Barriers to Designing Inclusive Ecological Momentary Assessment and Wearable Data Collection Protocols for AI-Driven Substance Use Monitoring in Hawai'i

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Ecological momentary assessment (EMA) and wearable sensors offer unprecedented opportunities to capture the dynamics of substance use through real-time, high-resolution behavioral and physiological data. These data streams are increasingly used to train AI/ML models for digital

phenotyping and predictive intervention, raising critical questions about fairness, bias, and inclusivity in model development. However, the adoption of these technologies, or the lack thereof, among diverse and historically marginalized groups raises questions and challenges of equity, cultural relevance, and participant trust. In this study, we conducted a four-week observational study with adults in Hawai'i where we combined continuous Fitbit monitoring and daily EMA surveys to document substance use patterns and cravings. Through semi-structured interviews and grounded theory analysis, we identified six primary barriers to study participation and adherence: (1) disruptions to daily routines, (2) physical and psychosocial discomfort associated with wearing the Fitbit device, (3) concerns about aesthetic compatibility and professional appearance, (4) phone-related issues, (5) challenges related to substance use and cravings, and (6) socially sensitive contexts. We also highlight participant-identified facilitators, such as the value of participant-driven scheduling, motivational feedback, and contextually adaptive protocols. Drawing on these collective findings, we propose a set of design guidelines aimed at advancing the inclusivity, engagement, and fairness of wearable-based EMA research.

Keywords: Digital Health Equity; Wearable AI; mHealth; mHealth Fairness; Digital Health Fairness; Ecological Momentary Assessment (EMA); Wearables; Human-Centered Design

1. Introduction

1.1 The Rise of EMA and AI/ML in Substance Use Monitoring

Ecological momentary assessment (EMA) and wearable sensing technologies have quickly transitioned from experimental research tools to core data sources in digital health and biomedical AI pipelines[1,2]. EMA involves capturing repeated, in-the-moment self-reports of mood, context, craving, or behavior, reducing recall bias and capturing the dynamic variability that characterizes substance use trajectories[3,4]. Wearables, including smartwatches, activity bands, biosensor patches, and connected mobile peripherals, can complement this approach by providing continuous or high-frequency passive data on physiology (e.g., heart rate variability), sleep, mobility, and biochemical correlates relevant to the outcome of interest[5-7]. When integrated with machine learning (ML) and predictive modeling[8,9], multimodal EMA and sensor data can be used to identify relapse risk windows, tailor just-in-time adaptive interventions (JITAIs), and model individual responses to treatment in close to real-time[10,11].

However, this promise has yet to be fully realized in real-world settings. Datasets powering substance use prediction models are disproportionately drawn from convenience samples that over-represent relatively homogeneous, higher-income, and more digitally connected populations[12,13]. Device design assumptions, such as about wrist circumference, skin tone reflectance, notification literacy, language, and connectivity stability, may encode sociotechnical and cultural biases even before any model is trained[14,15]. Downstream AI/ML systems using these digital health data thus risk amplifying representational gaps and producing performance disparities across groups whose lived experiences differ markedly from those in the training data.

1.2. Fairness in Practice: Wearables, EMA, and Inclusion

Calls for "fair AI" often emphasize algorithmic metrics, such as calibration, error rate parity, or representational balance in training datasets[16,17]. While absolutely necessary, these abstractions are insufficient when digital tools interface with minoritized communities whose experiences of health, surveillance, trust, land, and data sovereignty differ from mainstream clinical populations[18,19]. Operationalizing fairness in practice demands attention to relational, cultural, and material dimensions[14,20]. Wearable and EMA study procedures may inadvertently create barriers to inclusion through usability challenges: straps that do not fit larger wrists; optical sensors that lose accuracy across skin tones; prompts scheduled without considering working schedule, individual lifestyle, social norms, or cultural practice; data dashboards that fail to reflect relational models of wellness (e.g., family, peers, community)[21-24]. These are not merely usability bugs; they are sites where fairness either breaks or is built.

