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Key Elements that Influence Adaptive Learning Through Data Analytics

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Abstracts

Despite the obvious benefits and growing interest in the use of adaptive learning in teaching, its widespread implementation presents some challenges such as data privacy and the lack of information in the literature on how different variables affect adaptive learning. The purpose of this research was to develop a new way of exploring the elements that affect adaptive learning through data analytics. It was a mixed research, where a literature review and a structural analysis were carried out. A panel of twelve experts allowed to reveal important findings. The results underline the potential of adaptive learning to revolutionize education by addressing the particular needs of each student, through variables such as learning style, predictive models and analysis of learning patterns, among others. It is concluded, among other aspects, that the implementation of adaptive learning remains a challenge, but considering its possible advantages, investment in research on how to increase its adoption rate by managing the identified variables will bear fruit in student, institutional, and economic performance.

1. Introduction

Through information and communication technologies, man has developed ways to analyze data about human behavior at an exponential growth rate (Alyoussef & Al-Rahmi, 2022). The use of this data allows universities and colleges to understand why their students buy their products, the best times for offers, and how to improve learning. Big data has gained great momentum among academics and professionals (Vassakis et al., 2018). When included as a tool for adaptive learning (AL), it allows the analysis of a large volume of data to offer an educational model based on personalized education (Gligorea et al., 2023).

Learning analytics and AL are linked as both foster learner-centered education with technological support. Furthermore, AI-powered AL empowers students and provides them with essential skills to thrive in the digital age (Varshney et al., 2023). Likewise, it offers students personalized instruction tailored to their individual needs, preferences, and learning pace (Aggarwal, 2023). In this sense, data analytics is crucial to identify student needs as this is where AL starts (Villegas-Ch et al., 2020).

By analyzing and interpreting student data, AL systems make decisions to deliver personalized learning experiences, optimize learning outcomes, and improve learner engagement (Gligorea et al., 2023). Studies in the academic literature demonstrate the importance that AL has gained in recent years, for example, in Khan et al. (2022), the role of artificial intelligence and big data in e-learning system adaptation was examined, revealing that these tools facilitate the execution of the teaching and learning process smoothly. Similarly, Arsovic and Stefanovic (2020) presented an AL model for personalized learning, where the results of data analysis showed that students who learned from an adaptive course achieved better performance in several aspects.

The previous studies show the growth of literature on this topic. However, not much literature has been found on how different variables affect AL through big data. Thus, this study aims to examine the elements that influence AL when using data analytics. To achieve this, the structural analysis technique Cross-Impact Matrix with Multiplication Applied to a Classification (MICMAC) was used, since it is a tool that studies variables and their interactions, through the relationships of dependency and influence of each of the variables with respect to the others (Arango & Cuevas, 2014). Consequently, the classification of the variables into four categories was obtained. The results of this study are relevant because it offers useful information for both researchers and professionals in the field while highlighting future research directions.

2. Methodology

In this study, qualitative and quantitative methods were applied, so it was a mixed type of research (Sampieri, 2018). A literature review (LR) was carried out to identify and select the elements that make up the studied system, which in this case is the AL and data analytics. Likewise, it is non-experimental, descriptive, and correlational, because the phenomena and relationships or associations between variables are described without manipulating them (Hernández et al., 2014). The methodological procedure that was addressed for the development and obtaining of results in this research is described below.

A) Identification of experts and determination of the population sample: The sample was selected by non-probabilistic convenience sampling. Twelve (12) multidisciplinary experts were selected for their experience, availability, and proximity to the research. The sample consisted of experts in educational data analytics (1), experts in pedagogy and psychology (2), educational technology (2), educational assessment and measurement (2), information technology and security (2), and teachers with experience in educational technologies (3). These experts allow a comprehensive perspective where technical, educational, psychological, and ethical aspects are combined.

B) Literature review and variable selection: An LR was conducted over the last seven years on AL and big data in education. A total of 19 variables were found.

C) Application of the MICMAC technique: First, the influence and dependency matrix is built with the variables resulting from the previous stage and the influence that one variable exerts on another is assessed, without filling the main diagonal because a variable does not influence itself. Then, in the intersection box of each variable, a value corresponding to the scale between zero (0) and three (3) must be marked, where zero (0) means zero influence/dependency; one (1), indicates weak influence/dependency; two (2) means medium influence/dependence; and three (3) indicates strong influence. This process allows to show which are the key variables for the studied system.

D) Report and interpretation of results: Once the matrix is complete, the plans are graphed and the results are analyzed to obtain the variables that must be prioritized to provide solutions in AL through data analysis.

