# Machine Learning Applications in Mental health and Substance Use Research Among Lesbian, Gay, Bisexual, Transgender, Queer or Questioning and Two-spirit Population: Scoping Review

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## *Abstract*

**Background:** People at high risk of mental health or substance addiction issues among sexual and gender minorities may have more nuanced characteristics that may not be easily discovered by traditional statistical methods.

**Objective:** This review aimed at identifying literature that used machine learning to investigate mental health or substance use concerns among lesbian, gay, bisexual, transgender, queer or questioning and two-spirit (LGBTQ2S+) population as well as directing future research in this field.

**Methods:** MEDLINE, EMBASE, PubMed, CINAHL Plus, PsycINFO and IEEE Xplore, Summon databases were searched from November to December 2020. We included original studies which used machine learning to explore mental health and/or substance use among LGBTQ2S+ population and excluded studies of genomics and pharmacokinetics. Two independent reviewers reviewed all papers and extracted data on general study findings, model development and discussion of study findings.

**Results:** We included 11 studies in this review, of which 9 (82%) studies were on mental health and only 2 (18%) studies were on substance use concerns. All studies were published within last 2 years and majority were conducted in the Unites States. Among mutually non-exclusive population categories, sexual minorities male were the most commonly studied subgroup (n=5, 45%), while sexual minorities female were studied the least (n=2, 18%). Studies were categorized into 3 major domains: online content analysis (n=6, 55%), prediction modelling (n=4, 36%) and imaging study (n=1, 9%).

**Conclusions:** Machine learning can be a promising tool of capturing and analyzing hidden data of mental health and substance use concerns among LGBTQ2S+ people. In addition to conducting more research on sexual minority women, different mental health and substance use problems as well as outcomes, future research should explore newer environments and data sources and intersections with various social determinants of health.

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# Original Manuscript

**Review**

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## Abstract

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**Keywords:** Sexual and gender minorities; mental health; mental disorders; substance-related disorders; machine learning

## Introduction

Lesbian, gay, bisexual, transgender, queer or questioning and two-spirit (LGBTQ2S+) people experience significant mental health disparities and are at higher risk of substance use problems compared to their heterosexual and cisgender peers [1–5]. A meta-analysis of 25 studies revealed that lesbian, gay and bisexual individuals had 2.47 times higher lifetime risk of attempting suicide, 1.5 times greater risk of depression and anxiety disorders, and 1.5 times higher risk of alcohol and other substance dependence over a 12 months period [2]. Recent statistics from the 2015 National Survey on Drug Use and Health in the United States of America (USA) reported that sexual minority people had higher likelihood of past year use of illicit drugs, marijuana, and opioids; current use of cigarettes and alcohol; and past year diagnosis of any mental illness compared with sexual majority groups [6]. LGBTQ2S+ people also use mental health services and substance use treatment more frequently than cisgender and heterosexual individuals [6,7].

There is a robust evidence base documenting sexual orientation and gender identity as social determinants of health, whereby LGBTQ2S+ persons experience stressors from stigma, social and economic exclusion that contribute to increased mental health challenges and maladaptive coping strategies including problematic substance use [8–10]. In addition, intersecting experiences of marginalization such as race, ethnicity, disability and homelessness; lack of enough familial and peer supports; various acts of bullying, harassment, and hate crimes against them together with experience of self-stigmatization, such as internalized homophobia, biphobia and transphobia contribute behind further deterioration of their mental health and substance use concerns [8,11–16].

With advances in technology, novel statistical methods like machine learning have emerged as promising means of analyzing a vast range of complex data in public health informatics [17,18]. Machine learning uses computational power to identify or 'mine' data patterns, resultantly, have been increasingly used for content analysis and as a predictive modelling technique [17]. There are three major classes of machine learning, including supervised learning, unsupervised learning and semi-supervised learning. Supervised leaning aims to learn from labelled data to predict the class of unlabelled input data or outcome variable [19]. Unsupervised learning does not require an outcome variable, thereby allowing the algorithm to freely detect and recognize hidden patterns with minimum human interference [19,20]. Semi-supervised learning learns from both labelled and unlabelled data, where it can use readily available unlabelled data to improve supervised learning tasks when the labelled data is scarce or expensive [21]. A more advanced form of machine learning, deep learning, has gained popularity in health research in recent years and uses an artificial neural network model with multiple layers to hierarchically define and process data [22]. These machine learning methods provide the opportunity to understand data more thoroughly and effectively, as well as to yield meaningful findings beyond traditional statistical methods.

Several reviews, including 3 recent systematic reviews, have been conducted to summarize the application of machine learning in substance use and mental health sectors [20,23–25]. These systematic reviews have reported machine learning applications in 54 articles on mental health, 87 articles on suicidal behaviour, and 17 articles on addiction research and found good performance in predicting human behaviour [20,23,25]. However, most of these reviews and studies focused on broad categories and the general population or patient records. Though one scoping review has explored studies which predicted population-specific health with machine learning [26], the study did not identify machine learning applications among the LGBTQ2S+ population. There is a substantial gap in the literature with no existing review located focused on machine learning studies examining mental health and substance use among LGBTQ2S+ people. As a result, we conducted a scoping review to address these knowledge gaps with the aim of mapping the current status of machine learning studies focusing on this field and identifying the research gap to facilitate future research. In the context of persistent mental health and problematic substance use concerns and disparities among the LGBTQ2S+ population, the findings will provide useful insight to inform research and programs.

## Methods

This scoping review has followed the extension of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guideline for scoping reviews [27]. The review protocol was registered on the Open Science Framework [28] on December 17, 2020 to facilitate transparency and reproducibility of the study.

### Objectives and Methodology Framework

The objective of this review was to conduct a comprehensive search of studies using machine learning to investigate mental health or substance use among LGBTQ2S+ communities and find out the scope of future research. We followed the five-stage methodological framework developed by Arksey and O'Malley [29].

### Identifying Research Questions

Initially, we identified a broad set of preliminary questions for this scoping review:

- What is the volume of the literature that used machine learning analysis in the field of mental health and substance use among the LGBTQ2S+ population?
- What are the fields of LGBTQ2S+ mental health and substance use that have been studied by machine learning?
- Which subgroups of the LGBTQ2S+ population have been investigated? Are there any specific subgroups that have been studied more using machine learning analysis?
- What types of machine learning methods (e.g., supervised, unsupervised, semi-supervised, and deep learning) and algorithms (e.g., decision trees, random forest, logistic regression, and penalized regression) have been used to study LGBTQ2S+ mental health and substance use?
- What are the real-world implications of these studies? Are there any knowledge gaps or untouched domains that should be addressed in the future research?

