Data-Driven Detection of Alcohol Abuse Using Wearable Sensing: A Hybrid Approach of Systematic Review and Exploratory Predictive Modeling

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Abstract—**This paper presents a dual-contribution study: (1) a systematic review of the use of digital technologies for alcohol use disorder monitoring and detection, and (2) a pilot analysis integrating data from commercial wearable devices, specifically Fitbit, with electronic health records in a real-world setting. The systematic review synthesizes evidence from 20 empirical studies across five categories—wearables, mHealth, smartphone applications, virtual reality, and serious games—highlighting the feasibility, limitations, and research gaps of current digital monitoring and detection of Alcohol Use Disorder (AUD). Utilizing accelerometer data from participants in the *All of Us* program, we analyzed the influence of key features and physical activity on alcohol consumption patterns. An exploratory inference-driven predictive modeling framework was developed to examine associations between wearable activity metrics and alcohol abuse status. Our findings highlight the significant potential of wearable technology in monitoring and addressing alcohol abuse, providing early detection and intervention opportunities. Notably, the pilot analysis identified a counterintuitive positive association between vigorous physical activity and alcohol abuse, suggesting the need for further research and context-sensitive interpretation of behavioral data. Despite the promising results, the study acknowledges limitations related to data representation and volunteer-based data collection, indicating a need for more granular and diverse data in future research. This research underscores the transformative potential of wearable technology and data analytics in improving individual health outcomes and public health initiatives related to alcohol abuse.**

Keywords—**logistic regression, wearable devices, predictive modeling, digital health, passive sensing, machine learning, mHealth, electronic health records, alcohol use disorder**

I. Introduction

Alcohol Use Disorder (AUD) [1] remains a significant global public health concern, affecting over 7% of the population and contributing to more than 3 million alcohol-related deaths annually. In the United States alone, approximately 10% of individuals aged 12 and older meet the criteria for AUD, with over 140,000 alcohol-related deaths each year—equivalent to more than 380 deaths per day [1]. The burden of AUD extends beyond individual health, straining social systems, healthcare resources, and economic productivity. Recent reviews have highlighted continued advances in digital health and wearable technologies for Alcohol Use Disorder (AUD), emphasizing both the promise of mobile and sensor-based interventions and the remaining challenges in implementation and user engagement [2, 3]. Emergency department visits, workplace absenteeism, and pervasive treatment stigma underscore a crisis that traditional interventions often fail to adequately address [4, 5].

Conventional treatment strategies—such as counseling, inpatient rehabilitation, and peer support groups—have demonstrated value, but their effectiveness is frequently constrained by barriers such as limited access, high cost, stigma, and poor adherence [6]. Furthermore, traditional assessment methods relying on self-reports and surveys are prone to recall bias and underreporting, which compromise the accuracy of both clinical monitoring and research findings [7]. These limitations underscore the need for scalable, objective, and user-centered solutions to complement or enhance existing methods.

In recent years, digital health technologies have emerged as promising tools to address these challenges.

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[1] Alcohol Use Disorder: "Alcohol abuse" was the term used prior to the DSM-5, which introduced the equivalent diagnosis of alcohol use disorder (AUD). In this study, we use the terms interchangeably, as the NIH All of Us Research Program EHR data uses “alcohol abuse.”

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Wearable sensors, biosensors, mobile Health (mHealth) applications, Virtual Reality (VR)-based therapies, and serious games offer innovative opportunities to improve real-time monitoring, patient engagement, and treatment adherence. These technologies enable passive or semi-passive data collection and can be integrated into daily life with minimal disruption. Similar to how novel data-driven approaches have been applied to predict behavior patterns from digital platforms [8, 9], there is a growing interest in translating such methods to health contexts. However, the rapid pace of innovation has outpaced a comprehensive synthesis of the evidence regarding their effectiveness and implementation challenges.

To address this gap, we conducted a systematic review of empirical studies exploring the role of emerging technologies in AUD monitoring and detection. Our objective was to summarize current evidence, identify gaps in the literature, and provide actionable directions for future research. Specifically, the review examined the utility of wearable and mobile devices in reducing alcohol use, managing cravings, and improving adherence to treatment.

The review revealed strong support for the feasibility and acceptability of wearable devices—particularly biosensors and fitness trackers such as Fitbit—in tracking alcohol-related behaviors and supporting behavior change. However, the findings also indicated several limitations. Many studies involved small sample sizes (with ~30% enrolling fewer than 20 participants; see Table A1), and frequently relied on narrow demographic groups [10], limiting generalizability. Additionally, few studies accounted for contextual factors such as residential environments, which may influence drinking patterns and treatment outcomes. Compliance challenges were also noted, especially in relation to biosensors, which some participants perceived as invasive, stigmatizing, or impractical for daily use.

Notably, while technologies such as standalone smartphone applications and VR therapies show promise, further research is needed to validate their effectiveness and address usability concerns. Among the tools reviewed, consumer-grade wearable devices like Fitbit, consistently demonstrated high user compliance and positive long-term engagement. These findings informed the design of a subsequent pilot study aimed at leveraging wearable and behavioral data to support AUD monitoring, detection and treatment. To build on this work, we conducted a case study using data from the NIH *All of Us* Research Program, a nationally representative dataset that includes Fitbit activity metrics linked with health and behavioral data across a diverse population [11]. We developed a preliminary logistic regression model to examine associations between physical activity patterns and self-reported alcohol abuse. Initial results suggest that commercially available wearables may serve as effective tools for detecting and monitoring alcohol-related behaviors in real-world settings.

This study makes the following key contributions:

- *Multimodal data integration for AUD prediction*: To our knowledge, this is the first study to combine commercial wearable data (Fitbit) and electronic health record (EHR) data from the NIH *All of Us* Research Program to model alcohol use disorder outcomes in a large and diverse population.
- *Predictive modeling using passively collected sensor data*: Unlike prior work that focuses on descriptive use of wearables, our study builds predictive models that identify statistically significant association between physical activities (e.g., lightly active minutes) and AUD—offering a novel, data-driven approach for early risk detection.
- *Discovery of non-obvious behavioral signals*: Our findings reveal counterintuitive patterns, such as a positive association between vigorous activity and alcohol abuse, highlighting nuanced behavioral patterns that merit further investigation.
- *Systematic synthesis of the use of technology and AUD*: This work uniquely combines a systematic review of wearable technologies for AUD monitoring and detection with a pilot data analysis, offering a comprehensive landscape view and practical modeling insights.

