Curriculum and Workload Analysis

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1. Introduction

A course's workload is a relevant and crucial component that contributes to its design and value, and is composed of multiple factors that vary to accommodate the different learning outcomes for each course. Customarily credit systems established/adopted by tertiary education institutions, use credit hours to represent the course load. A notable credit system is the European Credit Transfer System (ECTS), which measures the implications of course loads across all programs at several European universities, where an academic year equals 60 ECTS credits making each course worth 6 credits (1 ECTS = 25 - 30 study hours). This suggests that they are all of equal value within their respective programs despite the differences in workload factors. Given that considerable variation in these factors (i.e contact hours, number of assessments) result in uniformed credit values, course credits are unlikely to be the most appropriate mode of differentiating course workloads.

Moreover, The University of the West Indies, St. Augustine calculates credits based on notional hours per week, which is referred to as the average amount of time a student spends to achieve the learning outcomes of a course. Being so, the university defines 3 credits as 9 notional hours for a 12 week period. Moreover, the Department of Computing & Information Technology (DCIT) offers two Computer Science programs (General and Special) that require students to enroll and pass thirty-one 3 credit courses. Of these courses the possibility exists where students spend more time and effort working on courses with heavier workloads, or more complex content opposed to courses with lighter workloads. Therefore, this suggests that course credits may not have a significant impact on defining the actual workload of a course. Thus, insinuating that the department lacks a method that rationally assesses and represents the workloads of their programs' courses. Therefore, the paper aims to categorize Computer Science courses into distinct groups based on their workload components and perceptions, in an attempt to reveal variations in 3 credit workloads to aid with a balanced curriculum review process within the department .

2. Literature Review

Curriculum and academic workloads for tertiary education, have been analyzed from multiple perspectives, each with varying aspects, as a standard measurement has not yet been developed. (Pogacnik et al., 2004) emphasized the importance of class attendance and personal study hours, which were used to explore student perceptions of their workload and how it directly impacts their academic outcomes. Courses with the lowest workload perceptions yielded the lowest grades, opposed to those with the highest workload perceptions which yielded intermediate grades, whilst those with moderate workload perceptions yielded the highest grades. Additionally, it was revealed that students' perceptions of their workload are shaped by factors such as course content, level of difficulty and the nature of assessments, whilst implying that students' perceptions of workload rather than the time spent on assessments were more closely associated with their learning outcomes (Kember, 2004; Kember et al., 1996; Kember and Leung, 1998). Although extensive reliance on student perceptions may imply significant amounts of bias, this approach has revealed valuable insights regarding the subjective nature of defining course workloads, in turn highlighting how temporal aspects combined with workload perceptions from the courses' primary stakeholders, students, can provide a clearer depiction of its workload. Additionally, using Biggs's 3P (Presage, Process, Product) model to understand students' perceptions and their underlying causes, by looking into workload and assessment factors, (Scully & Kerr, 2014) reported that students often study for less than the recommended amount of time for personal study per week and were aware that they were not spending enough time attempting to achieve the required learning outcomes. This suggests that time management is a contributing factor of workload perceptions, thus highlighting the importance of obtaining accurate representations of expected and actual notional hours, as they can be analyzed to pose implications as to why certain workload profiles are analogous.