### Identifying Relevant Studies

In order to gather a large quantity of relevant literature, we followed previous review studies with similar objectives [24,26] and searched the following databases: MEDLINE (Ovid), EMBASE (Ovid), CINAHL Plus, APA PsycINFO (Ovid), PubMed and Institute of Electrical and Electronics Engineers (IEEE) Xplore. We also searched the Summon (ProQuest) database used by the University of Toronto Libraries, which searches across many of the other databases, journal packages, e-book collections and other resources. Information technology database like IEEE Xplore was selected as a potential source of machine learning related literatures. Literature searches involved a combination of keywords (e.g., 'mental health', 'mental disease', 'mental health service', 'substance abuse', 'machine learning', 'sexual and gender minorities', 'LGBT', 'lesbian', 'gay', men who have sex with men', 'bisexual', 'queer', 'two-spirit', 'intersex', 'transgender') and Medical Subject Headings, if applicable. A librarian was consulted regarding the keywords and search terms.
Two reviewers (AK and RB) conducted the database search from November 25th to December 13th, 2020 and imported all citations to the Covidence online platform where duplicate papers were removed automatically. The databases were searched from the date of inception of the databases to the year 2020, with no filter in place for publication year. The bibliography lists of included studies and review papers were reviewed on December13th, 2020 to identify any potential studies. Multimedia Appendix 1 includes the full EMBASE search strategy, representing an example of search query applied for all other databases.

### Study Selection

We included studies if they used machine learning to investigate mental health or substance use behaviours of people within the LGBTQ2S+ population. Studies where machine learning was used partially, but not for main statistical analysis, were included in the review. We only included empirical investigations, thereby excluding editorials, opinion pieces and reviews. We also excluded papers which used logistic regression analyses but not as a machine learning algorithm; and the study objective was only determining LGBTQ2S+ identity status. In addition, studies where full texts could not be retrieved with institutional license; and studies of genomics, pharmacokinetics and those that were not directly relevant to humans were excluded.
Two reviewers (AK and RB) independently screened each title and abstract based on the eligibility criteria

and then completed full-text screening of remaining studies. Disagreements were resolved through discussions among three reviewers (AK, RB and MC) to yield a list of final included studies.

### Data Charting

In order to facilitate data charting and reporting, individual reviewers (AK and RB) first reviewed all studies and extracted key phrases and concepts from each study. We based our data extraction items on features identified in a recent biomedical guideline for reporting of machine learning studies [30]. Custom-made data extraction forms were developed from this guideline which included major extraction categories such as general study characteristics (i.e., author, year, country, target population, source of data, sample size, field of study, machine learning domains, machine learning methods, algorithms, and outcome); key components of model development (i.e., whether the studies discussed method of feature selection, resampling, model performance metrics, and method of validation); and discussion of study findings (i.e., importance ranking of features, intersectionality and other procedures or features applied).

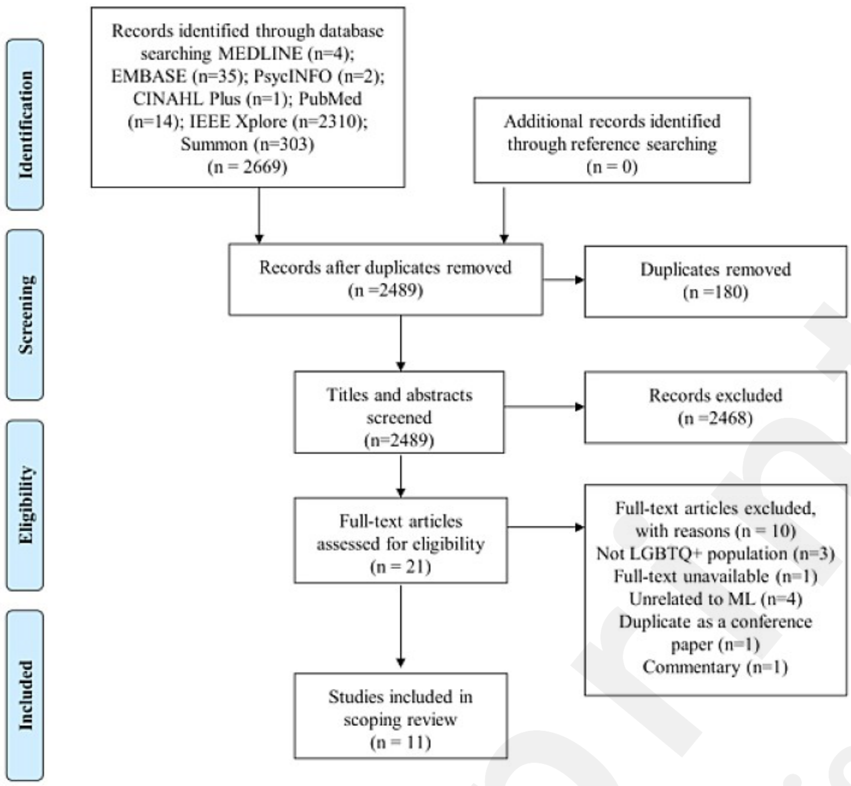
### Collating, Summarizing and Reporting Results

We present descriptive statistics for extracted datasets through calculating the total number and percentage of all studies in each category. To provide a visual overview of the range of data, we present a bar chart showing the frequency analysis of studies according to field of study and a pie chart to demonstrate the proportion of studies in major domains of machine learning. We used a narrative synthesis approach [31] to describe the findings of the studies in different machine learning domains and explore relationships in the data. Finally, we discussed the research gaps to facilitate future research.

## Results

The initial search of databases yielded 2,669 articles, of which 2,489 were retrieved after removing duplicates. We also searched the reference lists of potentially eligible articles and previous reviews but could not identify any studies which matched our inclusion criteria. After title and abstract screening, 21 articles were selected for full-text screening, of which we excluded articles which did not meet the target population criteria of LGBTQ2S+ population (n=3), full-texts could not be retrieved (n=1), unrelated to machine learning (n=4), being a duplicate article published in a conference proceeding (n=1) and a commentary (n=1). This resulted in 11 studies being included in the final review [32–42]. The detailed selection process of the articles is presented in the PRISMA flow diagram (Figure 1).

