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A Robust Risk Model to Identify Factors that Affect Students' Critical Achievement in Remote Lab Courses

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Abstract:

Purpose: *The research objective is to address the problem of students' critical achievement in remote lab courses aiming at identifying the risk factors of students' failure by exploiting e-learning learning analytics. A robust risk model is developed to serve this purpose. The research is orented into NI-Elvis remote lab courses given that they offer a stable environment in the context of which automation lab courses could be effectively delivered.*
Design/methodology/approach: *A robust risk model was developed by analyzing students' behavioral engagement data. The e-learning part of the remote lab course was used to provide the requisite dataset. In detail, a proper binary logistics regression scheme was employed to come up with the aforementioned risk model. The e-learning part was implemented by a specific e-learning platform that is suitable for NI-Elvis remote lab courses. The data was collected after the course completion.*
Findings: *Factors that are related to students' engagement (number of theory exercises completed and number of messages sent) appeared to be decisive.*
Originality/value: *The originality of our research lies in the fact that the issue of students' critical achievement in remote lab courses is not addressed in a fragmentary way by just carrying out a specific analysis and coming up with results, like many similar studies in the literature. Thereby, a concrete methodology was developed on the basis of an established generic risk management framework. The added value of our research is centered on the fact that our risk model could potentially be applied to any remote lab course to come up with the respective risk factors.*

Keywords: *Students' engagement, risk model, risk factors, remote labs.*

JEL codes: *A12, C53, I21, I23, I38.*

Paper Type: *A research study.*

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1. Introduction

1.1 The Need for Identifying Students at Risk in Remote Lab Courses

There has been a great boom in the employment of remote teaching during pandemic. That expedient has been achieved through the use of new instructional practices centered on digital technology and distance education (Zimmerman, 2020; Williamson, 2020). In that light, the use of modern educational technologies has become a main political concern in the face of the underlying crisis. In addition, the pandemic has paved the way for testing the new educational practices in the context of new laboratory courses (Anderson, 2020; Beckman *et al.*, 2018).

Laboratory courses aim at helping students to develop practical skills. These skills are mastered through well-designed experiments. Such experiments aid students to apply their gained knowledge in order to come up with solution to practical problems. These experiments include the use of specific instruments, circuits and other corresponding equipment. In the form of physical presence, students could easily interact with the activities of a laboratory course, utilizing the requisite equipment. In that environment, students can have the measurement outcome flashed before their eyes in a real-time mode.

Therefore, in the form of remote education, students can also have the benefit of getting measurements' results in teal time. Given that remote education is on rise, the need for a remote lab is getting to be ultimate A remote lab is based on the "digital twins" capabilities. The authors of "Environment and Planning B: Urban Analytics and City Science", 2018 clarify that the term "digital twin" refers to an absolute mirroring of a physical process. In that aspect, the digital twin executes the respective operation in the same way the physical process is executed.

Grieves (2014) explain that the use of digital twins has been expanded to answer to the purpose of entire systems. The system which mirrors the operation of another system could be deemed to be an abstraction of the key-features of the real system.

From that perspective, the operation of experiments could be mirrored by the respective digital twins. Digital twins ensure the success of the remote labs. Remote labs, during pandemic appear to be a potent implement in the case of remote education in the context of automation courses. A lot of remote lab courses include material mounted on an LMS. Thereby, the success of such remote lab courses is heavily dependent on the e-learning part (Tsaramisris *et al.*, 2016).

The literature reports a significant dropout of students in e-learning courses (Anderson, 2020). Although, there is not a specific dropout rate that has been reported in the literature in the case of remote labs, the fact that the e-learning system assumes a cardinal role in many remote lab courses makes us realize that the identification of students at risk in remote lab courses is of utmost importance.

In literature there are a lot of studies related to a remote lab-design for automation courses. Additionally, there are not substantial studies that take up the issue of identifying students at risk in remote lab courses. Some studies refer to a set of criteria for assessing the success of a remote lab venture. Nevertheless, these criteria have not been exploited in terms of a competent framework in order to predict students' critical achievement with a view to moving on a remedial action.

This paper demonstrates a specific framework in the context of which a risk model could be built in order to identify students at risk in remote lab courses. This framework takes advantage of the statistics elicited from the remote lab course e-learning part implementation.

1.2 Remote Labs' Features

Remote labs could be deemed to be experiments that are carried out and controlled through Internet (Chen *et al.,* 2010). Their purpose is encircled on aiding educational Institutions to cover their need for space, instrumentation, and human support (Song *et al.*, 2007). It is important to stress the fact that some issues should be considered on remote labs' accessibility (Chang *et al.*, 2002). These issues are related to the following processes: selection and installation of hardware, data digitization, and collection, visualization and network selection and installation (Chen *et al.*, 2009).

A client-server architecture is typical for the design of remote labs in order to deal with the issue of complexity (Heradio *et al.*, 2016). Two main parts stand out in this architecture. The first part is the Remote Lab Client which interacts with the server and the other part is the Remote Lab Server which is usually built in the philosophy of the LabView or MATLAB simulation.

It is also essential to lay emphasis on the benefits and challenges pertained to the remote labs (Mokhar et al, 2014). The benefits are:

- Various technologies could be employed to implement a remote lab tailored to students' needs.
- It is easy for students to perform assessment practices and experiments.
- Remote labs are suitable for industrial applications owing to their remote monitoring potential.

The challenges are related to the need for error management, to the need for re-usability and to the need for extra security due to liable malicious web pages (Mokhar *et al.,* 2014; Riman, 2011).

1.3 Interactive Remote Labs

Interactive remote labs could be viewed as experiments that are based on real-time control or observation. The technology which could be employed to implement interactive remote labs could be built upon the principles of web services (Hardison *et al.*, 2008; Hardison *et al.*, 2005). Such technology should give developers the opportunity to design and implement interactive remote labs which are tailored to students' needs.

