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Impact of Information Technologies on Modeling the Interrelationships among Learning Factors

Elena Fabiola Ruiz Ledesma[1], Blanca Alicia Rico[2], Laura Ivonne Garay Jiménez[2,*]

[1] Instituto Politécnico Nacional, Escuela Superior de Cómputo, Mexico

[2] Instituto Politécnico Nacional, Unidad Profesional Interdisciplinaria en Ingeniería y Tecnologías Avanzadas, Mexico

{eruizl, lgaray}@ipn.mx

Abstract. This article offers a systematic review of studies related to different models derived from the establishment of relationships between factors involved in the learning process. It examines how information and communication technologies influence the development of these relationships and the construction of models. The PRISMA method was used to select articles from two databases, IEEE Xplore and SCOPUS, covering the period from 2018 to 2024. After applying the necessary filters, 20 articles were read and analyzed. These articles met specific criteria, including reporting research that aimed to establish relationships or correlations between elements or factors affecting the teaching-learning process or measuring the impact of certain educational aspects on the academic performance of university students. They also expressed these relationships through models. Twenty-five percent of the studies employed Artificial Intelligence algorithms to assess the influence of LMS, social networks, YouTube, and self-assessment on academic performance. It was found that compulsive use of social networks negatively impacts school performance. Conversely, automated assessment combined with effective communication with peers and teachers enables students to receive feedback, which encourages continued engagement in their studies.

Keywords. Learning, learning factors, information technologies.

1 Introduction

The knowledge and information society has expanded rapidly in the 21st century, thanks to information and communication technologies. The integration of ICT and its growth within the social context has led to changes in cultural relations, communication, and learning. Learning is a complex process through which knowledge, skills, abilities, behaviors, or values are altered by instruction, reasoning, or experience. Additionally, learning adds value and meaning to knowledge, making it more applicable in the context in which it was acquired.

In the field of education, particularly during the learning process, ICT has demonstrated significant potential to support both students and teachers by enabling access to various information through different communication channels, as well as enhancing time management, increasing motivation for task completion, and facilitating collaborative work.

To enhance the efficiency of the learning process, it has been necessary to establish relationships, some of which are causal, thereby creating models that researchers in the educational field have studied and replicated. Additionally, the factors examined in relation to learning include academic, social, psychological, emotional, economic, and instrumental factors, among others.

This paper presents a systematic review of the literature on the relationships between elements or factors involved in the teaching-learning process and their representation as a model.

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A systematic review helps locate, select, and evaluate research contributions. It facilitates analyzing and synthesizing information to conclude what is already known and what still needs to be researched. According to Denyer & Tranfield (2009, p. 1), “conducting a systematic review should not be seen as a literature review in the traditional sense, but as a self-contained research project that investigates a clearly specified question.”

2 Methodology

2.1 PICO Technique

For any research, it is important to define a guiding question, which must be well formulated because it sets the guidelines and the specific problems to be addressed in the study. This stage of the process broadens knowledge about the subject, such as the theories proposed and the concepts used in the analysis. It also makes it possible to identify gaps in previous studies and extend the boundaries of what is known (Venturelli, 1997).

For the formulation of the question, we relied on the PICO technique, which stands for Population or Problem, Intervention, Comparison or Control, and Outcomes (Landa-Ramírez & Arredondo, 2014). This technique specializes in developing clinical questions, managing human and material resources, and using evaluation tools. It also helps improve the construction of research questions by increasing the specificity and conceptual clarity of the problem or population, leading to searches that produce higher-quality and more precise results. In this way, to formulate the question guiding the research, each aspect of this technique was considered. First, the problem and target population were identified. Then, the actions to address the problem—the intervention—were outlined. The comparison involved the group with whom we would compare ourselves, and the expected outcomes refer to what is anticipated to be achieved. Table 1 describes each element related to the work and aligned with the PICO technique.

Table 1. Description of PICO system components

Acronym and component	Identification of the elements
Problem and (Population)	Modeling the interrelationships between the factors or aspects that comprise the teaching-learning process in university courses for students.
I. Intervention	Modification of learning factors using ICTs.
C. Comparison	Assessment of Learning Factors during ICT Use.
O. Outcome	Model of the interrelationship between the learning factors under consideration

Source: Own elaboration

With respect to what is described in Table 1, the question was expressed as follows:

How are the factors or aspects that make up the ICT-based teaching and learning processes connected?

Based on the terms covered by the research question, including synonyms and related words, we searched for scientific articles that addressed them. The PRISMA (Preferred Reporting Items for meta-analysis) method was used for this purpose, as shown in the next section.