Moreover, The Nasa Task Load Index is a notable and widely-used model in academia for assessing workloads subjectively (G.Hart & Staveland, 1986). It is used to calculate overall workload scores based on six subscales: Mental Demands, Physical Demands, Temporal Demands, Own Performance, Effort, and Frustration for a select set of tasks determined by the user. According to (Rubio-Valdehita, 2017), conducting group work and attending practical classes were the two tasks that had the most significant impacts on student workload, in terms of the effort, mental,physical and temporal demand subscales. Additionally, a separate investigation conducted by (Rubio-Valdehita et al., 2014) supported these findings as they revealed that personal study, lecture attendance and group work in that order had the greatest workload perceptions amongst students. However, it was noted that the actual workload does not always align with the perceived workload (Olivares, 2001), This is worth mentioning as according to (Cabanach et al., 2016), the level of workload perceived can influence the level of academic achievement reached as well as the psychological well being of the student. Although, while the students' perception of their academic workload is undoubtedly important, a prevalent pattern among the literature is the focus on phenomenological studies, which seek to explain the nature of things through the way people experience them, primarily centered on assessing the academic workload from the student's perspective. Being so, (Mansouri et al., 2019) proposed a quantitative and more objective analysis of student workload. A collection of assessment weightings, their nature and durations for each week throughout an academic period, is weighed whilst taking into account coefficients such as group work (G_f) and procrastination (P_f), thus producing a weekly workload distribution indicator for each assessment. Mansouri's model is built upon the Workload Calculation Model (WCM), by Brooks and Nelson (2018) which was initially designed to measure faculty staff workload. However, despite the framework's original purpose, Mansouri's modified version has proven to add value to the field of study, by introducing a model that intends to quantify and promote better management of student workload regarding assessment distribution. Moreover, to comprehensively assess the effects of student workload perceptions on academic performance rates, (Gallego et al, 2016) implemented machine learning techniques that contradict Pogacnik's previously mentioned findings, as he revealed that as a student's perceived difficulty or time spent on a course increases, their performance tends to decline. This conclusion is supported by the negative correlation coefficients of -.0.49 for the association between course difficulty and course pass rates and -0.46 between time spent on achieving learning outcomes and course pass rates. All things considered, the existing literature does not clearly distinguish what characteristics encompass a heavy, moderate or light workload in an academic setting, nor does it highlight a defined set of variables that can be used for discernment of course workloads. As such, by focusing on the effort and temporal features of course workload highlighted throughout the literature, the study can incorporate these factors in an attempt to determine the differences in the workload profiles of 3 credit courses. The study incorporated both contact hours and personal study hours emphasizing their significance as highlighted by(Pogacnik et al., 2004; Rubio-Valdehita et al., 2014) in tandem with lecturers' expectations of study hours by (Scully & Kerr, 2014) and student workload perceptions which depicted notions regarding a course's difficulty and temporal demands as highlighted by (Kember, 2004; Gallego et al, 2016). It should be mentioned that these four key factors are referred to as the Major 4 (M4) factors throughout the study. Additionally, the study's analytical approach was adapted from Gallego's use of unsupervised machine learning, to cluster courses based on academic performance ratings, ECTS and course workload perceptions. This approach best aligns with study's goals to categorize Computer Science courses into distinct groups based on their workload profiles.

3. Proposed Scheme

To effectively attain the objective of the study, it was imperative to identify key factors that influenced both the perception of course workloads and the workload itself. Thus, contact hours, expected study hours, actual study hours and student workload perception were four key variables identified and included in the dataset from previous studies. Additionally, patterns within 10 official course outlines were sought out for the purpose of including supplementary variables to account for other relevant factors that may influence the analysis. These supplementary variables included the Σ assignments, Σ assignment durations, Σ exams, Σ exam durations, course credit perceptions, and the time spent on four common skills or competencies required for computer science courses, namely, reading, mathematical calculations, coding and research. Insight from both students and academic staff was essential in order to populate the dataset variables , specifically expected and actual study hours,workload magnitude perception, course credit perception, and perceptions for each of the four previously specified course competencies. This information can influence the grouping of courses, as it highlights the perceptions of two primary stakeholders of a course, its students and lecturers. Granted that each individual's perception is likely to differ, this improves the dataset's variance, which can be useful when characterizing courses within a particular category based on their differences and similarities. Moreover, in order to collect this data two surveys were developed to gather information regarding the workload perceptions of third-year Computer Science students and 10 lecturers from UWI DCIT's teaching staff. They each focused on factors such as time commitments, workload intensity and credit hour allocation for 10 courses taught by the 10 selected lecturers. Students provided responses by evaluating all 10 of the selected courses, whilst staff evaluated the courses they taught. Of the 100 student surveys distributed, 50% were completed, and all 10 staff surveys were completed.

