

Predicting the Effectiveness of a Mindfulness Virtual Community Intervention for University Students: A Machine Learning Model

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Predicting the Effectiveness of a Mindfulness Virtual Community Intervention for University Students: A Machine Learning Model

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Abstract

Background: Students' mental health crisis has been recognized before COVID-19 pandemic. Mindfulness Virtual Community (MVC), an eight-week web-based mindfulness and cognitive behavioural therapy (CBT) program has proven to be an effective web-based program to reduce symptoms of depression, anxiety, and stress. Predicting the success of MVC before a student enrolls in the program is important to advise students' accordingly.

Objective: This study objectives were to investigate: (1) if we can predict MVC's effectiveness using sociodemographic and self-reported features, and (2) how important was the exposure to mindfulness videos, in comparison with these features, in prediction of the intervention success.

Methods: Machine learning models were developed to assess MVC's effectiveness defined as success in reducing symptoms of depression, anxiety, and stress as measured using the Patient Health Questionnaire-9 (PHQ9), the Beck Anxiety Inventory (BAI), and the Perceived Stress Scale (PSS), to at least the minimal clinically important difference (MCID). A dataset representing a sample of undergraduate students (n = 209) who took the MVC intervention between Fall 2017 and Fall 2018 was used. Random forest was used to measure the features' importance.

Results: Gradient Boosting achieved the best performance both in terms of AUC and accuracy for predicting PHQ 9 (AUC=.85, Accuracy=.83) and PSS (AUC=1, Accuracy=1); and Random Forest had best performance for predicting BAI (AUC=.93, Accuracy=.93). The exposure to online mindfulness videos was the most important predictor for the intervention's effectiveness for PHQ9, BAI and PSS, followed by the number of working hours per week.

Conclusions: The performances of the models to predict MVC intervention effectiveness for depression, anxiety, and stress, are high. These models might be useful for professionals to advise students early enough on taking the intervention or choose other alternatives. The students' exposure to online mindfulness videos is the most important predictor for the effectiveness of the MVC intervention.

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Original Manuscript

Predicting the Effectiveness of a Mindfulness Virtual Community Intervention for University Students: A Machine Learning Model

ABSTRACT

Background: Students' mental health crisis was recognized before the COVID-19 pandemic. Mindfulness Virtual Community (MVC), an eight-week web-based mindfulness and cognitive behavioural therapy (CBT) program, has proven to be an effective web-based program to reduce symptoms of depression, anxiety, and stress. Predicting the success of MVC before a student enrolls in the program is essential to advise students accordingly.

Objective: The objectives of this study were to investigate (1) whether we can predict MVC's effectiveness using sociodemographic and self-reported features and (2) whether exposure to mindfulness videos was highly predictive of the intervention's success.

Methods: Machine learning models were developed to predict MVC's effectiveness, defined as success in reducing symptoms of depression, anxiety, and stress as measured using the Patient Health Questionnaire-9 (PHQ9), the Beck Anxiety Inventory (BAI), and the Perceived Stress Scale (PSS), to at least the minimal clinically important difference (MCID). A dataset representing a sample of undergraduate students ($n = 209$) who took the MVC intervention between Fall 2017 and Fall 2018 was used for this secondary analysis. Random forest was used to measure the features' importance.

Results: Gradient Boosting achieved the best performance both in terms of AUC and accuracy for predicting PHQ 9 (AUC=.85, Accuracy=.83) and PSS (AUC=1, Accuracy=1); and Random Forest had best performance for predicting BAI (AUC=.93, Accuracy=.93). The exposure to online mindfulness videos was the most important predictor for the intervention's effectiveness for PHQ9, BAI and PSS, followed by the number of working hours per week.

Conclusions: The performances of the models to predict MVC intervention effectiveness for depression, anxiety, and stress are high. These models might be helpful for professionals to advise students early enough on taking the intervention or choose other alternatives. The students' exposure to online mindfulness videos is the most important predictor for the effectiveness of the MVC intervention.