2.2 Research Strategy

The IEEE and Scopus databases were used to conduct a systematic search in accordance with PRISMA guidelines. First, in line with this approach, the keywords were selected based on the MeSH on Demand page. The keywords entered into the IEEE and SCOPUS databases with the respective combinations were as follows:

– (Learning OR Teaching) AND (Information OR ICT OR Technology) AND (Students OR Bachelors) AND Review AND Relationships.

– Learning factors AND associated AND (academic development OR qualifications AND (university students).

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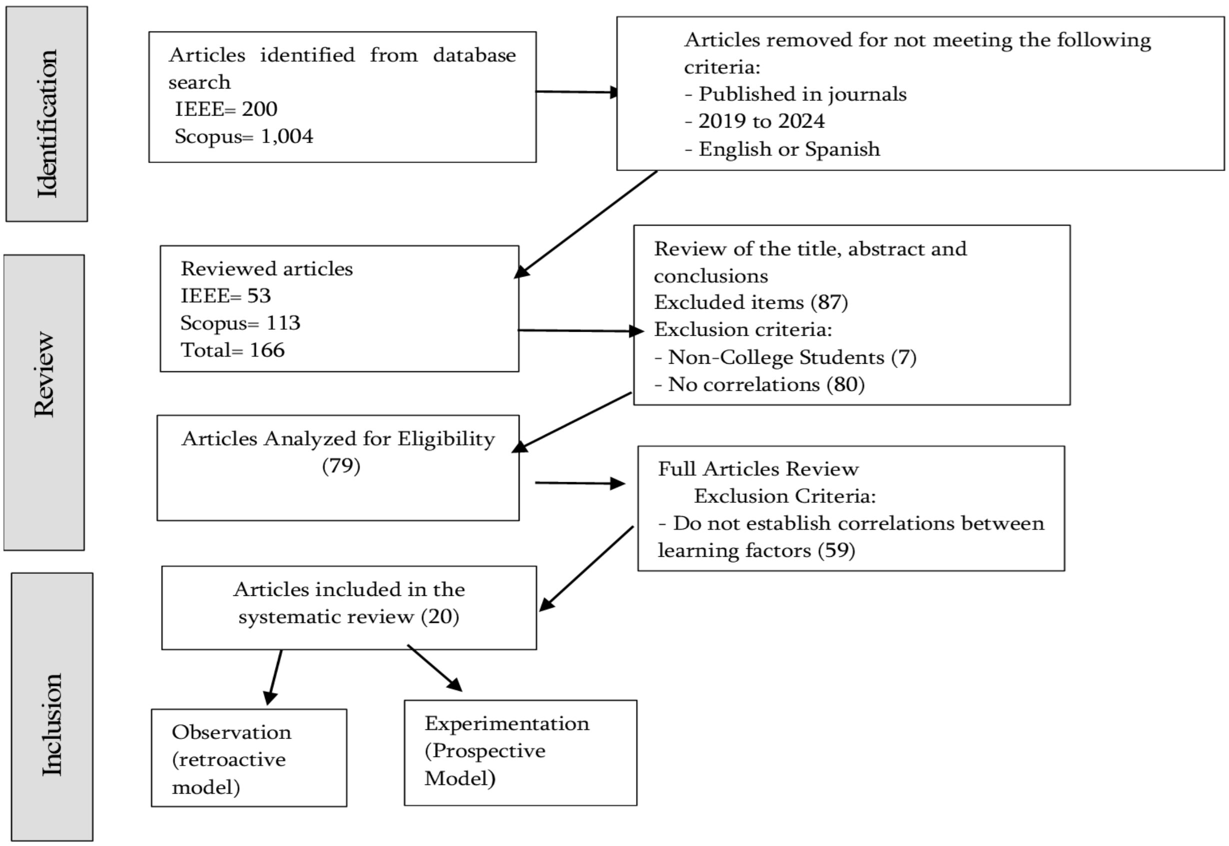

Fig. 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowcharts for database search, screening, and selection of studies

All publications up to the year 2024 were included. Initially, the IEEE database (n = 200) and the Scopus database (n = 1,004) were obtained.

2.3 Selection of Data for Studies

For the selection of studies to be reviewed in full, the process outlined by PRISMA was followed. An initial selection was based on the following inclusion criteria:

– Articles published from 2019 to 2024.
– Written in English or Spanish.
– Articles published in journals.
– Articles that were reviews.

