



## RESEARCH ARTICLE



# A Framework to Identify Non-Achievers in eLearning Business Informatics Lab Courses

Vassilis Zakopoulos<sup>1</sup>, Ioannis Georgakopoulos<sup>1,\*</sup> , Constantinos Dalakouras<sup>1</sup>,  
Panagiotis Dimitrakopoulos<sup>1</sup>  and Ioannis Liomas<sup>1</sup>

<sup>1</sup>Accounting and Finance (Business Informatics Lab), University of West Attica, Greece

**Abstract:** Learning management systems store valuable data in their repositories. Analyzing such data could contribute to identifying non-achievers in eLearning courses. This study presents an integrated framework (encompassing stages from a risk management process) to predict non-achievers in eLearning Business Informatics Lab Courses through a discriminant function analysis of student engagement data. In detail, data regarding with student interaction with the learning activities were elicited from the Moodle LMS log files. The paper also presents a specific eLearning Business Informatics Lab Course, designed upon Business Informatics competencies, tailored to a Business Informatics Curriculum for undergraduate Accounting Students. A discriminant function analysis was used to develop a competent prediction model. Linear discriminant functions were generated for achievers and non-achievers respectively. Students were classified into non-achievers or achievers according to the maximum score of the discriminant functions. The high classification percentage of our model indicates that our framework could be used to identify non-achievers in any eLearning Business Informatics Lab course sharing the same structure. A linear discriminant analysis was also employed to indicate the training potential of our model. The evaluation metrics of our trained model indicate that our model could potentially be used to develop an alert system.

**Keywords:** Business Informatics, competencies, prediction model, non-achievers

## 1. Introduction

Business Informatics is a discipline, designed upon IT skills and Business Competencies [1, 2]. Business Informatics courses aim at equipping all entities involved in an organization to solve enterprise problems. Therefore, Business Informatics competencies play a cardinal role in a business sustainability [1–4].

In general, competences and skills in Business Informatics encompass [5, 6]:

- 1) Understanding and evaluating the business process.
- 2) Analyzing and applying scientific knowledge in a business context.
- 3) Creating added value through innovation and software development.
- 4) Managing operational processes and utilizing software technology.
- 5) Understanding strategy and implementing technology in e-business.

In this spirit, most Business Informatics courses are designed upon the principles of Informatics, Statistics, Finance, and Business Administration [1, 3, 7–11]. Such courses are designed to provide students with the requisite theoretical framework in the previously mentioned fields, helping them to apply the respective knowledge

to solve real enterprise problems [3, 4, 7–9, 11]. Getting perspective on things, case studies drawn from real enterprise experiences and project simulations are transformed into learning activities [12]. Therefore, Business Informatics courses include theoretical and practical activities. These activities are designed to promote critical thinking, problem-solving, and communication skills [12]. eLearning Business Informatics courses implement such activities on Learning Management Systems [4]. Various methods are employed in the learning process, such as collaborative assignments, blended learning, and e-portfolios [13, 14]. Business Informatics lab courses focus on practical skills without brushing theoretical knowledge aside. Typical Business Informatics Lab courses familiarize students with Business Informatics tools [3, 10, 11, 15]. Hence, specific learning activities are created to familiarize students with spreadsheets, programming languages, visualization tools, simulation tools, and Management Information Systems [3, 15]. In parallel, students are given insight into the disciplines related to these tools. Therefore, statistical, administrative, financial, accounting, and informatics fundamentals stand out in the structure of the Business Informatics Lab Courses.

Generally, in the case of Universities, Business Informatics Lab Courses comply with the standards dictated by the Curricula. In this sense, the tools presented in these courses also vary according to each school student's needs. To ensure that the entire course will be tailored to the industry's needs, some Universities involve Industries and organizations in the design process. Such courses revolve around project management, business intelligence, and digital transformation [16–20]. Moreover, since Business Informatics

\*Corresponding author: Ioannis Georgakopoulos, Accounting and Finance (Business Informatics Lab), University of West Attica, Greece. Email: [igtei@uniwa.gr](mailto:igtei@uniwa.gr)

Courses aspire to foster innovation, artificial intelligence and machine learning are gradually incorporated into the new Business Informatics curricula [19].

Since Business Informatics courses taught in universities are designed to meet educational goals, the risk of student failure should be controlled. Moreover, Business Informatics courses involve informatics competencies that can help any professional. In this sense, to assess digital competencies is of utmost importance. Therefore, non-achievers should be predicted early to avoid a possible dropout in a Business Informatics course [21–23].

Non-achievement denotes academic failure regarding educational objectives. In some studies, lack of motivation and engagement are reported to affect student achievement in universities. Therefore, focusing on student effort (behavioral engagement) can contribute to identifying educational academic factors related to non-achievers [24–29].

Non-achievement critically impacts the entire educational foundation. First, non-achievement can curb student academic and professional prospects. Second, the lack of academic success can cause temporary or even permanent psychological disorders in students. Moreover, students who try hard to meet educational goals suffer from intensive stress that could lead to a possible dropout [30–32].

Furthermore, the lack of professional prospects can bring about poverty, doing huge economic damage to students and their families, who will strive to support them. In parallel, non-achievers cannot offer their professional services to the State, increasing the unemployment rate, and forcing the government to back them up financially [33].

In a nutshell, academic failure has social, psychological, and economic implications [34, 35]. Hence, identifying non-achievers and taking remedial action are of utmost importance. To answer this purpose, many studies refer to competent warning systems that predict non-achievers considering student engagement. Statistical and machine-learning methods can be used to develop efficient warning systems. In e-learning, measurable data can be elicited from the Learning Management Systems. However, this is not the case in conventional teaching. Although many warning systems are reported in the literature, the development process has not been based on a concrete framework.