Figure 1. PRISMA flow diagram documenting study exclusion.




## Study Characteristics

All 11 included studies [32–42] were published within the last 2 years (Table 1). Most of the studies were undertaken in the USA (n=7, 64%) [32,35,36,38–40,42]. Among the target population categories which were not mutually exclusive, sexual minorities male (gay, men who have sex with men (MSM), bisexual) were the most commonly studied (n=5, 45%) subgroups [33,37,39–41], followed by transgender (n=3, 27%) [34,36,42] and LGBTQ2S+ (n=3, 27%) [32,35,38]population at large, while sexual minorities female (lesbian, bisexual) (n=2, 18%) [40,42]were the least commonly represented population (Table 1).

Table 1. Summary statistics of included studies (N=11) [32–42].[a]

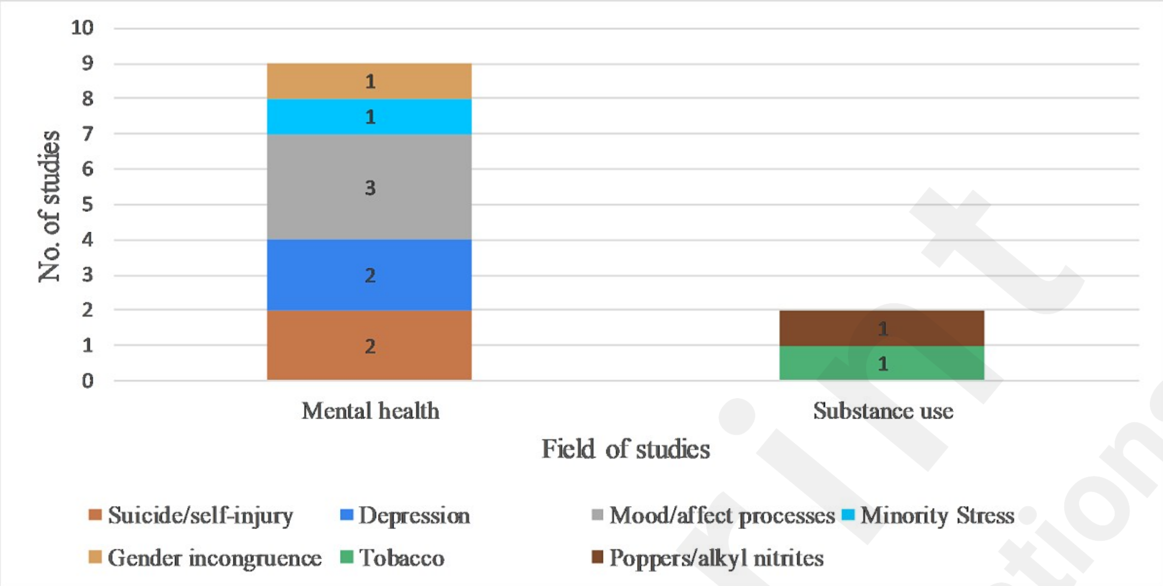
| Characteristics | Number of studies (percent), n (%) |
|---|---|
| **Countries** | |
| United States of America | 7 (64) |
| China | 2 (18) |
| Sweden | 1 (9) |
| Australia | 1 (9) |
| **Years published** | |
| 2019 | 5 (45) |
| 2020 | 6 (55) |
| **Field of study** | |
| **Mental health (N=9)** | |
| Suicide/self-injury | 2 (18) |
| Depression | 2 (18) |
| Mood/affect processes | 3 (27) |
| Minority Stress | 1 (9) |

| | |
|---|---|
| Gender incongruence | 1 (9) |
| **Substance use (N=2)** | |
| Tobacco | 1 (9) |
| Poppers/alkyl nitrites | 1 (9) |
| **Target population**[b] | |
| Sexual minorities male (gay, MSM[c], bisexual) | 5 (45) |
| Sexual minorities female (lesbian, bisexual) | 2 (18) |
| Transgender/ Gender minorities | 3 (27) |
| LGBT/LGBTQ2S+[d] | 3 (27) |
| **Domain(s) of machine learning** | |
| Online content analysis | 6 (55) |
| Prediction modelling | 4 (36) |
| Imaging study | 1 (9) |
| **Type of machine learning** | |
| Supervised | 9 (82) |
| Unsupervised | 3 (27) |
| Deep | 1 (9) |
| **ML algorithms**[e] | |
| LDA | 3 (27) |
| RF | 2 (18) |
| SVM | 2 (18) |
| CNN | 1 (9) |
| MLP | 1 (9) |
| NB | 1 (9) |
| Penalized regression (LASSO, elastic net regularized regression, ridge regression) | 2 (18) |
| Logistic regression | 1 (9) |
| Boosting (XGBoost, AdaBoost, GBM) | 3 (27) |
| Classification tree | 2 (18) |
| **Feature selection** | |
| Yes | 7 (64) |
| No | 4 (36) |
| **Discussed model performance** | |
| Used performance metrics | 9 (82) |
| Didn't use performance metrics | 1 (9) |
| Didn't discuss performance | 1 (9) |
| **Method of validation** | |
| Hold-out | 2 (18) |
| Cross-validation | 7 (64) |
| External validation | 2 (18) |
| Unspecified | 4 (36) |

[a]Multiple response options were possible for some study characteristics.
[b]Categories are not mutually exclusive.
[c]MSM: men who have sex with men.
[d]LGBT: lesbian, gay, bisexual and transgender; LGBTQ2S+: lesbian, gay, bisexual, transgender, queer or questioning and two-spirit.
[e]ML: machine learning; LDA: latent dirichlet allocation; RF: random forest; SVM: support vector machine; CNN: convolutional neural network; MLP: multilayered perceptron; NB: Naïve Bayes; LASSO: least absolute shrinkage and selection operator; XGBoost: eXtreme Gradient Boosting; AdaBoost: Adaptive Boosting; GBM: Generalized Boosted Model.

