Linking course competences to academic performance: a pilot study

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ABSTRACT

In this paper, we examine the academic performance of students in different courses to determine whether good performance in one course is related to good performance in other courses. Although certain predictive models emphasize the importance of course content for learning success, there are few studies that address how student performance in different courses is related to similar learning goals and skills. The interrelatedness of competences is still extremely under-explored area. This study attempts to address this gap by creating a preliminary framework that examines how academic performance is related to specific skills taught in courses at a higher education institution. We examined a set of student grades from nine different courses at the faculty from areas such as entrepreneurship, business processes, computer technology, mathematics, economics, marketing, innovation, English, and finance. We show that students with more exam retakes on average reached a lower grade rank than the students who only registered for the exam once. We used linear regression to show the significance of the relationships between student performance in computer technology course compared to their achievement in other courses. With a correlation matrix coefficient, we measured the strength of reciprocal interrelatedness between the grade ranks students attained in each of the nine courses. The results of this preliminary study indicate possible stronger association between academic achievement in courses that have similarities in terms of content or focus, such as business administration and entrepreneurship (correlation coefficient of 0.58). Further studies with detailed comparison of course-specific competences are needed for accepting the finding that interrelatedness between achievements in courses from similar versus different disciplines is stronger. The preliminary model could further be improved by a broader range of courses, input explanatory student factors and application of advanced analytical techniques.

KEYWORDS

course-specific competence, learning analytics, prediction models, student academic achievement, student academic performance

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1 INTRODUCTION AND RELATED WORK

Are students who achieve excellent results in one course more likely to achieve outstanding results in another? And vice versa? Does this depend on the specific course competences and learning objectives? Do the course competences and learning objectives themselves contribute to student learning outcomes? These are just some of the questions that triggered this research. The question of whether the interrelatedness between academic achievements and learning outcomes reflects the interrelatedness of competences and learning objectives, and how this interrelatedness in courses with similar learning goals and content could potentially alter prediction models, algorithms, and learning analytics in general further fueled the research.

In this research, we are focusing on the relationships between students' academic achievement in different courses from two different study programs at the faculty of entrepreneurship. Despite some prediction models suggesting the course content as one of the input explanatory variables, there is a significant lack of detailed research on the relationship between students' achievement in different courses from the same, similar, or entirely different discipline. Therefore, this preliminary study aims to develop a pilot model to investigate the relationship between academic success in various courses and course-specific competences, learning objectives, or topics.

Apart from the prediction model of academic achievement, interrelatedness between academic achievement in different courses compared to the course main topics, competences, and learning objectives is still largely missing. OECD [12] [13], for example, show a positive association between literacy and numeracy skills. Moreover, in our previous research [2], we showed that students who achieved better academic achievement in word skills were on average also more likely to achieve better achievement in excel skills. However, this does not imply that it is sufficient to develop only some of these skills, such as solely including word skills, excel skills, literacy skills, or just numeracy skills in the curriculum. Furthermore, this does not imply that students in a real situation cannot achieve much better results in a certain type of skill compared to another. Additionally, Fink and Vadnjal [3] conducted a pilot study that compared the development of generic and course-specific competences during a higher education course.

As previously mentioned, one could apply findings about the relationships between various course topics, contents, competences, or objectives to the development of predictive models and predictive algorithms. Prediction models are often used to find out ahead of time which students are likely to drop out or fail external exams. The schools aim to take intervention measures and steps to stop the bad predictions from coming true, and the success rate can be raised [16] [9]. There are a lot of different input explanatory variables that can have a big effect on how well and especially how accurately prediction models perform [16] [4] [7] [8] [9] [11] [1]. Some prediction models include related concepts to the course content [7], such as the course's learning objective, the course's main competences, the course topic [4], or even course preparedness [10].

In addition to the combination of input explanatory variables, various statistical methodologies and techniques, as well as different types of measurements and academic achievements, significantly influence the prediction model's power and performance. While adding additional or all relevant factors to the model does not always improve its performance, the right combination of input explanatory variables significantly influences the accuracy and other model performance measures [4]. In the end, the right combination of input variables largely determines the model's explanatory power, the accuracy of its predictions, and other performance measures [6], [15].