1.3 NI ELVIS-Remote Labs

According to the (NI-ELVIS Product Flyer), a NI-ELVIS Remote Lab offers:

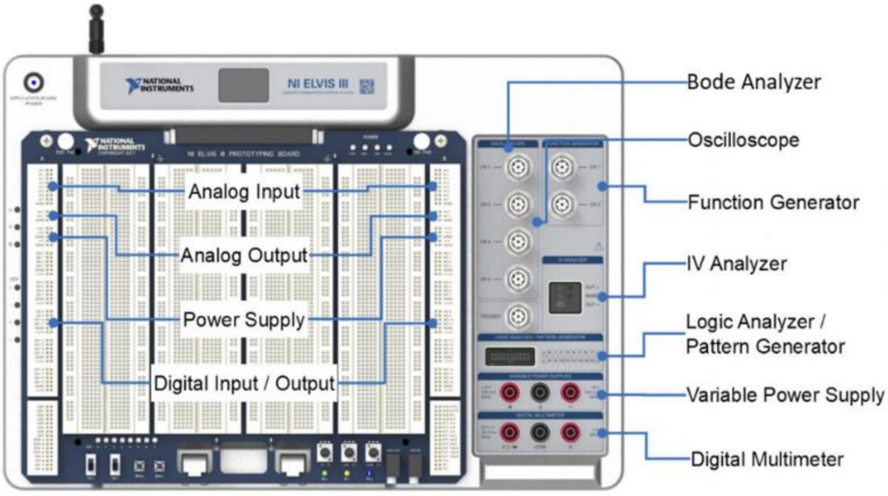
- Web-based operation supporting multimedia and popular operating systems;
- Interactive labs which add up to the theory and place emphasis on projects;
- Experiments that are executed on real hardware;
- The capability to share hardware among courses and departments;
- The usage of standard software which supports programming (Python and C);

Some NI-ELVIS Remote Labs (NI-ELVIS Product Flyer) are listed below:

- Help students to develop innovative qualities by the use of authentic experiments;
- Aid students to assimilate knowledge through the use of appropriate resources designed by experts;
- Stir students' engagement by offering a web-driven environment, augmenting students' desire to get involved in the learning process;

A cardinal function of NI-ELVIS Remote Labs is the real-time measurement outcome. The NI-Elvis measurement station is illustrated in Figure 1.

Figure 1. *NI Elvis Measurement station*



Source: *NI-ELVIS Product flyer.*

Additionally, a NI-ELVIS Remote Labs is based on an online teaching environment which provides students with theoretical material on syllabus and tests students' comprehension through appropriate exercises. This function is similar to the one implemented by e-learning systems. The theoretical material includes slides, videos and other multimedia resources whereas the exercises include multiple choices questions, true/false questions, matching elements' questions and specific experiments.

It is important to underline that these exercises are graded, and students will be notified about their grades. It is also essential to denote that educator can modify the context mounted on the respective e-learning system (LMS) in order to provide students with courses tailored to their needs. It is vital to place emphasis on the valuable statistical data the e-learning system offers in regard to students' engagement. As a potent LMS, the NI-Elvis e-learning system provides educators with meaningful data related to students' activities (activity/assignment grades and activity completion time). Therefore, educators can get an overall picture of students' performance.

2. Literature Review

2.1 Remote Labs' Assessment

A study has underlined that remote lab should be widely available and widely accessible and they should offer a safer experimentation environment in comparison to the traditional labs (Heradio *et al.,* 2016). Another study has scrutinized over 100 articles on remote labs and explains that some factors which affect the remote monitoring process in a remote lab are, the extent of difficulty, limitations in the number of users, reliability and security (Mokhar *et al.,* 2014).

Important research has peered into ELVIS Labview applications in automation clarifying that they should be embellished with a flexibility in design, and they should be equipped with slight modification code capabilities and advanced accessibility potential.

Another essential research points out that the success of virtual and remote laboratories is encircled on the appropriate software selection. The same research lists a set of criteria that should be met in order to select the appropriate Labview application software (Ertugrul, 2000). These criteria are affiliated with Labview application capabilities in every functional territory including modularity, compatibility of code and hardware, debugging potential, executability, performance and intuition.

Other studies contribute to getting perspective on the pedagogical issues related to the remote labs (Fiesel *et al.,* 2005). One of the studies referred to clarifies that ELVIS Labview applications aid students to practice their communication skills in order to be familiarized with the learning process at home. Thereby, students could take in the rudimentary knowledge on experiments through a mixture of conventional teaching and self-practice (Fiesel *et al.*, 2005). Additionally, students' comprehension of concepts increases through remote and virtual experimentation practices (Zacharia *et al.*, 2007). Another pedagogical aspect which affects the effectiveness of the remote labs is related to the opportunity given to students to learn through a failure learning process, insinuating that students could make mistakes and learn from them (Fiesel *et al.,* 2005).

Finally, another important piece of research indicates that Usability, Instructions' Comprehension, Total time allotted to exercises and experiments' completion along with Entire Procedure Reliability are some factors that should be taken into account in a remote lab process. The same study sheds light on this issue, placing emphasis on students' overall satisfaction as a cardinal metric which reflects the effectiveness of a remote lab (Nickerson *et al.*, 2007).

2.2 Factors Affecting Students' Performance in Remote Lab Courses

Some studies have proved that some factors which affect the students' final outcome in Remote Labs are (Bright *et al.*, 2008; Ng, 2007; Peng and Samah, 2006; Böhne *et al.,* 2002; Faltin *et al.*, 2004; Ovarzum *et al.*, 2018):

. The comprehension of the entire process;
. The instructor's assistance and guidance;
. Students' interaction with the learning material;
. Students' comprehension on hardware employed in Remote Labs;
. Students' social interaction;
. Students' preferences;

Finally, another research lays emphasis on students' comprehension on hardware, explaining that the technology used in the remote labs should contribute to students' comprehension of the hardware, giving students a taste of real experiments (Lindsay and Good, 2005).