Trial Registration: ISRCTN Registry ISRCTN12249616; <http://www.isrctn.com/ISRCTN12249616>

Keywords: machine learning, virtual community, virtual care, mindfulness, depression, anxiety, stress, students, online, randomized controlled trial, Canada

Introduction

Students' mental health crisis has been recognized before the COVID-19 pandemic and deepened during the pandemic. University students are experiencing increases in psychological distress on North American campuses. A student survey of 32 Canadian post-secondary institutions reported high anxiety (56.5%), hopelessness (54%), seriously depressed mood (37.5%) and overwhelming anger (42%) [1]. A similar survey in 2016 revealed higher distress levels [2]. In 2013, a study of 997 students at York University (site of the current study) indicated that 57% reported depression scores sufficient for diagnosable clinical depression, while 33% reported anxiety scores in ranges typically indicative of panic disorder and generalized anxiety disorder [3]. The situation appears similar at

universities in the United States [4, 5] and worldwide - in 2018, the World Health Organization reported increasing mental disorders in college and university students worldwide [6]. Distress during university attendance is critical to address for multiple reasons, mainly because 70% of all mental health problems appear before the age of 25 years and, when untreated, can become long-standing and significant impairments affecting multiple life domains [7]. COVID-19 has negatively impacted university students' mental health [8-10].

University student distress is both an individual and societal challenge. Losses in productivity during the study and at work due to distress and mental disorders are associated with indirect but significant economic burdens [11]. Canadian estimates show that mental disorders cost 51 billion dollars yearly, with 9.8% due to direct medical costs, 16.6%, and 18.2% due to long-term loss and short-term work loss, and 55.4% due to the loss of healthy function (i.e., loss of the utilities of vision, hearing, speech, mobility, dexterity, emotion, cognition and pain as assessed in the Health Utilities Index Mark 3 system) [12].

While mental distress and disorder are becoming more prevalent in students, the counselling offered in colleges and Universities needs to catch up with demand. For example, from 2007 to 2012, full-time enrollment in the Ontario college system increased from 167,000 to 210,600 (a 26% increase), while the number of counsellors employed in the college system increased from 146 to 152.7 (a 4.6% increase) [13]. This discrepancy leaves students underserved and counsellors overwhelmed amidst the increasing distress [14].

Mindfulness-based interventions have been demonstrated to positively impact psychological and physical health [15-17], with multiple meta-analyses demonstrating positive impacts in clinical and non-clinical populations [18-22]. However, with large numbers of students (50,000 to 60,000 on some campuses), there may not be enough trained personnel to convey helpful mindfulness-based practices directly. Instead, in the eHealth domain, virtual communities (VCs) [23], i.e., online communities, have been used in healthcare to provide e-education tools and online support to empower active participants in health enhancement [24-26]. VCs can scale up mindfulness interventions at lower costs to a broader range of students, especially those restricted from attending clinics due to time-place discontinuities. VCs preserve anonymity (with reduced stigmatization) while promoting voluntary, supportive, interpersonal connections.

We developed a web-delivered mindfulness program (Mindfulness Virtual Community: MVC) to reduce symptoms of depression, anxiety, and stress in university students and conducted a randomized control trial (RCT) targeting university students at a Canadian university to examine effectiveness. Following a successful RCT [26-30], we wanted in this secondary analysis (1) to develop a machine learning model to predict the effectiveness of the online mindfulness intervention on mental health outcomes using sociodemographic and self-reported features, and (2) to investigate if exposure to mindfulness videos was highly predictive of the intervention's success.

Methods

The prediction problem

The current study aims to predict the effectiveness (i.e., success vs. non-success) of the online mindfulness intervention on mental health outcomes; as such, this is a retrospective prognostic analysis of a classification problem per individual (i.e., participants in the MVC mindfulness intervention).