Different prediction models are based on different methodologies and include different input and output variables. Francis and Babu [4], for example, compare prediction models of student achievement that include the topic of the course as the input explanatory variable. They demonstrated that the course topic, along with many other factors, is one of the explanatory variables for academic achievement. However, their model found that academic factors, including the course topic, were less accurate in predicting students' academic achievement than demographic factors, behavior factors, and other factors such as absence days, parental satisfaction, and school survey responses. They developed, compared, and assessed performance measures of several prediction models. The model that included academic factors, behavior, and additional input explanatory variables showed the greatest improvement in accuracy. On the other hand, adding demographic factors on top of that reduced the accuracy of academic achievement prediction. Clearly, the addition of additional input variables, for example, the topic of the course, in different models contributes differently to improving prediction accuracy and other performance measures, depending on other input variables in the model.

2 HYPOTHESES

In this preliminary study, we aim to build a preliminary pilot research model on which we will test the interrelatedness between academic achievement in different courses. We suggest the following hypotheses:

H1. There is a reciprocal relationship between a student's performance in one course and their performance in another.

H2. As the number of exam retakes increases, the student's grade rank decreases.

3 DATASET AND METHODOLOGY

The dataset collection and preparation included several phases. First, we have collected students' grades for different courses at the higher education institution. The initial dataset included the grades of 210 students for 52 different courses.

In the second phase, we have refined and further prepared the dataset. Based on some simple data exploration and visualization techniques, such as plotting the missing values, plotting the distribution of the number of grades available per course, and plotting the distribution of the number of exam retakes per course, we have decided to eliminate the data of courses with less than 80 grades per course.

With that, we narrowed further analysis to the following nine selected courses: Business Economics, Informatics, Management and Leadership, Marketing and Market Analysis, Entrepreneurship, Business English, Accounting, Creativity and Innovation in Business Processes, and Business Mathematics and Statistics.

We compared the number of grades available per one course with the number of grades per two courses (the selected course and the informatics). The number of grades includes both those that indicate a student has passed the course and those that indicate a student has not. The courses with the highest student grades include Entrepreneurship, followed by Creativity/Innovation and Informatics (Table 1). Students who attended the exam in the Informatics course often also attended the exam in the Entrepreneurship, Management/Leadership, and Creativity/Innovation courses, as shown in Table 1.

Table 1: Number of grades per one and two courses

Course	Number of grades	
	for chosen course and informatics	per one course
Informatics for Entrepreneurs (P05_IP)		151
Business Economics (P03_EP)	117	135
Fundamentals of Management and Leadership (P11_OMV)	136	148
Fundamentals of Marketing and Market Analysis (P12_OMTA)	70	85
Entrepreneurship (P22_PODJ)	142	184
Business English (P23_PANGL1)	126	144
Accounting for Entrepreneurs (P29_RP)	128	139
Creativity and innovation in business processes (P30_UINO)	136	166
Business Mathematics and Statistics (P31_PMS)	116	135

In the third phase, we continued with the data exploration and visualization. We plotted the distribution of the number of grades achieved per grade rank for each of the selected nine courses (Figure 1). The grade ranks range from 0 to 10, where 0 represents not attending, 1 to 5 represents failed, 6 satisfactory, 7 average, 8 good, 9 very good, and 10 excellent. We found that

38 students attended at least one exam deadline for each of the nine courses.

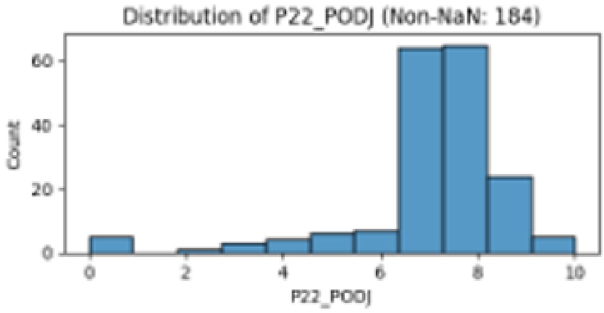

Figure 1: Distribution of number of grades per each grade rank per course example

In the next phase, we focused our investigation on how the grades that students achieved in the Informatics course behave compared to the grades they achieved in the remaining eight courses. We performed and visualized eight linear regression models describing the relationships between grade ranks students achieved in the informatics course and the grade ranks students achieved in other selected courses. When performing the linear regression, we included the grade rank achieved in informatics as an independent variable. Though we are aware that linear regression models assume the influence of the independent variable on the dependent variable and not the reciprocal relationships per se, we decided to mention this limitation and work further with the results obtained from the regression analyses in this preliminary pilot study.