This study presents a Business Informatics Lab course designed to cover the needs of an Accounting School at a Greek University (University of West Attica). Additionally, the study demonstrates a framework to identify non-achievers in the specific Business Informatics Lab course through a proper analysis of student behavioral engagement data. This framework could be used to achieve the same goal in each Business Informatics Lab course, sharing the same structure. It is essential to underline that our study contributes to the educational field in the following ways:

1. It accentuates the need for predicting non-achievers.
2. It proposes a robust framework (encompassing the stages of risk analysis and risk control) that can be used to predict non-achievers.
3. It proves that student engagement is a strong predictor of student final achievement.
4. It shows (through a machine-learning process) an efficient way to generate competent predictive models with high training potential.

## 2. Literature Review

A lot of warning systems are based on efficient prediction models [36–39]. The same holds true for educational forecast models, and alert systems [40–43]. Various data can be collected

to answer this purpose. In detail, one important study attempts to control students' attrition by analyzing students' graded activities [40]. Another study analyzes demographic factors and factors related to students' personality. In parallel, drivers related to students' social and financial status have also been considered [43]. Finally, a specific study focuses on academic competencies to early predict non-achievers [41].

Nevertheless, a few educational forecast models are reported in the case of e-learning courses [42, 44, 45]. In detail, one study proved that student behavioral engagement is a strong predictor of students' attrition in e-learning courses [44]. In parallel, another study indicates that non-achievers could be monitored and predicted by analyzing LMS engagement data whereas another study proposes the analysis of e-Portfolio data to yield the same result [45].

In the case of eLearning courses, this interaction is determined by the completion of specific learning activities. Students who fail to complete the requisite learning activities are non-achievers and represent students who fail the course. Since these activities are implemented through Learning Management Systems, analyzing the data stored in their log files could lead to measurable factors.

Statistical methods or machine-learning techniques can be used to analyze such data. In detail, regression analysis, discriminant function analysis, classifiers, classification trees, neural networks, and Bayesian methods are used to construct risk models to identify the risk factors. In parallel, various prediction models and early warning systems are also developed to control student failure [46–53]. One important study refers to a risk model and specific predictors for non-achievers in Business Informatics Courses [4].

There are some endeavors to predict non-achievers in Business Informatics Lab courses, taking advantage of the capabilities of predictive analytics. Predictive analytics uses historical data and machine-learning algorithms to predict future outcomes, including learner performance. In the context of e-learning lab courses, predictive analytics can identify students at risk by analyzing various parameters such as previous academic performance, level of engagement, and interaction with course material [24, 54–56]. In a case study by Huggins [57], predictive analytics was applied to an e-learning business IT lab course to identify low-achieving students. By analyzing data from previous cohorts, including grades, assignment submissions, and online activities, a predictive model was developed to predict student performance. The model identified students at risk of failure early in the course, allowing educators to intervene with individualized support strategies. In parallel, a study by Rakic et al. [58] used behavior analysis to identify non-learners in an experimental e-learning business informatics course. By analyzing patterns of learner interaction on the e-learning platform, such as clickstream data and time spent on tasks, the study identified learners who showed signs of poor learning motivation and difficulty.

The studies mentioned above have proved that risk drivers are course-oriented. Nevertheless, similar predictors of student failure are reported for courses with the same learning design. In most of studies, the results are based on various independent analyses without presenting an integrated framework [42, 46, 47, 49, 50, 52, 53]. In this study, a robust framework is developed to support our analysis. In detail, our method encompasses stages from a generic risk management process [59, 60]. In this sense, our method can be used in many Business Informatics Lab courses. However, the dataset could vary among courses.

Our Business Informatics Lab course is demonstrated in Section 2.1. Sections 3 and 4 focus attention on the proposed framework and the results. It is essential to underline that although our main research interest is to predict non-achievers,

our research investigates the effect of student engagement in predicting student final achievement, since the studies mentioned above have revealed the student engagement predicting potential. Therefore, our research assumption could be shaped as follows:

Student interaction with the learning activities on Moodle is a strong predictor of non-achievers in our Business Informatics lab course.

### 2.1. Our business informatics lab

Our Business Informatics lab is delivered at the Accounting department, at the University of West Attica, tailored to a Business Informatics curriculum for undergraduate students. The respective lab course combines theory with practice. The theory consists of the following activities implemented through Moodle:

1. Slides (PDF) on fundamental Business Informatics concepts (Enterprise scenarios, Business Informatics Tools, Business Statistics, Risk Management, Business Administration, Accounting and Finance, and Management Informatics Systems).
2. Self-assessment exercises (quizzes) on theory.
3. Appropriate videos (links on YouTube) on specific Business Informatics Tools.

The practical part consists of the following activities, also implemented through Moodle:

1. A set of exercises (enterprise scenarios) on Excel and Statistical Packages (SPSS), devoted to student practice.
2. A small-scale enterprise problem that is assigned to students. It constitutes a collaborative assignment that can be done using an appropriate Business Informatics Tool and uploaded to Moodle before the final online test.

The final online test includes theoretical questions (Multiple Choice or True/ False) that should be answered on Moodle. The test score is 60% of the final grade, whereas the practical exercise (assignment) makes up 40% of the final grade.

The self-assessment quizzes are completed if the maximum score is greater than 5. Three (tries) are allowed. Therefore, these quizzes do not contribute to the final grade, but they familiarize students with theoretical and practical aspects. Non-achievers are students who get a final grade below 5.

