workplace responsibilities included: work deadlines (S148), job demands (S19).

4.4.2 Frequency of disruptions. Disruptions were generally distributed evenly across daily, weekly, monthly, and less-than-six-month recurrence. However, emotional/cognitive disruptions were most often reported as recurring daily, and work disruptions were more frequently described as recurring weekly rather than at other recurrence intervals.

Disruptions recurring daily. 65 (43.6%) participants reported disruptions that disrupted their goals daily. They reported 170 (26%) such disruptions (Fig. 6), though some perceived some disruptions as recurring daily because they were persistent disruptions that lasted a long duration. For example, S42's goal of *"Looking for a home for my new family"* was disrupted every day by the persistent disruption of the high cost of living, a disruption that affected his goal every day. In contrast, participants also shared disruptions that were daily recurring events such as forgetting to pack lunch (S7), poor sleep (S44), being nervous doing homework (S34). Participants commonly reported that emotional/cognitive disruptions (45), physical/medical disruptions (30) and financial disruptions (35) occurred daily (Fig. 6.b).

Disruptions recurring weekly. 86 (57.7%) participants reported a disruption that interfered with their goals weekly. They reported 167 (25.6%) disruptions (Fig. 6), including circumstances and events such as, *"long hours at work prevented me from reaching my goal steps"- S5, "The food my mother has been bringing me isn't very healthy" - S43,* etc. Participants commonly reported that work disruptions (N=27) occurred weekly. Financial disruptions (N=17) were less often reported to occur weekly.

Disruptions recurring monthly. 86 participants (57.7%) reported disruptions that interfered with their goals monthly. They reported 189 (28.9%) disruptions (Fig. 6.a), which were categorized further into: recurring every other week (N=66, 10.4% disruptions) and recurring monthly (N=118, 18.5% disruptions). Participants reported events that disrupted their goals every other week, such as *"Chronic pain"- S123, "Muscle soreness due to a workout the day before"- S144*, etc. Others reported events that disrupted their goals every month, such as *"I had medical appointments"- S120, "family asking to borrow money" - S132,* , etc. Social interaction (N=35),



(a) Disruptions by frequency

(b) Disruptions by type for daily vs 6 months or less

Figure 6: (a) The number of disruptions reported by participants by frequency, including repeated disruptions (same disruption reported for different goals, with potentially different impact) and (b) The disruptions by type for daily vs 6 months or less frequency of occurrence.

physical/medical (N=30), and financial disruptions (N=40) often occurred every month.

Sporadic disruptions recurring every 6 months or less. 66 participants (44.3%) reported disruptions that interfered with their goals every 6 months or less. They reported 115 (17.6%) disruptions (Fig. 6.a), which included those that occurred every 6 months (N=39 participants, 26.2%) and yearly or less (N=34 participants, 22.8%). Examples of disruptions that occurred every 6 months, included *"house repairs"- S105 etc.* and less than a year, such as *"My brakes went out on me 2 days ago"- S149 etc.* Financial disruptions (N=35) were also reported as occurring sporadically (Fig. 6.b).

5 Discussion

We found that participants encountered 8 types of disruptions that produced four types of burden. Disruptions varied in duration and frequency of recurrence. We discuss how wellbeing technologies can better account for disruptions through adaptation based on disruptions' burden, temporality, relevance and scale of disruptions.

5.1 Designing wellbeing tools adaptive to disruption

Technologies exist that are centered around a specific large disruption, life events, such as the pregnancy journey or becoming a new parent [70, 72, 74]. While such tools serve specific needs of navigating that disruption, people also need to navigate health behaviors independent of the disruption: they might use their favorite exercise app during pregnancy or becoming a new parent, or might want to continue tracking food during such transitions. Only recently have personal informatics and health tools begun to explicitly design for disruptions. For example, the menstrual tracking app Clue can switch to a "pregnancy" mode temporarily [21], and the Peloton app includes pregnancy exercises [90]. This is one way to accommodate the disruption in the application. However, such examples are isolated and limited to specific disruptions. Researchers show that disruptions can make people disengage and re-engage with tools after long periods of inactivity [42, 67], and have just started to design to support resuming technology use [35] or preventing lapses [38]. However, such tools largely don't consider the reason for disengagement. Lapses are often treated as discontinuities in data collection or interface use, rather than design opportunities to support people in responding to the disruptions that are interfering with their goals.