1.3 Study Goals

We sought to understand the experiences of participants living in Hawaiʻi interacting with wearable-linked EMA tools through the context of substance use research as a demonstrative example of a digital health application area disproportionately affecting underserved populations. Through community-engaged recruitment, qualitative thematic analysis, and demographic disaggregation, we identified several sociotechnical barriers that hinder sustained and equitable participation in wearable-based EMA studies. Therefore, our study was situated at the intersection of biomedical AI fairness, digital inclusion, and sociotechnical analysis of wearable-based EMA. Specifically, we sought to answer: (1) What sociotechnical and cultural challenges arise when deploying wearable-based EMA tools among a population living in Hawaiʻi? (2) How can insights from these challenges inform more equitable and culturally responsive approaches to fairness in biomedical AI and digital health research?

2. Methods

2.1 Study Participants

Our study aimed to explore sociotechnical and cultural challenges in using wearable-linked EMA tools for substance use monitoring in Hawai'i. We recruited participants through three sites: a harm reduction outreach program, a residential treatment center, and the University of Hawai'i. Inclusion criteria of our study were: (1) at least 18 years of age, (2) current residence on the island of Oʻahu, (3) reliable access to a smartphone with either a data plan or consistent Wi-Fi connectivity, and (4) self-reported active substance use on at least two different days per week involving one or more of the following: methamphetamine, alcohol, cannabis, opioids, cocaine, sedatives/benzodiazepines, nicotine, psilocybin, or gamma-hydroxybutyrate (GHB).

Exclusion criteria included: (1) active homicidal or suicidal ideation, (2) inability to provide informed consent, (3) inability to complete interviews in English, (4) anticipated incarceration or relocation from Oʻahu during the study period, and (5) failure to provide contact information either by email or phone number. Our study was conducted following the Declaration of Helsinki and was

approved by the Institutional Review Board of the University of Hawai'i (Protocol No. 2022-01030, approved on March 22, 2023).

2.2 Device Deployment and EMA Protocol

At the initial intake meeting, participants were provided with Fitbit Charge 5 devices, which continuously collected physiological and behavioral data for a four-week period. During waking hours, the devices recorded heart rate (HR) and step count; during sleep, they monitored breathing rate (BR), blood oxygen saturation (SpO_2), and sleep quality. Participants were instructed to wear the device continuously, removing it only when necessary (e.g., for showering or water-based activities).

Concurrently, participants completed four EMA surveys per day using a custom mobile application called BanAware (Figure 1), developed for both iOS and Android platforms. The app prompted participants to report substance use events, cravings, and associated emotional states in real time. Specifically, EMA survey reminders were automatically sent four times a day at 9: 00 AM, 1:00 PM, 5:00 PM, and 9:00 PM. Additionally, participants could submit an EMA survey at any time when experiencing substance use or craving events. To reduce stigma and safeguard privacy, participants could opt to use fruit-based code names in place of specific substance names. After completing the four-week monitoring period, participants returned the devices and participated in semi-structured exit interviews to share their experiences. The full study protocol is described in detail by Sun et al.[25]
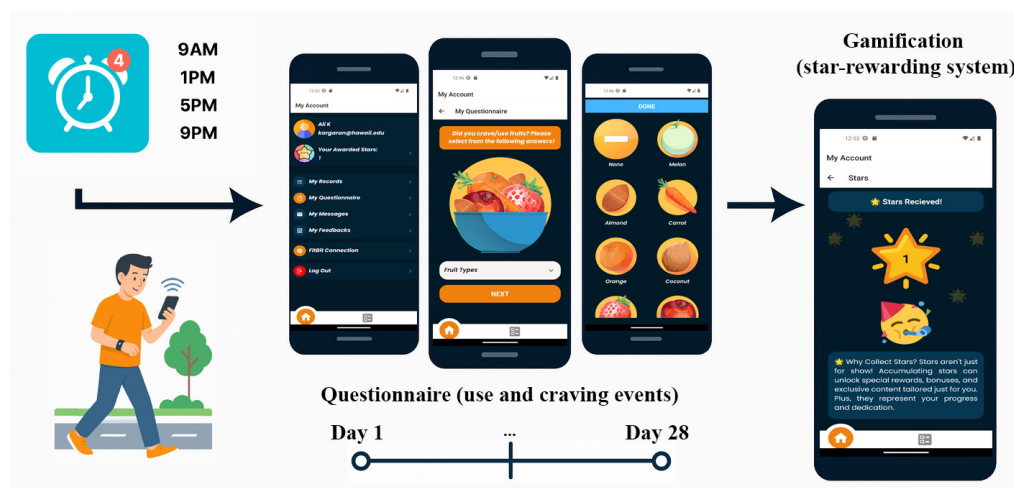

