A Machine Learning Approach to Analyzing the Role of Academic Workload on Mental Well-Being in First-Year Undergraduate Engineering Students

by

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Abstract

This study looked into the relationship between student Subjective Well-Being (SWB) and three self-reported academic workload measures, namely objective workload (i.e. the time spent outside of classroom to complete assigned work for a given course), transient objective workload (i.e. the extent of week-to-week variation in the total objective workload for all courses), and perceived workload difficulty (i.e. the extent of academic difficulty for a given course). Data was collected from a sample of first-year undergraduate engineering students at the University of Toronto (N = 851). At the aggregate level, all academic workload measures were found to be significantly higher in students reporting negative SWB compared to students reporting positive SWB. At the course level, findings from a machine learning binary classification model revealed that the objective workload of Engineering Strategies and Practice II course had the strongest negative influence towards the model's SWB predictions. Areas for future research is discussed.

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1 Introduction

1.1 Background and Motivation

The Public Health Agency of Canada (PHAC) defines mental health as "the capacity of each and all of us to feel, think, and act in ways that enhance our ability to enjoy life and deal with the challenges we face. It is a positive sense of emotional and spiritual well-being that respects the importance of culture, equity, social justice, interconnections and personal dignity" [1]. Whereas, the World Health Organization's definition of mental health states, "Mental health is a state of well-being in which an individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community."[2]. Both of these definitions point to a central idea that overall mental health is not just the absence of mental illness but also comprises of the state of well-being of the individual. This characterization is aligned with the dual continua model of mental health and illness [3]. The dual continua model states that the overall mental health of an individual is a function of two related but distinct dimensions comprising of mental well-being and mental illness. According to this model, people can have a low level of mental well-being, without experiencing a mental illness. A number of studies have provided evidence for the dual continua model, for example in American adults [4], American adolescents (ages 12 to 18) [5], Dutch adults [6], and South-African adults [7]. While traditional literature surrounding mental health has largely focused on the lack of mental illness, the dual continua model of mental health emphasis the importance of studying mental well-being as well, as an essential component in characterizing an individual's overall mental health.

High levels of student mental well-being is a desirable outcome. Students with high levels of well-being are more resilient [8], demonstrate better academic performance [12], and adopt more adaptive coping strategies to manage the student life [14]. Such findings motivate the need to understand the driving factors that influence student mental well-being.

1.2 Problem Statement and Study Aim

Students transitioning from high school to a post-secondary institution could potentially be exposed to numerous stressors. This includes adapting to increased academic demands; relocating away from the safety and comfort of the home and taking on new responsibilities (e.g.

independent living); leaving existing social support networks of close friends and family and forming new ones; financial difficulties; or adapting to the new culture of a new country altogether. Consequently, the transition marks a time period where there is an increased sensitivity and vulnerability amongst students [15], which has the potential to negatively influence student's mental well-being outcomes [16]. Empirical findings suggest that undergraduate students in Canada are more stressed on average than the general population [18, 19]. First-year undergraduate engineering students have also been found to be subject to high levels of stress. One study surveyed 351 first-year undergraduate across 7 Canadian universities and asked them to self-report how stressed they feel on average on a Likert scale of 1-5 (5 representing the highest stress level). The study found 61% of students responded with a value of 4 or higher [21] implying that first-year undergraduate engineering students experience high levels of stress. The daily hassles of student life has been shown to be a greater risk factor than life events in inducing stress [22], and has been found to be more detrimental to well-being than stressful life events [23].

Out of the various transition related stressors, high academic workload (e.g. volume of work and content difficulty) may play a significant role in influencing mental well-being outcomes in first-year undergraduate engineering students. One study surveyed 33,164 post-secondary students across 34 Canadian post-secondary institutions in 2014 and asked them to select the sources of stress that were "traumatic or difficult to handle in the last 12 months". The study found that academic stress was the most prevalent stressor, with 57% of students who reported experiencing it, followed by financial difficulties (37%) and sleep difficulties (32%) [24]. Another study specifically concerning engineering students in Canada asked students to rate their stress level related to their studies on a Likert scale of 1-5 (5 representing the highest stress level). The study found that 61% of students responded with a value of 4 or higher [25], implying that engineering students experienced high levels of stress related to their studies.

Given our understanding from these empirical findings, there is still limited research surrounding how the specific aspects of academic workload influence student mental well-being outcomes in first-year undergraduate engineering students across Canadian post-secondary institutions. Furthermore, prior studies in the Canadian academic context has largely understood student stress and well-being through an emphasis on the regulation of negative mental health outcomes (e.g. burnout, depression) [25, 26]. Whereas limited studies has been done with a focus on the factors that influence positive mental health (i.e. mental well-being).

In light of the observations noted above, this study aims to uncover the relationships between student mental well-being and the various aspects of academic workload in first-year undergraduate engineering students in the Canadian context.

2 Literature Review

2.1 Mental Well-Being

It becomes important to understand what mental well-being constitutes, to advance towards fostering mental well-being in first-year undergraduate engineering students. Current research on mental well-being has been derived from two overlapping yet distinct perspectives: the eudaimonic approach and the hedonic approach. In a broad sense, Eudaimonic Well-Being (EWB) focuses on the idea of realizing one's unique potential [28], through the means of optimal positive functioning through the act of striving [29]. On the other hand, the components of the hedonic approach to well-being or Subjective Well-Being (SWB), represents people's thoughts and feelings that they are living a desirable and rewarding life [30]. In other words, SWB encompasses both the cognitive and affective assessments made by people about their lives [30, 31]. While both EWB and SWB are important attributes to characterizing a student's overall well-being, this study focuses on understanding the factors that influence student SWB.

While a number of conceptualizations on SWB exist in literature, numerous studies commonly conceptualize SWB as comprising of three areas: positive affect, negative affect and life satisfaction [33]. Together, these make the Tripartite Model of SWB [36]. The first two areas represents the individual's positive and negative emotional reactions to their lives, which refers to the affective component of happiness [37]. In contrast, the third area of life satisfaction represents the cognitive component of happiness, referring to "the degree to which a person evaluates the overall quality of his or her present life-as-a-whole positively" [38]. While day-to-day events may influence the affective component of happiness, in this regard, SWB represents more than just being happy in the present moment, because the incorporation of life satisfaction also takes into account the individual's reflection of past experiences.