Dataset Source

This is a retrospective analysis, where we analyzed an anonymized dataset. The data was de-identified, and consent was obtained during the RCT; no further consent was sought for this secondary data analysis since non-identifiable data was used. The dataset was collected via a randomized control trial (RCT) described in detail elsewhere [31]. The parent study design consisted of a two-arm parallel design RCT, comparing a group assigned to the web-based Mindfulness Virtual Community (MVC) program to a wait-list control group (WLC). Participants in the study were students who were at least 18 years of age, reported English language fluency, self-reported high confidence in completing the study, and actively enrolled in an undergraduate program. The current article is based on the MVC intervention sample recruited in Fall 2017, Winter 2017, and Fall 2018. The MVC intervention was an eight-week program and was comprised of three components: 1) 12 online videos for mental health education 2) three anonymous discussion boards on depression, anxiety and stress; and 3) anonymous, 20-minute group-based live video conferences led by a mental health professional with training in mindfulness during which students could raise questions related to mindfulness (Figure 1).

Each of the 12 mental health modules consisted of one educational content video and one mindfulness practice video recorded in both male and female voices and offered in both high and low resolution (a total of 8 videos per module); participants could choose the type of video they wanted to watch for each module. The videos were available for participants 24 hours/day to watch or listen to on computers, phones, or tablets at their convenience. The module scripts and audio recordings were created by one of the investigators with extensive experience as a clinical psychologist and researcher in mindfulness. They were based on mindfulness and cognitive behavioural therapy (CBT) principles and informed by the prior student-based focus group study [37,38]—the choice of moving and still images used in creating the videos involved collaborative work. The topics of the 12 modules included the following topics: overcoming stress, anxiety, and depression; mindfulness and being a student; mindfulness for better sleep; thriving in a fast-changing world; healthy intimacy; destigmatization; no more procrastination; pain reduction and mindfulness, healthy body image; healthier eating, overcoming trauma; and relationships with family and friends.

The primary RCT outcomes were depression, anxiety, and perceived stress, following hypotheses that symptom scores for depression, anxiety and stress at T2 (after eight weeks) would be significantly better in the MVC group when compared with WLC. The outcomes were measured with the following validated scales: Patient Health Questionnaire-9 or PHQ9 [32]; Beck Anxiety Inventory or BAI [33]; Perceived Stress Scale or PSS [34]. The secondary aim was to assess the impact of three elements of the MVC intervention on the outcomes. Participants also completed a socio-demographic questionnaire section at the T1 (baseline) survey.

The previous study received the university's ethics approval from The Human Participant Research Committee (Certificate #: e2016 - 345). The current machine learning (ML) study received ethics approval from the same committee (Certificate #: e2023 – 012).

Participants

We aimed to build a model to predict who will likely benefit from the intervention, unlike the RCT study, where overall intervention effectiveness was determined (and supported by analysis) by comparing intervention and control groups. That's why we have analyzed intervention group data only to understand individual differences in response to the intervention. Participants in the original study had the option to receive an honorarium of CAD 50 (US \$37.5) or 2% in course grade (for

professors who gave this permission) or 3 credits (equivalent to 2% course grade) in the Undergraduate Research Participation Pool of the Department of Psychology.

Figure 1. The Mindfulness Virtual Community Design.

<Figure 1 here>

Data Preparation

The dataset consisted of 209 students who took the MVC intervention during Fall 2017, Winter 2018, and Fall 2018. The effectiveness of the intervention was determined using the minimal clinically important difference (MCID), i.e., the level of reduction in symptoms that psychologists consider clinically meaningful, for each of the mental health outcomes. We adopted evidence from psychology that determines the MCID to be a 5-point reduction in PHQ 9 for depression [35, 36], an 8.8-point reduction in BAI for anxiety [37, 38], and an 11-point reduction in PSS for stress [39, 40]. Any reduction equal to or above the MCID was labelled an effective intervention (label=1); otherwise, it was deemed ineffective (label=0).

To build a good prediction model from the training set, the data must be balanced. The class labels of the target variables, PHQ9, BAI, and PSS, used in this study were not balanced. In our case, the percentage of instances with label=1 was extremely low: 25.4% for PHQ9, 24.4% for BAI, and 4.1% for PSS, leading to a substantial imbalance. To alleviate the imbalanced data, we applied an oversampling method using `sklearn.resample` function available in Python V3.