Fig. 1. User interface of the BanAware mobile app. Participants were asked to complete an EMA 4 times a day at fixed times, asking for self-reported substance use and cravings. Participants had the option of coding substances as fruit names to ensure privacy.

In addition, we developed AI models using a subset of these data by implementing a baseline 1D convolutional neural network (CNN) with traditional supervised learning and an experimental self-supervised learning (SSL) model[10]. We found that the SSL models outperformed equivalent purely supervised models on average and demonstrated the feasibility of using wearable biosignals for personalized substance use prediction.

2.3 Data Collection

We employed a qualitative design to address the research questions through a combination of intake questionnaires and in-depth interviews. At the beginning of the study, all participants completed an intake questionnaire comprising both open- and closed-ended questions. These questions captured sociodemographic characteristics (e.g., "*How do you define your race/ethnic background?*"), substance use patterns, and treatment history.

After the 4-week wearable and EMA monitoring period, participants took part in semi-structured exit interviews, conducted in person by the first and second authors. Each interview lasted between 30 and 60 minutes and was audio-recorded with the participant's consent. Exit interviews explored participants' lived experiences with the Fitbit device and the BanAware application, with a focus on usability, physical comfort, privacy, and sociocultural relevance (e.g., "*How was your experience in this study?", "How comfortable was it to wear the Fitbit all the time?"*). Field notes were recorded during each session to capture non-verbal cues and contextual observations.

2.4 Data Analysis

2.4.1. Conceptual Framework

To guide our analysis and interpretation, we adopted the Social-Ecological Model (SEM), a well-established framework for examining the multiple and interacting influences on health-related behavior. SEM conceptualizes health as shaped by factors operating across four levels: individual, interpersonal, community or organizational, and societal or policy[26]. This model provides a structured lens for identifying and categorizing the sociotechnical and cultural challenges reported by participants in our study.

2.4.2. Analytic Strategy

All audio-recorded interviews were transcribed verbatim and uploaded into Dedoose[27] a qualitative analysis software platform. We employed a grounded theory approach to inductively identify themes and categories relevant to our research questions[28]. The initial round of coding was done line-by-line within transcripts, so that codes stayed close to the data and remained open. Short, descriptive phrases were assigned as codes that outline participants' barriers (e.g., "my phone is really slow," "lost the charger," "forgot to log EMA"). The second round of coding identified the most frequent or significant themes that can respond to the research questions (e.g., "device discomfort," "emotional stress," and "social context is sensitive"). The third round of coding focused on extracting themes for a conceptual understanding and aligning them with the SEM framework (e.g., individual barrier, structural barriers).

To link the emerging codes and themes with the SEM framework, we systematically reviewed and mapped different types of codes onto its four levels during the selective coding phase. The first and second authors independently coded the transcripts and met regularly to review and reconcile coding discrepancies. Divergences were resolved through reflective discussion, iterative memo writing, and cross-validation against the original transcripts and field notes to ensure interpretive rigor and consensus.

3. Results

3.1. *Baseline Characteristics of Participants*

21 participants completed both the 4-week wearable-based EMA protocol and entry and exit interviews. The final analytic sample included participants with diverse sociodemographic backgrounds. Gender identities included male (n = 11), female (n = 8), non-binary (n = 1), and transgender (n = 1). Ages ranged from 23 to 65 years (mean = 39.0 years), with distribution as follows: 20–29 years (n = 6), 30–39 (n = 5), 40–49 (n = 6), 50–59 (n = 3), and 60+ (n = 1).