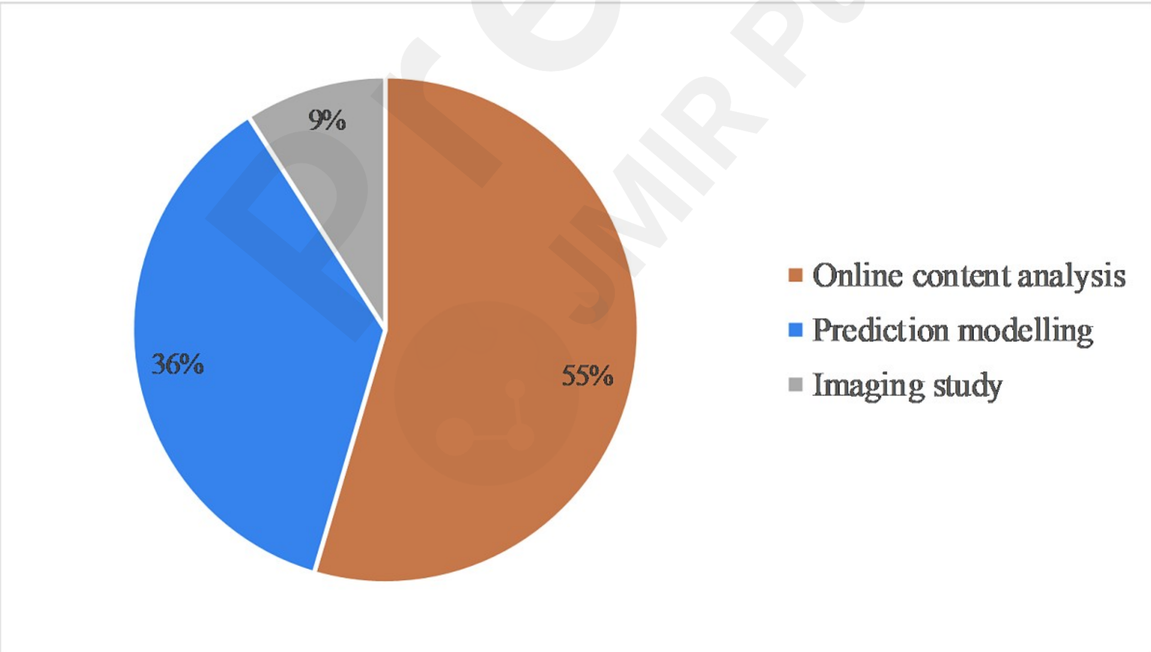
Most of the studies focused on mental health (n=9, 82%) [32–39,42] and only 2 studies (18%) [40,41] focused on substance use concerns. The studies examined several mental health issues, such as depression, suicide, mood/affect processes, minority stress, and gender incongruence [32–39,42], while the studies focused on substance use only examined tobacco and poppers/alkyl nitrites use [40,41]. No study has looked into mental health issues and substance use concerns among LGBTQ2S+ population simultaneously. The distribution of articles according to field of studies is presented in Figure 2.

Figure 2. Distribution of studies according to field of studies (N=11).




The studies were categorized into 3 major machine learning domains: online content analysis, prediction modelling, and imaging study. Over half of the studies were identified as online content analysis [32,33,35–38], 36% were on prediction modelling [39–42], and 9% (n=1) an imaging study [34] (Table 1, Figure 3).

Figure 3. Distribution of studies in the domains of machine learning (N=11).




The most commonly used class of machine learning methods was supervised (n=9, 82%) [33–36,38–42], followed by unsupervised (n=3, 27%) [32,33,37] and deep learning (n=1, 9%) [38] (Table 1). The most frequently used machine learning algorithms were latent dirichlet allocation (n=3, 27%) and boosting (n=3, 27%), followed by random forest, support vector machines, penalized regression (i.e., least absolute shrinkage and selection operator, elastic net regularized regression, ridge regression), classification tree, logistic

regression, Naïve Bayes, multilayered perceptron, convolutional neural network (Table 1).
64% of the studies [33–35,39–42] discussed their methods of feature selection, among which the median number of features used was 19 . Most of the studies used cross-validation method (n=7, 64%) [33–36,38,41,42], especially 10-fold cross-validation. 2 of the articles used hold-out method [36,38], 2 used external validation [33,38], and 4 articles (36%) [32,37,39,40] did not report how they validated their method. The majority of studies (n=9, 82%) [32–36,38–40,42] used at least 1 performance metric (e.g., area under ROC curve, precision , recall, or F1 score) for discussing model performance. However, the remaining studies either did not use any performance metric [41] or did not discuss any model performance [37] (Table 1).

### Machine Learning Domains

Table 2 summarizes the characteristics of the final 11 included studies [32,33,42,34–41] and Table 3 represents the machine learning methodology used by the studies.

Table 2. Summary of studies using machine learning analysis in mental health and substance use among LGBTQ2S+ population (N=11).

| Author and year | Target population | Sample size | Source of data | Field of study | Outcome(s) |
|---|---|---|---|---|---|
| **Online content analysis** | | | | | |
| Liang et al., 2019 [32] | LGBT[a] | 65K posts | Social media (LGBT Chat and Forums) | Suicide | Help-seeking behaviour related topics |
| Li et al., 2020 [33] | MSM[b] and non-MSM | 41 million posts | Social media (Blued and Twitter) | Depression | Depressive emotion expression |
| Saha et al., 2019 [35] | LGBTQ+[c] | 12K posts | Social media (Reddit) | Minority stress | Prejudice events, perceived stigma, internalized stigma |
| Haimson & Tiffany, 2020 [36] | Transgender | 41K posts | Social media (Tumblr) | Emotional response to sexual identity disclosure | Self-reported identity disclosure posts |
| Huang et al., 2019 [37] | Gay men | 1.6 million posts, 5 million votes and 407K comments | Social media (Blued) | Mood/ affect processes | Positive and negative emotions related to sensitive topics, voting outcome in 7 categories including drug use |
| Zhao et al, 2020 [38] | LGBTQ+ | 2.3 million tweets | Social media (Twitter) | Mood/ affect processes | Expressing positive emotions, negative emotions, anger, anxiety, sadness |
| **Prediction modelling** | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Barrett et al, 2020 [39] | MSM | 1729 MSM adults | Clinical cohort (Multicenter AIDS Cohort Study) | Depression | Clinically significant depressive symptoms (CES-D[d] score ≥ 20) |
| Azagba et al., 2019 [40] | Heterosexual and LGB | 28,811 students / adolescents | Public health data set (YRBSS[e] 2015 and 2017) | Cigarette smoking and e-cigarette use | Self-reported cigarette smoking status in past 30 days |
| Demant et al., 2019 [41] | Sexual minority men (gay, bisexual, other) | 836 adults | Cross-sectional survey data | Poppers (alkyl nitrites) use | Self-reported poppers use in past 3 months |
| Smith et al, 2020 [42] | Lesbian, bisexual and questioning females, gender minorities | 252 adolescents | Longitudinal cohort | Suicide/ self-injury | Self-reported self-injurious thoughts and behaviours in past 6 months follow-up period |
| **Imaging study** | | | | | |
| Moody et al., 2020 [34] | Transgender | 25 adults | Clinical and fMRI[f] trial data | Gender incongruence | Body index score, fMRI images |