Given that remote lab courses could be deemed to be fully online, it is important to examine whether factors affecting students' performance in online courses could potentially affect students' final outcome in remote lab courses. An important study has proved that students' interaction with the system (LMS) is a decisive factor that affects students' performance in online courses, pointing out that the factors that affect students' final outcome in online courses could be traced in the territory of students' behavioral engagement (Macfayden and Dawson, 2010; Anagnostopoulos *et al.,* 2020; Georgakopoulos *et al.,* 2018).

This argument is reinforced by another research that has underlined that students' interaction with the learning material (material study) along with the students' interaction with the self-assessment exercises are factors that affected students' performance in the respective online courses (Anagnostopoulos *et al.*, 2020).

According to many studies, risk factors are course-oriented. Therefore, the risk models are also course- dependent (Anagnostopoulos *et al.*, 2020; Georgakopoulos *et al.*, 2018; Georgakopoulos *et al.*, 2020; Tsakirtzis *et al.*, 2020; Hu *et al.*, 2014; Rostaminezhad *et al.*, 2013). The same seems to hold true for remote lab courses. Different factors appear to be correlated to the students' final outcome in remote lab courses in some studies (Bright *et al.*, 2008; Ng, 2007; Peng and Samah, 2006; Nickerson *et al.*, 2007; Lindsay and Good, 2005; Faltin *et al.*, 2004; Al-Barhamtoshy *et al.*, 2016).

2.3 Students' Satisfaction and Students' Performance

It is important to stress specific research that has proved that students' performance in remote lab courses is getting better while students' satisfaction is increasing (Nickerson *et al.*, 2007). This is also in line with another research which points out that students' preferences affect students' performance (Bright *et al.*, 2008). Given that students' preferences reflect students' satisfaction, we can understand that students' satisfaction is related to students' final outcome.

In parallel, the role of laboratory notes is accentuated in another study which has proved that the laboratory notes which fully clarify the activity involved along with the quality of the equipment used are cardinal factors that affect students' satisfaction in laboratory courses (Nikolic *et al.*, 2014). Another study that stands out in this territory places emphasis on four factors which affect students' satisfaction in laboratory courses delivered online. These are: facilities, instruction method, course content, and lecturer (Peng and Samah, 2006; Zhang *et al.*, 2020).

Additionally, another important research has proved that self-dependency which is encircled on giving students more control over what they learn is the factor that increases the level of students' satisfaction and that holds true especially on the case of remote labs (Elhabashi *et al.*, 2015). The issue of students' satisfaction in remote labs is also being taken up in another study which has indicated that students' satisfaction in remote labs increases analogically to students' comprehension on the remote lab operation (Tsiatsios *et al.*, 2014). In parallel, a factor that appears to be decisive on students' satisfaction in a specific remote engineering lab is the students' comprehension of the guidelines included in the laboratory sheet (Lal *et al.*, 2020).

Service quality appears to be a major factor which affects students' satisfaction in a significant study (Chuah, 2011). It is important to underline that some metrics which pertain to service quality in the respective study are access, communication, security, and understanding of customers. In the context of remote labs, communication could refer to the system's capability of delivering proper messages to students, keeping them informed on any aspect of the learning process.

Additionally, security could relate to the way the system provides a safe experimental environment. Access could be viewed as the systems' accessibility potential, denLting the extent to which students gain access to the remote lab system.

On the ground that students are the customers in a remote lab process, the understanding of customers could be matched with the understanding of students' needs. It is essential to point out that NI-Elvis Technology enables educators to create a lab course tailored to students' needs. Thereby, the extent to which content in a NI-Elvis Remote Lab course is adjustable to students' needs could be deemed to be a cardinal factor that defines the understanding of students and therefore that factor could be decisive on dictating students' satisfaction.

However, it is vital to focus on another research that has augmented the argument that the students' satisfaction in online courses is related to the course structure (Barnes, 2017). Given that remote lab courses are fully online courses, students' satisfaction in remote lab courses could also be course- dependent. Owing to the fact that students' satisfaction is a metric of the effectiveness of a remote lab course, we could conclude that there is not a specific set of factors that could be used to assess the effectiveness of any remote lab course (Barnes, 2017; Nickerson, 2007; Tsaramirsis *et al.,* 2014; Alkhamisi *et al.,* 2020; Maroukian *et al.,* 2017).

3. Research Objective

Our research is directed into identifying factors affecting students' critical achievement in remote lab courses, a part of which is implemented through Internet. Our endeavor is to develop a risk model on the basis of a potent risk management framework which considers factors related to remote lab's assessment in the light of students' behavioral engagement.

4. Research Methodology

Our method aims at identifying the risk factors of students' failure in remote lab courses by analyzing students' engagement data. The risk factors could be regarded as factors which indicate the relationship between the negative final students' outcome and their engagement. Our method is dependent on the stages of a generic risk management framework (Vose, 2008; Apostolopoulos *et al.*, 2016). Our method is based on the pillar of students' engagement through their interaction with LMS. Our method also demonstrates a way to build a risk model by analyzing such LMS data (Anagnostopoulos *et al.,* 2020; Georgakopoulos *et al.*, 2018; Georgakopoulos *et al.,* 2020; Tsakirtzis *et al.,* 2020; Macfayden and Dawson, 2010).

Though, this method has not been tested in the case of a remote lab. However, on the ground that remote lab courses could be viewed as fully online courses, the specific methodology could potentially be used in the context of remote labs with a view to identifying students at risk (Asher *et al.,* 2021; Yamin and Tsaramirsis, 2012;

Poermono and Tsaramirsis, 2008; Ades *et al.,* 2009). Our method is called 'UNIWA-RLA' which stands for UNIWA-Remote Lab Assessment, and includes the below phases:

Phase 1: Define the threshold for Students at Risk.
Phase 2: Identify the candidate risk factors.
Phase 3: Build the risk model.