The remainder of this paper is organized as follows: Section II reviews related work on digital technologies for AUD. Section III describes the dataset, preprocessing, and modeling methodology, presents the analysis and numerical results, and Section IV concludes with a discussion of findings, limitations, and directions for future research.

II. Related Work

Recent scholarship on AUD has increasingly examined how technology-based tools can support monitoring and intervention, particularly in secure or structured settings [12]. Traditional approaches, including group treatment programs, have demonstrated effectiveness [13]. However, the integration of innovative technologies and a deeper understanding of demographic and psycho-social factors offer new avenues for enhancing substance abuse interventions and monitoring.

This section synthesizes findings from studies that employ wearable sensors, mHealth applications, smartphone-based tools, virtual reality, and serious games to address AUD. It also highlights trends, limitations, and gaps that inform the design of our pilot study.

A. Search Strategy and Study Selection

A comprehensive literature search was conducted using PubMed and Google Scholar to identify relevant studies published in English between September 1, 2017, and March 18, 2025. The search strategy incorporated keywords such as "wearable technology," "alcohol use disorder," "mobile health," "smartphone applications," and "virtual reality." Studies were included if they (1) presented original empirical findings, (2) utilized wearable or mobile technology in the context of AUD, and (3) reported measurable outcomes related to alcohol consumption or treatment efficacy.

The initial search yielded 17,700 records. After removing 3,285 duplicates and screening 14,290 titles and abstracts (as shown in Fig. 1), 125 articles were selected for full-text review. Based on predetermined inclusion and exclusion criteria (see Appendix A), 88 papers were removed. Of the remaining 37 studies, 10 were identified as systematic reviews and 7 did not report sample size, resulting in 20 studies that met the final inclusion criteria. This selection process adhered to PRISMA 2020 Systematic Review guidelines [14].

The final set of studies represents a diverse set of technology-enabled use cases, which were grouped into five thematic categories: wearable sensors, mHealth platforms, smartphone applications and breathalyzers, virtual reality, and serious games.

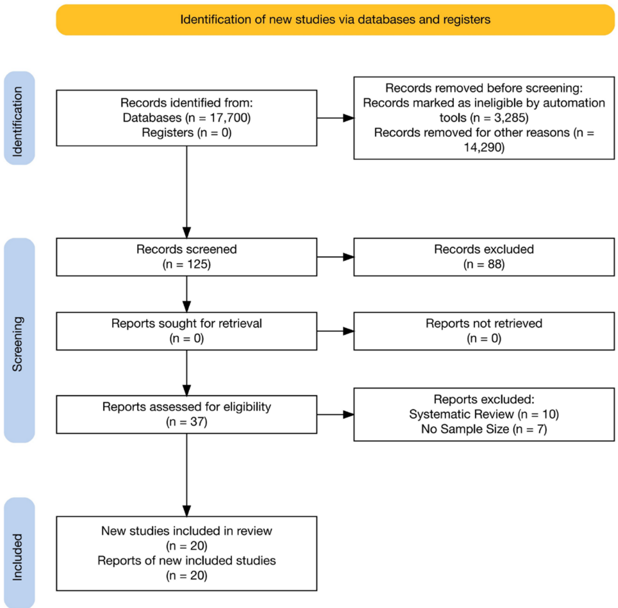

Fig. 1. PRISMA 2020 diagram displays the systematic review search and selection process.

B. Synthesis of Findings

The strategies identified across the studies vary in form and function but generally cluster into five main approaches. The following sections summarize key findings within each category, emphasizing both the demonstrated benefits and ongoing challenges highlighted in the literature.

1) Wearable sensors and biosensors

Several studies employed Transdermal Alcohol Sensors (TAS) and physiological biosensors to facilitate continuous monitoring of alcohol consumption and stress-related markers. Didier *et al.* [15] investigated the BACtrack Skyn® biosensor combined with machine learning algorithms, achieving 96.7% accuracy in detecting alcohol consumption. Similarly, Abrantes *et al.* [16] used Garmin wearables with an ecological momentary assessment application to monitor drug use recurrence among individuals with substance use disorders, with relapse detected in 44.2% of participants—often involving alcohol.

Brobbin *et al.* [17] validated the feasibility and clinical utility of continuous monitoring. For instance, a pilot evaluation of the SCRAMx ankle sensor [18] involving 84 participants reported an adherence rate of 81% and observed positive impacts on drinking behavior. Moreover, Brobbin *et al.* [19] comparing TAS data with self- reported alcohol use found high concordance, reinforcing the reliability of biosensors in outpatient settings. The Empatica E4 sensor was also used in Alinia *et al.* [20] to capture physiological signals associated with stress and emotion, though it did not directly predict alcohol cravings or relapse.

Further, a pilot randomized controlled trial combining TAS with contingency management [21] revealed that the addition of financial incentives significantly supported abstinence and engagement in treatment. High compliance rates and positive user feedback indicated strong acceptability. In a separate feasibility study, DiMartini *et al.* [22] involving patients with alcohol-related liver disease, 61% of participants wore the biosensor for more than three-quarters of the study duration, underscoring its tolerability and potential in clinical populations.

2) Mobile health platforms

A range of text-based and app-driven mHealth interventions have been investigated for their potential to reduce alcohol use and support recovery [10, 16, 23–27]. In one large-scale observational study, Vadhan *et al.* [23] evaluated Sunnyside®, a text messaging platform used by over 46,000 individuals, and found it was associated with a 33% reduction in weekly alcohol consumption over a 12-week period. The Fit&Sober application, which integrates with Fitbit devices, was evaluated in Abrantes *et al.* [16] using a cohort of 22 individuals in early recovery. Participants reported increased physical activity, improved abstinence rates, and reductions in anxiety, depression, and alcohol cravings.

In a randomized controlled trial conducted by Dulin *et al.* [27], researchers compared the Step Away mobile application with a conversational chatbot designed to reduce alcohol abuse. Both interventions demonstrated efficacy, though distinct patterns of user response emerged, the mobile app yielded higher levels of engagement, whereas the chatbot was more effective in enhancing participants' readiness to change. These findings suggest that different mHealth modalities may offer complementary benefits depending on user needs and treatment goals.

3) Smartphone applications and breathalyzers

Standalone smartphone apps and smartphone-integrated alcohol sensors represent a distinct category of digital intervention. A qualitative study by Östh *et al.* [24] explored apps such as Glasklart and iBAC, with participants reporting improved self-monitoring and increased motivation to reduce alcohol intake. However, the study noted user concerns regarding technical reliability and the stigma associated with using such tools in public or social settings.