Comparing our lab course to similar Business Informatics courses taught in Universities, we can deduce that our lab course complies with the standards of a typical Business Informatics course design since it fosters problem-solving and collaboration. In parallel, our course familiarizes students with specific Accounting Business Informatics tools (such as Excel). Moreover, electronic assessment methods are used to evaluate students. Moodle LMS (an electronic platform) is used to help students take in the rudimentary knowledge, through well-designed and orchestrated activities.

However, our course is not connected to the Industry needs like similar courses delivered in universities [16–20]. Although the course presents the capabilities of Business Informatics tools, it does not present Professional Accounting tools.

In parallel, the assessment process revolves around examining specific learning goals related to business informatics competencies, but these competencies are not linked to occupational needs of students. Moreover, the competencies are assessed in light of theoretical knowledge and practical skills, without students being categorized according to a specific level of competencies' development. This is because the entire course is designed in the philosophy of the “encyclopedia”, in the context of which many

curricula provide fundamental knowledge, and do not focus on market needs.

### 3. Methodology

Our framework encompasses stages from a general Risk Management Process, executed in the following steps depicted in Figure 1 [59, 60]. Two distinct phases stand out in a typical risk management framework, risk analysis and risk control. The risk analysis process revolves around identifying factors that contribute to the risk occurrence within the risk area. Efficient risk models are built using qualitative and quantitative techniques to identify these factors [60]. Since student engagement affects student performance (as indicated in many studies), in our case, the risk area, in which risk factors will be identified, is student engagement. In parallel, risk models are validated to generate prediction models based on risk factors. The validation outcome leads to an efficient warning system. The enactment of the warning system achieves risk control [60].

However, in our case, the objective is not to identify the risk factors, but to predict non-achievers. In this spirit, the stage of building the risk model can be omitted. Therefore, qualitative or quantitative methods should be employed to generate an efficient prediction model. In most cases, the selection of the method depends on the data type [60]. In our case, a quantitative data set is elicited from the log files of Moodle, and thus, quantitative methods can be used. In this sense, non-achievers can be identified after the enactment of the prediction model.

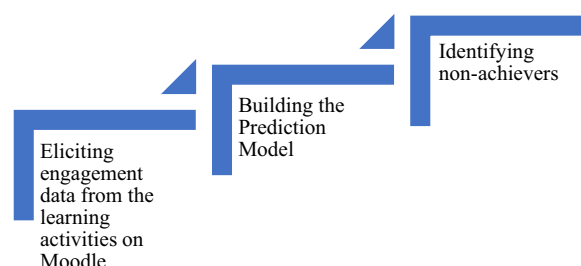
As shown in Figure 1, the first step includes a data collection process. Data regarding all activities implemented through Moodle are collected using the appropriate Learning Analytics Tool. The second step is devoted to generating the prediction Model by applying a competent statistical or machine-learning method to the collected data set. The quantitative collected data set is appropriately formatted to comply with the method used. The prediction model will classify students into achievers or not achievers.

In our case, the risk control process is also omitted since our research objective is to predict non-achievers and not to develop a remedial strategy. Nevertheless, the prediction model could be applied to many courses, and after being validated, it can lead to an early alert system, through which risk control will be fully achieved.

#### 3.1. Applying our framework

Our framework was applied to a specific Business Informatics Lab course, delivered at the University of West Attica in the “Accounting and Finance” Department. All activities were implemented through Moodle. The data collected are as follows:

Figure 1  
The proposed framework



1. Total number of slides (PDF) viewed
2. Total number of self-assessment exercises (quizzes) completed.
3. Total number of practical exercises completed.
4. Total number of YouTube videos watched.
5. Final score on the assignment.
6. Final score on the final online test.
7. Total logins to Moodle.

300 Accounting students participated in the final online test, constituting our sample. The course was mandatory, and therefore, all registered students took the final exams. In this sense, no students were excluded from our research, denoting that no outliers were detected in our sample. Since our main interest was to predict student final achievement regardless of demographic features, no specific sampling method was used, and all participants in the final online test were included in our research. The grades were collected after the final online test, whereas the rest of the data were collected one week before the final online test. Variables reflecting the data set collected were created. In parallel, the binary variable “achr” was modeled to reflect student performance [42, 59]. The value “1” indicated non-achievers, whereas “0” indicated students who passed the course. The values were calculated according to the student’s final grade (non-achievers got a final grade below 5).

A linear discriminant function analysis was employed. A competent prediction model was developed, to classify students into achievers and non-achievers [59, 61–64]. In detail, two discriminant functions were generated (a function for non-achievers (state 1) and a function for achievers (state 0)). After the final online test, the classification functions’ scores were calculated in a student-oriented approach. Therefore, students were classified into achievers if the discriminant function for achievers had the maximum score. Students were classified into non-achievers in any other case [61, 62, 64]. The following section (Section 4) focuses on the prediction model and the entire process.

The prediction model was generated by means of competent statistical packages (SPSS/JASP). The variables analyzed are listed in the following SPSS instance (Image 1).

In detail, the variable “grade” reflected the final grade (constituting by the assignment grade and the final online test grade). The variable “achr” was modeled to determine achievers (state 0, grade > 5) and non-achievers (state 1, grade < 5). Therefore, the variable “achr” was the dependent variable, and all other variables were the independent variables (coefficients) in the discriminant function analysis scheme.