Missing Data

Missing data in the outcomes were 12(5.74%) for BAI and PHQ9 and 13(6.22%) of the 209 records. Missing data for the outcomes were dropped from the dataset. There were no missing values in the predictors.

Labels and Features

The outcome variables were the three MCIDs associated with PHQ9, BAI and PSS of being met or not for each instance.

To investigate whether we can predict MVC's effectiveness using sociodemographic and self-reported features, we used the following features: Gender (male, female), country of birth (Canada, other), first language (English, other), education level (bachelor's degree, other), ethnicity (white, not white), marital status (married, other), age, number of weekly working hours, self-rated health (Poor, fair, good, very good, excellent).

To investigate the importance of exposure to mindfulness videos, in comparison with these features, in the prediction of the intervention success, we added the total number of mindfulness videos watched to the previous dataset.

Algorithms

Seven different classification algorithms, representing different learning paradigms, were used in this study: Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Adaptive Boosting (AdaBoost) and Gradient Boosting that showed good performance in previous studies that targeted depression, anxiety and stress [35, 41,

42]. The implementations of the classification algorithms provided in the scikit-learn machine learning library [43] were utilized. The dataset was split into 80% for training and 20% for testing. Hyperparameter tuning for each algorithm was performed using a grid search over a 10-fold cross-validation on the training dataset. The optimal hyperparameters for the classification algorithms and their values for the dataset without exposure to videos and the dataset with exposure to videos are presented in Table 1 and Table 2, respectively.

Each classifier's performance was compared with the best overall performance, leading to the selection the best prediction model for the psychological outcomes. The classifiers' performances were assessed based on several evaluation metrics, including the percentage of correctly classified instances or the accuracy, sensitivity, specificity, and area under the curve (AUC) of the receiver operating characteristics (ROC) curve. The best performance, as measured by the AUC score, was chosen for each algorithm.

Table 1: Algorithms and their corresponding optimal Hyperparameters found by grid search (dataset without videos).

Algorithm	Parameters
Logistic Regression (LR)	
PHQ9	C=1, Penalty=l1, solver= liblinear
BAI	C=1, Penalty=l1, solver= liblinear
PSS	C=1, Penalty=l1, Solver= liblinear
Support Vector Machine (SVM)	
PHQ9	C=10, gamma = .1, Kernel= rbf
BAI	C=10, gamma = .1, Kernel= rbf
PSS	C=10, gamma = .1, Kernel= rbf
Random Forest (RF)	
PHQ9	Max_features= auto, n_estimators=500, max_depth=8, Criterion=Entropy
BAI	Max_features= auto, n_estimators=500, max_depth=8, Criterion=gini
PSS	Max_features= auto, n_estimators=500, max_depth=8, Criterion=gini
Decision Tree (DT)	
PHQ9	Max_leaf_nodes=59, random_state=42, min_samples_split=2, Criterion=Entropy
BAI	Max_leaf_nodes=56, random_state=42, min_samples_split=2, Criterion=Entropy
PSS	Max_leaf_nodes=16, random_state=42, min_samples_split=2, Criterion=Entropy
K-nearest Neighbors (KNN)	
PHQ9	N_neighbors=2, weight=distance, leaf size=27, P=1
BAI	N_neighbors=2, weight=distance, leaf size=1, P=1
PSS	N_neighbors=1, weight=dniform, leaf size=1, P=1
Adaptive Boosting (AdaBoost)	
PHQ9	n-estimators=5000, max_depth=3, Learning rate= .5
BAI	n-estimators=5000, max_depth=3, Learning rate= .9
PSS	n-estimators=500, max_depth=3, Learning rate= .9
Gradient Boosting	
PHQ9	Learning rate= .05, max depth= 6, n-estimators=100,

BAI	subsample= .9, Max_features= <i>none</i> , min_samples_split=2 Learning rate= .02, Max depth= 10, n-estimators=1000, subsample= 1.0, Max_features= <i>none</i> , Min_samples_split=2
PSS	Learning rate= .01, Max depth= 6, n-estimators=1000, subsample= .9, Max_features= <i>sqrt</i> , Min_samples_split=2

To evaluate the features' importance in predicting intervention success, the dataset with the total exposure to mindfulness videos was used to build predictive models for the intervention success. The random forest algorithm was used to measure the features' importance. The hyperparameters used for the classification algorithms and their values that provided the optimal model are presented in Table 2.