[a]LGBT: lesbian, gay, bisexual and transgender.
[b]MSM: men who have sex with men.
[c]LGBTQ+: lesbian, gay, bisexual, transgender, queer or questioning
[d]CES-D Score: Center for Epidemiologic Studies Depression Scale score
[e]YRBSS: Youth Risk Behaviour Surveillance System
[f]fMRI: Functional Magnetic Resonance Imaging

Table 3. Summary of characteristics of machine learning methods used (N=11).

| Author and year | Type of ML[a] | ML algorithm (s)[b] | Feature selection | Re-sampling | Model performance | Method of Validation | Importance ranking | Inter-sectionality |
|---|---|---|---|---|---|---|---|---|
| **Online content analysis** | | | | | | | | |
| Liang et al., 2019 [32] | U | LDA | | | ✓ | NS[c] | | |
| Li et al., 2020 [33] | S; U | XGBoost; LDA | ✓ | ✓ | ✓ | Stratified five-fold cross validation; external validation | ✓ | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Saha et al., 2019 [35] | S | NB; logistic regression; RF; SVM; MLP | ✓ | ✓ | ✓ | Stratified κ-fold cross-validation (k = 5) | ✓ | |
| Haimson & Tiffany, 2020 [36] | S | AdaBoost | | ✓ | ✓ | 10-fold cross validation; Hold-out | | |
| Huang et al., 2019 [37] | U | Twitter-LDA | | | | NS | NA[d] | |
| Zhao et al, 2020 [38] | S; D | RF; SVM; CNNs | | ✓ | ✓ | 10-fold cross validation; Hold-out; external validation | NA | |
| **Prediction modelling** | | | | | | | | |
| Barrett et al, 2020 [39] | S | Classification tree | ✓ | ✓ | ✓ | NS | | ✓ |
| Azagba et al., 2019 [40] | S | GBM | ✓ | | ✓ | NS | | |
| Demant et al., 2019 [41] | S | Classification tree (CHAID) | ✓ | ✓ | ✓ | 10-fold cross validation | | |
| Smith et al., 2020 [42] | S | LASSO and elastic net regularized logistic regression | ✓ | ✓ | ✓ | 10-fold cross validation | ✓ | ✓ |
| **Imaging study** | | | | | | | | |
| Moody et al., 2020 [34] | S | LASSO; ridge regression | ✓ | ✓ | ✓ | N-5 Cross-validation | | |

[a] ML: machine learning; S, U and D denote supervised, unsupervised and deep learning.
[b]Machine learning algorithm(s): LDA: latent dirichlet allocation; XGBoost: eXtreme Gradient Boosting; NB: Naïve Bayes; RF: random forest; SVM: support vector machine; MLP: multilayered perceptron; AdaBoost: Adaptive Boosting; CNN: convolutional neural network; GBM: Generalized Boosted Model; CHAID: χ2 Automatic Interaction Detection; LASSO: least absolute shrinkage and selection operator.
[c]NS: not specified.
[d]NA: not applicable.

The six studies [32,33,35–38] in the online content analysis domain obtained their data from social media sources such as Twitter, Blued, Tumblr, reddit and LGBT Chat and Forums. The volume of data used ranged from 12,000 to 41 million online posts. Half of the studies used their data for analyzing mood/affect processes of the users related to their sexual and gender identities [36–38] (Table 2).

Among the four studies in the prediction modelling domain, 50% of the studies analyzed data on adult participants [39,41] and 50% on adolescents [40,42]. Only 1 study used a public health data set of 28,811

participants [40], while other studies used either cross-sectional data or cohort data from longitudinal studies [39,41,42]. Half of the studies focused on mental health (depression and suicide) [39,42] and half on substance use behaviour (cigarette, e-cigarette and poppers use) [40,41] (Table 2). Out of four studies, only one study [42] ranked their feature importance and 2 studies [39,42] examined intersectionalities (Table 3). One of them investigated intersection of income and other social and environmental stressors with racial/ethnic disparities and its impact on the depressive symptomology among MSM people [39], while another study focused on intersection between various social and behavioural determinants of health (self-image, race, education, socio-economic status, family support, friends, stigma, discrimination etc.) as risk factors of self-injurious behaviours among sexual and gender minority females [42].
There was one imaging trial study which used clinical and functional magnetic resonance imaging (fMRI) data of 25 transgender adults to identify the relationship between pre-therapy functional brain connectivity and post-hormone therapy body congruence [34]. All four studies [39–42] of prediction modelling domain and one imaging study [34] used the supervised method of machine learning, while studies in the online content analysis domain [32,33,35–38] used supervised (n=4, 36%), unsupervised (n=3, 27%) and deep learning (n=1, 9%) methods (Table 3).

## Discussion

Our results show that applications of machine learning for assessing mental health and substance use behaviour among the LGBTQ2S+ population are still new in health research, compared to the increasing use of machine learning techniques in other health research domains. Despite continued criminalization and lack of LGBTQ2S+ rights protection in 67 United Nations member states at the end of 2020 [43], there appears to be increasing acceptance of sexual and gender minority people in diverse contexts such as in the North American countries and Western Europe [44]. However very few of the included studies were conducted outside of the USA (Table 1).