With these criteria, the total number of articles from the IEEE database was reduced to (n=53), and from SCOPUS to (n=113). For the second selection, the 53 articles from the IEEE database and 113 from SCOPUS were exported to Excel, totaling 166 articles. Using this exported data, an Excel table was created. The table included the title, authors, DOI, year, abstract, and keywords. After creating the table, a filtering process was performed to remove articles that lacked a DOI or were duplicates. The number of articles remained the same in both IEEE and SCOPUS.

The final selection of the number of scientific articles to be worked with, i.e., those that fulfilled all the requirements to answer the research question, can be found in the following section, which presents the results.

3 Results

A review was conducted of the title, abstract, and conclusions of the 166 scientific articles obtained, aiming to select those that would provide helpful information for the discussion and conclusions, thereby addressing the research question.

Exclusion criteria:

- The study does not include university students.
- The study does not address the learning process.
- It does not focus on reviewing relationships between learning factors.
- The article presents preliminary results, or the authors say they are describing an exploratory study.

After reviewing the titles and abstracts of the 166 articles, 87 were withdrawn, resulting in 79 remaining articles. This was because the title or abstract did not include students at the university level but involved students from other educational levels, either primary or secondary education, and did not discuss correlations between educational elements.

79 articles were downloaded from both databases, read, and analyzed. Fifty-nine studies were found to have no correlations with learning factors and were therefore discarded. A more detailed reading of the remaining 20 articles was conducted, and the information gathered was used to complete Table 3, which includes 12 criteria incorporated into the systematic review. The results are presented in the following section. Figure 1 summarizes this information in a diagram.

In reviewing the 20 articles, the focus was on the relationships between learning elements and learning outcomes. The role of ICT in establishing these relationships was also examined. Ten criteria were developed to organize the information in the articles, which are described in Table 2.

Table 2. Information from the 20 articles across 6 criteria

	Authors	Relationship between learning factors	Variables
1	Rosman, et al., 2023.	Perceived engagement with LMSs and perceived academic performance	IV: user participation and engagement with the LMS. DV: task development, task satisfaction, and task innovation
2	Domínguez al., 2021	Relationship between self-assessment (A) and formative evaluation (FE)	IV: Regulated learning strategies. DV: Automatically captured online learning activities
3	Magano, et al., 2021	Relationship between Generation Z personality traits and project management soft skills.	IV: Personality traits: neuroticism, extraversion, openness to experience, agreeableness, resilience, and conscientiousness. DV: soft skills: commitment, interpersonal relationships, uncertainty, perseverance, self-control, and emotional maturity
4	Shoufan, et al., 2022	Relationship between strategies for using YouTube and student learning	IV: Content creation and evaluation, user attitudes and acceptance, usage strategies and behaviors. DV: Student learning
5	Klobas, et al., 2018	Relationship: Motivation and personality characteristics in compulsive or non-compulsive use of YouTube	IV: purpose, motivations and interests, lifestyle, self-personality, and communication skills. DV: YouTube use
6		Link between technological trends and digital transformation in higher education.	IV: Technology: educational platforms, augmented and virtual reality, internet of things. DV changes in students

13	Dorobăţ, et al., 2019	Relationship between trust, perceived usefulness of the LMS, and the success of the LMS at the University	IV: Trust and perceived usefulness. DV: Students' loyalty to the LMS.	Likert scale test items	324	Descriptive and inferential statistics. Structural Equations: Hypothesis Formulation and Testing.	Conceptual modeling using structural equations
14	Wang, et al., 2023	Relationship between active participation in online courses and academic performance.	IV: Regularity of study interval, number of online sessions, time spent on homework, late start, and late submission. DV: Academic performance	Variables are expressed through logarithms	230	Logarithmic functions.	Multiple regression to form equations, using logarithms
15	Kambourova, et al., 2021	Relationship: Self-assessment and learning	IV number of tasks, time to complete. DV Grades	Time, scale 0 to 10	210	Functions	Mathematical model
16	Vignery 2021	Relationships between university students' networks and academic performance.	IV: Use of social networks. DV: Academic performance	The number of times they use social networks. Grades in their subjects.	167	Hierarchical clustering and the structural equation algorithm	Mathematical model
17	Krasilnikov,t al., 2017	Relationship: Factors related to social adjustment and academic performance.	IV: Factors related to students' social adaptation. DV: Academic performance.	Time spent using the social network and the number of people with whom they communicated. Grades measured academic performance	68	ordinal logistic regression	Mathematical model using logistic regression
18	Sosibo, 2019	Relationship between self-assessment, skills development, and learning	IV: questionnaire items and tasks. DV: commitment, maturity, confidence.	Number of items, scale obtained from theory	143	Inferential statistics	Conceptual model