Table 2: Algorithms and their corresponding optimal Hyperparameters found by grid search (dataset with exposure to videos).

Algorithm	Parameters
Logistic Regression (LR)	
PHQ9	C=1, Penalty=l1, solver= liblinear
BAI	C=.1, Penalty=l2, Solver= newton-cg
PSS	C=100, Penalty=l2, Solver= lbfgs
Support Vector Machine (SVM)	
PHQ9	C=10, gamma = .01, Kernel= rbf
BAI	C=1, gamma = 1, Kernel= rbf
PSS	C=1, gamma = 1, Kernel= rbf
Random Forest (RF)	
PHQ9	Max_features= auto, n_estimators=500, max_depth=7, Criterion=Entropy
BAI	Max_features= auto, n_estimators=200, max_depth=8, Criterion=gini
PSS	Max_features= auto, n_estimators=500, max_depth=8, Criterion=gini
Decision Tree (DT)	
PHQ9	Max_leaf_nodes=39, random_state=42, min_samples_split=2, Criterion=Entropy
BAI	Max_leaf_nodes=53, random_state=42, min_samples_split=3, Criterion=gini
PSS	Max_leaf_nodes=16, random_state=42, min_samples_split=2, Criterion=gini
K-nearest Neighbors (KNN)	
PHQ9	N_neighbors=1 , weight=uniform, leaf size=14, P=1
BAI	N_neighbors=2 , weight=distance, leaf size=1, P=1
PSS	N_neighbors=2 , weight=uniform, leaf size=1, P=1
Adaptive Boosting (AdaBoost)	
PHQ9	n_estimators=500, max_depth=3, Learning rate= .5
BAI	n_estimators=500, max_depth=3, Learning rate= .7
PSS	n_estimators=2000, max_depth=3, Learning rate= .7
Gradient Boosting	
PHQ9	Learning rate= .5, max depth= 50, n_estimators=50, subsample=.9, Max_features= <i>sqrt</i> , min_samples_split=2

BAI	Learning rate= .04, max depth= 10, n-estimators=1000, subsample= .5, Max_features= none, Min_samples_split=2
PSS	Learning rate= .03, max depth= 8, n-estimators=1000, subsample= .5, Max_features= none, Min_samples_split=2

Results

Demographics

Table 3 presents the demographic characteristics of participants at baseline. Of 209 students, 73.2% were female, 8.1% married, and 21.1% were white. Most participants were born in Canada, and English was their first language. The median (IQR) of age and work hours per week and the total number of mindfulness videos watched were 21 (19, 23), 10 (0, 18) and 16 (9, 30), respectively.

Table 3: Characteristics of participants at baseline, n=209

Characteristics	n (%)
Gender	
Male	56 (26.8)
Female	153 (73.2)
Marital status	
Married	17 (8.1)
Other	192 (91.9)
Ethnicity	
White	44 (21.1)
Non-White	165 (78.9)
Language	
English	136 (65.1)
Other	73 (34.9)
Country of Birth	
Canada	119 (56.9)
Other	90 (43.1)
Education	
GED ¹ /College degree/Certificate program	182 (87.1)
Bachelor's degree	27 (12.9)
Self-reported General Health	
Poor/fair	43 (20.6)
Good/ very good/excellent	166 (79.4)
	<u>Median (IQR)</u>
Age	21 (19, 23)
Average number of hours at work per week	10 (0, 18)
Total number of mindfulness videos watched	16 (9, 30)

Objective 1: Predicting MVC's effectiveness using sociodemographic and self-reported features

Table 4 summarizes the evaluated models' performances: sensitivity, specificity, accuracy, and AUC,

using 10-fold cross-validation.