3. Results

Below are the results obtained after applying the proposed methodology. Table 1 shows the results of the LR of academic texts on AL and data analytics, which were selected because they are part of peer-reviewed indexed journals, the documents belong to the time period from 2017 to 2023. Six categories were identified: Student data, Student interactions, Educational content, Algorithms and analytical models, Educational environment and context, and Evaluations and feedback, for a total of nineteen variables. The table shows the six categories and the variables that make them up.

Table 1. Results of the LR on the AL and data analytics

#	Name	Description
1	Student data	
a)	Previous academic performance	Grades, exams, assessments and prior skills.
b)	Learning style	Visual, auditory, kinesthetic, etc.
c)	Study behavior	Time spent studying, reading patterns, participation in forums or online activities.
d)	Motivation and commitment	Level of intrinsic or extrinsic motivation, participation in activities and tasks.
e)	Demographic profile	Age, gender, socioeconomic level, and cultural context.
2	Student interactions	
a)	Interaction with educational platforms	Usage time, clicks, navigation in the virtual environment.
b)	Feedback	Comments received and given by the student, answers to exercises, self-assessments.
c)	Participation in collaborative activities	Online discussions, teamwork, forums and wikis.
3	Educational content	
a)	Difficulty of the content	Level of complexity of the topics, sequencing of the material.
b)	Content format	Types of resources (videos, readings, questionnaires), adaptability of materials.

c)	Content customization	Degree of customization based on the student's progress and needs.
4	Algorithms and analytical models	
a)	Predictive models	Algorithms that predict student success or need for intervention
b)	Adaptive recommendations	Personalized suggestions for content, activities or resources.
c)	Analysis of learning patterns	Identification of behavioral patterns that predict performance.
5	Educational environment and context	
a)	Technological infrastructure	Access to digital platforms, internet quality, devices used
b)	Institutional policy	Standards and guidelines for the implementation of AL.
c)	Teacher training	Level of knowledge and skills of teachers in the use of data analytics tools.
6	Evaluations and feedback	
a)	Frequency and type of assessments	Formative, summative, diagnostic, and self-assessments.
b)	Progress analysis	Comparison of current achievements with established objectives.

Source: Authors

Once the variables were established, those considered most relevant by the experts were filtered through group workshops. Table 2 shows the variables selected to apply the MICMAC technique. Twelve were selected, which act together to create learning environments adapted to the individual needs of students. The first column corresponds to the variable number; the second column, to a code assigned to the variable; and the third, to the name of the variable.

Table 2. Variables selected for the structural analysis with MICMAC.

#	Variable code	Variable Name
1	V1	Previous academic performance
2	V2	Learning style
3	V3	Study behavior
4	V4	Interaction with educational platforms
5	V5	Participation in collaborative activities
6	V6	Content customization
7	V7	Predictive models
8	V8	Adaptive recommendations
9	V9	Analysis of learning patterns
10	V10	Technological infrastructure
11	V11	Teacher training
12	V12	Progress analysis

Source: Authors

As a next step, the cross-impact matrix was built with the previously selected variables. The Matrix of direct influence/dependency can be seen in Figure 1, which shows the influence/dependency relationship of the variables. As can be seen, the first row and the first column correspond to the code assigned to each variable; the second row corresponds to the influence relationships of the variable Previous academic performance (V1) with the others. In this sense, the influence relationship between V1 and V1 is null (0); the relationship between V1 and V2 is strong (3); the relationship between V1 and V3 is equally strong; the relationship between V1 and V4 is moderate (2); the relationship between V1 and V5 is strong, the relationship between V1 and V6 is moderate. In this way, the Matrix of direct influence/dependency is interpreted.

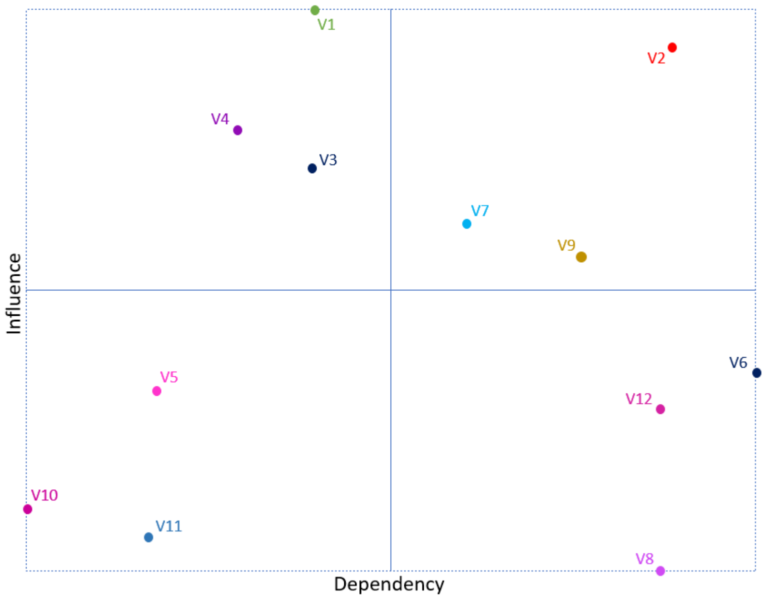
Figure 1. Matrix of direct influence/dependency