**Image 1**  
SPSS variables view

Name	Label	Values	Measure
grade	Assignment Gr...	None	Scale
tns	Slides	None	Scale
twv	Videos	None	Scale
pexc	Exercises	None	Scale
tls	Logins	None	Scale
tqc	Quizzes	None	Scale
achr	student risk	{0, achiever...	Nominal

#### 4. Results

The coefficients of the linear discriminant functions for achievers and non-achievers are shown in Table 1.

**Table 1**  
Coefficients of the discriminant functions

	Classification function coefficients	
	achr	
	0	1
tns	1,192	,195
twv	2,595	3,443
pexc	1,586	1,551
tls	1,556	1,410
tqc	2,445	2,048
(Constant)	-31,929	-31,863

Table 1 shows the classification functions’ coefficients for achievers and non-achievers, respectively (states 0 and 1).

As shown in Table 2, the prediction model achieves a 94.7 % correct classification percentage, indicating that only a small number of cases is not correctly classified.

**Table 2**  
Classification percentage

Classification Results <sup>a</sup>					
	achr	Predicted Group Membership		Total	
		0	1		
Original	Count	0	206	0	206
		1	3	0	3
	%	0	100,0	,0	100,0
		1	100,0	,0	100,0

a. 94.7% of original grouped cases correctly classified.

Figures 2 and 3 graphically illustrate the classification results for achievers and non-achievers respectively.

The values of the discriminant functions are replaced by the respective means (z-scores), and the density of the columns reflects the number of students classified as achievers or non-achievers, providing a graphical illustration of the classification table [61–64]. As shown in Figure 2, our model works better in case of achievers. Nevertheless, the high classification percentage shown in Table 2 is a proof that our model works sufficiently in all cases.

Although our model is course-dependent, a linear discriminant analysis (LDA) proved that it can be trained with promising results as shown in Table 3:

Therefore, our model can be trained to achieve 87.8% accuracy if applied to many courses. Figure 4 (ROC Curves Plot) depicts the training potential of our model indicating the true and false positive rate [61–64].

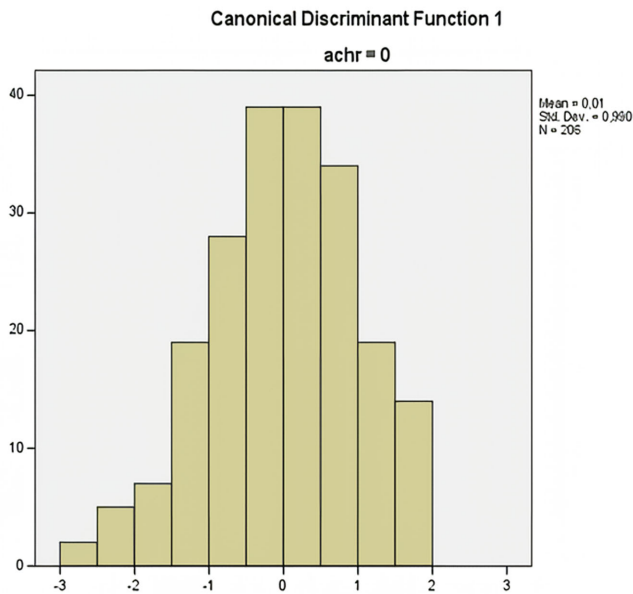
The ROC Curves plot indicates the sensitivity (True Positive Rate) and the specificity (false positive rate) of our trained model, indicating the number of real cases that are correctly classified, and the number of real cases that are incorrectly classified [61–64].

Table 4 explains the ROC Curves plot:

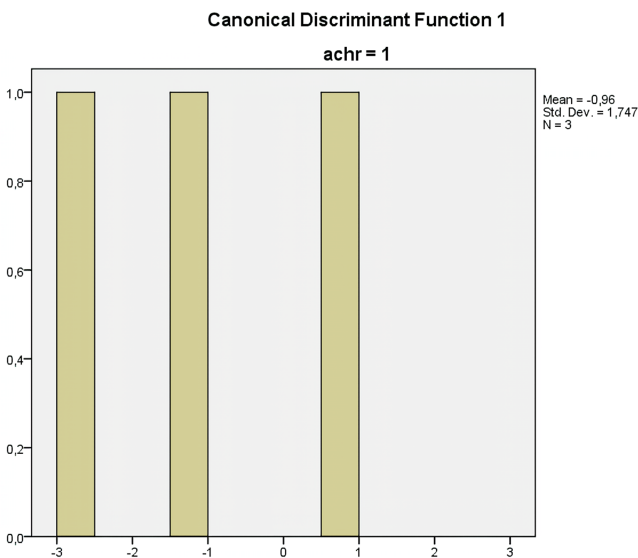
As shown in Table 4, the true positive rate is 0.878, and the false positive rate is 0.5. Looking at the other evaluating metrics (shown in Table 4), it appears that our trained model works better in case of achievers. However, it seems that our trained prediction model works sufficiently in all cases.