A separate pilot study by Lauckner *et al.* [10] evaluated the feasibility of smartphone-connected breathalyzers among individuals living with HIV/AIDS. Participants generally found the devices acceptable and easy to use, despite occasional technical malfunctions.

In addition, a mixed-methods study by Carreiro *et al*. [28] combined wearable sensors with smartphone to assess the real- time detection of stress and alcohol cravings. Among 30 participants, the model achieved 76.8% accuracy in classifying these events. While participants noted that the system enhanced their mindfulness and awareness, issues related to stigma and technological usability continued to present barriers to consistent use.

4) Virtual reality-based interventions

VR has emerged as a promising adjunct to conventional therapies for alcohol abuse. In the E-Reva randomized controlled trial [29], participants receiving Cognitive Behavioral Therapy (CBT) combined with Virtual Reality-Cue Exposure Therapy (VR-CET) reported a 40–50% reduction in alcohol cravings. Notably, improvements in emotional regulation were sustained for up to eight months post-intervention.

A VR-based cue refusal video game developed by Metcalf *et al*. [30], demonstrating a 50% improvement in alcohol and cigarette use outcomes over a four-week period. Although minor side effects such as dizziness were reported, these symptoms tended to diminish with continued use, suggesting good overall tolerability of VR-based approaches.

5) Serious games and motion-based gaming

A game utilizing machine learning algorithms to analyze gameplay behavior was employed by Intarasirisawat *et al.* [31], achieving 95% accuracy in identifying individuals with AUD among a sample of 80 participants.

The Guardian Angel game [30], designed for therapeutic use, was tested with 41 male veterans and was associated with reductions in alcohol cravings and improvements in self-efficacy. However, it did not produce significant changes in relapse rates. In Ref. [32], the Jib game, focused on enhancing awareness and education around alcohol use. Among 23 university students, the game achieved high engagement scores, although users reported a need for clearer instructions and more appropriate difficulty levels to improve its effectiveness.

Our systematic review highlights the strong feasibility of using wearable devices and biosensors to monitor alcohol consumption and support intervention efforts. Several studies demonstrated the successful integration of tools such as Fitbit within mHealth platforms, showing reductions in alcohol use and improvements in related health outcomes [16]. In contrast, standalone smartphone applications and breathalyzers, while promising, were associated with usability challenges, including perceived stigma and occasional technical malfunctions. VR-based interventions showed sustained improvements in alcohol-related outcomes, although some users reported minor side effects such as dizziness. Serious games and motion-based interventions also showed potential for engagement and short-term impact but often lacked evidence of long-term effectiveness and required improvements in design and usability.

In addition to these findings, our systematic review identified several notable gaps in the existing literature, such as studies with small sample size and inclusion of contextual factors (e.g., residential environments) which may influence treatment adherence and outcomes. Challenges related to biosensor compliance were also reported, often tied to perceptions of invasiveness, cost, inconvenience, or stigma.

Taken together, these findings underscore the need for further research to improve the use of technology in intervention and monitoring—particularly in the areas of smartphone applications and VR. Among the technologies reviewed, wearable devices such as Fitbit stood out for their high compliance and promising long-term outcomes. In response to these findings, we conducted a pilot study integrating Fitbit data with electronic health records to explore innovative solutions for monitoring and supporting individuals with alcohol abuse.

III. Analysis and Numerical Results

A. Data Source

The sample for this pilot study was drawn from the *All of Us* Research Program [11], funded by the National Institutes of Health, which includes participants from various sites across the United States. *All of Us* aims to collect comprehensive phenotypic data, including questionnaires, Electronic Health Record (EHR) data, physical measurements, and biospecimens, from a representative population. For this analysis, we included participants who voluntarily provided accelerometry data from their personal Fitbit devices.

Data selection was facilitated using the Cohort Builder tool, which allowed us to access demographic information, Fitbit data, and EHR domains. A total of 177 individuals met the criteria for alcohol abuse and had corresponding Fitbit activity data. Additionally, a random sample of 5,000 individuals without alcohol abuse was included in the study cohort for comparative analysis.

B. Data Analysis

All analyses utilized Python code in Jupyter Notebooks within the *All of Us* Research Workbench platform. A total of 6,838,102 Fitbit measurements were included in this analysis with 1,390,135 measurements (20.3%) from those with alcohol abuse.

Features consisted of both Fitbit and sociodemographic data. Fitbit information was derived from the Fitbit measurements module, which provided activity levels categorized as very active minutes, lightly active minutes, fairly active minutes, and sedentary minutes. Demographic information including age, sex at birth, and race/ethnicity. Additionally, we included the poverty scale which represents the percentage of individuals living below the poverty line within the participant's 3-digit ZIP code.

For the 177 participants that were identified as having alcohol abuse, alcohol abuse condition was explored by sex at birth (Fig. 2), race/ethnicity (Fig. 3), and age (Fig. 4). Fig. 2 shows that alcohol abuse (other than withdrawal, in remission, or continuous) was higher in Females and Other compared to Males. However, remission status was highest in Males.

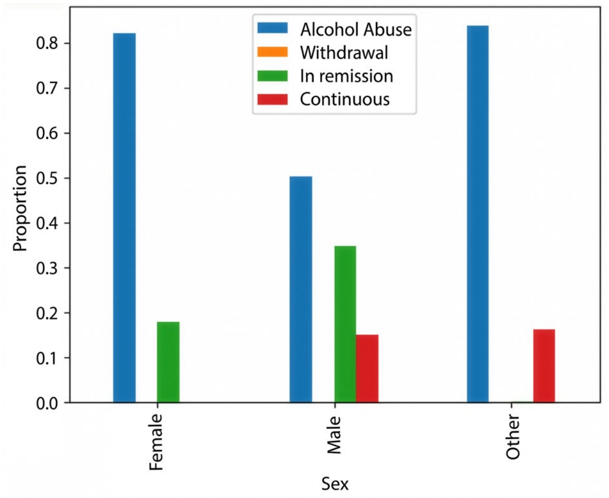

Fig. 2. Proportion of alcohol abuse condition by sex at birth.