The factors that influence SWB vary broadly. These include genetics [39], fulfillment of the basic and psychological needs of individuals [40], life circumstances (e.g. unemployment) [41], and socio-political factors (e.g. inequality) [42]. Since the potential factors that may influence SWB can vary broadly, the scope of this study will be limited to understanding the academic workload related influences on student SWB.

Fostering healthy levels of SWB has been widely recognized as an important personal and societal goal by both researchers and lay persons alike [42, 43]. It is conceptualized as being an indicator of optimal human functioning [44, 45]. Studies indicate that higher (relative to lower) levels of SWB to be associated with fewer symptoms of mental illness, stronger interpersonal relations, more functional health status, more adaptive dispositions and temperaments, more prosocial functioning, and more self-enhancing cognitive styles [32,47-50]. Researchers have also advocated for the creation of national accounts of well-being to facilitate monitoring SWB within and across nations, to help inform government policy and priorities [51]. In the academic context, healthy levels of student SWB has been found to be positively associated with hope, optimism and self-esteem [54], more frequent experiences of positive emotions and better cognitive and psychological engagement in learning [55], academic self-efficacy [57] , and positive beliefs about learning [58]. On the other hand, low levels of SWB has been found to be associated with negative mental health problems such as depression and maladaptive behaviors [61]. These findings highlight the importance of subjective well-being and emphasizes the need to study the factors that influence student subjective well-being.

2.2 Academic Workload

Academic workload factors may play a major role in influencing SWB outcomes in first-year undergraduate engineering students in the Canadian context. Anecdotally, first-year undergraduate engineering programs in Canada are often viewed as academically demanding, and it is common to hear terms such as “high workload” to refer to the extent of academic workload assigned to students. Similarly, in literature within the academic context, the term “workload” is used in an analogous way, but is considered to be more complex and a multi-dimensional construct. Some studies concerning academic workload tend to distinguish between two conceptualizations i.e. objective workload and perceived workload. In a broad sense, objective workload refers to the actual duration of the study time spent by the student, while perceived workload refers to the student's perceptions of the extent of the workload. These have been found to be weakly related, but distinct aspects of academic workload in empirical studies, including the study involving undergraduate engineering students in Hong Kong [63], and study involving undergraduate and postgraduate engineering students in Australia [64].

Excessive academic workload (i.e. both objective and perceived workload) subjects students to tremendous pressure. The student's experience of excessive workload is linked to experiences of difficulty, stress, anxiety and the desire to give up [65], and decreased performance, motivation to study, burnout, anxiety, and depression [66]. Moreover, students experiencing excessive workload are not capable of achieving positive learning experiences, as they resort to surface and rote learning rather than deep learning [65]. As such, it becomes important to understand each conceptualization (i.e. objective and perceived workload) particularly in relation to student mental well-being outcomes. In the sections below, the two conceptualizations of academic workload are explored in greater detail.

2.2.1 Objective Workload

Objective Workload

In its simplest sense, objective workload refers to the volume of assigned work. One approach to measuring this is to take the duration of timetabled contact hours of classes, and add that to the time spent towards independent study [83]. The relationship between objective workload and mental health outcomes has been mixed in the academic literature. For example, Lindsay 2010 [69] attempted to explore the relationship between objective workload and stress in a study comprising of 1,392 first-year engineering students in an Australian university. The study did not find any significant relationships between number of study hours spent towards independent study and stress, implying a more complex relationship than the simpler counterpart i.e. "more work means more stress". Another study which interviewed 20 Belgian engineering students [70] revealed most of the students feeling overwhelmed by the unmanageable workload due to too much time-pressure. Studies concerning engineering students in Canada suggests a similar narrative. For example, a study comprising of 3,936 engineering students across 44 accredited engineering schools in Canada asked students to identify the factor that caused the greatest stress and found the volume of workload as the primary cause [24]. Research situated at the University of Toronto [71] found that first-year undergraduate engineering students spend more than an average of 55 hours per week at a minimum on their studies (a combination of class time and independent study). In contrast, in Finland, undergraduate engineering students spend approximately an average of 25 hours per week studying, including both contact teaching and independent studying [73]. On the basis of these findings, the following hypothesis is derived,

Hypothesis 1: Students who report higher objective workload are more likely to experience negative student subjective well-being.

Transient Objective Workload

Heavy workloads has been the focus to the discussion of well-being in the academic context. However, fluctuations in workloads has received limited attention [74], even though objective workload and transient objective workload may have independent effects on well-being. In the academic context, transient objective workload refers to the changes or deviations in the objective workload on a daily or a weekly basis. Students may have aspects of stability in their living patterns, including their sleep cycles, study hours and nonstudy hours. In this context, variations in the academic demands has the potential to disrupt a student's study-nonstudy interface, and in turn, may influence student well-being outcomes. It is important to note that the underlying mechanism for this possible influence is not because of the extent of objective workload, but precisely because of the impact of these variations on the stable living patterns of a student. In this way, the transient nature of objective workload may have effects that are independent to that of objective workload on well-being.

While there are limited studies in the academic context, however in the workplace setting, variability in objective workload has been found to diminish well-being dimensions in numerous studies [74,78-81]. On the basis of these findings, the following hypothesis is derived.

Hypothesis 2: Weekly variability in the academic demands is negatively related to student subjective well-being.

2.2.2 Perceived workload

Perceived workload is more qualitative in nature and refers to the student's individual perceptions of the extent of academic demands assigned to them. In academic literature, perceived workload has been discussed to be a function of various factors. These may be categorized into quantitative and qualitative perceived workload.

Quantitative perceived academic workload comprises of all the factors that constitutes student academic workload perceptions measured in units of time. For example, Nijhuis, Segers, & Gijselaers, 2008 [79] propose quantitative perceived academic workload to refer to the student perceptions on the study time needed to meet academic demands, which can be different from the actual time spent (i.e. objective workload). On the other hand, Marsh, 2001 [80] proposes to distinguish between good, useful workload and bad workload. In which, useful workload equals the hours spent in class believed by the student to be valuable, while bad workload is the total number of hours minus the good hours.