Influence	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1	0	3	3	2	3	2	3	3	2	3	1	3
V2	3	0	2	1	2	2	3	3	3	2	3	3
V3	1	3	0	2	1	3	2	2	3	1	2	3
V4	1	3	2	0	2	3	3	3	3	1	0	3
V5	2	2	1	2	0	3	1	1	1	1	2	1
V6	1	2	1	1	2	0	1	2	3	1	2	1
V7	2	3	2	2	2	1	0	3	3	1	1	2
V8	2	0	1	1	1	3	1	0	0	0	2	1
V9	2	2	2	3	1	3	1	2	0	2	0	3
V10	1	2	2	1	0	1	2	1	1	0	1	2
V11	2	1	1	1	1	2	1	1	1	1	0	1
V12	1	2	1	1	1	1	2	2	2	1	2	0

Source: Authors

As a result of the matrix of direct influence, the Plane of direct influence was drawn, which visually reveals the classification by categories of the variables: Key (high influence and high dependency), Determinants (high influence and low dependency), Autonomous (low influence and low dependency) and Results (low influence and high dependency). As can be seen in Figure 2, in the quadrant of the key variables (upper right quadrant), the variables V2, V7, and V9 were located; in the quadrant of the determinant variables (upper left quadrant), the variables V1, V3, and V4 were located; in the quadrant of the autonomous variables (lower left quadrant), the variables V5, V10, and V11 were located; and in the quadrant of the Results variables (lower right quadrant), V6, V8, and V12 were located.

Figure 2. Plane of direct influence



Source: Authors

To clearly explain the results obtained from the application of the MICMAC technique, the results are detailed in Table 3. As can be seen, the table is composed of three columns, Variable Type (category in which it was classified), Variable (name of the variable), and the Code.

Table 3. Classification of variables/factors by direct influences and dependencies

Variable Type	Variable	Code
Key, strategic or challenge	Learning style	V2
	Predictive models	V7
	Analysis of learning patterns	V9
Determining or influential	Previous academic performance	V1
	Study behavior	V3
	Interaction with educational platforms	V4
Autonomous or excluded variables	Participation in collaborative activities	V5
	Technological infrastructure	V10
	Teacher training	V11
Dependent or result	Content customization	V6
	Adaptive recommendations	V8

	Progress analysis	V12

Source: Authors

Interpretation of results

As can be seen in the table above, the key variables are Learning style (V2), Predictive models (V7), and Analysis of learning patterns (V9). These variables are characterized by having a high impact on the personalization of learning, but they are only effective if they are supported by the analysis of data collected from other sources in the educational environment.

The variables classified as determinants are Previous academic performance (V1), Study behavior (V3), and Interaction with educational platforms (V4). This group of variables is characterized by having a high impact on the personalization and adjustment of learning, but they can act relatively independently of other variables. Their data are direct and do not need as much support from other variables to provide related information.

The variables classified as autonomous are Participation in collaborative activities (V5), Technological infrastructure (V10), and Teacher training (V11). These variables have a low influence and dependency within AL systems since their impact on personalization and adaptation takes a backseat and they do not depend on other variables to function correctly.

The variables classified as results are Content customization (V6), Adaptive recommendations (V8), and Progress analysis (V12). These variables, although important in the general educational context, have a low direct impact on AL systems and, at the same time, depend heavily on other variables or conditions to have a significant effect on the teaching-learning process.

4. Discussions

AL is constantly improving as significant investments are made in the implementation of new technologies and techniques (Muñoz et al., 2022). On the other hand, big data is observed by organizations around the world and faces many dilemmas and challenges similar to those posed for years by the exchange of information and knowledge, the prioritization of technology over human sociology, and the phenomenological perspective of knowledge (Ruh, 2023). In this sense, the actual use of AL in courses remains low, despite the positive attitudes of institutional leaders toward its adoption and promising results from early studies on its effectiveness (Mirata et al., 2020).

The aim of this research was to develop a new way of exploring the elements that affect AL through data analytics. According to the proposed methodology, the relationships between the twelve variables were examined: Previous academic performance, Learning style, Study behavior, Interaction with educational platforms, Participation in collaborative activities, Content customization, Predictive models, Adaptive recommendations, Analysis of learning patterns, Technological infrastructure, Teacher training, and Progress analysis.

The results validated and explored the variables to investigate the structure of the AL and the analysis of big data. The findings of this research show that, within this system, the most critical variables, due to their high influence and high dependency, are Learning style (V2), Predictive models (V7), and Analysis of learning patterns (V9). These variables have a high influence, therefore, they significantly impact the AL, but they also depend on the other variables related to the previous data.