**Figure 2**  
Classification outcome for achievers



**Figure 3**  
Classification outcome for non-achievers



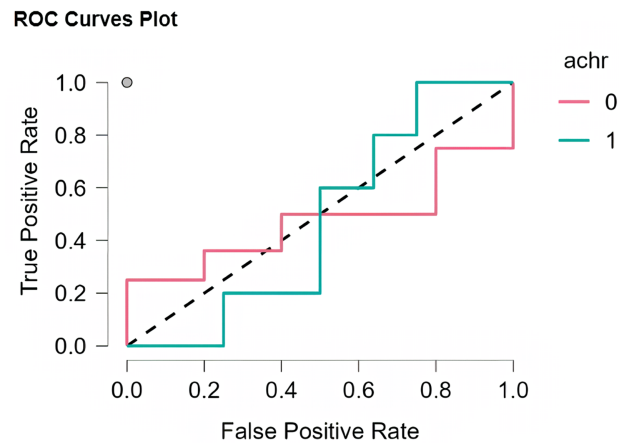
**Table 3**  
Training performance characteristics

**Linear Discriminant Classification**

Linear Discriminant Classification

Linear Discriminants	Method	n(Train)	n(Test)	Test Accuracy
1	Moment	168	41	0.878

**Figure 4**  
ROC curves plot: True and false positive rate



**5. Discussion**

Our prediction model achieves a high classification percentage (Table 2). Figures 3 and 4 indicate that our model works sufficiently in all cases. Our model’s accuracy is course-dependent. That finding is supported by the literature where the prediction models reported are also course-dependent [42, 59]. However, our model could be trained with promising results, as shown in Table 3. The evaluation metrics in Table 4 indicate that our trained model works sufficiently in all cases, and therefore, it can be applied to many courses.

However, the possibility that our model will work better in courses with similar structure cannot be ruled out. Our model has not been tested in various courses to ensure its accuracy. In this sense, our model should be validated being applied to many different courses before it constitutes the basis on which a prediction model can be developed. Therefore, the intrinsic characteristic of prediction models, that are course-dependent, is the main limitation of our study, denoting that the results cannot be easily generalized.

**Table 4**  
Evaluation metrics

Evaluation Metrics	0	1	Average / Total
Support	36	5	41
Accuracy	0.878	0.878	0.878
Precision (Positive Predictive Value)	0.878	NaN	0.771
Recall (True Positive Rate)	1.000	0.000	0.878
False Positive Rate	1.000	0.000	0.500
False Discovery Rate	0.122	NaN	0.122
F1 Score	0.935	NaN	0.821
Matthews Correlation Coefficient	NaN	NaN	NaN
Area Under Curve (AUC)	0.472	0.472	0.472
Negative Predictive Value	NaN	0.878	0.878
True Negative Rate	0.000	1.000	0.500
False Negative Rate	0.000	1.000	0.500
False Omission Rate	NaN	0.122	0.122
Threat Score	3.600	0.000	1.800
Statistical Parity	1.000	0.000	1.000

Note. All metrics are calculated for every class against all other classes.

In parallel, if our model is applied to different courses, the possibility of emerging risk factors (coefficients of the model) will not be ruled out. In this case, the classification potential of our model could vary among courses. This is also a finding supported by literature [4, 42, 48].

Moreover, the data used in the linear discriminant function analysis are calculated after the final online test. Therefore, our model predicts non-achievers after the final exams, indicating another limitation of our study. Hence, it constitutes a prediction model after the first course run, a finding also mentioned in some studies [59, 65]. However, the training potential of our model proves that our model could constitute the basis of an early warning system on the condition that the discriminant functions will be calculated before the final exams to facilitate remedial action.

At this point, it should be noted that achievers and non-achievers are identified according to their final grade. Therefore, the competencies of achievers are reflected in their grade. However, Business Informatics Labs are designed upon the principles of Business Informatics competencies. A more efficient way to assess the students' competencies might be needed. Therefore, another essential limitation of our study is that the assessment of the course success is not implemented considering students' competencies, since the student failure is only related to a negative final achievement (reflected by low grades). However, sufficient student performance could indicate that a student has developed the requisite competencies. In parallel, a risk model (built before the prediction model) could reveal risk drivers, focusing on competencies that have not been developed in the case of non-achievers.

From an educational perspective, the students' interaction with self-assessment quizzes, practical exercises, and interactive learning material was among the predictors of student performance in our study, a finding that is also supported by many studies in literature, especially in the case of e-learning courses. Therefore, student interaction with the learning activities on Moodle proved to be a strong predictor of students' final achievement, verifying our research assumption. In parallel, predictors of student achievement stemmed from both theoretical and practical parts of the course, a finding that is also reported in a specific study. Moreover, the e-learning part (reflecting students' interaction with learning activities on Moodle) proved to play a cardinal role in predicting student critical achievement, a finding that is aligned with some studies in literature [2, 4, 58].

In our case, the training potential of our model is high, indicating that our model could constitute the pillar of an early warning system, accentuating our model's dynamics, a finding that is also reported in some studies based on predictive analytics [24, 57, 61–64].

## 6. Conclusions and Future Expectations

The paper demonstrates a concrete framework to identify non-achievers that encompasses stages from a generic risk analysis process. Therefore, our study does not address the issue of students at risk in a fragmented way, but the identification of non-achievers is well-grounded. In parallel, the paper presents a specific Business Informatics Course, designed upon the Business Informatics competencies. The results proved that student engagement (reflected by the students' interaction with the theoretical material and practical exercises) proved to be a decisive factor in our prediction model, denoting that a proper analysis of student engagement data could lead to efficient prediction models. Our model could be applied to any Business Informatics Course to identify non-achievers after the first course run.

Our team is currently working on validating our model in terms of different courses to develop an early warning system for

non-achievers. In addition, our team is working on applying our framework in courses delivered in the context of face-to-face teaching to indicate emerging risk factors and a possible change in the accuracy maximum percentage.

## Acknowledgement

We are grateful to the UNIWA Moodle administrators for providing us with the requisite learning analytics tools to collect the data.

## Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

## Data Availability Statement

The data that support the findings of this study will be available to researchers upon demand.