On the other hand, qualitative perceived academic workload emphasizes the qualitative aspects of academic workload. A broad range of qualitative factors comprises of this category including, feelings of overburden [81] , feelings of pressure [82], experiences of content difficulty [81], perceptions about the learning environment (e.g. course instruction and organization)[70] and personal characteristics (e.g. study habits) [70].

While current literature discusses various factors that characterizes perceived academic workload, content difficulty may play an important role in characterizing the perceived academic workload of engineering students. Several studies have also found negative relationships between perceived difficulty and student mental health outcomes in engineering students. For example, one study of 1,302 engineering students from an Australian university found that the student's evaluation of task difficulty was positively related to perceptions of stress Lindsay 2010 [69]. Another study of 3,936 engineering students across 44 accredited engineering schools in Canada asked students to identify the factors that caused the greatest stress. From the study, 61% of respondents reported course difficulty as a factor that contributed to the greatest stress [24]. On the basis of these findings, Hypothesis 3 is derived as mentioned below. In addition, to account for the cumulative effects of all of the above academic workload aspects, Hypothesis 4 is also derived as mentioned below.

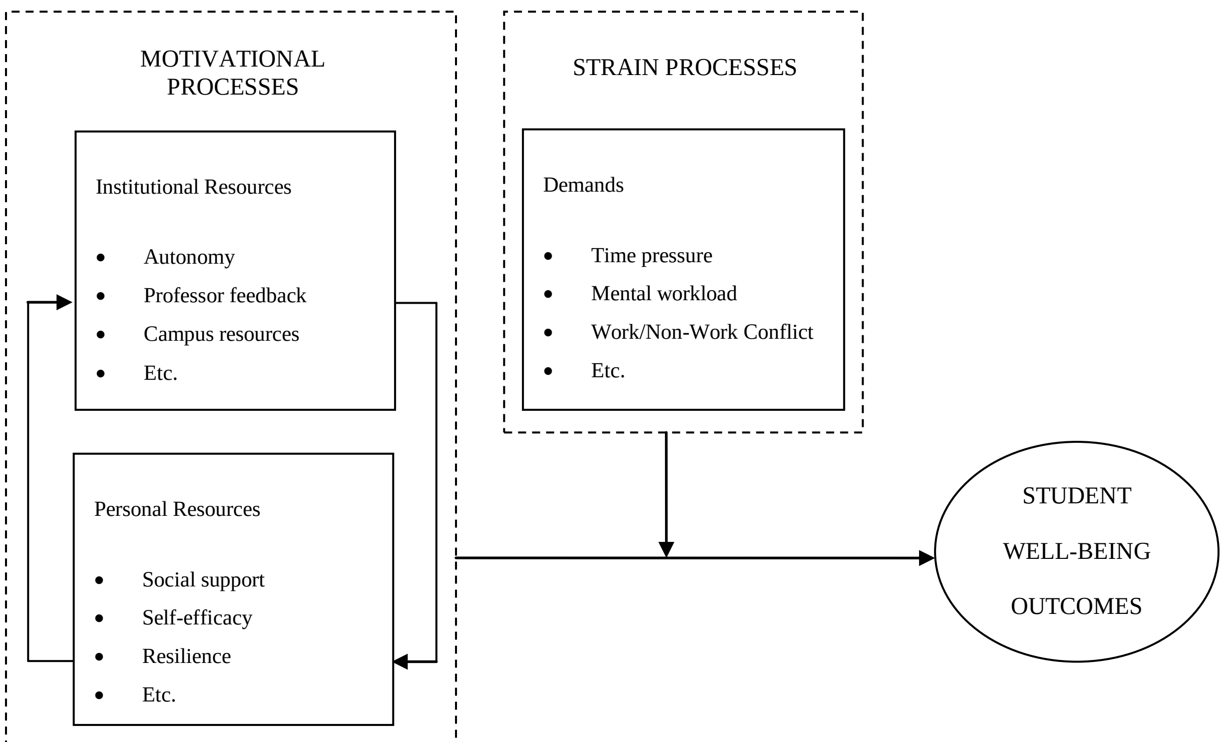
Hypothesis 3: Perceived difficulty is negatively related to student subjective well-being.

Hypothesis 4: Objective workload and perceived academic difficulty influence student SWB in the negative direction for all courses.

3 Theoretical Framework

Pathways to student subjective well-being can be viewed through the lens of the Job Demands – Resources (JD-R) model. The Job Demands-Resources model or (JD-R) model proposes that well-being outcomes is the result of an imbalance between demands and the resources that the individual has available to deal with those demands [85]. In this way, the JD-R model does not only focus on negative mental health outcomes variables (e.g. burnout), but also includes positive mental health outcomes, as the mental health outcome depends on the balance between demands and resources or strain and motivational processes respectively. Figure 1 illustrates the JD-R model adapted to the academic context.

Figure 1: JD-R Model Adapted to the Academic Context



As per Figure 1, the demands contribute to strain processes and are defined as all physical, social, or organizational aspects that call for sustained physical and mental costs [87]. These include time pressure, mental workload, or conflict between the work and non-work interface.

On the other hand, resources contribute to the motivational processes, and are defined as all physical, psychological, social, and organizational characteristics that can increase personal growth and development while reducing academic demands [87]. Some resources that post-secondary students have at their disposal include social support, campus resources, professor feedback, decision-making latitude (e.g. lecture attendance, planning time for school work) [87] and personal resources (e.g. academic self-efficacy) [88]. In this manner, the JD-R model proposes that the overall student well-being is a consequence of the interaction between the strain and the motivational processes. Hence, negative well-being outcomes are a result of strain processes exceeding the motivational processes. In line with this model, this paper proposes that excessive academic demands is predictive of negative student subjective well-being outcomes.

4 Methodology

4.1 Participants and Procedure

Every week, during the fall and winter semesters of the school calendar years of 2018 and 2019, a sample of 20 students from each engineering discipline within the first-year of the undergraduate engineering program at the University of Toronto (UofT) were randomly selected and were invited to participate. Invitations were sent via. an email with a Google Forms link to an online questionnaire. No incentive was provided for students to participate in the survey. The average response rate of the survey was about 50%. The resulting survey data comprised of responses from N = 851 students, with N = 512 students who reported experiencing negative SWB, while N = 339 who reported not experiencing negative SWB. Each survey participant provided informed consent prior to completing the questionnaire. The University of Toronto ethics review board approved all procedures and materials used in this study.