4.1 Applying Our Framework

4.1.1 Our Remote Lab

We applied our framework to our remote lab, the design of which is further described (Randhawa *et al.,* 2017; Randhawa *et al.,* 2020 (a); Randhawa and Shanthagiri, 2015; Braiek *et al.,* 2008; Randhawa *et al.,* 2020 (b); Poernomo *et al.,* 2008; Tsaramirsis *et al.,* 2019).

We selected the NI technology given that it lives up to the below standards:

- Experiments are executed on real hardware.
- The same hardware can be used in various courses.
- It is embellished with programming capabilities supporting C and Python language.
- The curricula offered are built on a large collection of teaching resources.
- The 'adding" and "modifying" functions allow designers to provide students with content that is tailored to their needs.
- Educators could provide students with valuable feedback on activities having defined the feedback messages in the design process.
- Educators can use a potent LMS to monitor students' progress.

Our remote lab was designed in a way to mirror the operations of the respective conventional lab. The conventional lab course is designed to include laboratory exercises which are broken down into the below categories:

- Experiments.
- Theory- Based exercises.
- Programming skills' development exercises.

It is important to explain that the conventional lab course is in line with the respective theoretical course, in the context of which students gain knowledge on the data acquisition process, they are familiarized with instruments and devices, and they are acquainted with a graphical way to program devices to perform a data acquisition process. In that spirit, the theoretical course is built on the pillar of LabView Instruction.

The way the remote lab for the Data Acquisition Course has been designed shows how similar automation courses could also be designed. The underline course consists of specific modules divided into the below parts:

. Overview
. Theory and Background
. Report

The 'Overview' focuses on the goals of the module and on the hardware and software needed to achieve the goals. The 'Theory and Background' part contains the theoretical material along with the corresponding exercises. The theoretical material includes slides and videos designed to aid students to gain knowledge on the theoretical background. The exercises are designed on the basis of two levels of competency.

The first level is related to the way knowledge is assimilated through practical exercises which are not affiliated with measurement; instrumentation and experiments. Such exercises include multiple- choice questions; true/false questions; short answers to questions and similar content-based exercises. The second level of competency is correlated to the way the gained knowledge can be applied to real experiments and it is also correlated to the way the assimilated knowledge can be used to solve real problems.

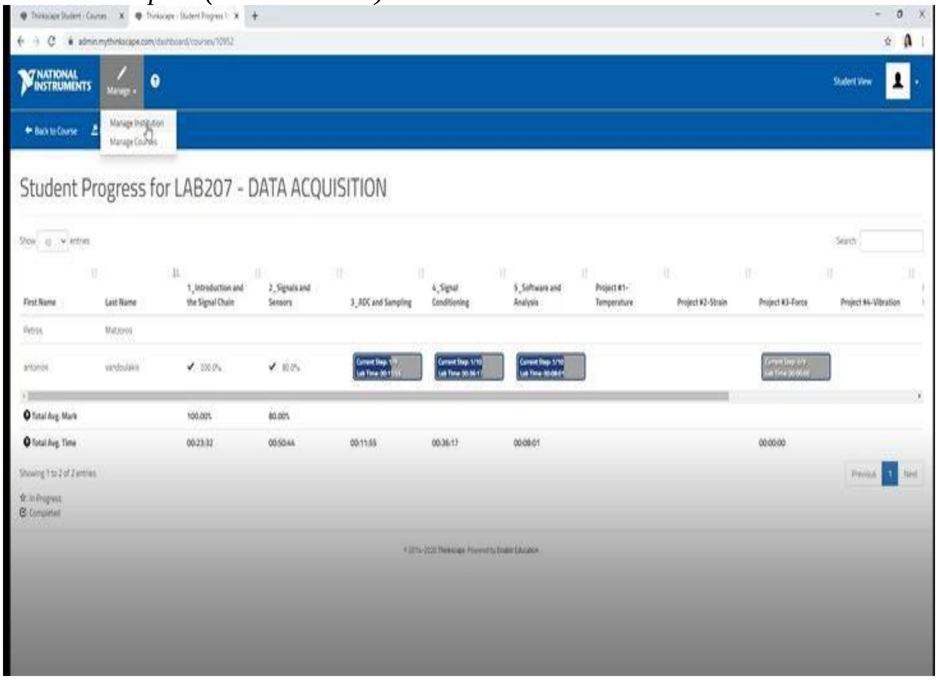
To answer this purpose, students are facilitated with a safe experimental environment in which real problems are modeled as experiments and instrumentation and measurement exercises. In a more elaborate detail, students get access to a plethora of instruments needed to do the experiment and they can deploy the respective instruments to perform the requisite measurement task and get results in real- time. In addition, the equipment provided in the context of the remote lab can be combined with specific equipment provided in terms of a conventional lab. In that spirit educators could initially connect the required devices in the conventional lab and then students could take measurements using the remote lab equipment to fully understand the exercise.

Students should complete a report on the module in the "Report Part" and submit their report. The students' report includes a list of questions (free answer, multiple-choice questions and true/false questions) which examines the overall knowledge gained on the module. The submitted report is being graded.

In terms of the first level of competency, educators could design their curricula on the base of feedback messages through which students can be informed on the correctness of their answers and that enables students to understand their fallacious reasoning. in parallel, educators could monitor students' progress through the report provided by the existing LMS, encouraging students who are not excelling at exercises to study the relative theoretical material harder.