## Author Contribution Statement

**Vassilis Zakopoulos:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing, Supervision. **Ioannis Georgakopoulos:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Constantinos Dalakouras:** Investigation. **Panagiotis Dimitrakopoulos:** Investigation. **Ioannis Liomas:** Software, Investigation.

## References

- [1] Zabukovšek, S. S., Tominc, P., & Bobek, S. (2020). Business informatics principles. In V. Pászto, C. Jürgens, P. Tominc, & J. Burian (Eds.), *Spatonomy: Spatial exploration of economic data and methods of interdisciplinary analytics* (pp. 93–118). Springer.
- [2] Zakopoulos, V., Georgakopoulos, I., Kossieri, E., & Kallivokas, D. (2021). Controlling attrition in blended courses by identifying students at risk: A case study on MS-Teams. *International Journal of Finance, Insurance and Risk Management*, 9(3), 57–68.
- [3] Tumbas, P., Sakal, M., Pavlicevic, V., & Rakovic, L. (2019). Digital competencies in business informatics curriculum innovation. In *INTED2019 Proceedings*, 9655–9664. <https://doi.org/10.21125/inted.2019.2400>
- [4] Zakopoulos, V. (2022). A framework to identify students at risk in blended business informatics courses: A case study on moodle. *International Journal of Economics & Business Administration*, 10(1), 239–247.
- [5] Helfert, M. (2007). Teaching information quality skills in a business informatics programme. In *Proceedings of the MIT Information Quality Industry Symposium*, 908–912.
- [6] Seres, L., Tumbas, P., Matkovic, P., & Pavlicevic, V. (2017). Embedding digital competencies in business informatics curriculum. *Second Conference on Innovative Teaching Methods*, 28, 220–227.
- [7] Korczak, J., Mach, M., Nowicki, A., & Owoc, M. (2011). Design of “Business Informatics” study program. Model,