7	Howard, et al., 2018	Relationship between continuous assessment and use of the LMS with prediction of their grade	IV: student background, continuous assessment and student engagement with the use of the LMS. DV: prediction of their grade.	Measurement of the time spent in the LMS, counting of the exercises deposited in their portfolio, grades of their in-class exercises, exams, and assignments	136	Algorithms BART	model: Bayesian additive backward trees.
8	Hussain, et al., 2018	Relationship between the level of engagement and student performance	Input variables: the assessment score and the number of clicks on the VLE activities. The output variable was the level of student engagement in the different activities	To predict the level of student engagement, algorithms were applied to the dataset	384	Algorithms	Decision trees
9	Ma, Z, H., et al., 2020	Relationship: Use of tutor recommendation system and learning performance in operational skills in computer applications.	IV: Tutor recommendation system, automated assessment. DV: Learning performance in computer application operational skills.	computer vision technology	360	Control group and experimental group.	Graphs with the results of the control group and the experimental group.
10	Jayakodi, et al., 2016	Relationship between WordNet, along with the cosine similarity algorithm, and the level in Bloom's taxonomy, the exam question	The WordNet similarity algorithm depends on the verbs extracted from the exam question	The cosine similarity algorithm was based on the identification of patterns of questions	45 questions label pattern generation module	Algorithms	A grammar generation module, a parser generation module, and a cosine similarity check module
11	Troussas, C., et al., 2023	Relationship between learning styles and recommended collaborative activities	IV: Dimensions of learning styles and activity bank. DV: different percentages of collaborative activities in which students can participate	Gardner and Korth's framework for identifying dimensions of students' collaborative learning styles.	254	The system was evaluated using an established framework and statistical hypothesis testing.	Artificial neural networks
12	Seth, et al, 2023	Relationship between computer workbooks, class assignments, tutorials, and homework with the learning of multidisciplinary concepts	IV: computer workbooks, class assignments, tutorials, and homework. DV: multidisciplinary concepts and content	Grades	128	Descriptive and inferential statistics	Conceptual model

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- Objective. The purpose of the study was checked to ensure that it related to factors in the teaching-learning process and that these factors were correlated with each other.
- Relationship between learning factors. This refers to the connection among educational elements involved in the teaching-learning process. They were classified into seven.
- Methodology. It was classified into three types: quantitative, qualitative, and mixed.
- Use of statistical tests. When obtaining results, it requires the use of a statistical or probability measure, such as the mean, standard deviation, variance, chi-square, or t-student, either manually or using software like SPSS.
- Gender. If a distinction is made based on the students' gender, it is considered in the results.
- Conceptual model in research. It is based on identifying and organizing the relevant variables or concepts involved in the phenomenon, as well as the relationships and connections between them. This conceptual model serves as a guide for research design and hypothesis formulation, allowing for the establishment of a logical and coherent structure that helps in understanding and explaining the phenomenon under study.
- Mathematical model. The variables are represented through a function.
- Graphical model. The information is shown with a graph, which can be a bar chart or a pie chart.
- Tabular model. The values of the variables are displayed in a table.

Table 3 shows the 10 criteria in the first column, and in the following columns, an asterisk is placed if the study analyzed meets the criterion shown.

Based on previous information, it was found that 80% of the 20 research studies reviewed focused on understanding how certain factors or elements involved in the teaching-learning process affect school performance. Five groups of variables that can influence school performance are identified and summarized below.

- Student characteristics, including demographics, personality traits such as self-esteem, and previous experiences (Magano, Silva, Figueiredo, Vitória, & Nogueira, 2021).
- Use of learning management systems (LMSs), confidence in their use, perceived engagement, and involvement with LMSs (Rosman, Alias, Arshad, Hamid, and Idris, 2023; Wang, Mousavi, Lu, and Gao, 2023; Dorobăţ, Corbea, and Muntean, 2019).
- Use of social media and platforms, such as YouTube, as classroom support (Shoufan & Mohamed, 2022; Klobas, McGill, Moghavvemi, and Paramanathan, 2018).
- Students' efforts dedicated to educational activities, such as attending classes (online or in person) and submitting assignments (Troussas, Giannakas, Sgouropoulou, and Voyiatzis, 2023; Howard, Meehan, and Parnell, 2018; Hussain, Zhu, Zhang, and Abidil, 2018; Jayakodi, Bandara, and Meedeniya, 2016; Ma, Hwang, and Shih, 2020).
- Interactions with faculty, staff members, and peers (Kambourova, González-Agudelo, & Grisales Franco, 2021; Krasilnikov & Smirnova, 2017; Bell, Portilla, & De la Llana, 2019; Vignery, 2021).