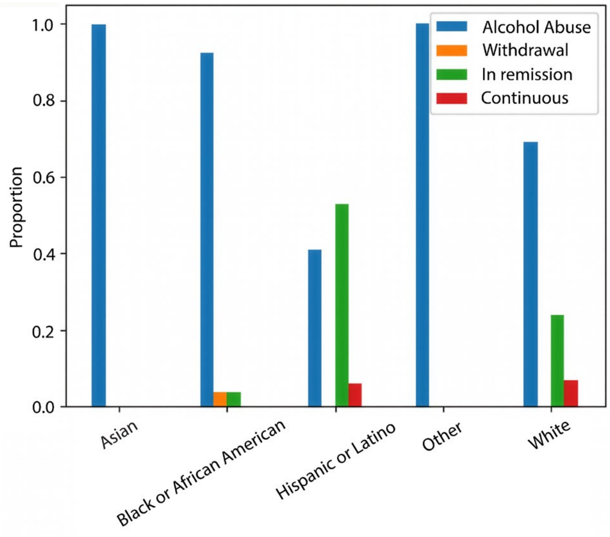

Fig. 3. Proportion of alcohol abuse condition by race and ethnicity.

As shown in Fig. 4, the median age was highest among participants with continuous alcohol abuse, while those in withdrawal exhibited the lowest median age. To improve the stability of our statistical estimates, the Asian race/ethnicity category was collapsed with the Other group to its small sample size.

Activity levels and demographic distributions between individuals with and without alcohol abuse are present in Tables I–IV. For those without alcohol abuse, the average age is 51.84 years, compared to 57.62 years for those with alcohol abuse. A higher percentage of females are present in the nonalcohol abuse group (67.87%) compared to the alcohol abuse group (55.39%). The vast majority of individuals in the alcohol abuse group identified as White (92.02%).

As illustrated in Fig. 5, the median of lightly active minutes (in log scale) recorded for Fitbit activity were comparable across sex at birth categories for all alcohol abuse conditions.

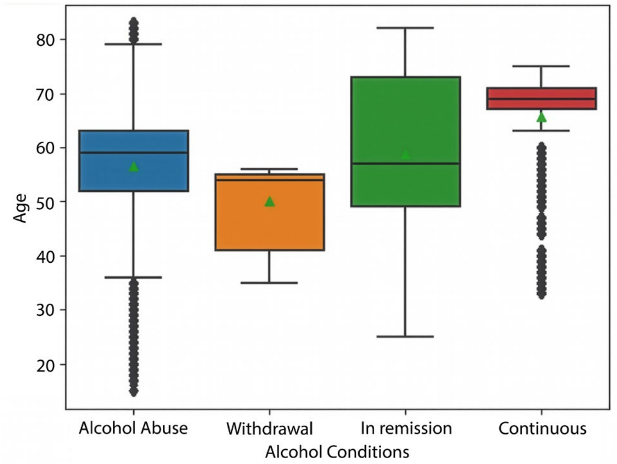

Fig. 4. Age of participants by alcohol abuse condition.

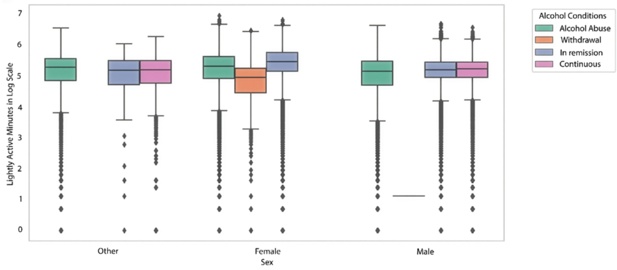

Fig. 5. Distribution of fitbit activity (lightly active minutes) by sex at birth, stratified by alcohol abuse condition.

As shown in Fig. 6, the median lightly active minutes in log scale were also similar across most race/ethnicity groups by alcohol abuse condition. However, the lowest overall median was observed among Black/African Americans participants with continuous alcohol abuse. Despite the use of log scale transformation to improve distribution of lightly active minutes, substantial variability remained.

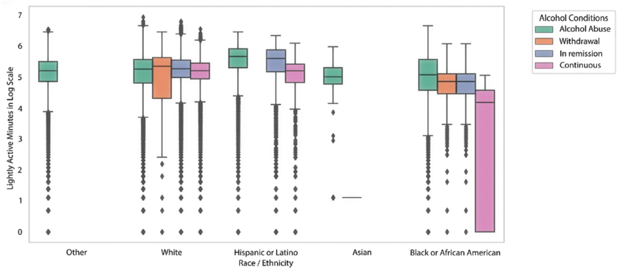

Fig. 6. Distribution of fitbit activity (lightly active minutes) by race/ethnicity, stratified by alcohol abuse condition.

Tables I–IV present descriptive statistics of study cohort. Quantitative variables are reported as mean ± standard deviation, while categorical variables are presented as count and percentages (n, %).

Table I shows the mean Fitbit activity levels stratified by alcohol abuse status. Participants with alcohol abuse exhibited higher average sedentary minutes and lower lightly active minutes compared to those without alcohol abuse. However, fairly active and very active minutes were higher among participants with alcohol abuse, which is an unexpected trend that nonetheless aligns with previous findings in the literature [10, 15]. Additionally, the standard deviation for both activity categories exceeded the mean, indicating high variability in activity levels across participants.

Table II displays the distribution of age and poverty level among participants with and without alcohol abuse. Participants with alcohol abuse were slightly older (mean age = 57.62) than those without alcohol abuse (mean age = 51.84). The average poverty level was comparable across both groups. Notably, the average ages in our dataset were much higher than the 2022 U.S. population median age estimate of 38.5 [1].

Table III presents the distribution of sex at birth categories by alcohol abuse status. Among individuals with alcohol abuse, 41.65% were male, compared to 28.39% of those without alcohol abuse.

Finally, Table IV shows the distribution of alcohol abuse by race/ethnicity. Among individuals with alcohol abuse, 92.02% identified as White, while 1.20% identified as Black or African American.