Our findings suggest that although available evidence indicates a higher prevalence of mental health issues among the LGBTQ2S+ population compared to cisgender and heterosexual counterparts [2,4], there were not many articles published on this subject that used machine learning techniques. Among the major mental health problems, only suicidal behaviour, depression, emotional distress and mental health issues among trans population were examined by a few studies (Table 1, Fig 2). Yet no studies were located on other mood disorders (e.g., mania, persistent depressive disorder), anxiety disorders, or post-traumatic stress disorder, which also disproportionately effect LGBTQ2S+ people [4]. Compared to mental health issues, substance use problems among LGBTQ2S+ individuals were almost untouched. Despite evidence of higher rates of alcohol use disorder, opioid misuse, cannabis and other illicit drug use compared to heterosexual/cisgender counterparts [2,6], only tobacco and poppers use were explored using machine learning techniques (Table 1, Fig 2). Moreover, both of these studies predicted present use of substances [40,41], and no studies examined future substance use, cessation, or substance use treatment-seeking behaviour.
The majority of studies were in the online content analysis domain, indicating social media to be a potentially useful epidemiological resource for collecting data on LGBTQ2S+ people and analyzing the data using machine learning (Table 2, Fig 3). We found that unsupervised machine learning has also been applied in these studies with data drawn from social media [32,33,37], thus holding the potential to support qualitative research by handling large textual datasets with its computational power. This is particularly useful in LGBTQ2S+ health research given stigma-related and structural barriers towards identity disclosure that may inhibit data collection through other methodologies [45–48].
Though electronic health records have been used as a promising data source for machine learning techniques to predict population health in other research areas [24,26], this resource was not identified in our findings. This may be related to sexual orientation, and more commonly, gender inclusivity to integrate transgender persons' experiences, not being captured in electronic health records [45,46]. However, other data sources like cross-sectional survey data, longitudinal cohort and administrative data sets have been used for prediction modelling (Table 2). Another important finding was the small sample sizes used in most of the predictive modelling studies (Table 2), small datasets can affect the model performance [49]. Using large population-

based datasets for future research can overcome this problem and fully leverage benefits of machine learning. Compared to the other two domains, there was a significant gap in machine learning research using imaging data (i.e., fMRI or electroencephalography) to examine mental health and substance use among the LGBTQ2S+ population (Table 1, Fig 3).

Despite evidence of influence of intersections of various social and behavioural determinants of health on increased prevalence of mental health and substance use concerns among LGBTQ2S+ population [11–16], only two studies have examined the intersection of sexual and gender identity with ethno-racial identities, and several social, economic and behavioural factors (i.e., income, social stigma, discrimination, family support) and their impact on depression and self-injurious behaviours [39,42]. No such studies in our review explored intersectionality in the substance use field. Identifying these intersections through leveraging machine learning techniques would have practical implications through determining risk and protective factors as well as informing strategies for promoting mental well-being and substance use prevention and intervention with and for LGBTQ2S+ people. In the context of varied techniques used in intersectional research, both qualitative and quantitative and recent trend of mixed method research [50], machine learning can be a very useful tool through processing vast quantity of data, data mining and clustering, and classifying attribute relationships [51,52]. Apart from the partial dependency-based measures, newer techniques and methods [53,54] in machine learning have been emerging for analyzing interaction effects, more suitable for assessing intersectionality.

Following the current guideline for reporting machine learning studies in biomedical research [30], we documented the range of explanatory findings seen in the included studies and found that the majority of studies mentioned their performance metrics, method of feature selection and method of validation of their model (Table 1, Table 3). However, only 3 out of 11 studies [33,35,42] adopted the approach of approximating a relative importance score of individual features that reflected their overall contributions to the model (Table 3). The implications of providing importance score to features is particularly valuable for predictive modelling studies, where most important predictors are targeted for future strategy adoption. Another notable finding was about half (n=2) [39,40] of the predictive modelling studies didn't report any method of validation for their models (Table 3). Validation is an important aspect of the predictive modelling process which increases reproducibility and generalizability of the model [55]. Hence, future studies in this domain should follow existing guideline to validate their models [30].

## Future Research Directions

We detected significant research gaps to address in machine learning applications for mental health and substance use research among LGBTQ2S+ populations. First, future research should investigate other mental health issues (i.e., anxiety disorders and mood disorders) and substance use behaviour and problems (i.e., alcohol, opioids, illicit drug) among LGBTQ2S+ people. Second, the potential of machine learning applications in predicting substance use related outcomes (i.e., cessation, overdose events, routes of administration, driving impairments, other adverse reactions), mental health service access and mental health related outcomes (i.e., disabilities, symptom management, suicide and suicide attempts, economic burden, health care costs) should be explored.

Third, Further research is also needed on sexual minority women. The small number of studies included (Table 1) did not allow exploration of shared and different health needs and priorities between and within the LGBTQ2S+ populations. Fourth, as the legal and societal context in which LGBTQ2S+ people live differs significantly between countries [44], more research should be carried out in countries outside the USA. Fifth, specific research initiatives targeted at investigating the intersection of sexual and gender minority identity with other social determinants of health (i.e., race, ethnicity, citizenship, socio-economic status, housing condition) are necessary to better understand their potentials for risk and resilience regarding mental health and substance use. Finally, different data sources should be used for machine learning studies. Large population level administrative datasets should be used for prediction modelling studies for accurate application of machine learning models. In addition, with the advancement of technology, the digitalization of health care, and where LGBTQ2S+ status is captured in electronic health records, these health records can be a potential data resource for machine learning studies with real-world clinical implications for LGBTQ2S+ people.

## Strength and Limitations

To the best of our knowledge, our review is the first of its kind to explore the use of machine learning applications in examining mental health and substance use among the LGBTQ2S+ population. We adopted a comprehensive search strategy, including searching various multidisciplinary peer-reviewed databases to identify relevant articles as much as possible. Findings of our review need to be interpreted with the consideration of one key limitation. Due to the low number of studies, highly heterogenous characteristics of included studies and inconsistent reporting of model development and validation, we could not perform a critical appraisal of the studies and therefore cannot comment significantly on the overall performance of the machine learning techniques. However, the main objective of this scoping review was to give a general account of machine learning literature in the field of mental health and substance use among the LGBTQ2S+ population and identify research gaps to inform future research rather than assessing the quality of reporting.

## Conclusion

Despite exponential growth of machine learning applications in other health research sectors, few studies have used these techniques in the mental health and substance use field among the LGBTQ2S+ population. In addition to undertaking more research, future researchers should focus on applying machine learning algorithms with considerations for real-world implications through public health interventions and adopting policies that aim to improve health equity.

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## Authors’ Contributions

MC contributed to the design of the study, obtaining funding and supervision. AK and RB conducted the database search, article screening, and data extraction. AK conducted data analysis and primary drafting of the manuscript. All authors, AK, MC, RB, DG, RF, CHL, BB, CY, NM and RS contributed to the conceptualization, drafting of the manuscript, reviewed and approved the manuscript for submission.