Our findings show that disruptions are varied in terms of relevance or impact on goals, burden, and temporality, requiring accounting for more than one disruption at a time, and more systematic design approaches. We present implications for wellbeing behavior tools below, and how they might adapt during disruptions. Such tools in large part include personal informatics tools (tools that support tracking, and generally encourage health behaviors), but our implications go beyond that to tools that might not explicitly be about tracking, but that include functionalities to support health behaviors (e.g., mindfulness apps).

In organizing our discussion, we draw on techniques that promote resilience [11, 51, 59], a technique used by HCI researchers in the past to discuss disruptive events. Inspired by Lorenz's resilience framework [69], we discuss opportunities for technology providing adaptive resilience strategies (e.g., goal changes for prolonged disruptions) or coping resilience strategies (e.g., coping activities for emotional burden). We organize the rest of the discussion based on different types of technology adaptation and considerations in light of our results.

5.2 Support adaptation of wellbeing tools based on disruption burden

All disruptions caused one or multiple burden in participants which interfered with their goals and required responding to. We describe implications for accounting for different burdens.

Adaptation for emotional burden. Half of the participants were burdened by emotional load from all types of disruptions. Burdens required people to attend to them before they could enter the required headspace to engage with goals. Currently, many physical activity or eating healthy apps do not necessarily provide emotional regulation support, but our study shows people need that when disruptions occur. We see opportunities for tools to adapt the interventions or the activities they recommend when disruptions occur, based on the emotional burden that disruptions produce. Given that emotional burden and disruptions were so prevalent, this can be a default option available in technologies that people could turn to. Such work can draw insights from research in the

workplace that has piloted ways to insert mental health interventions into work practices [118], to manage boundaries between work and non-work [104], or to incorporate interventions through work companion conversational agents [25]. We argue that tools, in addition to supporting adaptation in terms of timing of reminders [46, 48] can integrate brief emotional regulation interventions (e.g., mindfulness prompts, self-reflection exercises) that could help users transition into a goal-engagement mindset.

Adaptation for logistical burdens. Logistical burdens resulted from a wide range of disruptions and interfered with a third of people's engagement with goals. We know that people need to manage coordination burdens, such as managing appointments during pregnancy or a chronic condition [72, 108], or coordinating grocery shopping in the family while sick [43]. However, logistical coordination produced by different types of disruptions is not incorporated into many personal informatics technologies. Currently, personal informatics tools support lowering goals or setting margins for goals based on performance [56, 63]. Wellbeing tools can, additionally, explicitly support recovery from logistical burdens by adapting plans by helping people estimate "logistical coordination time" for upcoming or ongoing disruptions. For example, if someone is handling appointments, groceries, injury care, personal informatics tools could pre-define time slots that account for the duration of such tasks, or AI-generated plans for tasks [106].

Adaptation for physical burdens. Physical burdens primarily resulting from physical/medical disruptions and work responsibilities limited people's physical functioning. Physical activity tool research already supports adapting daily goals based on self-efficacy [8]. Researchers have called for accounting for injuries in technology [3, 4]. Given the prevalence of physical burden, we see opportunities for physical activity tools to support adaptation based on physical limitations and to adapt engagement activities to be more proactive in supporting recovery. Tools can capture daily or weekly physical capacity through pain scales and body maps, thereby adjusting the suggested activities accordingly. Instead of reducing or switching to easier goals, tools need to differentiate between the underlying reason for the physical burden- injury vs long day- and suggest appropriate adjustment- shorter workout vs stretching routines.

Adaptation for financial burdens. Financial burdens were primarily due to financial disruptions, which created additional expenses and affected financial goals. Financial disruption was not associated with other goals, surprisingly. That is perhaps why financial disruptions were long-lasting, and people might have adapted their other goals to their novel circumstances. Our results suggest that we need to design for financial disruption in finance-specific technologies, rather than broader wellbeing tools. However, we see a need for future research to understand if at the start of the transition into financial disruption, tools supporting other health goals can support a person in potentially transitioning to a more financially sustainable plan to pursue their goals.