3.1 First Set of Variables in Relation to Academic Performance (Student Characteristics and Personality Traits)

Although students acquire remarkable theoretical knowledge throughout their courses, they lack transferable competencies, such as soft skills, which are rarely considered in engineering education. The characteristics of Generation Z differ from those of previous generations and must be considered in new educational approaches and methods (Magano, Silva,

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Figueiredo, Vitória, and Nogueira, 2021). They conducted a study to determine whether there is a correlation between Generation Z personality traits and the development of soft skills. The personality traits included in the test given to a sample of 147 engineering students (57% male and 43% female) were: neuroticism, extraversion, openness to experience, agreeableness, resilience, and conscientiousness, while the soft skills they evaluated were: commitment, interpersonal relationships, adaptability to uncertainty, perseverance, emotional self-control, and emotional maturity.

They found that resilience, agreeableness, and conscientiousness were positively linked to engagement, interpersonal relationships, uncertainty, and perseverance. However, a positive connection with emotional self-control and emotional maturity could not be assured. Only neuroticism showed a negative correlation. Survey participants reported low levels of openness. The results suggest that women exhibit greater sensitivity to others, higher levels of empathy, emotional contagion, and agreeableness, and lower levels of neuroticism. Conversely, men demonstrated statistically significantly higher scores in emotional self- control.

3.2 Second Set of Variables in Relation to Academic Performance (Use of And Trust in LMS)

The LMSs have gained significant importance since the confinement caused by the COVID-19 pandemic, during which classes at all educational levels were conducted remotely (Rosman, Alias, Arshad, Hamid, and Idris, 2023). They examined the perceived commitment to LMSs and perceived academic performance. They developed a conceptual model using structural equations, where perceived engagement was measured through two variables: user participation and involvement with the LMS, while perceived performance was assessed with three variables: task performance, task satisfaction, and task innovation. Metrics included frequency of use, time spent, and grades obtained in activities. Their findings show that the current level of user engagement with the LMS is moderate, and learner engagement in e-learning is on a positive rise. A significant and positive relationship exists between perceived engagement and perceived performance, aligning with the findings of Wang, Mousavi, Lu, and Gao (2023), who note that login time, frequency of accessing course pages, number of online sessions, and timely assignment submission have a positive influence on students' academic performance. Conversely, starting online classes late, irregular study intervals, and late submissions have a negative impact. They also state that students' academic performance in fully online courses largely depends on how well they perform online activities, including time spent on the platform solving tasks and attending classes. Dorobăţ, Corbea, and Muntean (2019) explored trust and perceived usefulness of LMSs, focusing on students' loyalty to these systems. They concluded that LMS success is achieved when students are satisfied with the LMS, trust it, and ultimately become loyal to it.

3.3 Third Set of Variables in Relation to Academic Performance (Use of Social Networks and Platforms Such as Youtube as Support in the Classroom)

Regarding the third set of variables, the research conducted by Shoufan and Mohamed (2022) aimed to determine the reliability of the learning content on YouTube and how YouTube influences students' academic performance and behavior. The results they obtained are as follows:

First, YouTube is an easy-to-use platform that offers a wealth of information through videos, many of which can be used for learning different subjects depending on the desired content. However, because not everything that appears is trustworthy, the teacher needs to select the

Table 3. Data from 20 articles were organized into 10 criteria

Criteria/Article	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Objective	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Relationship between learning factors	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Perceived engagement with LMS and academic performance	*												*	*						
Self-assessment and learning		*													*			*	*	*
Personality traits and skills development			*		*												*			
YouTube and academic performance				*	*															
Technology trends and digital transformation						*						*								
Use of AI models in prediction and level of prediction accuracy							*	*	*	*	*									
Trust and perceived usefulness of LMSs and loyalty to LMSs													*							
Trust and perceived usefulness of LMSs and loyalty to LMSs																*				
Quantitative methodology	*	*	*		*		*	*		*	*		*	*		*	*			
Qualitative methodology						*			*						*				*	*
Mixed methodology				*								*						*		
Using Statistical Tests	*	*	*		*		*	*		*	*		*	*		*	*			
Gender Study		*	*		*															
Conceptual model	*	*			*								*							
Mathematical model							*	*		*	*			*		*	*			
Graphic model				*					*	*		*							*	*
Tabular model			*						*			*			*			*	*	*
Descriptive model						*														

content and information that students can use for learning.

On the other hand, the impact of YouTube on student learning showed positive results in areas such as improved skills, competencies, interest, motivation, participation, test performance, engagement, and learning English as a second language.