Participants self-identified as White (n = 6), Native Hawaiian (n = 5), Filipino (n = 3), Hispanic (n = 2), Samoan (n = 3), Japanese (n = 1), and Chinese (n = 1). Educational attainment included high school (n = 10), college (n = 6), master's-level students (n = 2), PhD students (n = 2), and one PhD holder (n = 1). In terms of occupation, 15 participants were employed or actively enrolled as students, while six were not working at the time of the study. Regarding EMA reporting, 15 participants opted to use substance names, and 6 chose fruit code names for privacy. Seven participants, including White (n = 4), Chinese (n = 1), Japanese (n = 1), and Filipino (n = 1), reported prior experience using wearable devices (e.g., Apple Watch, Fitbit, Samsung Galaxy). These baseline characteristics are summarized in Table 1.

Table 1. Demographic characteristics of participants.

ID	Gender	Age	Race	Log Type	Education
5	Male	65	White	Substance	College
9	Male	39	Native Hawaiian	Substance	High School
10	Male	24	Japanese	Fruit	College
12	Male	41	Hispanic	Substance	College
13	Female	24	Samoan	Fruit	Master
14	Male	32	White	Substance	Master
15	Female	28	Filipino	Substance	College
16	Non-binary	27	White	Substance	PhD Student
19	Female	55	White	Fruit	High School
20	Female	42	Native Hawaiian	Fruit	High School
23	Male	24	White	Substance	College
24	Female	25	Filipino	Substance	College
26	Male	42	White	Substance	PhD Student
27	Female	56	Native Hawaiian	Fruit	High School
28	Female	32	Chinese	Substance	PhD
29	Male	51	Filipino	Substance	High School
30	Female	40	Native Hawaiian	Substance	High School
32	Male	41	Samoan	Substance	High School
33	Transgender	34	Hispanic	Fruit	High School
34	Male	41	Native Hawaiian	Substance	High School
35	Male	35	Samoan	Substance	High School

3.2. *Sociotechnical Barriers to Wearable-Based EMA Participation*

We explored the sociotechnical and cultural changes experienced during participation in wearable-based EMA studies. Guided by the SEM framework, we identified six sociotechnical factors that influenced the sustainability and fairness of EMA engagement.

3.2.1. *Individual Factors*

Daily Routine

Participants reported difficulty responding to EMA survey prompts during specific periods of the day, such as early mornings, late evenings, work hours, classes, church services, driving, swimming, or while traveling. For example, participant 9 explained the challenges of responding during work hours, despite having phone access on the job: "*I've been working at Best Buy for two years, so I'm always doing something around 1:00 PM. I might be in the middle of helping a customer, or there's a busy line.*" Notably, timing preferences varied across groups. Some participants indicated that they preferred later EMA survey prompts. For example, participant 25 reported that the EMA survey is too early for them: "*There are sometimes in the morning. I think it was 9:00 AM. If I have class on that day, it will be fine. But on the weekends, I am sorry, I am not waking up at that time.*"

In contrast, participants 5 and 26 stated that the EMA survey prompts were too late for them and described themselves as morning people. In some cases, disruptions to daily life further hindered participation. For example, participant 28 described the logistical and physiological challenges of participating in the study while traveling: "*…I was traveling for 2 weeks of the study. I lost the charger. Because it was an unfamiliar environment, I didn't check for all of my belongings before I left.*"

Wearable Device Discomfort

Participants reported skin irritation or physical discomfort from the Fitbit's rubber band, particularly when it was wet. For example, participant 29 stated, *"I was allergic to rubber."* Similarly, participant 10 described a related issue: "*I don't like the rubber band. I tried it for the first day, and I think I had it too tight. ... when I go swimming, it would be really uncomfortable.*"

In addition to the discomfort caused by the rubber band during the daytime, four participants reported that wearing the devices while sleeping was uncomfortable and intrusive. For example, participant 14 described their experience of wearing the Fitbit when sleeping: "*I did not really like sleeping in it. I prefer not to have. It's just like I will take my earrings out when I sleep. ... I could feel it digging into my wrist or cheek.*"

This physical discomfort was exacerbated by psychosocial stress, as participants 14 and 28 preferred to sleep without wearing any digital devices, which they associated with a sense of bodily freedom. Furthermore, participants 5, 13, and 14 mentioned that they did not have the habit of wearing digital devices when sleeping before participating in the study and needed to adjust.