4.2 Measures

This study aims to measure three aspects of the first-year undergraduate student experience i.e. subjective well-being, objective workload and the perceived workload difficulty. To address the broad range of factors that influence SWB, the survey question was specifically phrased to assess specifically the academic workload related influences on SWB. Moreover, for greater granularity and understanding of the academic workload factors, the responses to the objective and perceived workload difficulty measures were collected with respect to each course the student identified to be taking during the semester. Furthermore, perceived workload was further broken down into conceptual difficulty and operational difficulty. The survey questions and the measurement approach used are provided in Table 1. The courses and their abbreviations used in this study are provided in Table 2.

Table 1: Survey Questions and Measurement Approach

Measure	Survey Question	Measurement Approach
Subjective Well-Being	To what degree has your academic workload over the past week impacted your mental and emotional wellbeing?	Using a 5-point Likert scale as follows: 1-Very Negatively 2-Negatively 3-Not At All 4-Positively 5-Very Positively
Objective Workload	How much focused time did you spend an all assignments for this course outside of class this week?	Responses collected for each course and measured as number of hours.
Perceived Workload Difficulty	How difficult were the assignments conceptually? (didn't know where to start, but once started it was easy to finish)	Responses collected for each course measured using a 5-point Likert scale as follows: 1-Very easy 2- Somewhat easy 3-Neither difficult nor easy 4-Somewhat difficult 5-Very difficult
Perceived Workload Difficulty	How difficult were the assignments operationally? (knew where to start, but the steps to complete it were challenging and/or tedious)	Responses collected for each course a student is enrolled in and is measured using a 5-point Likert scale as follows: 1-Very easy 2- Somewhat easy 3-Neither difficult nor easy 4-Somewhat difficult 5-Very difficult

Measure	Survey Question	Measurement Approach
Objective and Perceived Workload Difficulty	Do you have any other comments that will help us better understand first-year student workload?	Comments were parsed and categorized into objective and perceived workload measures (as appropriate) to serve as additional data to aid the analytical methods used in this study

Table 2: List of Courses and their Abbreviated Named Used in this Study

Course Code	Course Code and Name	Abbreviated Name {courseName}
APS100	Orientation to Engineering	oe
APS110	Engineering Materials and Chemistry	emc
APS111	Engineering Strategies and Practice I	esp1
CHE112	Physical Chemistry	phys_chem
CIV100	Mechanics	mech
MAT186	Calculus I	calc1
MAT188	Linear Algebra	lin_alg
APS164	Intro. Chemistry from a Materials Perspective (ONLINE)	chem_mat
APS163	Calculus for Engineers II (ONLINE)	calc2_online
APS160	Mechanics (ONLINE)	mech_online
APS112	Engineering Strategies & Practice II	esp2
MAT187	Calculus II	calc2
APS106	Fundamentals of Computer Programming (Python)	py_prog
ECE110	Electrical Fundamentals	elec
MIE100	Dynamics	dyn

Course Code	Course Code and Name	Abbreviated Name {courseName}
APS105	Computer Fundamentals	comp
MSE101	Intro. to Materials Science	mat
CME185	Earth Systems Science	earth
CHE113	Concepts in Chemical Eng.	chem_eng
APS191	Intro to Engineering	int_eng
MIE191	Intro to MIE	int_mie

4.3 Analytical Methods

The analysis was conducted using various libraries available in Python including scipy.stats for statistical tests and sklearn for machine learning classification and text processing. The following analytical methods were used in this study.

4.3.1 Statistical t-Tests

To test Hypothesis 1, 2 and 3, independent paired-samples t-tests was conducted to test whether there was a significant difference in means between positive SWB and negative SWB scores. A criterion of $p < 0.05$ was adopted to determine statistical significance for these tests.

4.3.2 Text Processing

Pointwise mutual information (PMI) was used to parse the student's responses to the question "Do you have any other comments that will help us better understand first-year student workload?" PMI is measure of association between two words in a text corpus. It is defined mathematically as below:

$$pmi(x;y) = \log \frac{p(x,y)}{p(x)p(y)}$$

In the above equation, x and y refer to the two words in the text corpus, p(x) and p(y) refer to the number of occurrences of x and y respectively, and p(x,y) refers to the number of co-occurrences of x and y. As per the above equation, a high PMI value indicates greater association between the two words based on their co-occurrence. In this case, x refers to each word in the student's response, and y refers to the positive or negative SWB outcome (refer to Section 4.4 Data Pre-Processing for more details on processing steps employed on the SWB survey data). The top 5 words with the highest PMI associated with the negative subjective well-being were chosen for each classification model, since those terms were most associated with the scope of this study. These words were "lot", "tests", "work", "difficult" and "hard". The words "lot", "tests" and "work" were categorized as representing the objective workload measure. This is because most of the responses involving these words were made in the context of volume of work, for example "*First-year student workload is not light and requires a lot of work and time…*", "*The amount of tests/assessments back to back can sometimes feel overwhelming*" and "*Although some coursework is easy to finish, the amount of work and assessments from different courses results in a time-consuming day*". Whereas the words "difficult" and "hard" were categorized as representing the perceived workload difficulty measure as these words were mostly used in the context of content difficulty. For example, "*For students with no background to computer fundamentals, labs are extremely difficult*" and "*I think some courses are much harder than others like APS105, the computer coding course*".

4.3.3 Modelling

To test Hypothesis 4, classification models were created to attempt to predict the student SWB outcomes based on academic workload variables outlined in Table 3. Three Machine Learning (ML) binary classification models were applied, namely K-Nearest Neighbor, Support Vector Machine (SVM) and XGBoost. They are explained briefly below.

K-Nearest Neighbor (kNN): kNN is an instance based algorithm which delays the induction or generalization process until classification is performed [90]. We use the Euclidean distance as the distance metric. Since the performance of kNN may be impacted by different values of k, we set k from 1 to 10, and report the best performance (in terms of F1-score) among the 10 values of k.