Statistical measures were used to determine these outcomes.

However, not everything about YouTube use is positive. It is important to identify what makes its use compulsive for students to help address excessive use. In research conducted by Klobas, McGill, Moghavvemi, and Paramanathan (2018), they examined the relationship between what motivates students to use YouTube, their personality types, and compulsive YouTube use.

They sampled 807 university students, comprising 57% males and 43% females. Regarding motivation, they considered two factors: entertainment and the information the platform provides.

The personality traits analyzed included extroversion, introversion, neuroticism, indecisiveness in decision-making, and the frequency of YouTube usage.

The authors proposed two hypotheses, which were tested using linear regression analysis. A mathematical model was developed for each hypothesis. The first model illustrated the relationship between motivation for information seeking and compulsive consumption, revealing that motivation to use YouTube for information was significantly linked to compulsive use.

The second model examined entertainment motivation and personality traits, finding that indecisiveness was positively associated with compulsive YouTube use. Additionally, neurotic students were more prone to compulsive behavior with the platform. No relationship was found between extroversion and compulsive use.

19.8% of the students reported that they did not control their use of YouTube; of these, more than half were male, and only one-third were female. These results suggest that a high proportion of university students, mainly males, struggle to limit their use of YouTube.

These users are considered compulsive because they cannot control their platform usage, which significantly affects students. When they have homework involving searching for information, they are easily distracted by the videos that appear.

3.4 Fourth Set of Variables (Social Networks and Platforms)

Both educational platforms, as well as those not specifically designed for educational purposes, enabled the inclusion of educational materials such as notes, slides, quizzes, and other information presented in various formats. Additionally, the use of social networks like WhatsApp, Telegram, forums, and chat groups increased, allowing students to communicate more easily with their classmates and teachers. This facilitated sharing educational content and receiving feedback on questions they had solved. In this way, they developed soft skills (Bülbül, 2021).

In the research reported and analyzed, five studies used Artificial Intelligence (AI) to predict students' performance or whether they faced challenges that could lead to dropping out of their degree programs. Haward, Meehan, and Parnell (2018) developed a system that identified students at high risk of dropping out mid-semester. Hussain, Zhu, Zhang, and Abidil (2018) employed an AI model to assess students' level of career engagement.

Conversely, in a study by Ma, Hwang, and Shih (2020), the use of intelligent tutors for practicing mathematical operations, problem solving, and computer work supported students at home for homework or exam preparation. In another area of research, the development of intelligent tutors drew the attention of scientists and companies. For instance, researchers created AI tutors to teach computer science and mathematics topics and to help psychology students practice reading and writing.

Additionally, the intelligent tutors also helped identify errors and provided feedback to students to improve their studying. This way, teachers benefited from the AI-based peer tutor recommendation system and could save time for other activities (Ma, Hwang, and Shih, 2020).

Artificial Intelligence was also utilized in another study (Jayakodi, Bandara, and Meedeniya, 2016), but here it was applied to automate the evaluation of student activities and tests. For this automation, natural language processing was used to classify the text appearing in assessment instruments designed by the teacher.

In summary, using AI to develop automatic classifiers for exam questions made it easier to classify them and increased the accuracy and efficiency of the classifier.

AI was also used to develop adaptive and personalized systems, allowing students to approach their learning process at their own pace and according to their learning styles, levels of knowledge complexity, or based on their interests and needs. AI also facilitated personalized learning by considering the learner's style, interests, and background to create experiences tailored to their needs. These innovative AI-based systems enabled more targeted interventions for struggling learners and helped identify areas where students needed additional support.

The work by Troussas, Giannakas, Sgouropoulou, and Voyiatzis (2023) proposed a series of tasks and activities designed for team-based work, tailored to students' needs and preferences. This was achieved using an artificial neural network.

3.5 Fifth Set of Variables (Interactions with Faculty, Staff Members, And Peers)

In this set of variables, elements were included that facilitated students' communication with their peers or teachers, as well as the relationship between this communication and their academic performance. One key factor that supported student communication was self-assessment. In this regard, Kambourova, González-Agudelo, & Grisales-Franco (2021) mention that self-assessment helps students build self-confidence, develop critical thinking, enhance their intellectual maturity, improve communication with peers and teachers, and understand that the assessment process is complex.

The relationship between self-assessment and academic performance was explored by Krasilnikov and Smirnova (2017), as well as by Bell, Portilla, and De la Llana (2019), who examined at different points in the semester how students' social adjustment affected their academic performance. They discovered that a high level of group integration at the start of the semester did not benefit performance, whereas by the middle of the semester, being well integrated into the group was positively correlated with academic success. Additionally, high community involvement through social networks at the beginning of the semester was found to impact grades negatively. However, by mid-semester, it had a positive effect on academic performance.