In addition to the discomfort caused by the device or the rubber band, participants 14, 18, and 26 reported experiencing fatigue due to continuous device use, citing a lack of relaxation and reduced bodily autonomy. For example, participant 18 stated that wearing the Fitbit device constantly made them less relaxed: "*I cannot ignore it every time it vibrates, because it's physically on my body. ... It's more open to distractions from people who try to get in touch with me.*"

Additionally, participant 26 stated that repeated EMA surveys can lead to a sense of surveillance: "*The check-in was like I was on probation, and I was constantly contacted by my probation officer.*"

Phone Issues

Participants reported phone-related disruptions, including outdated or slow devices, switching phones during the study, which led to failing to receive EMA survey prompts or disengagement. For example, participant 34 described how phone-related issues prevented them from continuing participation: "*I was on the point in the first week, and my phone stopped working. My phone was super slow, and sometimes I wouldn't receive notifications. ... Then, I got a new phone two weeks ago, but I didn't think about connecting back to the study since I missed so much.*"

In addition, participant (ID 29) described a challenge related to not being able to charge the device in a safe environment: "*I don't have my own place yet. I don't have my car. I don't have a job. I don't have my benefits. I lived in a shelter. ... There is a common area I can charge. But I didn't want to leave the charger there. Somebody can grab it.*"

Substance Use and Craving

Participants reported that substance use and cravings interfered with their ability to engage with the study, due to reasons such as irregular sleep patterns, active use periods, and experiencing relapse. For example, participant 33 described how substance use disrupted their sleep schedule, resulting in missed EMA survey prompts: "*I use substances to stay up. ... my sleep schedule is crazy. Sometimes when I get up, I have already missed two alerts. ... it feels like I haven't logged in my data for the day, so I'm trying to catch up, sometimes I have a craving, and then I forget [to log].*" Missing EMA survey prompts can further contribute to the stress of catching up, making engagement even more stressful. Beyond these immediate effects, substance use can affect EMA compliance indirectly. For example, participant 30 shared how a relapse, triggered by multiple life stressors, contributed to disengagement from the study: "*…things are stressed, like relationship-wise, and then I lost my car, and then financial issues, and now I am trying to get a new job. So I relapsed, and it caused me to isolate and draw away from people. …. I think it was because of my whole relapse, I guess I just did not want to do it.*"

Aesthetic Compatibility and Professional Appearance

Participants expressed concerns related to the aesthetic compatibility of the wearable device with their daily outfits, particularly in social and professional settings. This concern was raised by three female participants and one male participant. For example, participant ID 25 described removing the Fitbit to comply with the dress code at a nightclub: "*We would go out to the clubs, but they did not allow specific things, such as a Fitbit. If I wore it, they would ask me to throw it away. ... you have to dress up nicely because it is a club, so it doesn't fit.*" Similarly, participant 14 noted that they would not wear their bracelets and Fitbit together since the two did not look aesthetically compatible. Beyond informal general aesthetic and specific dress code concerns, the professional image was also a source of tension. Specifically, participant 28 expressed hesitation

about wearing a Fitbit in professional environments: "*I like the rainbow band. However, since I'm often in a professional setting, that kind of material and color is not the most professional. That makes me a little self-conscious.*"