Support Vector Machine (SVM): Support Vector machine (SVM) [91] is developed from statistical learning theory, and it constructs a hyperplane or a set of hyperplanes in a high dimensional space, which are used for classification. SVM selects a small number of critical boundary instances as support vectors for each label (in this case, the labels are negative and positive SWB), and builds a linear or non-linear discriminant function to form decision boundaries with the principle of maximizing the margins among training instances belonging to the different labels.

eXtreme Gradient Boosting (XGBoost): XGBoost is a state-of-the-art implementation of gradient boosted decision trees. More particularly, it uses an ensemble technique to sequentially add predictors and iteratively learns and corrects the previous models. However, instead of assigning weights to the classifiers after every iteration, this method fits the new model to new residuals of the previous prediction to minimize error loss [92].

Model Evaluation Approach

For each classifier, a 5-fold Cross Validation (CV) methodology was used to evaluate the consistency of the model across five randomly selected train-test set splits. A train-test set split of 80%-20% was used. Similar to how a multiple linear regression model optimizes or trains its beta coefficients to fit the independent variables to a dependent variable, the model parameters of the ML models were optimized or trained to fit the data on only on 80% of the records (known as the training set). Then, each model was made to predict the dependent variable i.e. “negative” or “positive” SWB on the remaining unseen 20% of the records (known as the test set) using only the values of the independent variables and the model parameters optimized earlier during the model training phase. The effectiveness of the model is evaluated based on the consistency of the model evaluation metric across different train-test set splits (known as folds), and the performance of the model on the test set.

Model Evaluation Metric

In terms of prediction outcomes from the models, for each student, there would be 4 possible outcomes: a student is classified by the model as experiencing negative SWB when the student truly reports negative SWB (true positive, TP); the student can be classified by the model as negative SWB when the student does not report experiencing negative SWB (false positive, FP);

the student can be classified by the model as positive SWB, when the student when the student truly reports experiencing positive SWB, (false negative, FN); or the student can be classified by the model as experiencing positive SWB, when the student does not report experiencing positive SWB (true negative, TN). Based on these possible outcomes, we calculate the precision, recall and F1-score for each negative SWB outcome to evaluate the performance of the classification models as follows.

Negative SWB Precision: The proportion of students that are correctly labeled by the model as experiencing negative SWB among those students who reported experiencing negative SWB, i.e. P(NSWB) = TP / (TP+FP)

Negative SWB Recall: The proportion of negative SWB students that are correctly labeled by the model, i.e. R(NSWB) = TP/ (TP+FN)

Negative F1-score: Also known as the harmonic mean of precision and recall, it represents a summary measure that evaluates if an increase in precision outweighs a reduction in recall. The F1-score of students who reported experiencing negative SWB is provided below. In this study, we use the F1-score metric to evaluate the effectiveness of each classification model.

$$\mathrm{F(NSWB)} = \frac{2 \times \mathrm{P(NSWB)} \times \mathrm{R(NSWB)}}{\mathrm{P(NSWB)} + \mathrm{R(NSWB)}}$$

Interpreting the XGBoost Model

To understand the SWB predictions made by the XGBoost model as a function of the academic workload variables, the state-of-the-art method SHapley Additive exPlanations (SHAP) [93] was employed. This technique is inspired by game theory, which determines how much each “player” in a collaborative game has contributed to the game’s success. SHAP values denote the average marginal contribution of an independent variable towards the prediction over all possible coalitions. Hence, it is not the difference of the predicted value after removing the variable from the model, but rather the contribution of a feature value to the difference between the actual prediction and the mean prediction given all independent variable values. The higher the SHAP absolute value of an independent variable relative to other variables, the higher the relative influence that variable has towards the model’s prediction (i.e. in this case, prediction of either negative SWB or positive SWB).

4.4 Data Pre-Processing

The following key data pre-processing steps were performed in this study.

- Records with null SWB values were removed from the study.

- Records with missing values in the objective workload measure were filled with a value of 0 hours.

- Normality assumption for the t-tests was preserved by removing the outliers. This includes objective workload responses (i.e. hours of independent study in a week) that were reported to be greater than 80 hours. It also includes the entries where the obj_weekly_difference values were above or below 40 hours and -40 hours respectively.

- Responses to the SWB measure were grouped into two categories i.e. the “negative” category if the response was 1 or 2, and the “positive” category, if the response was 3, 4 or 5.

- Responses to the perceived workload difficulty measure for both conceptual and objective perceived workload difficulty were grouped into three categories i.e. the “not_difficult” category if the response was 1, 2 or 3, and the “difficult” category if the response was 4 or 5, and the “null” category if no response was available.

- Several new academic workload variables were calculated from the survey data for both the objective and the perceived workload difficulty measures to potentially improve the effectiveness of the classification models. The measure they represent, their explanation, and the abbreviations used in this study to represent them are provided in Table 3.

- A Variable Inflation Factor (VIF) threshold of 10 was used to remove the multi-collinear academic workload variables prior to applying the models.

Table 3: Academic Workload Variables Considered In this Study

Measure	Explanation	Abbreviated Variable Name*
Objective Workload	Response to the objective workload measure question, "How much focused time did you spend an all assignments for this course outside of class this week?" for a given course	obj_{courseName}
	Response to the objective workload measure question summed for all courses	obj_total
	Represents a measure of weekly workload fluctuation within the specific engineering discipline. This is calculated by taking the week to week differences in the average value of the total objective workload reported by students of the same engineering discipline for each week	obj_weekly_difference
	Takes a binary value signifying whether or not the student's comment included the word "lot"	obj_comment_lot
	Takes a binary value signifying whether or not the student's comment included the word "tests"	obj_comment_tests
	Takes a binary value signifying whether or not the student's comment included the word "work"	obj_comment_work

Measure	Explanation	Abbreviated Variable Name*
Perceived Workload Difficulty	Response to the question, “How difficult were the assignments conceptually? (didn't know where to start, but once started it was easy to finish)” grouped into three categories for a given course	pwd_con_{courseName}_difficult or, pwd_con_{courseName}_not_ difficult or, pwd_con_{courseName}_null
	Response to the question, “How difficult were the assignments operationally? (knew where to start, but the steps to complete it were challenging and/or tedious)” grouped into three categories for a given course	pwd_opp_{courseName}_difficult or, pwd_opp_{courseName}_not_difficult or, pwd_opp_{courseName}_null
	The number of courses in which, the student responded with a value of 1 i.e. representing least perceived academic difficulty including both conceptual or operational perceived workload difficulty	pwd_low_diff_courses_count
	The number of courses in which, the student responded with a value of 5 i.e. representing greatest perceived academic difficulty including both conceptual or operational perceived workload difficulty	pwd_high_diff_courses_count