We performed additional analysis based on the correlation matrix between the grade ranks students achieved in each of the nine selected courses. We draw a correlation matrix with significant ($p < 0.05$) correlations among regression coefficients between the nine selected courses to determine which of the nine courses is related to another one. We then examined the strength and significance of the reciprocal relationship that the correlation matrix coefficient measures.

Next, we further compared the characteristics of our data for the selected nine courses with the characteristics of the data for all the courses. We used data visualization techniques such as plotting to compare the distribution of the average grade of nine selected courses and all the courses. The distribution of average grade for the nine selected courses seems fairly similar to the distribution of average grade for all the courses, as shown in Figure 2.

Although we cannot claim that an analysis of the entire data set would yield similar results to the analysis of the selected nine courses based solely on the similar distribution of average grades, we cannot completely rule out the possibility that on average, somewhat similar associations would emerge among the other courses.

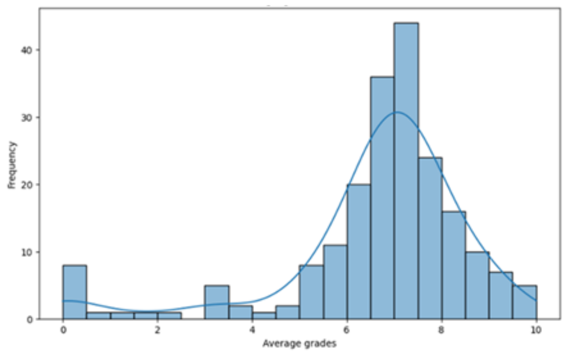

Figure 2: Distribution of number of grades per each grade rank per course example

In the final phase of this preliminary pilot research, we performed the regression analysis between the grade rank that the student achieved and the number of exam retakes of the student.

4 RESEARCH FINDINGS

The nine selected courses served as the basis for the analysis, which focused on identifying reciprocal relationships between the grade ranks of one course and those of another course. We selected the courses based on the number of grades available after exploring, visualizing, cleaning, and refining the data. In addition to linear regression models, we calculated the correlation matrix's correlations (Figure 3) that investigate the reciprocal association between the grade ranks students achieved in one course compared to another.

Overall, we investigated 36 reciprocal relationships (H1) between the grade ranks of one course with the grade ranks of another course. Among these, thirty correlations are significant ($p < 0.05$) compared to six correlations that are not significant. Among the significant correlations, seven correlation coefficients from the correlation matrix exhibit a moderate relationship (between 0.5 and 0.7) between the grade ranks of one course and the grade ranks of another course. Fifteen correlations show a weak correlation (between 0.3 and 0.5), while eight correlations show a negligible or low correlation (below 0.3) between the grade ranks of two selected courses.

The strength of significant coefficients varies from 0.19 all the way up to 0.58. Many of the coefficients that we would otherwise have placed in the group of weak correlations are very close to 0.5, which indicates moderate correlation. There are also many coefficients that we have otherwise placed in the group of negligible correlations close to the value of 0.3, which indicates a weak correlation. This preliminary analysis is a useful basis for further research and analysis.

Let's examine the concrete correlations between the grades of the two courses. There is a moderate correlation between Economics and Entrepreneurship (0.58), followed by Marketing/Market Analysis and Entrepreneurship (0.53), Informatics and Mathematics/Statistics (0.53), Entrepreneurship and Mathematics/Statistics (0.52), Economics and Accounting (0.51), Marketing/Market Analysis and Creativity/Innovation (0.51), and Economics and Mathematics/Statistics (0.50).

Weak correlation exists between Informatics and Marketing/Market analysis (0.49), Economics and Informatics (0.48), Entrepreneurship and Informatics (0.47), Economics and Management/Leadership (0.44), Creativity/Innovation and Entrepreneurship (0.44), Informatics and Accounting (0.42), Economics and Business English (0.42), Business English and Entrepreneurship (0.42), Management/Leadership and Accounting (0.41), Business English and Mathematics/Statistics (0.38), Management/Leadership and Business English (0.36), Entrepreneurship and Accounting (0.34), Business English and Accounting (0.34), Management / Leadership and Entrepreneurship (0.33), Creativity/Innovation and Accounting (0.32).