## Conflicts of Interest

None declared.

### Multimedia Appendix 1

EMBASE search query.

| Search Terms |
|---|
| 1. exp mental health/ |
| 2. exp mental disease/ |
| 3. exp mental health care/ |
| 4. exp mental health service/ |
| 5. ((mental or psychiatric or depressi* or anxiety or mood or bipolar or eating or schizophren* or Psycho* or suicid*) adj2 (disorder* or issue* or condition* or ideation or attempt*)).tw,kw. |
| 6. exp substance abuse/ |
| 7. exp drug dependence/ |
| 8. exp drug dependence treatment/ |
| 9. exp harm reduction/ |
| 10. ((Substance or drug or Alcohol or cannabis or Marijuana or cocaine or opioid* or tobacco or nicotin*) adj2 (use* or abuse* or dependen* or addicti* or withdraw* or cessation or treat*)).tw,kw. |

11. 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10
12. exp machine learning/
13. ((supervised or unsupervised or deep or machine) adj2 learning).tw,kw.
14. 12 or 13
15. exp LGBT people/
16. (Lesbian or gay or bisexual* or Homo or homosexual* or MSM or men sex with men or queer or two-spirit or transgender or intersex or LGBT*).tw,kw.
17. 15 or16
18. 11 and 14 and 17

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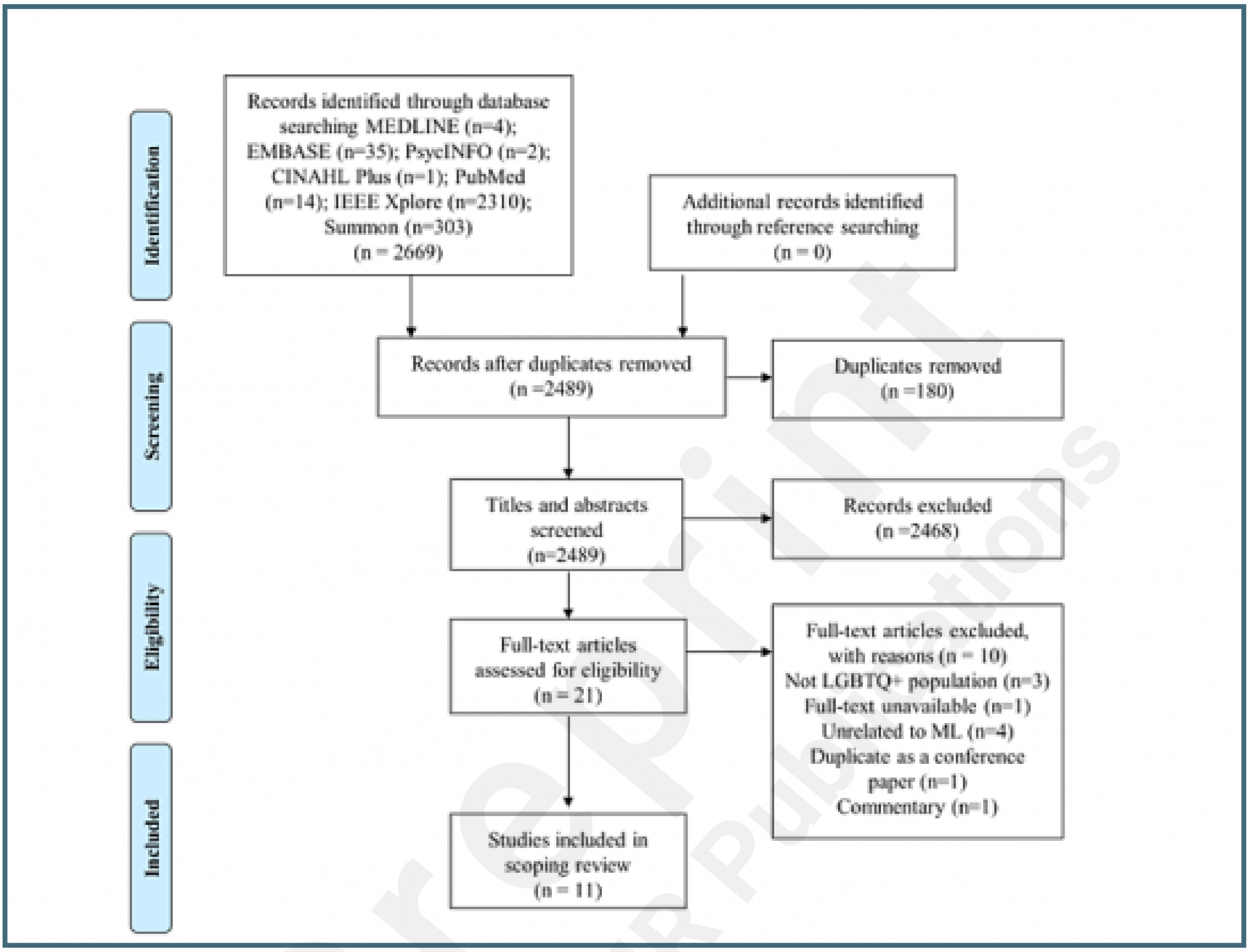
## Abbreviations

fMRI: functional magnetic resonance imaging
LGBTQ2S+: lesbian, gay, bisexual, transgender, queer or questioning and two-spirit
MSM: men who have sex with men
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
USA: United States of America