- curriculum and perspectives. In *SITE 2011: Informing Science + IT Education Conference*, 11, 295–304.
- [8] Kuz'mina, E. V., P'yankova, N. G., Tret'yakova, N. Y. V., & Botsoeva, A. V. (2020). Using data analysis methodology to foster professional competencies in business informaticians. *European Journal of Contemporary Education*, 9(1), 54–66. <https://doi.org/10.13187/ejced.2020.1.54>
- [9] Martz, B., Braun, F., & Hughes, J. (2011). Business informatics and the information systems perspective: Implementing the IS 2010 curriculum. *Journal of Business & Finance Librarianship*, 16(3), 229–242. <https://doi.org/10.1080/08963568.2011.581187>
- [10] Paul, P., Aithal, P. S., & Bhimali, A. (2017). Business informatics: A possible specialization of MSc-Information Science & Technology (IST): Challenges and opportunities in developing countries context. *International Journal on Recent Researches in Science, Engineering & Technology*, 5(10), 54–63.
- [11] Pavlicevic, V., Tumbas, P., Matkovic, P., & Sakal, M. (2015). Innovative approach to business informatics curriculum redesign. In *INTED2015 Proceedings*, 5711–5717.
- [12] Bower, M., Hedberg, J. G., & Kuswara, A. (2010). A framework for Web 2.0 learning design. *Educational Media International*, 47(3), 177–198.
- [13] Garrison, D. R., & Kanuka, H. (2004). Blended learning: Uncovering its transformative potential in higher education. *The Internet and Higher Education*, 7(2), 95–105. <https://doi.org/10.1016/j.iheduc.2004.02.001>
- [14] Laurillard, D. (2013). *Rethinking university teaching: A conversational framework for the effective use of learning technologies*. UK: Routledge. <https://doi.org/10.4324/9781315012940>
- [15] Morozov, N. V., Norkina, A. N., Prokhorov, I. V., & Filatov, A. A. (2019). The development of competence in practical work with big data in mastering the master's program in the field of "Business Informatics". In *Суперкомпьютерные дни в России* (pp. 163–168). Russian Supercomputing Days 2019.
- [16] Buřita, L., & Rosman, P. (2014). Informatics at the Czech public universities for bachelor students in the business programs. *Programme Committee*, 35.
- [17] Helfert, M., & Duncan, H. (2005). Business informatics and information systems – Some indications of differences in study programmes. In *Proceedings of UKAIS Conference*.
- [18] Helfert, M. (2011). Characteristics of information systems and business informatics study programs. *Informatics in Education – An International Journal*, 10(1), 13–36.
- [19] Klačnja-Milićević, A., Ranković, N., & Ivanović, M. (2019). Integration of "Business Intelligence" course to master academic studies in informatics. In *Proceedings of the 20th International Conference on Computer Systems and Technologies*, 308–315.
- [20] Suša, D. (2014). Digital immigrants and digital natives: Learning business informatics at higher educational level. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy*, 5(2), 84–96. <https://doi.org/10.2478/bsrj-2014-0012>
- [21] Casanova, J. R., Gomes, C. M. A., Bernardo, A. B., Núñez, J. C., & Almeida, L. S. (2021). Dimensionality and reliability of a screening instrument for students at-risk of dropping out from higher education. *Studies in Educational Evaluation*, 68, 100957. <https://doi.org/10.1016/j.stueduc.2020.100957>
- [22] Ortiz-Lozano, J. M., Rua-Vieites, A., Bilbao-Calabuig, P., & Casadesús-Fa, M. (2018). University student retention: Best time and data to identify undergraduate students at risk of dropout. *Innovations in Education and Teaching International*, 57(1), 74–85. <https://doi.org/10.1080/14703297.2018.1502090>
- [23] Singell, L. D., & Waddell, G. R. (2010). Modeling retention at a large public university: Can at-risk students be identified early enough to treat? *Research in Higher Education*, 51, 546–572. <https://doi.org/10.1007/s11162-010-9170-7>
- [24] Jia, P., & Maloney, T. (2015). Using predictive modelling to identify students at risk of poor university outcomes. *Higher Education*, 70, 127–149. <https://doi.org/10.1007/s10734-014-9829-7>
- [25] Kuh, G. D. (2005). *Assessing conditions to enhance educational effectiveness: The inventory for student engagement and success*. Jossey-Bass.
- [26] Kuh, G. D., Kinzie, J., Schuh, J. H., & Whitt, E. J. (2011). *Student success in college: Creating conditions that matter*. USA: John Wiley & Sons.
- [27] Mäkinen, J., Olkinuora, E., & Lonka, K. (2004). Students at risk: Students' general study orientations and abandoning/prolonging the course of studies. *Higher Education*, 48, 173–188. <https://doi.org/10.1023/B:HIGH.0000034312.79289.ab>
- [28] Sarra, A., Fontanella, L., & Di Zio, S. (2019). Identifying students at risk of academic failure within the educational data mining framework. *Social Indicators Research*, 146, 41–60. <https://doi.org/10.1007/s11205-018-1901-8>
- [29] Seidman, A. (2012). Taking action. In *College student retention: Formula for student success* (pp. 267–293).
- [30] Kehm, B. M., Larsen, M. R., & Sommersel, H. B. (2019). Student dropout from universities in Europe: A review of empirical literature. *Hungarian Educational Research Journal*, 9(2), 147–164. <https://doi.org/10.1556/063.9.2019.1.18>
- [31] Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students: A third decade of research. Volume 2*. USA: Jossey-Bass.
- [32] Srairi, S. (2022). An analysis of factors affecting student dropout: The case of Tunisian universities. *International Journal of Educational Reform*, 31(2), 168–186. <https://doi.org/10.1177/10567879211023123>
- [33] Latif, A., Choudhary, A. I., & Hammayun, A. A. (2015). Economic effects of student dropouts: A comparative study. *Journal of Global Economics*, 3(2), 1–4. <https://doi.org/10.4172/2375-4389.1000137>
- [34] Aina, C., Baici, E., Casalone, G., & Pastore, F. (2022). The determinants of university dropout: A review of the socio-economic literature. *Socio-Economic Planning Sciences*, 79, 101102. <https://doi.org/10.1016/j.seps.2021.101102>
- [35] Stăiculescu, C., & Ramona, R. N. E. (2018). University dropout. Causes and solution. *Mental Health: Global Challenges Journal*, 1(1), 71–75. <https://doi.org/10.32437/mhgcj.v1i1.29>
- [36] Huth, V., Biral F., Martin, O., & Lot, R. (2012). Comparison of two warning concepts of an intelligent curve warning system for motorcyclists in a simulator study. *Accident Analysis & Prevention*, 44(1), 118–125. <https://doi.org/10.1016/j.aap.2011.04.023>
- [37] Kalkstein, A., & Sheridan, S. C. (2007). The social impacts of the heat-health watch/warning system in Phoenix, Arizona: Assessing the perceived risk and response of the public. *International Journal of Biometeorology*, 52, 43–55. <https://doi.org/10.1007/s00484-006-0073-4>
- [38] Finch, A., Lambert, J., & Schaalje, B. (2001). Psychotherapy quality control: The statistical generation of expected recovery curves for integration in an early warning system. *Clinical Psychology and Psychotherapy*, 8(4), 231–242. <https://doi.org/10.1002/cpp.286>
- [39] Lowe, R., Bailey, T. C., Stephenson, D. B., Graham, R. J., Coelho, C. A. S., ..., & Barcellos, C. (2011).