3.2.2. *Community and Organizational Factors*

Social Context

Participants reported that social environments can be a barrier to EMA compliance. Specifically, they expressed the fear of being judged if others became aware of their substance use or study participation. For instance, participant ID 35 shared their experience of being questioned by their coworkers: "*There is a guy at work. He always asked me about the Fitbit. For a moment, I didn't want to tell him what it was, but probably by the second week, I had to tell him because I grew tired of him asking. I told him what Fitbit is for and the study, ... and he gave me one look, and I didn't like it.*" Similarly, participant ID 18 explained how they failed to comply when receiving the EMA survey during the class: "*I get a reminder at 1:00 PM to log in. I wouldn't log because I'm in class, and there was a little tiny thought like, what if somebody looks over [my phone]? I chose to use the substance name.*"

3.2.3. *Explicit Participant Suggestions*

Four participants expressed confusion about how and when to log substance cravings, which hindered accurate and consistent EMA compliance. For example, participant 10 emphasized the lack of a clear time anchor for reporting cravings: "*It was kind of confusing. ...If I had cravings, there's no time that I can associate with putting on the craving.*" In addition to this confusion, participants 14 and 15 reported that they typically recorded substance use rather than craving, as the craving and subsequent use often occurred in close succession.

Participants 13, 20, and 26 suggested more frequent reminders. For example, participant 26 stated that they preferred a text-based reminder to sync the Fitbit data: "*I would like to get an update about refreshing the Fitbit data, because I've got updates regularly from BanAware, but I wasn't getting any updates about the Fitbit. And I'd have to remember at some points, but I wouldn't remember every day.*" Similarly, participants 13 and 20 echoed this preference, noting that text-based reminders would help them stay on track with syncing the device.

Additionally, three participants (ID 18, ID 28, ID 33) proposed visual summaries of personal data, such as craving and usage trends, to enhance user engagement and self-awareness. Two participants (ID14, ID20) recommended incorporating gamified features to strengthen motivation. Two participants (ID 18, ID 28) expressed interest in learning more about the data they provided.

4. Discussion

4.1. *Lesson Learned and Design Recommendations for Culturally Responsive and Participant-Centered EMA Implementation*

Drawing on our qualitative findings and participant feedback, we identify design considerations for improving the feasibility, equity, and sustainability of wearable-based EMA studies.

Participant-controlled scheduling and context-aware notifications reduce disruption and fatigue. Poorly timed notifications, which were reported by 13 out of the 21 participants, emerged

as a major reason for missed EMA entries. Participants requested the ability to schedule prompts around their daily routines and temporarily "snooze" reminders during rest, work, or other socially and culturally significant events. When possible, study protocols should prioritize participant autonomy in notification timing and context-sensitivity to protect daily rhythms and increase adherence.

Comfort, customization, and device compatibility are essential for long-term engagement. Our findings highlight that physical comfort and device aesthetics, reported by eight and four participants, respectively, are central determinants of sustained use. Future studies can invest in a range of device and accessory options, offer education on optimal fit, and actively address concerns around social visibility to foster consistent engagement.

Digital equity, social adaptability, and cultural relevance can broaden participation and reduce exclusion. Practical barriers, such as unreliable device/charging access and concerns about being questioned in public, reported by five and four participants, respectively, threatened inclusion for some participants, who were co-affected by socioeconomic and cultural factors. Privacy concerns and fear of stigmatization also shaped willingness to log sensitive events, especially in socially sensitive environments. Protocols that offer alternative data collection methods, portable chargers, and flexible grace periods for non-compliance can enable higher compliance. Equally important are features that empower autonomy and confidentiality: discreet notification options, anonymous user interfaces, and the ability for participants to withhold or delay entries when privacy cannot be assured. Allowing generic branding or dual-purpose device presentation and supplying participants with neutral explanations for their wearable use (e.g., "It's for a wellness challenge") can reduce both stigma and unwanted attention in real-world settings.

Supportive, nonjudgmental re-engagement pathways are critical after life disruptions. Emotional distress and life events, reported by five participants, can interrupt participation. Study protocols should anticipate these disruptions by offering friendly, judgment-free check-ins, supportive re-engagement features, and explicit permission to "restart" or recalibrate their engagement after lapses. Framing all data as valuable, regardless of lapses, can help participants return to the study when ready.