A low correlation below 0.3 exists between Accounting and Mathematics/Statistics (0.29), Informatics and Management/Leadership (0.26), Economics and Creativity/Innovation (0.26), Management and Leadership and Creativity/Innovation (0.26), Marketing/Market Analysis and Accounting (0.25), Business English and Informatics (0.24), Management/Leadership and Mathematics/Statistics (0.21), and Creativity/Innovation and Mathematics/Statistics (0.19).

It's no coincidence that the Marketing and Market Analysis course, which of all the courses contains the fewest data points, exhibits the insignificant correlation with as many as four out of eight other courses. Altogether, we find no significant correlation between Management/Leadership and Marketing/Market Analysis, Marketing/Market Analysis and Economics, Marketing/Market Analysis and Business English, Marketing/Market Analysis and Mathematics/Statistics, Business English and Creativity/Innovation, and Informatics and Creativity/Innovation.

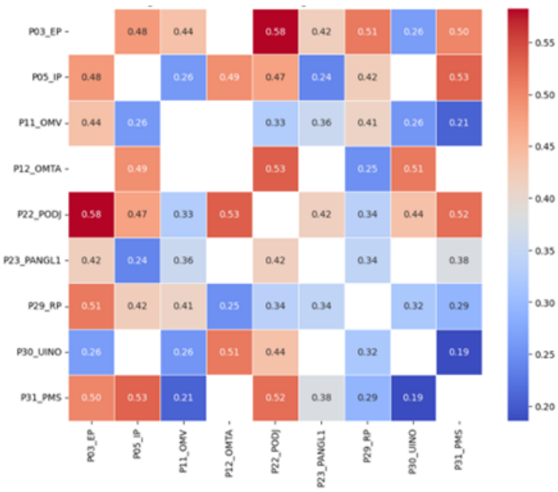

Figure 3: Correlation matrix with significant correlations

The results of the regression analysis between the grade rank that the student achieved and the number of exam retakes (H2) the student took show that the students with more exam retakes on average reached a lower grade rank than the students who only registered for the exam once ($\beta = -0.45$, $p = 0.00$). The data also showed that most students register for the exam once, fewer students register for the exam twice, and even fewer students register for the exam third time.

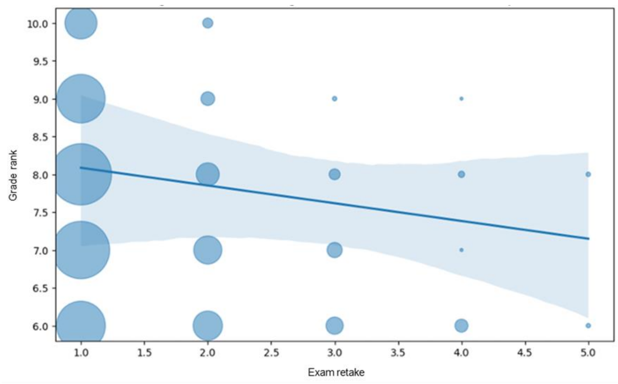

Figure 4: Regression analysis between number of exam retakes and grade achieved

5 CONCLUSION

The purpose of this study was to lay the groundwork for further research and to present initial findings regarding the correlation between different course-specific competences. In this paper, we aim to enhance our comprehension of the intricate relationship between competences, an area that remains largely unexplored. The preliminary analysis revealed the existence of interrelatedness among grades students achieve in different courses, and showed that a student's academic performance in one course influences their performance in another. We also show that students with more exam retakes on average reached a lower grade rank than the students who only registered for the exam once.

To determine whether there is a stronger correlation between academic achievements in courses from the same or similar discipline than in courses from completely different disciplines, further research is required to explore how much the interrelatedness between courses depends on the competences, learning goals, and discipline of the course.

Since this is a preliminary pilot analysis, we considered additional opportunities to improve our research in the future. We could enhance this study by utilizing additional methods like cluster analysis, network analysis, and structural equation modeling, along with popular prediction model-making techniques like data mining [11] [1], neural networks [5], or decision trees [14]. Furthermore, we could enrich the model by increasing the number of observations and the number of courses included in the analysis.

To capture more subtleties in these relationships, we could potentially build and test the model's performance with additional input variables such as information about general knowledge, broad outlook, ambitions, and psychological characteristics. Additionally, we could compare different cohorts of students, the semester, the study program and track, forms of study (full-time, part-time), types of study programs (undergraduate, postgraduate, higher vocational program), and study modes (classroom, blended, online).

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