Measure	Explanation	Abbreviated Variable Name*
Perceived Workload Difficulty	The average value of perceived workload difficulty (i.e. both conceptual and operational) for all courses	avg_difficulty_index
	Takes a binary value signifying whether or not the student's comment included the word "difficult"	pwd_comment_difficult
	Takes a binary value signifying whether or not the student's comment included the word "hard"	pwd_comment_hard

* refer to Table 2 for a list of abbreviated course names {courseName} used in this study

5 Results

To check univariate normality to perform the t-tests, one guideline [94] suggested a cut-off of absolute values of +/-3.0 and +/-8.0 for skewness and kurtosis, respectively. The skewness and kurtosis for the obj_total was found to be -0.90 and -0.88 respectively. The skewness and kurtosis for obj_weekly_difference was found to be -0.74 and 1.95 respectively. The skewness and kurtosis for avg_difficulty_index was found to be 0.43 and 0.94 respectively. These results indicate that these variables were relatively normally distributed.

Hypothesis 1 in this study was that students who report higher objective workload are more likely to experience negative student subjective well-being outcomes. Results supported that students who reported negative SWB (N = 493, M = 27, SD = 15) were found to report significantly more time in independent study (i.e. obj_total) compared to students who did not report negative SWB ((N = 324 , M = 19, SD = 12) , $t(815) = -7.3$, $p < .001$).

Hypothesis 2 in this study, was that weekly variability in the academic demands is negatively related to student subjective well-being. Results supported that the extent of week to week workload fluctuations (i.e. obj_weekly_difference) was observed to be significantly higher for students who reported negative SWB (N = 493, M = 1.4, SD = 7.96) compared to students who did not report negative SWB ((N = 324, M = 0.10, SD = 8.8), $t(815) = -2.2$, $p < .05$).

Hypothesis 3 in this study, was that perceived difficulty is negatively related to student subjective well-being. Results supported that students who reported negative SWB (N =493, M = 3.4, SD = 0.60) were found to report significantly more difficulty in their studies (i.e. avg_difficulty_index) compared to students who did not report negative SWB ((N = 324, M = 3.04, SD = 0.63), $t(815) = -8.4$, $p < .001$).

Hypothesis 4 in this study, was that objective workload and perceived academic difficulty influence student SWB in the negative direction for all courses. To test this, three machine learning classification models (i.e. kNN, SVM and XGBoost) were evaluated for its prediction effectiveness, and then the direction of influence of the 68 academic workload variables with SWB. Table 4 shows the F1 scores of the three classifications models. Out of all the models, the XGBoost model showed the best performance. It demonstrated good robustness across different train-tests splits as shown by the low standard deviation in the F1-scores across the 5 folds i.e. 0.061. It also showed the highest F1-score value of 0.76 for negative SWB, demonstrating good overall effectiveness in predicting student negative SWB. SHAP values were used to explain how each academic workload variable influences SWB predictions by the XGBoost model, and the corresponding degree of influence. Only the top 20 academic workload variables are considered (in terms of the magnitude of SHAP values) since they represent the most influential variables in determining the prediction of the XGBoost model. The degree and magnitude of the influence of these variables on SWB in terms of their SHAP values is illustrated in Figure 2. The degree of influence of each variable is denoted by the length of each bar. The colour denotes the direction of the influence on the SWB outcomes. A red coloured bar denotes a positive influence of the variable on the SWB, while a blue coloured bar denotes a negative influence of the variable on the SWB. Results show all perceived workload difficulty variables for all courses to influence SWB in the expected directions. However, the objective workload for the Fundamentals of Computer Programming (i.e. py_prog) course and the Computer Fundamentals (i.e. comp) course were found to influence SWB in the positive direction. Hence, Hypothesis 4 was only partly supported in this study.

Table 4: Precision, Recall and F1-Score for Three Classification Models

Evaluation Criterion	kNN	SVM	XGBoost
CV F1-Score Std. Dev.	0.057	0.150	0.061
Negative SWB Precision	0.62	0.65	0.70
Negative SWB Recall	0.82	0.87	0.82
Negative SWB F1-Score	0.70	0.74	**0.76**