TABLE I. DESCRIPTIVE STATISTICS OF STUDY COHORT OF FITBIT ACTIVITY LEVEL

Fitbit Activity	Alcohol Abuse	
	No	Yes
Very Active Minutes	19.56 ± 34.65	22.52 ± 37.58
Lightly Active Minutes	200.21 ± 115.33	193.73 ± 108.99
Fairly Active Minutes	19.82 ± 34.10	22.12 ± 35.85
Sedentary Minutes	877.65 ± 305.08	882.52 ± 313.76

TABLE II. DESCRIPTIVE STATISTICS OF STUDY COHORT OF AGE AND POVERTY LEVEL

Variables	Alcohol Abuse	
	No	Yes
Age	51.84 ± 15.20	57.62 ± 12.20
Poverty Level	13.87 ± 4.82	14.20 ± 4.92

TABLE III. DESCRIPTIVE STATISTICS OF STUDY COHORT OF SEX AT BIRTH

Sex at Birth	Alcohol Abuse	
	No	Yes
Female	3697737 (67.87%)	769983 (55.39%)
Male	1546710 (28.39%)	578994 (41.65%)
Other	203520 (3.74%)	41158 (2.96%)

TABLE IV. DESCRIPTIVE STATISTICS OF STUDY COHORT OF RACE AND ETHNICITY

Race/Ethnicity	Alcohol Abuse	
	No	Yes
Hispanic/Latino	284094 (5.21%)	57883 (4.16%)
Black/African American	225591 (4.14%)	16666 (1.20%)
White	4458583 (81.84%)	1279183 (92.02%)
Other	479699 (8.81%)	36403 (2.62%)

The descriptive analysis highlights a potential limitation of the data, as participants tend to be older, and there is limited representation for racial and ethnic minority groups.

C. Predictive Modeling

This section presents an exploratory predictive modeling analysis designed to generate interpretable insights and inform future large-scale predictive applications. Logistic regression was used to examine the association between Fitbit activity levels and alcohol abuse. Separate models were constructed for each activity metric (very active, lightly active, fairly active, and sedentary minutes). A significance level of $\alpha = 0.05$ was used for all models to establish statistical significance (p-value). Each model was adjusted for age, race/ethnicity, sex at birth, and poverty level, as previously described. Logistic regression was selected as the primary modeling approach due to the small size of the positive (alcohol abuse) cohort and the pilot nature of the study. This method provided interpretable results while enabling estimation of the strength and direction of associations between activity metrics and alcohol abuse status, adjusting for relevant covariates. More complex machine learning models, such as random forests, gradient boosting machines, or neural networks, were not implemented in this analysis due to the limited sample size and inference-focused objectives. Accordingly, model performance was evaluated in terms of estimated odds ratios, 95% confidence intervals, and p-values, rather than classification metrics such as AUC-ROC or F1-Score.

Table V presents separate logistic regression analyses examining the associations between alcohol abuse and four different Fitbit measurements in log scale. Note that OR denotes the odds ratio; CI denotes the confidence interval. All Fitbit measurements were statistically significant at p-value < 0.05. For every 1% increase in very active minutes, there was a 0.8% increase in odds of alcohol abuse (OR: 1.008, 95% CI: 1.007, 1.009), suggesting a slight increase with higher levels of vigorous physical activity. Conversely, lightly active minutes had a negative association with alcohol abuse (OR: 0.981, 95% CI: 0.980, 0.982), with a 1.9% decrease in odds of alcohol abuse with every 1% increase in lightly active minutes. Fairly active minutes showed an OR of 1.034 (95% CI: 1.034, 1.036), implying a positive association and 3.4% increase in odds of alcohol abuse. Lastly, a 1% increase in sedentary minutes was associated with 0.949 times, or 5.1% decrease in odds (OR: 0.949, 95% CI: 0.946, 0.952), indicating that more sedentary behavior was associated with a lower likelihood of alcohol abuse.

TABLE V. LOGISTIC REGRESSION MODELING OF FITBIT ACTIVITY METRICS AND ODDS RATIOS OF ALCOHOL ABUSE (ADJUSTED FOR DEMOGRAPHIC COVARIATES)

Fitbit Activity (minutes)	Alcohol Abuse OR (95% CI)
Very Active	1.008 (1.007, 1.009)
Lightly Active	0.981 (0.980, 0.982)
Fairly Active	1.034 (1.034, 1.036)
Sedentary	0.949 (0.946, 0.952)

The following Figs. 7–10 show the probability of alcohol consumption by activity level and demographic groups. Table VI shows the base values used in the prediction of each of the figures.

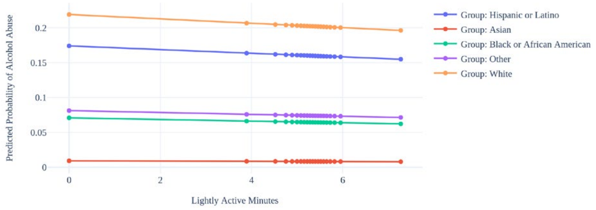

Fig. 7. Probability of alcohol consumption by activity level and demographics group.

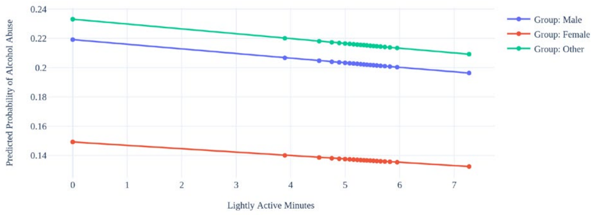

Fig. 8. Probability of alcohol consumption by activity level and sex at birth.

TABLE VI. REFERENCE DEMOGRAPHIC AND SOCIOECONOMIC STRATA USED FOR MARGINAL PREDICTION ANALYSIS

Variables	Strata		
	Sex	Age	Poverty Level
Sex	-	Male	Male
Age	42	-	42
Race	White	White	White
Poverty Level	10%	10%	-

Trends in the predicted probability of alcohol abuse were obtained by using marginal probabilities after accounting for average values of race/ethnicity, sex at birth, age, and poverty levels as illustrated in Table VI. After adjustment, there were distinct trends in the predicted probability of alcohol abuse that emerged when stratified by age (see Fig. 9) and sex at birth (see Fig. 8).

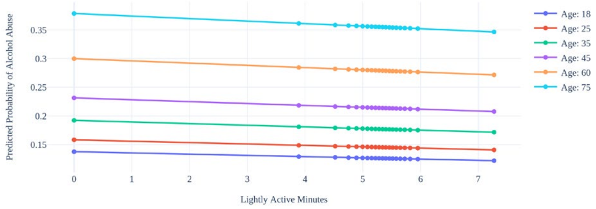

Fig. 9. Probability of alcohol consumption by activity level and age group.