Previous research such as those developed by Deng et al. (2020) and Mirata et al. (2020), indicate that the high dependency of these variables on others implies that AL needs reliable data to function effectively. In this sense, it is important to have data analysis systems capable of capturing data on the student's previous academic performance, and interactions with educational platforms (Cheung et al., 2021), from different sources of information (Taylor et al., 2021). However, the associated issues around privacy protection, especially its implications for students as data subjects, have been an obstacle to its large-scale adoption (Tsai et al., 2020).

On the other hand, the variables classified as Determinants are Previous academic performance (V1), Study behavior (V3), and Interaction with educational platforms (V4). They are highly influential, but their dependency on other variables is low, which makes them autonomous pillars within the AL system. These results coincide with previous research such as the one developed by Khan & Ghosh (2021), where it is stated that the variable V1 plays a critical role in personalization since it acts as a reliable predictor of the student's needs.

So et al. (2023) also show that both the V3 and V1 variables play a key role when implementing AL systems. This indicates that well-managed historical data provide a basis for AL systems, even in the absence of real-time monitoring of behavior. Similarly, Srinivasa et al. (2022) reveal that Study behavior is a crucial indicator that allows the system to adjust the pace and difficulty of materials almost automatically in AL. This reinforces the idea that certain student habits and patterns can be more direct predictors and, therefore, easier to manage.

The Autonomous variables characterized by their low influence and low dependency are Participation in collaborative activities (V5), Technological infrastructure (V10), and Teacher training (V11). These variables facilitate AL through data analytics but do not show a high impact. Studies such as the one carried out by Marienko, et al. (2020), show that variables V10 and V11 are essential for the functioning of the system, but do not generate a differentiating impact on the personalization of learning. In this sense, AL entails new requirements for students, teachers, and staff, so it is necessary to develop the necessary skills and experience.

Regarding the variable V5, Raj & Renumol (2022) point out that in AL, this variable does not have a direct impact, because these systems are designed to adjust individual learning, based on data from each student autonomously. Likewise, Marienko et al. (2020) highlight that collaboration between students in itself does not provide structured data that the system can directly use to adapt resources. Although this variable can be beneficial with respect to social skills and personal development, its contribution to individual performance through AL systems is more indirect.

The result variables, characterized by their low influence and high dependency, are Content customization (V6), Adaptive recommendations (V8), and Progress analysis (V12). These variables are fundamental to understanding how the AL responds to student data and how it continuously adapts and improves the educational experience in a personalized way. Likewise, these variables are the result of the adaptive process and reflect how learning systems adjust according to the data obtained from the student's behavior, performance, and progress.

The variable V6 is the result of managing the other variables in the AL. According to Hwang et al. (2020) and Taylor et al. (2021), AL technology provides personalized learning at scale by assessing the student's activity profile, learning analytics data, and machine learning and student skills.

For its part, the variable V8 is the result of key variables such as V7 and V9, since they suggest resources, activities, or specific learning paths for each student. Martin et al. (2020) note that the variable V8 depends on the information provided by the analysis of the determinants V1, V3, and the key variable V9. Finally, the variable V12, responsible for monitoring the student's progress, is fundamental in the AL system. According to Tempelaar (2020), this variable shows whether the student has achieved the established learning objectives to make the necessary adjustments, facilitating this process for the student.

One of the aims of the study was to classify the variables associated with AL using analytics. However, the classification presented cannot be said to be exhaustive, as it is based on the experience of a few experts, therefore, it would be beneficial to have a larger number of experts (Bazen et al., 2021). For the same reason, it is not intended to generalize the findings at this time, although some qualitative researchers oppose the term generalization, it could still be achieved under certain conditions (Creswell & Poth, 2016). Likewise, the number of variables or those selected may also limit the results. On the other hand, possible biases of experts are also taken into account. However, the resulting classification is the first systematic attempt to categorize the influential elements in AL.

5. Conclusions

Despite the obvious benefits and growing interest in using AL in teaching, its wide implementation presents some challenges such as data privacy and lack of information in the literature on how different variables affect AL. In this sense, the results of this research suggest that, to improve the adoption of AL through data analytics, the variables V1, V2, V3, V4, V7, and V9 should be taken into account. It also highlights the challenges faced by AL through data analytics, such as the privacy of students' data.

Future research should focus on exploring other variables besides those excluded in this study and the interdependency between the challenges in order to develop efficient strategies to overcome them. Furthermore, the results obtained can serve as a basis for future research on AL. Finally, the implementation of AL remains a challenge, but, considering its potential advantages, investment in thorough research on how to increase its adoption rate by managing the identified variables will pay off in terms of student, institutional, and regional economic performance.

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