Figure 2: SHAP values of Top 10 features of the XGBoost model

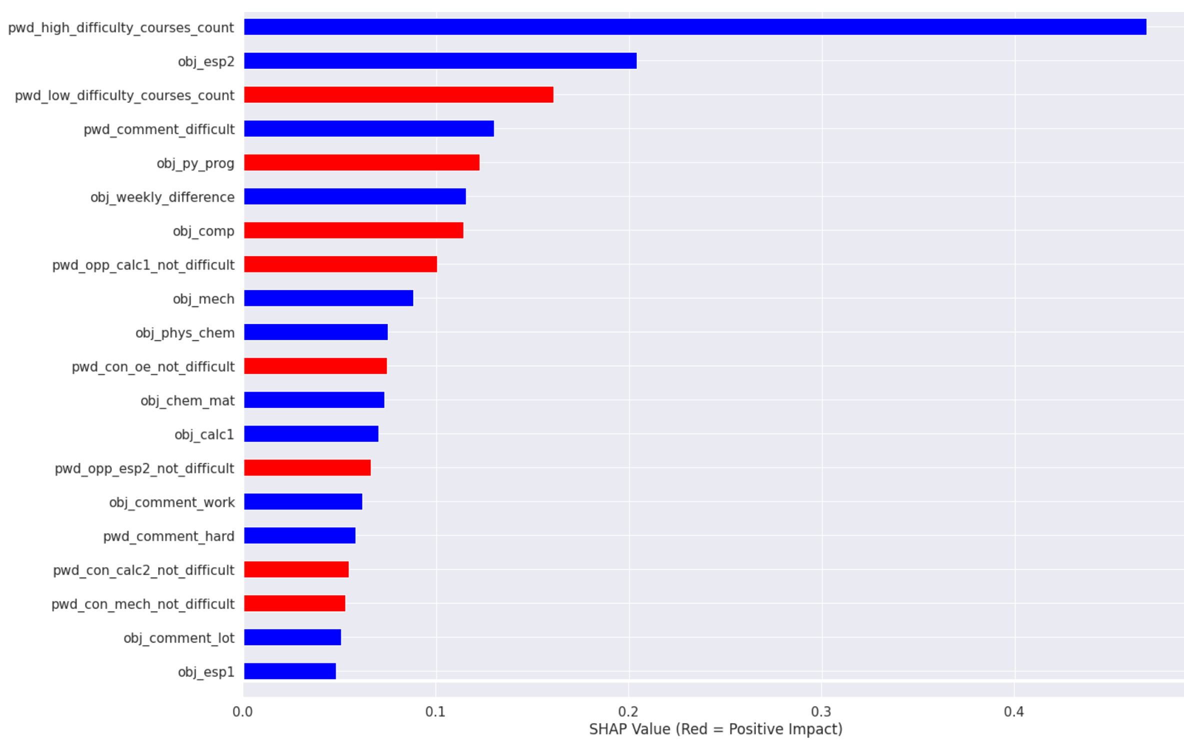
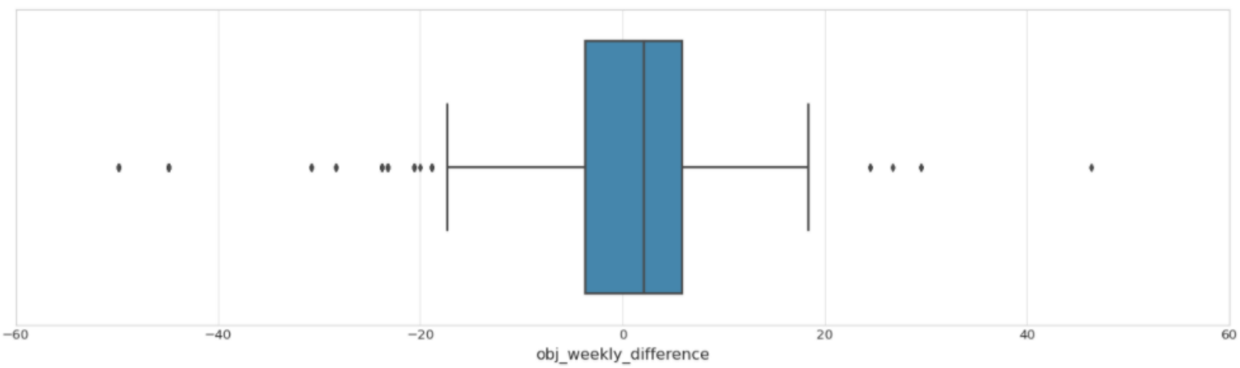


Table 5: Descriptive Statistics of Objective Workload in Select Courses for a Given Week

Course	N	% Negative SWB	Mean for Positive SWB	Median for Positive SWB	Mean for Negative SWB	Median for Negative SWB
esp2	292	61%	4.8	3.0	9.4	3.0
mech	407	61%	4.8	4.0	6.4	4.0
phys_chem	209	61%	4.1	3.0	5.9	3.0
py_prog	148	56%	4.1	4.0	6.2	4.0
comp	119	56%	4.8	4.0	8.3	4.0
others	765	60%	4.6	4.0	6.6	5.0

Figure 3: Box Plot of Transient Objective Workload



6 Discussion

The aim of this study was to analyze the nature of the relationships between different aspects of academic workload and subjective well-being (SWB) in first-year undergraduate engineering students in Canada. To better understand these relationships, four hypotheses were derived for this study.

The first three hypotheses derived for this study each concerned a specific dimension of the academic workload i.e. objective workload (Hypothesis 1), transient objective workload (Hypothesis 2) and perceived academic difficulty (Hypothesis 3). Findings reveal that each of these academic workload aspects are significantly and negatively related to SWB when at high levels. This finding aligns with the JD-R model that posits that negative well-being outcomes are the result of excessive strain processes that are not sufficiently balanced by the motivational processes. Furthermore, the findings of this paper concerning student SWB aligns with previous studies on stress in engineering students in Canada [25], thereby suggesting that student stress and student subjective well-being may be interrelated. Such a relationship has been observed in other studies as well in the academic context [95].

The fourth hypothesis was that objective workload and perceived academic difficulty influence student SWB in the negative direction for all courses. The analysis was specifically adapted to the first-year undergraduate engineering program, as it explored the academic workload measures at the course level of the program. The XGBoost model demonstrated to be an effective model, as it was able to predict most of the negative SWB outcomes in the data consistently across the folds (F1-score = 0.76, precision = 0.70, recall = 0.82). This implies that the academic workload variables considered in this study are important factors to consider when attempting to understand the key academic workload determinants of negative SWB outcomes in first-year undergraduate engineering students. To understand the degree and direction of influence of each academic workload variable on student SWB, SHAP values were calculated for each academic workload variable at the course level. The SHAP value signifies the average marginal contribution of a variable to the difference between the actual prediction and the mean prediction of the XGBoost model. Hence, a high SHAP value denotes a high degree of influence of the variable (i.e. either positive or negative) on the model's SWB predictions.

Results show that the variable with the highest magnitude of SHAP value was pwd_max_diff_course_count, which is variable within the perceived workload difficulty measure. This variable refers to the number of courses a student reported to be "very difficult" including both conceptual and operational difficulty. A strong negative influence of this variable was found on the model's SWB predictions, which implies that the number of "very difficult" courses (as perceived by the student) is highly predictive of negative SWB outcomes in the model. All other variables within the perceived workload difficulty measure were found to influence SWB in the expected directions. For example, the variable min_diff_courses_count, which refers to the number of courses a student finds conceptually or operationally "very easy", was found to have a positive influence on SWB as expected. These results are in line with the JD-R model, which posits that excessive demands (e.g. perceived workload difficulty) signifies an excess of strain processes in relation to the motivational processes, which results in negative well-being. On the other hand, when demands are adequately compensated by the available resources, it signifies a healthy balance between the strain and motivational processes, which in turn, results in positive well-being. These findings also aligns with other studies analyzing the relationship between perceived workload difficulty and mental health outcomes in the academic context [81].