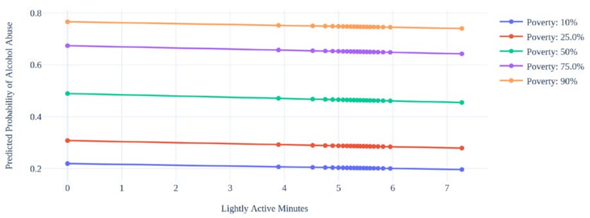

Fig. 10. Probability of alcohol consumption by activity level and poverty group.

Contrary to what was expected, we found opposite trends in fairly active minutes and very active minutes, with higher adjusted log-minutes associated with increased probability of alcohol abuse. Similarly in sedentary minutes, we saw that there was a decrease in predicted probability of alcohol abuse for increased adjusted log-minutes. These trends were noted across age, sex at birth, and poverty level strata (data not shown as stratified results were consistent with the main findings). Average values selected for marginal predicted probabilities included a base value of white for race/ethnicity, potentially limiting our ability to generalize results to other race/ethnicities for all stratified models. These findings are exploratory, and future work using larger datasets will incorporate predictive modeling approaches with appropriate validation to assess generalizability.

The dataset used in this study was highly imbalanced, with 177 cases of alcohol abuse and over 5,000 controls. Because our analysis was inference-focused rather than prediction-focused, we did not apply synthetic oversampling techniques such as SMOTE, which may alter the underlying data distribution and bias parameter estimates in regression models. Instead, we addressed class imbalance analytically by including relevant covariates and interpreting effect estimates with caution. We acknowledge that this imbalance may affect the precision and stability of our odds ratio estimates. Future research aimed at predictive modeling will incorporate appropriate imbalance-handling strategies, such as class weighting or alternative sampling approaches, in combination with validation procedures.

In this study, "predictive analytics" refers broadly to the application of statistical modeling to wearable and EHR data to generate insights that can inform future prediction tasks. Our analyses in this pilot phase used logistic regression to quantify associations between activity metrics and alcohol abuse status, prioritizing interpretability and robustness given the limited sample size. While this framework was not intended for immediate deployment as a predictive classifier, it establishes a foundation for subsequent work applying and validating more complex models, such as generalized mixed-effects models, random forests, gradient boosting machines, and deep learning approaches once larger, more balanced datasets are available.

IV. CONCLUSION

This work offers a pragmatic contribution to the evolving field of AUD monitoring by combining a systematic review of digital health interventions with a pilot analysis of real-world wearable and EHR data. Our review confirms that while digital approaches, particularly wearables, show strong potential for supporting behavior change and improving engagement, the evidence remains mixed and often limited by small, homogenous samples and short-term follow-up.

The pilot study extends this literature by demonstrating that features derived from commercially available wearables, when integrated with EHR data, can help identify behavioral patterns associated with alcohol misuse. Notably, the positive correlation observed between higher-intensity activity and alcohol abuse raises important questions about the complexity of interpreting passive data and underscores the need for more context-aware models. In addition, unmeasured confounders such as mental health conditions, medication use, and lifestyle factors may influence the observed associations and should be considered in future analyses. Future studies integrating psychosocial and pharmacologic data will help disentangle these complex relationships.

Despite promising results, the study's limitations, including sample representativeness and reliance on volunteer-collected data; should temper enthusiasm. These findings point to clear priorities for future research: expanding to larger, more diverse cohorts, refining analytical approaches, and considering additional behavioral and contextual factors that influence alcohol abuse. In summary, our findings suggest that wearables and predictive analytics hold value as supplementary tools for AUD risk detection and monitoring, but their role in routine care is still emerging. Ongoing research and broader data integration will be essential for translating these early insights into reliable, actionable tools for both clinicians and individuals affected by alcohol abuse.

APPENDIX A: SYSTEMATIC REVIEW

A. Summary Table of Systematic Review

TABLE A1. SUMMARY OF STUDIES THAT USE WEARABLE TECHNOLOGIES FOR ALCOHOL ABUSE MONITORING AND DETECTION THAT WERE INCLUDED IN THE SYSTEMATIC REVIEW

Title	Authors	Study objective	Method of collecting data	Model used	Sample size	Results
An Automated Mobile Game- based Screening Tool for Patients with Alcohol Dependence	Intarasirisawat *et al.* [31]	The study explores a mobile game- based tool that uses gameplay data and machine learning to non-intrusively screen for alcohol dependence by detecting cognitive and motor impairments.	Experimental, Observational, Cross-sectional study involving 40 alcohol- dependent patients and 40 healthy adults.	Logistic Regression, Linear Support Vector Machine & Random Forest, Supervised machine learning algorithms (e.g., Random Forest, Logistic Regression).	80	Statistical analysis showed that patients exhibited greater device movement (median 1.028) compared to healthy individuals (median 0.996). Using gameplay, touch, and motion data, the tool identified alcohol dependence with 95% accuracy, sensitivity, and specificity.
Study on the efficiency of virtual reality in the treatment of disorder: study protocol for a randomized controlled trial.	Nègre *et al.* [29]	The primary objective of the E-Reva study is to assess the efficacy of combining VR-CET with CBT in decreasing the cumulative number of standard drinks consumed by patients with AUD over an eight-month period.	Longitudinal and observational	Linear Regression model, Cox & mixed models, linear mixed model	156	The primary outcome is the total number of standard drinks consumed at 8 months, with secondary outcomes including reductions in craving and improvements in mental health. Results are pending, as the study is still ongoing.
Self-reported alcohol consumption during participation in a text messaging-based online drinking moderation platform	Vadhan *et al.* [23]	Evaluate changes in alcohol consumption during participation in Sunnyside®, an SMS-based alcohol moderation app. Identify individual characteristics (e.g., drinking severity, concern levels) influencing program outcomes.	Self-reported drink tracking via Sunnyside® text messaging.	Generalized mixed-effect growth models.	46411	At baseline, 64.3% of members reported drinking daily, but weekly drink counts dropped by 33%, with the steepest decline in the early weeks. Those with more severe alcohol use and higher concern at baseline experienced greater relative benefits.
Keeping Track of My Drinking - Patient Perceptions of Using Smartphone Applications as a Treatment Complement for Alcohol Dependence	Östh *et al.* [24]	The study aimed to understand how patients with alcohol dependence experienced self-monitoring smartphone apps as part of their treatment. It focused on app usage patterns, user perceptions, and the apps' perceived impact on treatment outcomes.	Individual, semi-structured interviews were conducted via video or phone calls with 21 participants, all of whom had used the apps for 12 weeks as part of a randomized controlled trial (RCT). Data were analyzed using Qualitative Content Analysis (QCA).	Qualitative Content Analysis (QCA), guided by inductive thematic coding, was employed to extract themes from participant interviews.	21	The study identified facilitators and barriers to app use. Facilitators included increased awareness, motivation, and improved clinician-patient communication, while barriers involved technical issues, unfit features, and social stigma around using the app in public or at work.
The feasibility of using smartphones and mobile breathalyzers to monitor alcohol consumption among people living with HIV/AIDS	Lauckner *et al.* [10]	To examine the feasibility of using smartphones and mobile breathalyzers to monitor alcohol consumption among people living with HIV/AIDS	Longitudinal, Observational Qualitative data were collected through semi-structured exit interviews	Descriptive Statistics, Paired Samples t-Tests, Correlation Analyses, Qualitative Coding	Enrolled participants: 20 Completed monitoring tasks: 17	Baseline self-reported binge drinking was linked to more drinking days and higher average blood alcohol content, as measured by breathalyzer and mobile surveys. While participants generally viewed the technologies positively, some reported technical issues.