Similar to Gallego's method of measuring the impact of a student's workload perception on academic performance. These variables were then subjected to statistical analysis using the IBM SPSS Statistics software, where a Principal Component Analysis (PCA) was conducted to reduce the dimensionality of the dataset, in an attempt to only consider variables that make up most of the it's variance. This step is pivotal as it ensures that the diverse distribution of perceptions gathered, are carefully accounted for, improving the interpretability of the output. The Python IDE, Google Collab, equipped with multiple python libraries such as matplotlib.pyplot, sklearn.cluster, NumPy, pandas and scipy.cluster.hierarchy, was used to conduct a Hierarchical Cluster Analysis (HCA) on the principal components previously obtained. This process groups each of the 10 courses into a specific number of clusters, determined by the clustering algorithm which then allows for discernment of the characteristics of courses that group together. Due to the dataset's small size, the study's aim to detect patterns in course workload factors and the courses' clear hierarchical structure based on their anticipated year of study and prerequisites, the use of a hierarchical clustering algorithm is undoubtedly a notable method of data analysis that aligns with the study's needs. Thus, by using hierarchical clustering courses with similar workload profiles, Implications of which workload characteristics constitute the perception of a heavy, light, or moderate workload can be deduced. Following the clustering of courses, descriptive statistics for each cluster was retrieved, most importantly, the mean of each workload factor. This was done for two reasons, firstly to provide statistical data that facilitates an accurate and detailed analysis of the clusters formed, and secondly to feed the cluster's mean M4 factors into a formula that was developed, (See Appendix) the Workload Profile Indicator (WPI) , that was used to classify workload profiles. The formula's output will only ever fall between numbers 1 - 5 thus establishing a range for workload profiles, which was then split into three equally smaller sub-ranges. These sub-ranges 1-1.66, 1.67-3.32 and 3.33 - 5 represent light, moderate and heavy workloads respectively.

4. Experimental Results

Several statistical analyses were conducted to determine which courses have similar workload profiles and what were the defining characteristics of these courses. Conducting a correlation matrix revealed significant instances of multicollinearity throughout the dataset, variables with strong correlation coefficients greater than 0.599 and p-values less than 0.05 include the following: contact hours and minimum expected study hours (0.688), contact hours and maximum expected study hours (0.662), contact hours and coding volume (0.749), student credit perceptions and student workload perceptions (0.662). Although multicollinearity does not negatively affect the clustering process, having numerous variables that are closely related can affect the interpretability of the data points in the clusters. The PCA conducted, reduced the dimensionality of the dataset by generating three principal components FAC_1,FAC_2 and FAC_3 that represent 70.8% of the data variance, each with Eigenvalues greater than one.

Principal Components	Eigenvalue	Initial Eigenvalues % of variance	Main Associated Variables	Correlation Coefficients
FAC_1	3.692	33.560 %	Minimum expected study hours	.941
			Maximum expected study hours	.911
			Contact hours	.808
			Coding volume	.715
FAC_2	2.697	24.518 %	Student credit perception	.847
			Student workload magnitude perception	.843
			Actual study hours	.754
FAC_3	1.399	12.723 %	ΣExam durations (hours)	.725
			Calculation volume	.714

Table 1: Results of the Principal Component Analysis with only significant correlations represented (Coefficient > 0.6)

The first component, FAC_1 can be understood to represent the time expectations students are required to meet in order to achieve course learning outcomes and the temporal demand for the coding aspects of the syllabus. As for the second principal component , FAC_2 it can be considered as a representation of the workload intensity and actual temporal demand of course. As for the third principal component FAC_3, this represents course temporal demands for examinations and the application of the mathematical concepts outlined by the syllabus. From the extracted principal component variables, which were calculated using participant cases, the data points per variable were grouped by course allowing the three mean component values for each variable to be derived for each of the 10 courses. Using these aggregated values, a hierarchical clustering algorithm allowed for the visualization of distinct course clusters.

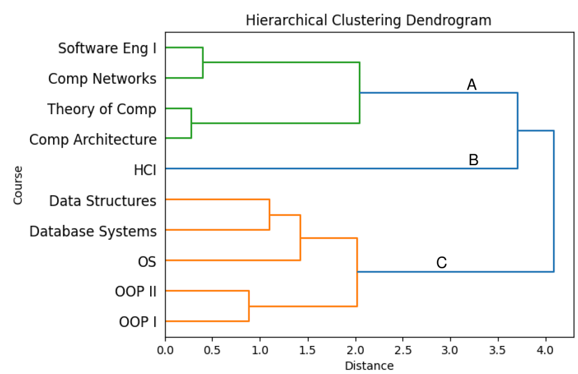

Figure 1:Course Workload Dendrogram

The agglomerative clustering process began with ten clusters, each representing one course, and ended with 1 final cluster. There are three main clusters that eventually go on to merge and form the last cluster iteration.