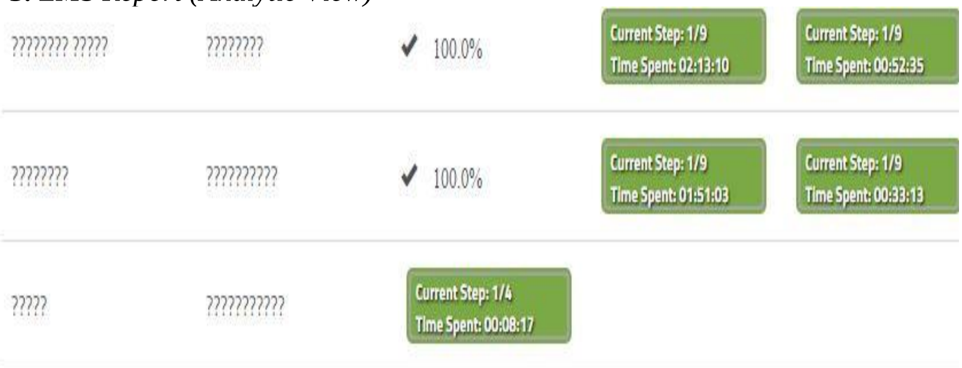
A sample of the LMS report is shown in Figures 2 and 3.

Figure 2. *LMS Report (Generic View)*



Source: *Own study.*

Figure 3. *LMS Report (Analytic View)*



Source: *Own study.*

The Generic LMS report shows the number of modules completed by students and the students' module completion percentage. Through this report, educators could be aware of the modules which were not completed by students in order to come up with extra help. in parallel, the Analytic LMS report underlines the students' attempts by indicating the number of steps completed. The steps denote the exercises that should be done or the questions that should be answered in order for the module to be completed. These steps are deemed to be activities needed to be completed. Additionally, the Analytic LMS report provides information on the time spent by students on each step, reflecting the time allotted to any respective activity. Finally, Figure 4 depicts the Aggregate LMS report which points out the aggregate class performance.

Figure 4. *LMS Report (Aggregate View)*

Total Avg. Mark	97.24%	63.70%
Total Avg. Time	00:18:31	01:27:00

Source: *Own study.*

The Aggregate LMS Report includes the average mark of each module and the total average time which is spent by the entire class on each module.

4.1.2 Identifying Factors of Students' Failure

Students' score on the final project below the numeric threshold of 5 denoted risk. The Measurement Exercises and the Theory-Based Exercises were preparing the students for the final project culmination.

In the light of the studies of some studies which has previously referred to, we came up with the below data in relation to students' interaction with the Remote Lab's LMS. This data constitutes to be candidate risk factors of students' failure (Anagnostopoulos *et al.*, 2020; Georgakopoulos *et al.*, 2018; Georgakopoulos *et al.*, 2020; Tsakirtzis *et al.*, 2020). This data set is listed below:

1. The Number of Measurement Exercises Done (Completed).
2. The Number of Theory-Based Exercises Done (Completed).
3. The Number of Messages Sent by Students asking for Feedback.
4. Students' Score on Measurement Exercises.
5. Students' Score on Theory- Based Exercises.
6. Time spent on Measurement Exercises.
7. Time spent on Theory-Based Exercises.

It is important to underline that the data set was collected out of 300 students who were enrolled in the specific remote lab course. The data were collected after the first- course run. All data except for the messages sent by students were elicited from the log files kept into the LMS and they were visualized in the Generic and Analytic LMS Reports. The data regarding the messages sent were collected by means of the respective webmail statistics.

Finally, we modeled the variable risk to describe the risk state. On the case of risk occurrence, the variable risk was taken the value 1. In any other case, the variable risk was take the value 0 (Macfayden and Dawson, 2010). All variables (those reflecting the data collected along with the variable risk) were employed in terms of a binary logistics regression analysis in order to build the risk model (Vose, 2008).

5. Results

The following Table 1 shows the risk model characteristics:

***Table 1**. Risk Model Characteristics*

Nagelkerke R^2	0.901
Cox & Snell R^2	597

***Source:** Own Study.*

It is important to underline that our model accounts for 90.1 % of the liable risk factors (Nagelkerke R^2) implying that approximately only 9.9 % of the liable risk factors are not identified. Our model is a good model given that the Nagelkerke R^2 value is close to 1 (Allison, 2014; Smith and McKenna, 2013). The same argument is reinforced by the Cox and Shell R^2 value.

Table 2 indicates the correct classification percentage which our model achieves.

***Table 2.** Classification Table*

Classification Table

		Observed		Predicted risk 0	1	Percentage Correct
Step 1	Risk		0	230	0	100
			1	2	68	97.1
	Overall Percentage					99.3

***Source:** Own study,*

According to Table 2 our model classifies correctly the 99.3 % of the cases. Thus, our model classifies a great majority of risk cases correctly.

5.1 Risk Factors

Table 3 shows which of the candidate risk factors are real risk factors. The risk factors result from the significance value (p). A factor that is statistically significant ($p<0.05$) could be deemed to be a real risk factor that has contributed to the risk occurrence. The risk factors constitute to be the coefficients of the model.

***Table 3**. Risk Factors*

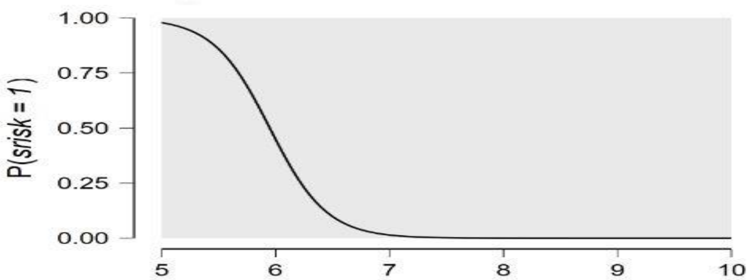
Coefficient	**B**	**p-value**
Number of Theory-Based Exercises Completed	- 4,69	0
Number of Messages Sent	-2.02	0

***Source:** Own study.*

According to Table 3 the risk factors were the number of theory-based exercises completed and the number of messages sent by students. The column B on Table 3 points out the effect of each risk factor on the reduction of the probability of the risk occurrence. Thereby, the most significant risk factor is the number of theory-based exercises.