The results showed that both Gradient Boosting (AUC=.85, Accuracy=.83) and DT (AUC=.84, Accuracy=.81) are slightly better compared to AdaBoost and KNN (AUC=.82, Accuracy=.80) as well as SVM (AUC=.81, Accuracy=.80), and outperform the remaining classification algorithms for predicting a clinically significant reduction in PHQ9.

The best classifiers for predicting a clinically significant reduction in BAI were RF (AUC=.93, Accuracy=.93) followed by AdaBoost (AUC=.92 Accuracy=.92) and Gradient Boosting (AUC=.87, Accuracy=.87), which outperform the remaining classifiers.

Two classifiers, Gradient Boosting and DT, gained the perfect accuracy and AUC (AUC=1, Accuracy = 1) for predicting a clinically significant reduction in PSS, followed by the near-perfect scores for SVM and AdaBoost (AUC=.99, Accuracy=.99).

Meanwhile, LR had the lowest performance for PHQ9, BAI and PSS in terms of AUC (.64, .75 and .73, respectively) and Accuracy (.66, .75 and .73, respectively).

Table 4: Classification report of the machine learning algorithms for outcomes

Algorithm	AUC	Accuracy	Sensitivity	Specificity
Logistic Regression				
PHQ9	.64	.66	.57	.72
BAI	.75	.75	.75	.75
PSS	.73	.73	.73	.74
Support Vector Machine				
PHQ9	.81	.80	.90	.75
BAI	.77	.77	.79	.75
PSS	.96	.96	1.0	.91
Random Forest				
PHQ9	.78	.76	.87	.69
BAI	.93	.93	.86	1.0
PSS	.99	.99	1.0	.97
Decision Tree				
PHQ9	.84	.81	.96	.72
BAI	.84	.83	.93	.75
PSS	1.0	1.0	1.0	1.0
K-nearest Neighbors				
PHQ9	.82	.80	.91	.72
BAI	.78	.78	.68	.88

PSS	.96	.96	1.0	.91
Adaptive Boosting				
PHQ9	.82	.80	.91	.72
BAI	.92	.92	.89	.94
PSS	.99	.99	1.0	.97
Gradient Boosting				
PHQ9	.85	.83	.91	.78
BAI	.87	.87	.86	.88
PSS	1.0	1.0	1.0	1.0

Objective 2: Importance of exposure to mindfulness videos in comparison with socio-demographics and self-reported features in prediction of the intervention success

After the introduction of the total exposure to the mindfulness videos to the data set, new predictive models were built (Table 5).

Table 5: Classification report of the machine learning algorithms for outcomes (data set with exposure to videos)

Algorithm	AUC	Accuracy	Sensitivity	Specificity
Logistic Regression				
PHQ9	.62	.63	.57	.67
BAI	.60	.60	.61	.59
PSS	0.79	0.80	0.85	0.74
Support Vector Machine				
PHQ9	.78	.75	.96	.61
BAI	.93	.93	.86	1.00
PSS	1.00	1.00	1.00	1.00
Random Forest				
PHQ9	.84	.83	.87	.81
BAI	.90	.90	.86	.94
PSS	1.00	1.00	1.00	1.00
Decision Tree				
PHQ9	.84	.81	.96	.72
BAI	.80	.80	.86	.75
PSS	.97	.97	1.00	.94
K-nearest Neighbors				
PHQ9	.81	.78	.96	.67
BAI	.84	.83	.89	.78
PSS	.99	.99	1.00	.97

Adaptive Boosting

PHQ9	.84	.81	.96	.72
BAI	.93	.93	.89	.97
PSS	1.00	1.00	1.00	1.00

Gradient Boosting

PHQ9	.89	.88	.96	.83
BAI	.91	.92	.86	.97
PSS	1.00	1.00	1.00	1.00

The results were close to those found in the models built without video exposure. While Gradient Boosting (AUC=.89, Accuracy=.88) was the best predictor for a significant reduction in PHQ9, followed closely by AdaBoost and DT (AUC=.84, Accuracy=.81), which outperformed the remaining classification algorithms.