	N	Minimum	Maximum	Mean	Std. Deviation
Contact Hours	200	36	36	36.00	.000
Expected Study Hours	200	6	6	6.00	.000
Expected Study Hours Max	200	9	9	9.00	.000
Actual Study Hours	200	3	12	6.35	2.573
Assignments Duration (Days)	200	28	56	40.50	10.260
Exam Duration (Hours)	200	3.0	7.3	4.825	1.5983
Reading Volume	200	0	70	40.30	14.637
Calculation Volume	200	0	95	30.08	24.219
Coding Volume	200	0	90	10.28	16.528
Research/Report Volume	200	0	90	18.85	24.667
Credit Perception	200	2	4	3.28	.515
Workload Magnitude Perception	200	1	5	3.47	1.051
Valid N (listwise)	200				

Table 2: Table illustrating descriptive statistics for Cluster A

Firstly, Cluster A grouped 4 courses (Software Engineering I, Computer Networks, Theory of Computing, Computer Architecture) together. These are all tutorial-based courses with 36 contact hours and a range of 6 - 9 expected study hours per week. It has the highest average workload magnitude perception of 3.47 out of 5 and the second highest course credit perception of 3.28 out of 5. This cluster consists of courses that don't require a significant amount of time to be spent on coding given its coding competency volume of 10.28%, However students are required to spend a considerable amount of time on required readings and mathematical aspects of the syllabus , as the cluster is associated with a 40% reading competency volume and a 30% calculation competency volume. Notably, the temporal demand for examination hours within this cluster range from 3 to 7.3 hours for the semester. Moreover, it can be said that the courses are evidently similar due to their early merging, regardless of Software Engineering I and Computer Network's integration at a fairly later instance indicating minor differences in workload factors.

	N	Minimum	Maximum	Mean	Std. Deviation
Contact Hours	50	36	36	36.00	.000
Expected Study Hours	50	2	2	2.00	.000
Expected Study Hours Max	50	4	4	4.00	.000
Actual Study Hours	50	3	12	4.86	2.259
Assignments Duration (Days)	50	63	63	63.00	.000
Exam Duration (Hours)	50	1.0	1.0	1.000	.0000
Reading Volume	50	10	60	35.20	13.513
Calculation Volume	50	0	40	2.40	8.283
Coding Volume	50	0	20	1.70	4.908
Research/Report Volume	50	0	90	60.70	19.140
Credit Perception	50	2	4	2.96	.348
Workload Magnitude Perception	50	1	5	2.64	.875
Valid N (listwise)	50				

Table 3: Table illustrating descriptive statistics for Cluster B

Cluster B contains only one course which is known as Human and computer Interaction (HCI), which is also a tutorial-based course. In comparison to Cluster A, this cluster's workload perception differed by .83 units, which is the most sizable difference in workload perceptions observed in the dataset. With a workload perception of 2.64 and a credit perception of 2.96, it is evident that the substantial disparities between workload factors may have been the underlying cause of the cluster's solo occupancy outcome. Such contrast may be associated with the courses' low actual study hours per week (4.86), as well as the vast differences observed among the cluster's competencies, with a coding competency volume of 1.7 %, reading competency volume of 35.20% and research and report competency volume of 60.70%. Whilst the cluster's both share a similar feature of having synonymous coding and reading competencies, this cluster's main focal point is research, whereas Cluster A is more reading focused.

	N	Minimum	Maximum	Mean	Std. Deviation
Contact Hours	250	48	48	48.00	.000
Expected Study Hours	250	6	8	7.60	.802
Expected Study Hours Max	250	8	12	11.20	1.603
Actual Study Hours	250	4	16	8.50	3.198
Assignments Duration (Days)	250	39	84	50.60	16.881
Exam Duration (Hours)	250	3.0	5.0	4.000	.6337
Reading Volume	250	0	90	23.86	18.563
Calculation Volume	250	0	70	7.44	13.711
Coding Volume	250	0	100	63.42	30.819
Research/Report Volume	250	0	90	5.26	16.411
Credit Perception	250	2	4	3.32	.538
Workload Magnitude Perception	250	1	5	3.46	.974
Valid N (listwise)	250				