Within the objective workload measure, the variable obj_esp2 was found to have the highest magnitude of SHAP value in the negative direction. The variable obj_esp2 refers to the objective workload for the course Engineering Strategies & Practice II (i.e. esp2). A strong negative influence of this variable was found on model's SWB predictions, which means that the extent of time a student spends towards tasks of this course tends to have a high negative influence on the model's SWB predictions. Some other (but not all) variables within the objective workload measure were found to have a negative influence on the model's SWB predictions, including the course Mechanics (i.e. mech) and Physical Chemistry (i.e. phys_chem), but to a lesser degree of influence. The transient objective workload variable (i.e. obj_weekly_difference) also tended to have a relatively high negative influence on the model's SWB predictions. The obj_weekly_difference variable is a measure of the weekly workload fluctuation within the specific engineering discipline, calculated by taking the week to week differences of the average value of the total objective workload reported by students for each week, in the same engineering discipline. The role of transient objective workload was not found to be widely studied in the Canadian engineering academic context, specifically in relation to student SWB. Hence, this finding emphasizes the importance of this variable as a determinant to student SWB outcomes within the first-year engineering program. In line with the JD-R model, both excessive objective workload and excessive transient objective workload signify a state of imbalance between the demands and the available resources. More specifically, it signifies that the demands (that contribute to strain processes) exceed the available resources (that contribute to motivational processes), which then results in negative well-being outcomes.

To understand the extent of objective workload reported for courses Engineering Strategies & Practice II (i.e. esp2), Mechanics (i.e. mech) and Physical Chemistry (i.e. phys_chem), Table 5 is provided above. Table 5 presents the descriptive statistics for the objective workload reported by students for select courses for a given week. Results from Table 5 shows that even though students tend to spend more time on average in the Engineering Strategies & Practice II course than other courses, the difference in the objective workload between esp2 and other courses is not considerable, given that the objective workload represents the total hours spent in a week. This suggests that it is not the high volume of objective workload in esp2, mech, and phys_chem courses that is contributing to the relatively high negative influence of these variables towards the SWB predictions. This in turn, suggests that there may be other academic workload factors (besides objective workload and perceived workload difficulty considered in this study) that may be driving the SWB outcomes in these courses. In this way, this finding adds another layer of nuance and complexity to the results of the prior study which found objective workload as the most prevalent stressor in engineering students in the Canadian context [23]. Further studies that aims to better understand the relationships between well-being and the specific driving factors (both from the strain and motivational process dimensions) at play within these courses is recommended.

To understand the extent of the transient objective workload variable, Figure 3 is provided above. Figure 3 shows the univariate box plot of the transient objective workload variable (i.e. obj_weekly_difference). The results from Figure 3 shows some variation in the week to week objective workload i.e. minimum and maximum values (excluding outliers) to be -19 hours and +19 hours respectively. As per the JD-R model, this suggests that the extent of transient objective workload may be contributing towards the imbalance between the strain and motivational processes. This finding aligns with other studies that demonstrate a negative relationship between transient objective workload and well-being in the workplace context [74,78-81].

However, not all the variables within the objective workload measure were found to have a negative influence towards the model's SWB predictions. For example, the variable obj_py_prog (i.e. objective workload in the Fundamentals of Computer Programming course) and the variable obj_comp (i.e. objective workload in the Computer Fundamentals course) both tended to have a positive influence towards the model's SWB predictions. Results from Table 5 reveals that the objective workload in these courses is not considerably lower relative to other courses. This finding provides further evidence of other factors driving more positive SWB outcomes in these courses. Consequently, further studies exploring this area in the py_prog course and the comp course is recommended.

7 Limitations

This study has several limitations. Firstly, the study utilized a single-item instrument to assess SWB, and hence do not provide specific information regarding the separate facets of SWB.

Future research could use multi-dimensional instruments such as the Positive Affect Negative Affect Schedule [98] along with the Satisfaction with Life Scale [99]. Moreover, to decrease survey fatigue, the objective workload measure in this study only considered the time spent towards independent study and did not include the number of contact hours of a student towards classes. Furthermore, this study only considered the content difficulty variable of perceived academic workload, and did not consider other aspects of perceived academic workload including quantitative perceived workload and qualitative perceived workload (e.g. perceptions about the learning environment [70] and personal characteristics). Furthermore, due to the cross-sectional nature of the study, causality between academic workload factors and SWB cannot be established. Moreover, the results of this study is subject to response bias because SWB and the academic workload factors were measured using self-report instruments [100]. In addition, these results cannot be generalized as it is restricted to particular cohorts of first-year undergraduate engineering students from one Canadian university. More information should be collected in future studies, including the student's demographic data, social environment, learning environment, characteristics of the stressors, and the eudaimonic well-being level.

8 Conclusion and Next Steps

Mental well-being serves as an important dimension in defining an individual's overall mental health. Subjective Well-Being (SWB) is an aspect of mental well-being that includes one's perceptions of their state of happiness and their satisfaction with life. Numerous studies in the academic context have found healthy levels of Subjective Well-Being (SWB) to be associated with various positive outcomes, including higher resilience [7,8], greater hope and optimism [54], better cognitive and psychological engagement in learning [55,56], and more positive beliefs about one's academic capabilities [57]. Consequently, researchers have widely recognized fostering SWB in individuals as an important societal goal [42, 43]. First-year undergraduate engineering students are subject to a variety of stressors that can endanger the mental well-being of these students. Given that current findings suggests academic workload to be the highest risk factor [23, 24], an understanding of the relationships between academic workload and well-being becomes an important first step to fostering mental well-being in these students. This begins by analyzing the specific strain and motivational processes operating at the course level, as suggested by the findings from this study. For example, findings from this study revealed the objective workload of the Engineering Strategies and Practice II to highly influence student SWB in the negative direction. However, the objective workload for the programming courses Fundamentals of Computer Programming and Computer Fundamentals tended to influence student SWB in the positive direction. These findings opens doors to future studies that aims to better understand the underlying demand and resource factors that drive student well-being outcomes for each course. Insights from such studies may prove highly beneficial to minimize the risk posed by academic demands, thereby fostering improved mental well-being outcomes in first-year undergraduate engineering students in Canada.

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