The best classifiers for predicting a clinically significant reduction in BAI were AdaBoost and SVM (AUC=.93, Accuracy=.93), followed closely by Gradient Boosting (AUC=.91 Accuracy=.92) and RF (AUC=.90 Accuracy=.90), which outperform the remaining classifiers.

Four classifiers, Gradient Boosting, AdaBoost, Random Forest and SVM, gained the perfect AUC and accuracy (AUC=1, Accuracy = 1) for predicting a clinically significant reduction in PSS, followed by the near-perfect score for KNN (AUC=.99, Accuracy=.99) and DT (AUC=.97, Accuracy=.97).

Meanwhile, LR had the lowest performance for PHQ9, BAI and PSS in terms of AUC (.62, .60 and .79, respectively) and Accuracy (.63, .60 and .80, respectively).

Using the second dataset (i.e., enriched with the exposure to videos) we used random forest to detect features' importance in relation to the three outcomes. The most predictive feature for the PHQ 9, BAI, and PSS was the total exposure to the mindfulness videos, followed by the average number of working hours per week and age for PHQ 9 and BAI. In contrast, Age and the average number of working hours per week were the second and third most important predictors for PSS. Figure 2 presents the feature importance for the three outcomes.

Figure 2. Feature importance for PHQ9(left), BAI (middle), and PSS (right) using random forest.

<Figure 2 here>

Discussion

Principal Results

The study investigated the predictability of the effectiveness of a Mindfulness Virtual Community (MVC) designed for undergraduate students to reduce symptoms of depression, anxiety and stress as measured by PHQ 9, BAI and PSS. The effectiveness was measured by the minimal clinically important difference for PHQ9, BAI and SPSS. Several algorithms were used to predict the minimal clinically important difference.

Predicting intervention success with sociodemographic and self-reported measures

We successfully built machine learning-based models that predicted the effectiveness of the MVC intervention. The highest AUC was achieved for Gradient Boosting to predict the intervention effectiveness for PHQ9 and PSS (AUC=.85 and AUC=1 respectively), followed closely by DT (AUC=.84 and AUC=1 respectively) and AdaBoost (AUC=.82 and AUC=.99 respectively). The RF model had the highest AUC to predict BAI (AUC= .93), followed closely by AdaBoost (AUC=.92). AdaBoost might be an algorithm of choice for the three outcomes as it is fairing a close second best for BAI and a close third best for PHQ 9 and PSS. Gradient Boosting and AdaBoost are both good choices to predict the intervention success for the three outcomes; it might be argued that AdaBoost might be preferable given that it is usually less prone to overfitting than gradient boosting; however, there is no need to use the same algorithm to build the three predictors for the three outcomes.

We could not make a direct comparison with other studies that measured the three outcomes among university students using the same validated scales (PHQ9, BAI, and SPSS). However, for PHQ 9, the level of predictability of our study is higher than a previous study among adults in Korea using the Center for Epidemiologic Studies – Depression scale 11 (CES-D-11) (AUC=.87; Accuracy=.86) [42] as well as a study in the USA that defined the success of the intervention a 5-point reduction in PHQ9 or a 4-point reduction in the General Anxiety Disorder screener – 7 values (GAD) (AUC=.60; Accuracy=.71) [35]. Regarding anxiety, the predictive model developed in our study had a higher performance (accuracy=.92) than another study that used the Self-Rating Anxiety Scale (SAS) that did not report AUC but reported an accuracy of .84.

Feature Importance

The exposure to mindfulness videos was the most important factor in predicting the intervention's success. This study has demonstrated a link between the MVC intervention's success and exposure to mindfulness videos. It also confirms the results of the previous MVC pilot study that proved that the exposure to mindfulness videos alone, without interaction between participants via an online discussion forum, and without weekly videoconferencing with a coach, effectively reduced symptoms of depression, anxiety and stress [26]. In other words, it indicates the ability of MVC to be deployed at a large scale without an increase in human resources. Scalability is a critical factor for eHealth intervention deployment in large populations. This finding suggests that scaling up an effective e-mental health MVC is possible in a cost-effective manner; scalability is one of the recognized failures in e-health implementations [44].