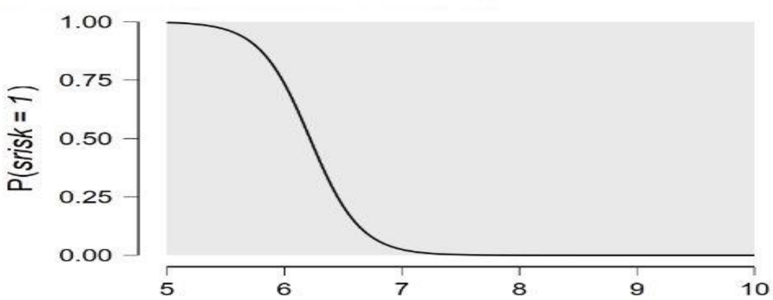
The estimates for the risk factors are illustrated in the below Graphs 1 and 2:

***Graph 1.** P(risk=1). Number of Theory-Based Exercises Completed by Students*
Number of Theory-Based Exercises



***Source:** Own study.*

***Graph 2.** P(risk=1). Number of Messages Sent by Students asking for feedback*
Number of Messages Sent



***Source:** Own study.*

Graph 1 depicts how the probability of the risk occurrence changes with the number of theory-based exercises completed. The graph shows that the probability of the risk occurrence is reducing while the number of the theory-based exercises completed is increasing. In detail, one unit increase in the number of theory-based exercises completed leads to a 0.469 unit decrease in the probability of the risk occurrence.

In parallel, Graph 2 depicts how the probability of the risk occurrence changes with the number of messages sent by students. The graph shows that the probability of the risk occurrence is reducing while the extent of the number of messages sent is increasing. Being more elaborate, one unit increase in the number of messages sent by students leads to a 0.202 unit decrease in the probability of the risk occurrence.

6. Discussion

Table 1 has proved that our model accounts for a great percentage of the liable risk factors. Table 2 shows that our model achieves a great correct classification percentage, adding up to the robustness of our model. Table 3 has indicated that the number of theory-based exercises completed, and the number of messages sent critically affect the students' final outcome in the remote lab. Column B on Table 3 indicates that the number of theory-based exercises completed is the cardinal risk factor.

Therefore, in terms of this remote lab, the students' familiarization with theory through well-designed exercises is the main critical factor in the respective remote lab. It is also important to denote that students' comprehension of concepts through the material and the respective exercises are included in the pedagogical benefits of any remote labs and could be viewed as a main indicator on a remote lab's assessment (Singh *et al.,* 2016; Zacharia *et al.,* 2007; Feisel *et al.,* 2005). In parallel, the students' completion of theory-based exercises reflects students' interaction with the learning material, a factor which is accentuated in another study (Ng, 2007).

It is also important to lay emphasis on the number of messages sent by students to ask for feedback which proved to be an essential risk factor. The number of messages sent by students in the quest for feedback denotes the students' interaction with the teacher, a factor which is also underlined by some studies (Bright *et al.,* 2008; Ng, 2007; Peng and Samah, 2006; Böhne *et al.,* 2002).

It is essential to point out that students' comprehension on concept through the material and the respective exercises are factors which appear to be decisive in the online courses referred to in some other studies (Anagnostopoulos *et al.,* 2020; Georgakopoulos *et al.,* 2018; Georgakopoulos *et al.,* 2020; Tsakirtzis *et al.,* 2020).

However, it is vital to clarify that the risk factors depend on the learning design (Georgakopoulos *et al.,* 2018; Georgakopoulos *et al.,* 2020; Tsakirtzis *et al.,* 2020). Thereby, we cannot insinuate that the respective risk factors affect students' performance in any remote lab course, but we can underline that these factors hold for the underlying course. More remote lab courses would be needed to reach the conclusion that the respective risk factors hold for any remote lab course. It is also essential to underline that the risk factors could be viewed as factors that indicate the relationship between the negative students' final learning outcome and their engagement.

Thereby, the comprehension on concept through the material and the respective exercises are factors that assume a vital role in the context of the underlying relationship.

7. Conclusion

The paper demonstrates a risk model for students at risk in remote lab courses. The paper shows that a data acquisition remote lab could cover the need for the underlying automation course and the proposed framework could contribute to assessing the success of such remote lab by identifying factors that critically affect students' final outcome in this remote lab course. The risk factors point out the areas of the course design which call for amendment. Though, such course amelioration is only attainable after the first course run.

Thereby, a specific limitation in that research outcome is that any intervention along with any remedial action could not be early implemented. Such remedy is only feasible after the first course run. Nevertheless, our framework could be employed to build a risk model by analyzing data elicited before the end of the course.

Our risk model could pave the way for a prediction model generation which could lead to a warning system for students at risk in similar remote lab courses. Additionally, our team is currently working on applying our framework to many remote lab courses in order to examine the probability of emerging risk factors. In parallel, our method could be used to generate an early warning system for students at risk based on a risk model which could be built upon the analysis of data elicited before the course culmination.

The paper indicates that students' engagement significantly affects students' performance. The paper lays emphasis on the way the critical achievement is affected by students' involvement in learning activities. However, our team is currently working on identifying the way the positive final outcome is affected by students' engagement with a view to fully identifying this relationship.

References:

Ades, Y., Sani, N.K., Nistazakis, M., Poernomo, I., Yamin, M., Tsaramirsis, G. 2009.