Clear definitions and flexible temporal anchoring are essential for accurate event logging. Ambiguity about when and how to log cravings versus substance use events was a consistent source of confusion, reported by four participants, leading to under-reporting or misclassification, reported by four participants. EMA platforms should provide clearer distinctions between event types, as well as the ability to retrospectively log events. EMA tools can also make temporal context explicit, through visual summaries, reminders of event definitions, and support for logging, to ensure reliable data and participant confidence in reporting.

Motivational feedback and tangible progress can sustain engagement beyond initial curiosity. Sustained participation depended on meaningful feedback and motivation. Features such as congratulatory messages, visual progress charts, and milestone rewards, reported by four participants, could have helped participants perceive their contributions as valuable and encouraged continued logging, making them feel more "motivated". Designers should integrate ongoing feedback mechanisms, goal-setting, and positive reinforcement to maintain momentum, especially as novelty wanes. Taken together, these qualitative insights demonstrate how fairness can be enhanced not only through algorithms but also by making human-centered design choices that reduce digital inequalities, offer scheduling flexibility, and support culturally sensitive device use.

4.2. *Limitations*

Our study has several limitations. First, our inclusion criteria required participants to have access to a smartphone with either a data plan or consistent Wi-Fi connectivity, which may have excluded individuals with limited digital access or unstable living conditions, factors especially relevant in substance use and underserved populations who often overlap. Second, our study relied on a relatively small sample size, which limits statistical generalizability and reduces our ability to capture subgroup-specific barriers, particularly among Native Hawaiian and Pacific Islander (NHPI) communities, which were reported by prior studies[29,30]. Third, our findings did not identify significant sociotechnical barriers at the interpersonal (e.g., social support) or societal/policy levels (e.g., stable housing), as noted in prior studies[31,32]. Fourth, while our findings highlight several sociotechnical barriers to EMA compliance, these factors were often deeply intertwined, making it difficult to isolate their specific impacts. Moreover, these sociotechnical factors can be linked to broader social and cultural norms. For example, concerns about aesthetic compatibility and professional appearance may be influenced by gender norms, peer pressure, or expectations from senior colleagues, factors that are often associated with youth culture or hierarchical social settings[33,34]. Yet, participants internalized these concerns as personal preferences, suggesting how broader social and cultural norms can subtly shape EMA compliance in ways that both participants and researchers may overlook, which were not fully explored in our study. Fifth, the four-week observation period may not reflect long-term patterns of engagement or the sustainability of EMA and wearable use. Sixth, the sample was broad and heterogeneous, with participants varying in both substance use severity and the type of substances used. Not all substances carry the same risks or patterns of use, and as a result, participants experiences were likely quite different. Lastly, it is noteworthy that all NHPI participants in this study reported lower educational attainment compared to participants from other racial or ethnic groups. This disparity may affect the generalizability of the findings to broader or more diverse populations.

4.3. *Opportunities for Future Work*

In future work, we aim to include larger, demographically disaggregated samples, especially within NHPI populations, to identify sociotechnical and culturally specific barriers and to ensure that Indigenous perspectives are meaningfully incorporated into fairness frameworks. Qualitative approaches will be essential for surfacing nuanced challenges to digital health engagement in NHPI and other underserved communities[35,36]. Second, we aim to leverage the design insights described here to develop new EMA systems that prioritize comfort, offer customizable, socially adaptable, and culturally responsive designs, and incorporate data visualization and motivational feedback to support diverse user needs and encourage sustained engagement. Third, we plan to implement more restrictive eligibility criteria or substance-specific subgroups to enable clearer interpretation of outcomes and ensure that differences related to substance type and severity are appropriately captured. We also intend to examine differences in participant context, such as housing status, age group, or educational attainment, to better understand how situational factors shape substance use experiences and to improve generalizability. Finally, we would like to include longer-term deployments to evaluate how life events, daily routines, and the presence or absence of support mechanisms influence the effectiveness of EMA health research over time.

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