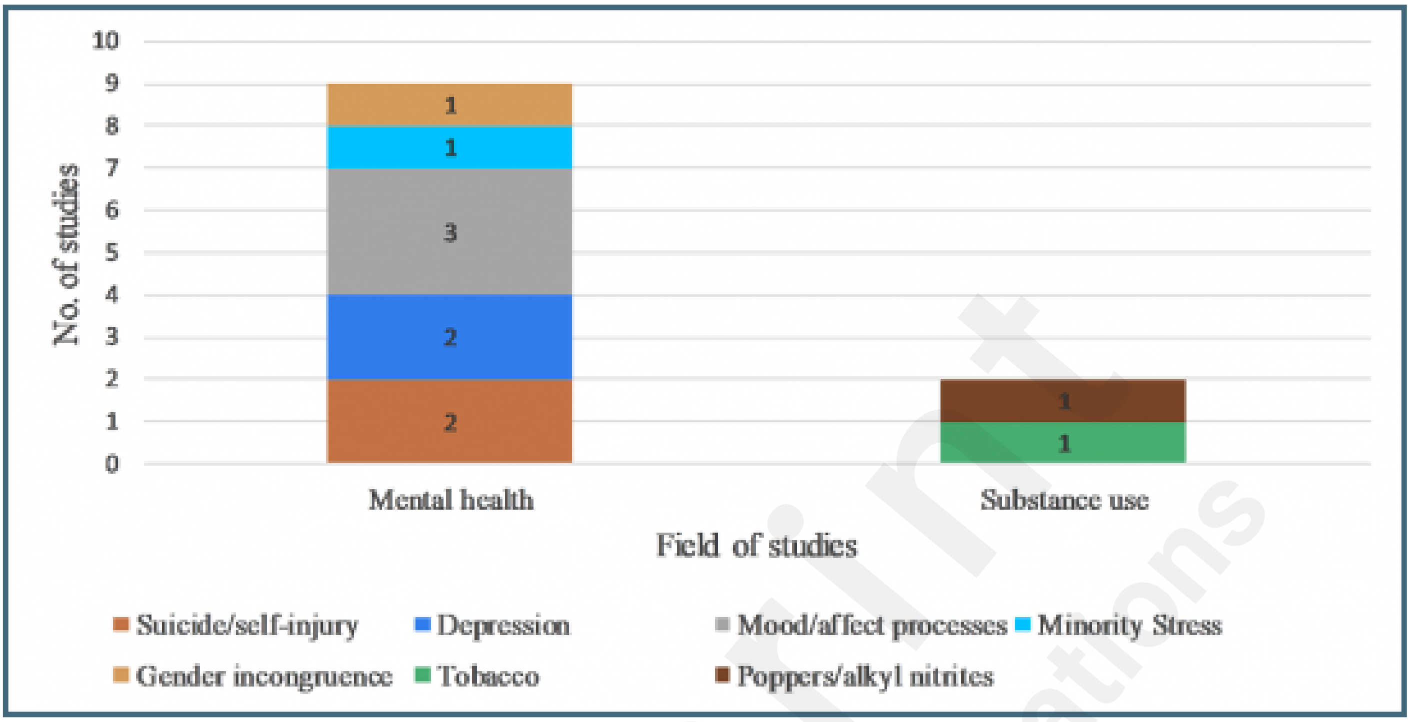
# Supplementary Files

# Figures

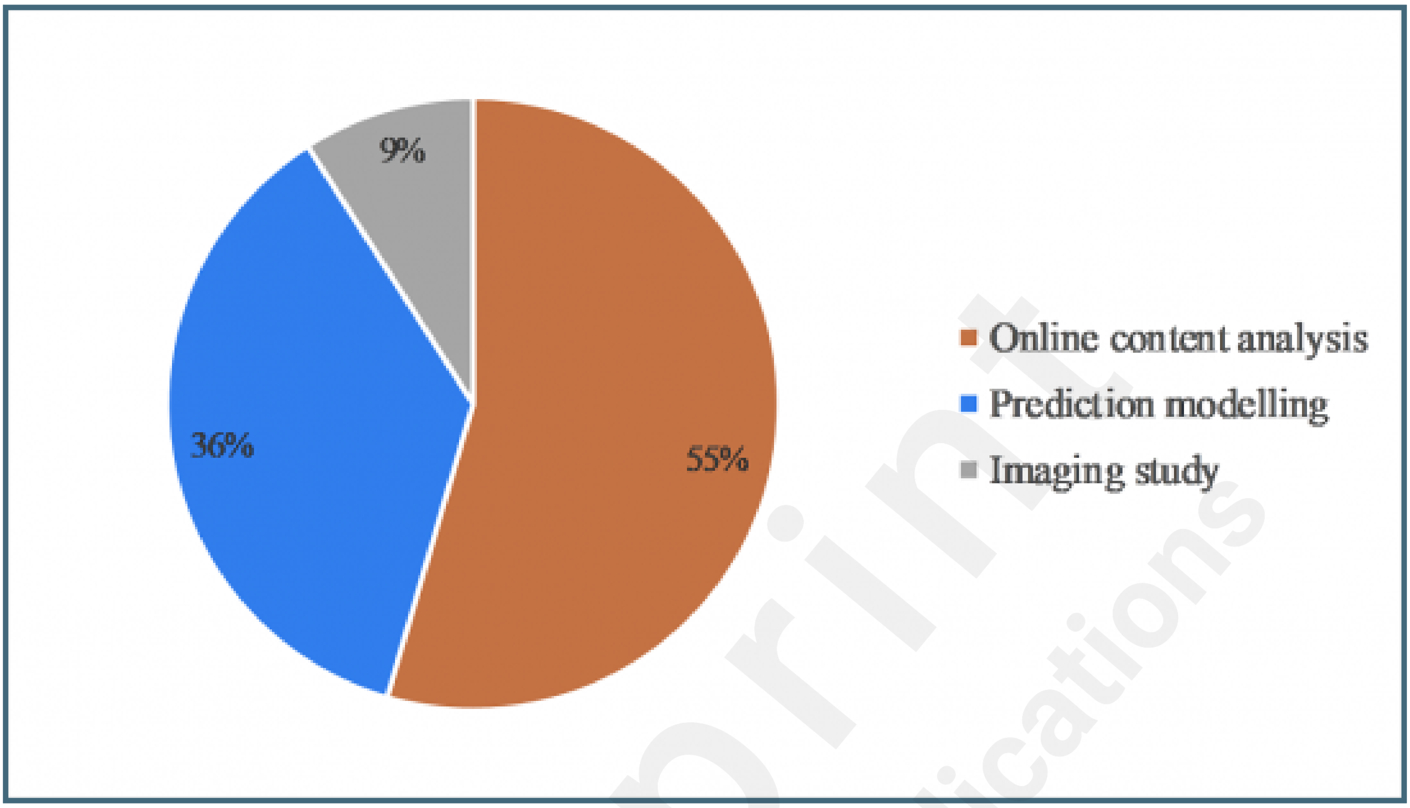
PRISMA flow diagram documenting study exclusion.



Distribution of studies according to field of studies (N=11).



Distribution of studies in the domains of machine learning (N=11).



# Multimedia Appendixes

EMBASE search query.
URL: http://asset.jmir.pub/assets/ea564b2f37da3975c07959d3473918ac.docx