- Spatio-temporal modelling of climate-sensitive disease risk: Towards an early warning system for dengue in Brazil. *Computers & Geosciences*, 37(3), 371–381. <https://doi.org/10.1016/j.cageo.2010.01.008>
- [40] Balfanz, R., & Legters, N. (2004). Locating the dropout crisis. Which high schools produce the Nation's dropouts? Where are they located? Who attends them? Report 70. *Center for Research on the Education of Students Placed at Risk CRESPAR*.
- [41] Beck, H. P., & Davidson, W. D. (2001). Establishing an early warning system: Predicting low grades in college students from survey of academic orientations scores. *Research in Higher Education*, 42, 709–723. <https://doi.org/10.1023/A:1012253527960>
- [42] Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an “early warning system” for educators: A proof of concept. *Computers & Education*, 54(2), 588–599. <https://doi.org/10.1016/j.compedu.2009.09.008>
- [43] Pinkus, L. (2008). *Using early-warning data to improve graduation rates: Closing cracks in the education system*. USA: Alliance for Excellent Education.
- [44] Morris, L. V., Finnegan, C., & Wu, S. S. (2005). Tracking student behavior, persistence, and achievement in online courses. *The Internet and Higher Education*, 8(3), 221–231. <https://doi.org/10.1016/j.iheduc.2005.06.009>
- [45] Hu, Y. H., Lo, C. L., & Shih, S. P. (2014). Developing early warning systems to predict students' online learning performance. *Computers in Human Behavior*, 36, 469–478.
- [46] Alam, A., & Mohanty, A. (2023). Predicting students' performance employing educational data mining techniques, machine learning, and learning analytics. In *International Conference on Communication, Networks and Computing*, 166–177. [https://doi.org/10.1007/978-3-031-43140-1\\_15](https://doi.org/10.1007/978-3-031-43140-1_15)
- [47] Aleksandrova, Y. (2019). Predicting students performance in Moodle platforms using machine learning algorithms. In *Conferences of the Department Informatics*, 177–187.
- [48] Anagnostopoulos, T., Kytagiias, C., Xanthopoulos, T., Georgakopoulos, I., Salmon, I., & Psaromiligkos, Y. (2020). Intelligent predictive analytics for identifying students at risk of failure in Moodle courses. In *International Conference on Intelligent Tutoring Systems*, 152–162. [https://doi.org/10.1007/978-3-030-49663-0\\_19](https://doi.org/10.1007/978-3-030-49663-0_19)
- [49] Büyükoztürk, Ş., & Çokluk-Bökeoğlu, Ö. (2008). Discriminant function analysis: Concept and application. *Egitim Arastirmalari: Eurasian Journal of Educational Research*, 33, 73–92.
- [50] Fauszt, T., Erdélyi, K., Dobák, D., Bognár, L., & Kovács, E. (2023). Design of a machine learning model to predict student attrition. *International Journal of Emerging Technologies in Learning*, 18(17), 184–195. <https://doi.org/10.3991/ijet.v18i17.41449>
- [51] Georgakopoulos, I., Chalikias, M., Zakopoulos, V., & Kossieri, E. (2020). Identifying factors of students' failure in blended courses by analyzing students' engagement data. *Education Sciences*, 10(9), 242. <https://doi.org/10.3390/educsci10090242>
- [52] Kabathova, J., & Drlík, M. (2021). Towards predicting student's dropout in university courses using different machine learning techniques. *Applied Sciences*, 11(7), 3130. <https://doi.org/10.3390/app11073130>
- [53] Lourens, A., & Bleazard, D. (2016). Applying predictive analytics in identifying students at risk: A case study. *South African Journal of Higher Education*, 30(2), 129–142.
- [54] DeBerard, M. S., Spielmanns G. I., & Julka, D. L. (2004). Predictors of academic achievement and retention among college freshmen: A longitudinal study. *College Student Journal*, 38(1), 66+.
- [55] Liz-Domínguez, M., Caeiro-Rodríguez, M., Llamas-Nistal, M., & Mikic-Fonte, F. A. (2019). Systematic literature review of predictive analysis tools in higher education. *Applied Sciences*, 9(24), 5569. <https://doi.org/10.3390/app9245569>
- [56] Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, 138(2), 353.
- [57] Smith, M., Dass, S., Dillon, C., & Long, R. (2018). Data analytics and training effectiveness evaluation. In K. Huggins (Ed.), *Military applications of data analytics* (pp. 79–96). Auerbach Publications.
- [58] Rakic, S., Softic, S., Vilkas, M., Lalic, B., & Marjanovic, U. (2018). Key indicators for student performance at the e-learning platform: An SNA approach. In *2018 16th International Conference on Emerging eLearning Technologies and Applications*, 463–468. <https://doi.org/10.1109/ICETA.2018.8572236>
- [59] Georgakopoulos, I., Kytagiias, C., Psaromiligkos, Y., & Voudouri, A. (2018). Identifying risks factors of students' failure in e-learning systems: Towards a warning system. *International Journal of Decision Support Systems*, 3(3–4), 190–206. <https://doi.org/10.1504/IJDS.2018.100187>
- [60] Vose, D. (2008). *Risk analysis: A quantitative guide*. USA: John Wiley & Sons.
- [61] Izenman, A. J. (2013). Linear discriminant analysis. In A. J. Izenman (Ed.), *Modern multivariate statistical techniques: Regression, classification, and manifold learning* (pp. 237–280). USA: Springer. [https://doi.org/10.1007/978-0-387-78189-1\\_8](https://doi.org/10.1007/978-0-387-78189-1_8)
- [62] Manly, B. F. J., McDonald, L. L., Thomas, D. L., McDonald, T. L., & Erickson, W. P. (2002). Discriminant function analysis. In B. F. J. Manly, L. L. McDonald, D. L. Thomas, T. L. McDonald, & W. P. Erickson (Eds.), *Resource selection by animals: Statistical design and analysis for field studies* (pp. 171–178). Springer. [https://doi.org/10.1007/0-306-48151-0\\_10](https://doi.org/10.1007/0-306-48151-0_10)
- [63] Ye, J., Janardan, R., & Li, Q. (2004). Two-dimensional linear discriminant analysis. *Advances in Neural Information Processing Systems*, 17.
- [64] Xanthopoulos, P., Pardalos, P. M., & Trafalis, T. B. (2013). Linear discriminant analysis. In P. Xanthopoulos, P. M. Pardalos, & P. M. Trafalis (Eds.), *Robust data mining* (pp. 27–33). Springer. [https://doi.org/10.1007/978-1-4419-9878-1\\_4](https://doi.org/10.1007/978-1-4419-9878-1_4)
- [65] Georgakopoulos, I., & Tsakirtzis, S. (2021). Generating a model to predict secondary school students at risk in mathematics. *International Electronic Journal of Mathematics Education*, 16(2), em0630. <https://doi.org/10.29333/iejme/10877>

**How to Cite:** Zakopoulos, V., Georgakopoulos, I., Dalakouras, C., Dimitrakopoulos, P., & Liomas, I. (2024). A Framework to Identify Non-Achievers in eLearning Business Informatics Lab Courses. *Journal of Comprehensive Business Administration Research*. <https://doi.org/10.47852/bonviewJCBAR42022808>