Table 4: Table illustrating descriptive statistics for Cluster C

Cluster C is composed of the following 5 courses; Data Structures, Database Systems, Operating Systems (OS), Object Oriented Programming I(OOP I), and Object Oriented Programming II (OOP II). These are all lab-based courses with 48 contact hours and a range of 8 - 12 expected study hours per week, with the exception of OOP I which has a range of 6 to 8 expected study hours per week. However, they are characterized by 8.50 hours of actual study time. Despite the difference in weekly temporal expectations, Cluster A and C displayed almost identical measures of workload and credit perception. However, the Cluster C differed significantly regarding the division of time allotted for the varying course competencies. In comparison to Cluster A's 10. 28%, Cluster C had the highest coding competency volume observed, at 63.42% and a reading volume of 23.86 % that is significantly lower compared to that of Cluster A. Additionally, Cluster C had an average actual study hours value of 8.50 hours per week which is 26.16 hours more for every semester than Cluster A. Additionally, a notable observation within this grouping is the uniformity on 3 assignments each and a range of 2 - 3 examinations including a Final examination, save for OOP II. Furthermore, of the five components. Two single occupancy sub-clusters;OOP I and OOP II clustered first, followed by another pairing of Data Structures and Database Systems who were then accompanied by Operating Systems. Thus highlighting how closely associated the cluster components are with each other. Overall, whilst there are apparent similarities between the M4 factors of Cluster's A and C , this suggests they are associated with similar workload profiles opposed to Cluster B whose M4 factors are significantly lower and is likely to be associated with a lower workload profile to that of A and C. To confirm this theory, the computation of each cluster’s workload profile indicator, revealed that Cluster’s A and C were associated with a moderate workload profile, due to their WPI’s of 1.72 and 2.28 respectively, whereas Cluster B was associated with a light workload profile given its WPI of 1.15. In this context the workload profile can be understood as the temporal and perceptual weight of the courses it's associated with, thus the cluster’s mean competencies are what characterizes it. As such it can be said that courses that place more time emphasis on required reading and research and report writings are associated with light workload profiles. Whereas courses that place more time emphasis on coding and mathematical calculations are associated with moderate workload. Speculations of what characteristics compose a heavy workload were deemed inconclusive.

5. Discussion

As supported by the aforementioned positive correlation coefficients, courses with more contact hours tend to have higher ranges of expected study hours and courses perceived as having a higher credit value bore a higher perception of workload magnitude. It is evident that these instances of collinearity partially influenced the clustering process, as courses with greater contact hours and expected study hours were associated with Cluster C. Additionally, regarding the clustering of courses based on high credit and workload perceptions , the opposite holds true as well. The tutorial-based course HCI, which is the entirety of Cluster B, failed to immediately merge with its other tutorial counterparts, with whom it shares identical contact and expected study hours with.This is likely due to its low workload magnitude and credit perceptions. While it is evident that the clusters were formed based on whether they were tutorial or lab based courses, this shows that there is some relation between the two types. It can be inferred that courses prioritizing reading, research/reporting, tend to match with lighter workload profiles. On the other hand, courses which emphasize on coding and mathematical aspects are associated with moderate workload profiles. However, given the inconclusiveness of defining the characteristics of heavy workload profiles, this highlights the need for further study into the distinct factors influencing workload perceptions and its profile classification.

6. Conclusion

Regarding the implications of course workload profiles, with respect to time and effort related factors, Computer Science courses that have a need for more time emphasis on calculation or coding competencies are said to be associated with a moderate workload profile, where as courses with more time emphasis placed on required reading and research and report writing are associated with a light workload profile. The dataset was un-suitable for characterizing a high workload profile, as only a select group of courses were analyzed. To further improve the accuracy of the clusters and their workload allocations, it recommended all courses of the two Computer Science programs (General/Special) be analyzed using the study's proposed schemed to further validate the workload profile associations.

7. References

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8. Appendix

Workload Profile Indicator Formula:

$$X = \frac{\text{Contact hours} + (\text{Mean Expected Study Hours(min)} + \text{Mean Expected Study Hours (max)}) / 2 + \text{Mean Actual Study Hours}}{\text{Numerators nearest 10th}}$$

$$\text{Workload Profile Indicator} = X * \text{Mean Workload Magnitude Perception}$$