Implementing SNF-compliant software: MDA and Native Technology. Procedings of ICISO2009, Beijing.
Al-Barhamtoshy, H., Fattouh, A., Tsaramirsis, G. 2016. Student Tracking Model using Mixed Reality. In: The 3rd International Conference on Mathematical Sciences and Computer Engineering, Langkawi, Malaysia.
Alkhamisi, A.O., Buhari, S.M., Tsaramirsis, G., Basheri, M. 2020. An integrated incentive and trust-based optimal path identification in ad hoc on-demand multipath distance vector routing for MANET. International Journal of Grid and Utility Computing, 11(2), 169-184.
Allison, P.D. 2014. Measures of fit for logistic regression. In: Proceedings of the SAS global forum 2014 conference, 1-13. Cary, NC, SAS Institute Inc.
Anagnostopoulos, T., Kytagias, 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. Springer, Cham.
Anderson, J. 2020. The coronavirus pandemic is reshaping education. Quartz Daily Brief. Retrieved from https://qz. com/1826369/how-coronavirus-is-changing-education/.
Apostolopoulos, C., Halikias, G., Maroukian, K., Tsaramirsis, G. 2016. Facilitating organisational decision making: a change risk assessment model case study. Journal of Modelling in Management.
Asher, S.W., Jan, S., Tsaramirsis, G., Khan, F.Q., Khalil, A., Obaidullah, M. 2021. Reverse Engineering of Mobile Banking Applications. Comput. Syst. Sci. Eng., 38(3), 265-278.
Braiek, N.B., Jerbi, H., Bacha, A. 2008. A technique of a stability domain determination for nonlinear discrete polynomial systems. IFAC Proceedings Volumes, 41(2), 8690-8694.
Barnes, C. 2017. An Analysis of Student Perceptions of the Quality and Course Satisfaction of Online Courses. Journal of Higher Education Theory & Practice, 17(6).
Beckman, K., Apps, T., Bennett, S., Lockyer, L. 2018. Conceptualising technology practice in education using Bourdieu's sociology. Learning, Media and Technology, 43(2), 197-210.
Böhne, A., Faltin, N., Wagner, B. 2002. Self-directed learning and tutorial assistance in a remote laboratory. In Interactive Computer Aided Learning Conference (ICL), 25-27).
Bright, C., Lindsay, E., Lowe, D., Murray, S., Liu, D. 2008. Factors that impact learning outcomes in both simulation and remote laboratories. In EdMedia+ Innovate Learning, 6251-6258. Association for the Advancement of Computing in Education (AACE).
Chang, T., Jaroonsiriphan, P., Sun, X. 2002. Integrating Nanotechnologv into Undergraduate Experience: A Web-based Approach. International Journal of Engineering Education, 18(5), 557-565.
Chen, X., Jiang, L., Shahryar, D., Kehinde, L., Olowokere, D. 2009. Technologies For Development of Virtual and Remote Laboratories: A Case Study. In: 2009 Annual Conference and Exposition, 14-1168.
Chen, X., Song, G., Zhang, Y. 2010. Virtual and remote laboratory development: A review. Earth and Space 2010: Engineering, Science, Construction, and Operations in Challenging Environments, 3843-3852.
Chuah, C.W., Sri Ramalu, S. 2011. Students' satisfaction towards the university: Does service quality matters? International Journal of Education, 3(2), 1-15.

Elhabashy, A.E., Abdelhamid, S.E., Reid, K.J., Camelio, J.A. 2015. Factors Affecting Better Use of Laboratory Courses in Engineering. In: the 7th Annual First Year Engineering Experience (FYEE) Conference.

Ertugrul, N. 2000. Towards virtual laboratories: A survey of LabVIEW-based teaching/learning tools and future trends. International Journal of Engineering Education, 16(3), 171-180.

Evaluation Plan and Preliminary Evaluation of a Network of Remote Labs in the Maghrebian Countries. 2018. Environment and Planning B: Urban Analytics and City Science, 45(5) 817-820. DOI: 10.1177/2399808318796416.

Faltin, N., Böhne, A., Wagner, B. 2004. Evaluation of reduced perception and tele-tutorial support in remote automation technology laboratories. In: International Conference on Engineering Education and Research, Progress through Partnership. Ostrava, Czech Republic.

Feisel, L.D., Rosa, A.J. 2005. The role of the laboratory in undergraduate engineering education. Journal of engineering Education, 94(1), 121-130.

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.

Georgakopoulos, I., Kytagias, 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.

Grieves, M. 2014. Digital Twin: manufacturing excellence through virtual factory replication: A whitepaper, original edition. Available at: http://innovate.fit.edu/plm/documents/doc_mgr/912/1411.0_ Digital_Twin_White_Paper_Dr_Grieves.pdf 2002.

Hardison, J., Zych, D., Del Alamo, J.A., Harward, V.J., Lerman, S.R., Wang, S.M., ... Varadharajan, C. 2005. The microelectronics WebLab 6.0–an implementation using Web services and the iLab shared architecture. In: International conference on engineering education and research, 1-5.

Hardison, J.L., DeLong, K., Bailey, P.H., Harward, V.J. 2008. Deploying interactive remote labs using the ilab shared architecture. In: 2008 38th Annual Frontiers in Education Conference, S2A-1. IEEE.

Heradio, R., De La Torre, L., Galan, D., Cabrerizo, F.J., Herrera-Viedma, E., Dormido, S. 2016. Virtual and remote labs in education: A bibliometric analysis. Computers & Education, 98, 14-38.

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.

Kulshreshtha, M., Chandra, S.S., Randhawa, P., Tsaramirsis, G., Khadidos, A., Khadidos, A.O. 2021. OATCR: Outdoor autonomous trash-collecting robot design using YOLOv4-tiny. Electronics, 10(18), 2292.

Lal, S., Lucey, A.D., Lindsay, E.D., Treagust, D.F., Long, J.M., Mocerino, M., Zadnik, M.G. 2020. Student perceptions of instruction sheets in face-to-face and remotely-operated engineering laboratory learning. European Journal of Engineering Education, 45(4), 491-515.

Lindsay, E.D., Good, M.C. 2005. Effects of laboratory access modes upon learning outcomes. IEEE transactions on education, 48(4), 619-631.