Another study (Vignery, 2021) found that, overall, groups of friends tend to have similar academic performance. When a young person has a friend who performs better, their grades usually improve. Conversely, having a low-achieving friend often leads to lower grades.

4 Conclusions

It is crucial to understand the different relationships that can exist between the factors involved in the teaching-learning process and to assess the levels at which one influences the others. This enables the teacher to recognize that a student's performance is not solely based on how much they have memorized or what they have written on an exam, but is the result of many factors.

The review of the 20 articles shows that student performance depends on many variables, which are categorized in this document as: personal, social, academic, technological, and communication.

These relationships, due to how they are addressed in the research, have been depicted through models, whether conceptual, mathematical, or graphical.

It was also observed that researchers are increasingly interested in examining how the use of LMSs affects university students' performance, as well as other platforms not specifically

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designed for education but used as educational resources, such as YouTube and social networks. There are both positive and negative aspects, with the teacher playing a crucial role as an advisor—ensuring that the selection of materials, such as videos, questionnaires, and activities, is beneficial for students, while also guiding their work.

Therefore, teachers must assess how to effectively incorporate online social platforms into their teaching while also educating students about the negative consequences of misusing these platforms.

Other studies have investigated how students' personality traits influence their academic performance, so teachers need to be aware of their students' behavior and actions. For example, teachers need to recognize students' feelings of isolation in online learning environments, as they must ensure that less active students can access learning materials and are encouraged to participate in collaborative activities.

Some actions to support students, especially the younger generation, in their learning process include increasing communication in the physical or virtual classroom, incorporating technology, and modifying teaching methods. Emphasis should be placed on approaches that involve visual elements, not just verbal communication. The use of videos is an effective technique.

References

1. **Portilla, R., Portilla, Y., de la Llana, E. (2019).** Aportes de la autoevaluación para la activación del aprendizaje de los estudiantes en el Instituto Superior Tecnológico de Formación, Memorias del Quinto Congreso Internacional de Ciencias Pedagógicas de Ecuador, pp. 112–123.
2. **Bülbül, M. (2021).** Social Learning Analytics: Learning How We Learn on YouTube, Advancing the Power of Learning Analytics and Big Data in Education, pp. 190-206.
3. **Calzada Prado, F. J. (2020).** Avanzar en el aprendizaje autónomo y social: integración de autoevaluación y evaluación por pares como herramientas y evaluación formativa, Innovación Docente e Investigación en Educación, pp. 211–219.
4. **Capellato, P., Vasconcelos, L. V. B., Ranieri, M. G., Sachs, D. (2020).** Método de ensino ativo utilizando avaliação por pares e autoavaliação: peer and self-evaluation using active teaching methods. Research, Society and Development, Vol. 9, No. 7, doi:10.34448/rsd-v9i7.3495.
5. **Denyer, D., Tranfield, D. (2009).** Producing a Systematic Review. The Sage Handbook of Organizational Research Methods, pp. 671–689.
6. **Domínguez, C., García-Izquierdo, F. J., Jaime, A., Pérez, B., Rubio, L. Zapata, M. A. (2021).** Using Process Mining to Analyze Time Distribution of Self-Assessment and Formative Assessment Exercises on an Online Learning Tool. IEEE Transactions on Learning Technologies, Vol. 14, No. 5, pp. 709–722, doi:10.1109/TLT.2021.3119224.
7. **Dorobăţ, I., Corbea, A. M., Muntean, M. (2019).** Integrating Student Trust into a Conceptual Model for Assessing Learning Management System Success in Higher Education: An Empirical Analysis. IEEE Access, Vol. 7, No. 1, pp. 69202-69214, doi:10.1109/ACCESS.2019.2919100.
8. **Howard, E., Meehan, M., Parnell, A. (2018).** Contrasting Prediction Methods for Early Warning Systems at Undergraduate Level. Internet Higher Educ., Vol. 37, No. 1, pp. 66–75, doi:10.1016/j.iheduc.2018.02.001.
9. **Hussain, M., Zhu, W., Zhang, W., Abidi, S. M. R. (2018).** Student Engagement Predictions in an E-learning System and Their Impact on Student Course Assessment Scores. Comput. Intell. Neurosci., Vol. 18, No. 1, pp. 1–21.
10. **Interaction Design Foundation - IxDF. (2016).** ¿Qué son los modelos conceptuales? IxDF Literature.
11. **Jayakodi, K., Bandara, M., Meedeniya, D. (2016).** An Automatic Classifier for Exam Questions with WordNet and Cosine

Similarity, Proc. Moratuwa Eng. Res. Conf. (MERCon), pp. 12–17.