Objective continuous monitoring of alcohol consumption for three months among alcohol use disorder treatment outpatients	Alessi *et al.* [33]	This study used transdermal alcohol sensing technology to objectively and continuously monitor alcohol use. It aimed to characterize alcohol consumption patterns among outpatients undergoing treatment for alcohol use disorder in two clinical trials.	Longitudinal, Observational	Algorithm for Estimating Breath Alcohol Concentration (eBrAC), Statistical Analysis (SPSS, Correlation, chi-square)	63	Results indicate that most patients drank while in outpatient care.
Use of Transdermal Alcohol Sensors in Conjunction with Contingency Management to Reduce Alcohol Consumption in People with Alcohol Dependence Attending Alcohol Treatment Services: Protocol for a Pilot Feasibility Randomized Controlled Trial	Brobbin *et al.* [21]	This feasibility randomized controlled trial examines the use of transdermal alcohol sensors (TAS) to monitor alcohol consumption in individuals undergoing treatment for alcohol use disorder (AUD). It also explores how TAS works with or without rewards (CM) to support sobriety.	Participants were randomized into control and CM groups, using TAS (BACtrack Skyn) to monitor alcohol consumption for two weeks. Self- reported Timeline Followback (TLFB) and postwear surveys were also collected.	Randomized Controlled Trial (RCT) with descriptive statistical analysis and feasibility assessment.	32	The study showed high participant compliance and TAS acceptability, with most completing the trial and returning devices. CM effectively reduced alcohol consumption through financial incentives, and despite some technical issues, both TAS and CM supported behavior change and treatment engagement.
Challenges and Solutions for Monitoring Alcohol Use in Patients With Alcohol-Related Liver Disease: Pilot Study of a Wearable Alcohol Biosensor	DiMartini *et al.* [22]	This study aims to assess the acceptability and feasibility of wearable alcohol biosensors for patients with alcohol-associated liver disease (ALD). It explores patient experiences, acceptance, and challenges of using the technology in a pilot setting.	Mixed-methods approach: 3-month randomized control trial (RCT) - Quantitative: TAM2 subscales (acceptability, usability), proximity sensors for device wear. - Qualitative: Open-ended feedback from participants regarding device use, issues, and comfort.	Technology Acceptance Model 2 (TAM2)	34 eligible participants; 97% enrolled (33). - 27 completed Time 1, 21 completed Time 2.	The study found high acceptance of the biosensor technology, with 61% of participants wearing the device for at least 77% of the time despite some non-compliance and reports of discomfort. Newer devices like the BACtrack Skyn® may improve data transmission and reduce user concerns.
Using mobile phone technology to treat alcohol use disorder: study protocol for a randomized controlled trial	Danielsson *et al.* [25]	The objective of this study is to evaluate how mobile phone applications and breathalyzers can make treatment more accessible and appealing to individuals reluctant to seek help for alcohol dependence.	Participants were randomized into three groups and used Glasklart or iBAC with standard treatment. Alcohol use was tracked via app data, self-reports, biomarkers, and post-study interviews.	A three-armed RCT with repeated measures ANOVA for primary and secondary outcomes. Qualitative data were analyzed through thematic coding.	375	Heavy drinking days significantly decreased in both intervention groups compared to standard treatment alone, with notable reductions in weekly alcohol consumption and biomarker levels.
Wearable sensor-based detection of stress and craving in patients during treatment for substance use disorder: A mixed methods pilot study	Carreiro *et al.* [28]	To determine the accuracy of wearable sensors in detecting stress/craving episodes in SUD patients and to understand user perceptions.	Physiological data was collected via wrist-mounted Empatica E4 sensors, which included accelerometry, EDA, heart rate, and temperature over four days; patient self-reports of craving/stress were also logged.	Fine Gaussian Support Vector Machine (SVM) was the primary model used for classifying stress and craving events.	30	Accuracy for distinguishing states: stress vs. no-stress (81.3%), craving vs. no-craving (82.1%), craving vs. stress (80.7%).
Virtual Reality Cue Refusal Video Game for Alcohol and Cigarette Recovery Support: Summative Study	Metcalf *et al.* [30]	Developed and assessed the Take Control game, a partially immersive Kinect for Windows platform game that allows users to counter substance cues through active movements (hitting, kicking, etc).	Conducted a small wait-list control trial using a quasi-random sampling technique (systematic)	substance use, cravings, satisfaction with the game experience, self-efficacy related to recovery, and side effects from exposure to a virtual reality intervention and substance cues	76	Participants found the game enjoyable and supportive of recovery, with substance use decreasing during the intervention. Alcohol recovery participants saw greater benefits, and side effects and cravings decreased over time.