Maulana, R., Helms-Lorenz, M., Irnidayanti, Y., van de Grift, W. 2016. Autonomous motivation in the Indonesian classroom: Relationship with teacher support through the lens of self-determination theory. The Asia-Pacific Education Researcher, 25(3), 441-451.

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.

Ng, K.C. 2007. Replacing face-to-face tutorials by synchronous online technologies: Challenges and pedagogical implications. International Review of Research in Open and Distributed Learning, 8(1), 1-15.

Nickerson, J.V., Corter, J.E., Esche, S.K., Chassapis, C. 2007. A model for evaluating the effectiveness of remote engineering laboratories and simulations in education. Computers & Education, 49(3), 708-725.

NI-Elvis Product flyer. Retrieved from: https://www.ni.com/pdf/product-flyers/ni-elvis.pdf.

Nikolic, S., Ritz, C., Vial, P.J., Ros, M., Stirling, D. 2014. Decoding student satisfaction: How to manage and improve the laboratory experience. IEEE Transactions on Education, 58(3), 151-158.

Oyarzun, B., Stefaniak, J., Bol, L., Morrison, G.R. 2018. Effects of learner-to-learner interactions on social presence, achievement and satisfaction. Journal of Computing in Higher Education, 30(1), 154-175.

Patel, A., Sharma, P., Reddy, N., Princy, R., Tsaramirsis, G., Pavlopoulou, A., ... Piromalis, D. 2021. Bio-Virus Spread Simulation in Real 3D Space using Augmented Reality. Engineered Science, 16, 319-330.

Peng, P.J., Samah, A. 2006. Measuring students' satisfaction for quality education in a e-learning university. UNITAR e-journal, 2(1), 11-21.

Poernomo, I., Tsaramirsis, G. 2008. Prototype generation from ontology charts. In the Fifth International Conference on Information Technology: New Generations, March, Vol. 17.

Poernomo, I., Tsaramirsis, G., Zuna, V. 2008. A methodology for requirements analysis at CIM level. In the 1st International Workshop on Business Support for MDA, co-located with Tools Europe 2008.

Randhawa, P., Shanthagiri, V. 2015. Concept of operations to system design and development-an integrated system for aircraft mission feasibility analysis using STK engine, matlab and labview. International Journal of Instrumentation and Control Systems (IJICS), 5(4).

Randhawa, P., Shanthagiri, V., Kumar, A. 2017. A review on applied machine learning in wearable technology and its applications. In 2017 International Conference on Intelligent Sustainable Systems (ICISS), 347-354. IEEE.

Randhawa, P., Shanthagiri, V., Kumar, A., Yadav, V. 2020. Human activity detection using machine learning methods from wearable sensors. Sensor Review.

Randhawa, P., Shanthagiri, V., Kumar, A. 2020. Violent activity recognition by E-textile sensors based on machine learning methods. Journal of Intelligent & Fuzzy Systems, 39(6), 8115-8123.

Riman, C. 2011. A Remote Robotic Laboratory Experiment Platform with Error Management. International Journal of Computer Science Issues (IJCSI), 8(1), 242.

Rostaminezhad, M.A., Mozayani, N., Norozi, D., Iziy, M. 2013. Factors related to e-learner dropout: Case study of IUST elearning center. Procedia-Social and Behavioral Sciences, 83, 522-527.

Smith, T.J., McKenna, C.M. 2013. A comparison of logistic regression pseudo R2 indices. Multiple Linear Regression Viewpoints, 39(2), 17-26.

Song, G., Olmi, C., Bannerot, R. 2007. Enhancing Vibration and Controls Teaching with

Remote Laboratory Experiments. In 2007 Annual Conference & Exposition (pp. 12-677).

Tsakirtzis, S., Georgakopoulos, I. 2020. Developing a Risk Model to identify factors which critically affect Secondary School students' performance in Mathematics. Journal for the Mathematics Education and Teaching Practices, 1(2), 63-72.

Tsaramirsis, G., Al-jammoor, S., Buhari, S.M. 2014. Proposing a new hybrid-controlled loop.

Tsaramirsis, G., Buhari, S.M., Al-Shammari, K.O., Ghazi, S., Nazmudeen, M.S., Tsaramirsis, K. 2016. Towards simulation of the classroom learning experience: Virtual reality approach. In 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom), 1343-1346. IEEE.

Tsaramirsis, G., Buhari, S.M., Basheri, M., Stojmenovic, M. 2019. Navigating virtual environments using leg poses and smartphone sensors. Sensors, 19(2), 299.

Tsiatsos, T., Douka, S., Mavridis, A., Tegos, S., Naddami, A., Zimmer, T., Geoffroy, D. 2014. Evaluation Plan and Preliminary Evaluation of a Network of Remote Labs in the Maghrebian Countries. International Journal of Online Engineering, 10(5).

Vose, D. 2008. Risk analysis: a quantitative guide. John Wiley & Sons.

Williamson, B., Eynon, R., Potter, J. 2020. Pandemic politics, pedagogies and practices: digital technologies and distance education during the coronavirus emergency. Learning, Media and Technology, 45(2), 107-114.

Yamin, M., Tsaramirsis, G. 2012. Cloud Economy and Its Implications for Saudi Arabia. In Proceedings of Fourth Annual American Business Research Conference, New York.

Zacharia, Z.C. 2007. Comparing and combining real and virtual experimentation: an effort to enhance students' conceptual understanding of electric circuits. Journal of Computer Assisted Learning, 23(2), 120-132.

Zhang, M.H., Su, C.Y., Li, Y., Li, Y.Y. 2020. Factors affecting Chinese university students' intention to continue using virtual and remote labs. Australasian Journal of Educational Technology, 36(2), 169-185.

Zimmerman, J. 2020. Coronavirus and the great online-learning experiment. Chronicle of Higher Education, 10(3).