5.3 Adaptive wellbeing tools based on the temporal nature of disruptions

5.3.1 Adapting for disruptions based on their duration. Our findings show that disruptions varied substantially in duration, meaning people's ability to pursue their goals was impacted for very different lengths of time, with some disruptions being persistent for over a year, and others short-lived for under a day. These findings show a discrepancy with many personal informatics and behavior-change technologies, which assume stable routines and continuous engagement. These systems rely on fixed reminders and repetitive prompts, which quickly become misaligned when people's circumstances [2, 16, 103]. This suggests that wellbeing tools should tailor adaptations to the disruption duration.

Our results have implications for the broader personal informatics literature, which has explored forms of goal adaptation, but has not examined how long an adaptation should last. Based on our study, some disruptions lasted for a few minutes to a couple of hours. For such disruptions, tools might not need to suggest any adaptation. For day-long disruptions, such as emotional/cognitive, physical/medical, work-related, or social interaction disruptions, technologies could suggest temporary adjustments, such as reducing the difficulty of the day's goals or a streak freeze.

However, persistent disruptions in our findings, especially financial constraints or chronic life instability, spanned months and sometimes over a year. In such cases, making only small adjustments to a goal's parameters is unlikely to be appropriate. Long-term disengagement reflects more than a temporary break. Prior work shows that after long periods of abandonment, people may not return to the same plan or tool at all [36]. A more supportive strategy is to help users re-evaluate their goals entirely, acknowledge the period of abandonment, and offer a fresh re-entry point when they are ready.

Finally, because some people can anticipate the duration of a disruption [103] tools could incorporate mechanisms that let users indicate or negotiate how long they expect to be off-track. This would allow systems to align adaptations with the disruption window, rather than assuming uniform engagement timelines.

5.3.2 Adapting for disruptions based on their frequency and predictability. Wellbeing tools can adapt based on the frequency of recurring disruptions by designing for predictability. Recurring stressors that prevent engagement with goals become no longer an exception but rather a pattern that can be accounted for. Our participants reported many disruptions that recurred daily and weekly. Emotional/cognitive disruptions were most often reported as recurring daily, and work disruptions were more frequently described as recurring weekly. Such disruptions would be best supported through the adaptation of plans around routines, rather than one-off adaptations. Sporadic disruptions, on the other hand, may require just-in-time adaptation, as they cannot be easily predicted. Some disruptions can be anticipated or known, such as weather, while others are unanticipated or unexpected, such as social visits and injuries [120]. However, even though people might have a hard time anticipating various disruptions and stressors in their lives, at a population level, the types of stressors that people are likely to experience are well-studied [7]. This creates the opportunity to have better goal-setting and planning tools that can be disruption-responsive and can better anticipate disruptions.

5.4 Tailor adaptation based on relevance and scale of disruptions to goals

Personal informatics tools should provide adaptation support based on which disruptions are relevant to the goal and how many of the individual's goals the disruption would impact. In our findings, emotional/cognitive disruptions and work disruptions affected all types of goals, including health, relationship, financial, and career/education goals. Adaptive tools currently support creating backup or secondary goals [19] or personalizing planning based on routines [4]. We see an opportunity for adaptive tools to support the creation of backup plans based on common disruptions relevant to that goal. For example, physical activity goal tools can help users anticipate and account for emotional/cognitive disruptions, workplace disruptions, and physical/medical disruptions by creating backup plans.

6 Limitations

We focused on a general sample of U.S. American adults as participants. Future work is needed to understand how other participants, potentially with different demographics, may have different goals and disruptions, including children or users in non-US contexts. This U.S.-based sample also limits the generalizability of our findings; future studies should extend this work to non-U.S. contexts to capture a broader range of experiences. The survey instrument might not have captured all the disruptions that participants actually experienced in the past days in the same way that an EMA survey might. Because we relied on a 48-hour recall window, we were unable to track how disruptions change over time. Capturing experiences at finer-grained intervals would allow researchers to examine temporality more directly and provide a clear direction for future work.

7 Conclusion

This study characterized how people experience disruptions when managing personal health and wellbeing goals through a survey of 149 US adults. The findings describe eight types of disruptions and the four resulting burdens (emotional, physical, logistical, and financial). These disruptions varied in the goals they affected, the time they lasted, as well as how often they disrupted. The study contributes to the design of personal informatics and wellbeing technologies by illustrating adaptation design for disruptions based on burdens, duration, frequency, relevance and scale of goals.

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