12. **Kambourova, M., González-Agudelo, E. M., Grisales Franco, L. M. (2021).** University Students' Self-assessment: Literature Review. Teoría de la Educación. Revista Interuniversitaria, Vol. 33, No. 2, pp. 217–264, doi:10.14201/teri.23672.
13. **Klobas, J. E., McGill, T., Moghavvemi, S., Paramanathan, T. (2018).** Compulsive YouTube Usage: A Comparison of Use Motivation and Personality Effects. Computers in Human Behavior, Vol. 87, No. 1, pp. 129–137, doi:10.1016/j.chb.2018.05.038.
14. **Krasilnikov, A., Smirnova, A. (2017).** Online Social Adaptation of First-year Students and Their Academic Performance. Computers & Education, Vol. 113, No. 1, pp. 327-338, doi:10.1016/j.compedu.2017.05.012.
15. **Landa-Ramírez, E., De, A., Arredondo-Pantaleón, J. (2014).** Herramienta Pico para la formulación y búsqueda de preguntas clínicamente relevantes en la psicooncología basada en la evidencia. Psicooncologia, Vol. 11, pp. 259–270.
16. **Ma, Z., Shih, T. K. (2020).** Effects of a Peer Tutor Recommender System (PTRS) with Machine Learning and Automated Assessment on Vocational High School Students' Computer Application Operating Skills. J. Comput. Educ., Vol. 7, No. 3, pp. 435–462.
17. **Magano, J., Silva, C. S., Figueiredo, C., Vitória, A., Nogueira, T. (2021).** Project Management in Engineering Education: Providing Generation Z with Transferable Skills. Revista Iberoamericana de Tecnologias del Aprendizaje, Vol. 16, No. 1, pp. 45–57, doi:10.1109/RITA.2021.3052496.
18. **Rosman, M. R. M., Alias, N. R., Arshad, I. H., Hamid, H. A.. Idris, Z. (2023).** Assessing Students' Perceived Engagement and Perceived Performance for E-Learning in East Coast Malaysia: A Partial Least Squares Structural Equation Modeling Approach. IEEE Engineering Management Review, Vol. 51, No. 1, pp. 63–75, doi:10.1109/EMR.2022.3196929.
19. **Seth, S. A., Redonnet, Liem, R. P. (2023).** MADE: A Multidisciplinary Computational Framework for Aerospace Engineering Education. IEEE Transactions on Education, Vol. 66, No. 6, pp. 622–631, doi:10.1109/TE.2023.3281825.
20. **Shoufan, A. & Mohamed, F. (2022).** YouTube and Education: A Scoping Review. IEEE Access, Vol. 10, No. 1, pp. 125576–125599, doi:10.1109/ACCESS.2022.3225419.
21. **Sosibo, Z. (2019).** Self-assessment: a learner-centered approach towards transforming traditional practices and building self-directed learners. South African Journal of Higher Education, Vol. 33, No. 5, pp. 76–97, doi:10.20853/33-5-3586.
22. **Troussas, C., Giannakas, F., Sgouropoulou, C., Voyiatzis, I. (2023).** Collaborative Activities Recommendation Based on Students' Collaborative Learning Styles Using ANN and WSM. Interact. Learn. Environ., Vol. 31, No. 1, pp. 54–67.
23. **Truong, T. C., Diep, Q. B. (2023).** Technological Spotlights of Digital Transformation in Tertiary Education. IEEE Access, Vol. 11, No. 1, pp. 4954-4966, doi:10.1109/ACCESS.2023.3270340.
24. **Venturelli, J. (1997).** Educación médica: nuevos enfoques, metas y métodos. Organización Panamericana de la Salud, No. 5.
25. **Vignery, K. (2021).** Findings and Methodologies sbout Student Networks, Learning, Performance, and Academic Achievement in Higher Education: A Literature Review on Quantitative Studies. Review of Education, Vol. 9, No. 3, doi:10.1002/rev3.3308.
26. **Wang, Q., Mousavi, A., Lu, Ch., Gao, Y. (2023).** Examining Adults' Behavioral Patterns in a Sequence of Problem-solving Tasks in Technology-rich Environments. Computers in Human Behavior, Vol. 147, No. 1, pp. 67–71, doi:10.1016/j.chb.2023.107852.

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**Corresponding author is Laura Ivonne Garay Jiménez.*