Associations Between Physiological Signals Captured Using Wearable Sensors and Self-reported Outcomes Among Adults in Alcohol Use Disorder Recovery: Development and Usability Study	Alinia *et al.* [20]	This study aims to explore the relationship between physiological signals—electrodermal activity (EDA) and heart rate variability(HRV)—and self-reported experiences such as alcohol use, stress, emotions, and cravings in adults undergoing AUD treatment.	Daily EMAs on emotions, cravings, and stress via web surveys. Continuous stress monitoring with Empatica E4 wristband. Interviews to assess alcohol use and validate stress markers.	Negative Reinforcement Model	11	The Empatica E4 wearable sensor's physiological data were useful and significantly linked to self-reported outcomes, including stress events, alcohol use, emotions, and pain. Key physiological features correlated with these factors effectively.
Experiences with SCRAMx alcohol monitoring technology in 100 alcohol treatment outpatients	Alessi *et al.* [18]	To assess feasibility, acceptability, and adherence with the SCRAMx® transdermal alcohol monitoring technology in alcohol treatment outpatients	Recruitment of participants from four community- based clinics; SCRAMx® data uploaded regularly; alcohol breath tests; urine tests for substance use; participant surveys	SCRAMx® wearable device for transdermal alcohol monitoring, including contingency management (CM) intervention for treatment attendance or abstinence	595 screened, 116 consented, 100 randomized	Feasibility, acceptability, and adherence to continuous transdermal alcohol monitoring
Comparison of transdermal alcohol concentration and self-reported alcohol consumption in people with alcohol dependence attending community alcohol treatment services	Brobbin *et al.* [19]	The aim is to assess the accuracy and wearability of a transdermal alcohol sensor (TAS) (BACtrack Skyn) with people currently receiving treatment at alcohol services.	a mixed methods observational study across three NHS alcohol services in South London.	Spearman Rank Correlation coefficient	16 subjects (7 Male, 9 Female), completed by 15 subjects	TLFB and Skyn reported 70 alcohol- drinking days, but discrepancies occurred due to device errors, improper wear, and data not meeting alcohol event criteria. Some self-reported drinking days were undetected by the TAS.
Identifying biomarkers of drug use recurrence using wearable device technologies and phone applications	Mahoney III *et al.* [26]	Objective of the study is to identify predictors of drug use by providing commercially available wearable device that continuously monitors biometric signals (e.g., heart rate/variability [HR/HRV], sleep characteristics).	Integrated Digital Health Data Collection Method This method combines automated data uploads from an EMA app and Garmin wearable device into a centralized platform (Smartabase), enabling synchronized, high-frequency physiological and self-report data collection for analysis in R.	RNI NeuroCAT - EMA App developed by Rockefeller Neuroscience Institute (RNI) Garmin Vivosmart4 - Garmin Watch Garmin Connect Phone Application	77	44.2% of participants experienced DUR, with methamphetamine and cannabis being the most common substances. The study suggests that EMA-APP and wearable devices could help predict DUR, with future research planned to explore predictors in a larger cohort.
Computer simulation games as an adjunct for treatment in male veterans with alcohol use disorder	Verduin *et al.* [34]	This study explores using low-cost games to help Alcohol Use Disorder (AUD) patients practice new skills in safe, realistic environments. The objective is to boost engagement and improve outcomes by making treatment more interactive and motivating.	1. Mini International Neuropsychiatric Interview Self-report ratings of alcohol dependence (ADS), alcohol craving (OCDS, AUQ) and self- efficacy (TSSE- RP) 3. Random Screening	Relapse rates were compared using logistic regression, while times to relapse and dropout were analyzed with Cox Regression Survival Analysis. Time-related differences in AUQ and OCDS ratings were assessed using Generalized Estimating Equations (GEE)	Participated 41, Completed by 31	The OCDS results were significant, showing fewer obsessive thoughts about alcohol in the game condition. Participants who played the game also achieved higher self-efficacy sooner, which is clinically significant given its link to improved drinking outcomes.
A Smartphone Physical Activity App for Patients in Alcohol Treatment: Single-Arm Feasibility Trial	Abrantes *et al.* [16]	To evaluate the feasibility, acceptability, and potential outcomes of the Fit&Sober app in early alcohol recovery	Self-reported app use, Fitbit metadata, client satisfaction questionnaires, system usability scales, and accelerometer wear time	- Social Cognitive Theory Self-Determination Theory	22	After 12 weeks of app use, participants showed improvements in physical activity, mental health, and alcohol consumption. The app was well- received, with high satisfaction and notable effects on these outcomes.

Signal Processing and Machine Learning with Transdermal Alcohol Concentration to Predict Natural Environment Alcohol Consumption	Didier *et al.* [15]	To evaluate the effectiveness of machine learning models using Skyn biosensor data to distinguish alcohol from non-alcohol drinking episodes.	Data collected via Skyn biosensor (TAC data) during alcohol and non-alcohol drinking episodes. Participants self-reported alcohol use. Data quality was ensured using a cleaning algorithm.	Elastic net logistic regression and random forest model.	36	Random forest and logistic regression models predicted alcohol use with 96.7% accuracy, 93.3% sensitivity, and 100% specificity.
Contrasting a Mobile App with a Conversational Chatbot for Reducing Alcohol Consumption: Randomized Controlled Pilot Trial	Dulin *et al.* [27]	Compare a mobile app and a chatbot for alcohol reduction effectiveness.	Self-reported alcohol intake via an app or chatbot.	Randomized controlled trial with app and chatbot interventions.	150	Both interventions reduced drinking, with the chatbot improving readiness to change. The app had better engagement and usability.
A Game to Deal with Alcohol Abuse (Jib): Development and Game Experience Evaluation	Carvalho *et al.* [32]	This study aimed to explore the development and evaluation of a serious game for smartphones to present a novel approach to address the issue of alcohol abuse.	Alcohol Use Disorders Identification Test (AUDIT) and the Game Experience Questionnaire (GEQ)	Quantitative Analysis	23	The overall GEQ evaluation showed that the game presents a more positive than negative affect on all users, besides showing the other desirable characteristics of serious games.

B. Inclusion Criteria

Papers selected follow these criteria: (i) article published in English; (ii) should focus on alcohol dependence and its treatment; (iii) selected papers should report outcomes or movement towards alcohol treatment interventions; and (iv) the publication date must fall within the range of 2017 to 2025.

C. Exclusion Criteria

Papers following these criteria are excluded: (i) article with small sample size less than or equal to 6 (ii) review articles, systematic reviews, or meta-analyses; (iii) publications duplicating the same data or information; (iv) articles that are not specifically centered on the topic of interest (e.g., alcohol dependence and treatment) and; (v) incomplete studies or providing partial results only (e.g., abstracts without full text).

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

EH and BB jointly conceptualized and supervised the study as co-principal investigators. EH, BB, and PRG performed data extraction, logistic regression analyses, and visualization using Python and the NIH All of Us Research Workbench. EH, BB, OA, RA, JAS, and NG collectively conducted the systematic review and synthesis of the literature. BB served as the corresponding author and led the manuscript revisions and final editing. All authors reviewed and approved the final version of the manuscript.

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