Practical and Policy Implications

The MVC intervention does not provide clinical support; it is a platform that offers self-management of mental health symptoms (depression, anxiety, and stress). The MVC intervention proved to be effective [27-29] in reducing symptoms of depression, anxiety, and stress in university students. The current study builds a predictive model that predicts intervention success using sociodemographic and self-reported measures; this will allow counselling services on university campuses to assess the usefulness of MVC for a particular student before taking the intervention and advise them accordingly to use MVC or to opt for another type of intervention. This will enable counselling services to personalize the advice to students' profiles and allow students to manage their symptoms with the most appropriate intervention.

The other finding related to videos being the most important factor in predicting intervention success confirms the ability of MVC to be deployed at a large scale without an increase in human resources.

The number of working hours is another important predictor of the success of the intervention. Although the provincial governments in Canada support university education, students must pay for their education and bear the cost of living. Not surprisingly, they work long hours, especially if they belong to a marginalized community. Our findings align with other studies that suggest that longer working hours outside the university and difficulty paying bills were recognized as predictors of poor mental health among students [45]. In Ontario, where the sample was taken, Statistics Canada recently reported an increased reliance of academic institutions on students' fees in higher education, to the extent that 54% of all college revenues in 2019/2020 were downloaded on students, which translates into an overall decline in public funding [46]. This situation pushed students to longer working hours; one can argue that since student debt has been recognized as negatively associated with mental well-being and academic outcomes [47, 48], providing access to free higher education, supported by taxes such as in most of Europe, could enhance students' mental well-being as it would relieve them from the need for long working hours.

Strengths and Limitations

One of the strengths of this study is the ability to predict the intervention's success based on a few demographics and one question about self-rated health. Hence, the predictive model can be used in real life to indicate the suitability of online mindfulness intervention for specific individuals and possibly suggest alternatives if the model predicts non-effectiveness. The excellent AUC and accuracy measures make the models suitable for implementation and evaluation in real-life scenarios. However, the machine learning models must be monitored continuously if implemented for daily use (e.g., a counselling service) [49, 50].

A limitation of this study is that it relied on research done on one site; future research with larger samples with participants from multiple universities and colleges would better test the generalizability of results as it allows us to test the effectiveness of the models on external data.

Conclusions

Our results suggest that we can build high-performing models to predict MVC intervention effectiveness for depression, anxiety, and stress based on simple socio-demographics and self-reported features and that exposure to mindfulness videos is the most important predictor for the effectiveness of the intervention. Our findings provide evidence that scaling MVC can be done without additional cost for support and that the predictive models might be useful for professionals to advise students early enough on taking the intervention or choose other alternatives.

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Authors' contributions

CE, FA and PR designed the original MVC study questionnaire, received the funds and contributed equally. CE supervised FT, who performed and reported the analysis. CE verified the analysis and prepared the first draft; all authors provided critical feedback and revised it. The MVC Team members are Sahir Abbas, BSc; Yvonne Bohr, PhD; Manuela Ferrari, PhD; Wai Lun Alan Fung MD, ScD, FRCPC; Louise Hartley, PhD; Amin Mawani, PhD; Kwame McKenzie, MD, FRCPC; and Jan E. Odai, BA.; they made contributions to several aspects of the project and results' development. They all approve the final version and agree to be accountable for all aspects of the submitted paper. The trial protocol could be accessed on reasonable request to corresponding authors.

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Data Availability

The data used to train and evaluate the machine learning model in this study are not publicly available due to limitations in the Ethics Approval. However, the authors are willing to address reasonable requests for data sharing on a case-by-case basis. To submit a request, please contact the corresponding author, Dr. Christo El Morr, at elmorr@yorku.ca.

Conflicts of Interest

It is the understanding of the university and researchers that the Project Intellectual Property belongs to the CM, FH and PR. The industry partner [ForaHealthyMe.com](https://www.forahealthy.com) owns all rights and titles to the copyrights of any computer source code software developed from this research project.

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Supplementary Files

Figures

The mindfulness virtual community design.



Feature importance for PHQ9(left), BAI (middle), PSS (right) using random forest.

