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Predictive Models for Higher Education Dropout: A Systematic Literature Review[1]

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Abstract: School dropout is considered a complex problem and one that cuts across several levels of analysis. The development of predictive models has been a more dynamic and proactive response to tackle this problem. This research offers a systematic literature review on dropout prediction in higher education. The analysis period was from 2010 to 2020, searching scientific studies in six databases and working with a sample of 48 studies. The results indicate methodological and contextual characteristics of the cutting-edge literature on dropout prediction and enable the

[1] This is an unofficial English translation of the original Portuguese article provided by the authors, and it was not peer-reviewed.

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proposition of a research agenda for future studies. The analysis revealed an absence of research reporting or proposing management actions and educational policies that go beyond applying dropout predictive models.
Keywords: higher education dropout; state of the art; predictive models; university management

Aplicación de métodos predictivos en el abandono de la educación superior: Una revisión sistemática de la literatura
Resumen: Se considera que el abandono escolar es un problema complejo y que atraviesa por varios niveles y diemensiones de análisis. El desarrollo de modelos de predicción ha sido una respuesta más dinâmica y proactiva a este problema. La investigación tuvo el objetivo de revisar sistemáticamente la literatura sobre predicción de la deserción en la educación superior. El período de análisis fue de 2010 hacia 2020, compreendendo seis bases de datos de artículos científicos, y una muestra de 48 estudios. Los resultados indican características metodológicas y contextuales del estado del arte de la literatura científica en predicción de deserción y permiten proponer una agenda para investigaciones futuras. La muestra de estudios analizados evidenció la ausencia de investigaciones que reporten o propongan acciones de gestión y políticas educativas para más allá de la aplicación de modelos predictivos de deserción.
Palavras-clave: evasión en la educación superior; estado del arte; modelos predictivos; gestión universitaria

Aplicação de métodos preditivos em evasão no ensino superior: Uma revisão sistemática da literatura
Resumo: A evasão escolar é considerada um problema complexo que perpassa diversos níveis e dimensões de análise. O desenvolvimento de modelos preditivos tem sido uma resposta mais dinâmica e proativa ao enfrentamento desse problema. O objetivo desta pesquisa foi o de revisar sistematicamente a literatura sobre predição de evasão no ensino superior. O período de análise foi de 2010 a 2020, compreendendo seis bases de dados de artigos científicos e uma amostra de 48 estudos. Os resultados indicam as características metodológicas e contextuais do estado da arte da literatura em predição da evasão universitária, bem como permitem propor uma agenda de pesquisa para estudos posteriores. A amostra de estudos analisados evidenciou a carência de pesquisas que relatem ou proponham ações de gestão e de políticas educacionais para além de aplicação dos modelos preditivos de evasão.
Palavras-chave: evasão no ensino superior; estado da arte; modelos preditivos; gestão universitária

Predictive Models for Higher Education Dropout: A Systematic Literature Review[2]

Higher education in Brazil expanded significantly from the 1990s onward, and student demand for this level of education resulted in several challenges for educational managers, including student retention and dropout (Santos Junior et al., 2020). Student dropout is a recurrent phenomenon in higher education and has gained relevance in the educational policy agenda (Bernárdez-Gómez & Belmonte, 2020). According to the Higher Education Map (SEMESP, 2019),

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in 2017, the dropout rate in Brazilian regular higher education programs reached 18.6% in public and 25.8% in private institutions. The same research pointed out that the dropout rate in the distance higher education reached 27.9% in public and 34.9% in private institutions in 2017.

Higher education dropout can be analyzed at different levels — from nano to macro-dropout[3] — and permeates several other issues, such as student access, retention, and success (Lima & Zago, 2017). Thus, student dropout has countless impacts on the individual, institutional, and structural dimensions.

For the student, this process represents losing the opportunity of obtaining an undergraduate degree, implying the loss of time and financial resources. For the educational institution, student dropout means operational inefficiencies and losses due to the underutilization of organizational resources such as facilities, technology, and personnel (Silva et al., 2020).

Despite the multiple causes and effects related to dropout, it is possible to address this issue by trying to predict its occurrence and intervening preventively. With the increasing use of educational data mining since 2014 (Agrusti et al., 2019), several methodological strategies for dropout prediction have emerged, such as decision trees (Hasbun et al., 2016), Bayesian networks (Sarra et al., 2019), logistic regression (Zhang & Rangwala, 2018), and neural networks (Martinho et al., 2013).

Against this backdrop, this research offers a systematic literature review on applying predictive models to higher education dropouts. The findings can be helpful for researchers and public managers to develop their own predictive models and plan and implement effective educational public programs and policies to fight and manage this problem in Brazilian higher education institutions (HEIs).

This article has five sections, including this introduction. Section 2 presents a context of uses and studies related to applying predictive models to student success in higher education. Section 3 describes the methods used to carry out the systematic literature review (SLR). Section 4 presents the results obtained and discusses the findings, followed by section 5 with final considerations and adopted references.

Predictive Models Applied to Student Success in Higher Education

The first studies on retention, dropout, and success in higher education emerged in the US between the 1930s and 1960s, and the production of empirical data marked this period. The first theories on the issue of student retention and dropout emerged only after the 1970s, with the seminal works of William Spady and Vincent Tinto (Berger et al., 2012). Since then, vast literature was developed over the next two decades as a response to the structural and demographic changes in the US education system.

The technological revolution in the late 1990s and early 2000s imposed a new transformation on the American educational system. New and sophisticated Internet-based software technologies allowed universities to manage large academic and institutional databases and explore online distance learning (Picciano, 2012). The expansion of these educational programs increased concerns about

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[3] *Nano-dropout* refers to small administrative changes such as changing the time of the lessons or the teaching modality (to classroom or distance learning) or choosing a different type of degree (degree with a teaching diploma or bachelor's degree). Thus, the student goes through changes in how they attend the program without dropping out completely. *Macro-dropout*, in contrast, refers to triple student dropout. The student leaves the program, the institution, and the higher education system. There are also intermediate levels: *micro-dropout*, where students leave the program but enter another program of the same institution, for example; and *meso-evasion*, where students leave the program and the institution but enter a program in another institution, i.e., they are still in the higher education system (Lima & Zago, 2017).

dropout behavior since student dropout rates were higher for online than in regular programs (Park & Choi, 2009). Therefore, this period witnessed a review of existing theoretical dropout models to adapt them to the context of online distance learning (Rovai, 2003).

Information and communication technology continued to advance dramatically in the United States in the first two decades of the twenty-first century. This progress facilitated the emergence, in the early 2000s, of computational solutions to prevent dropout behavior, which helped university managers to understand the problem considering demographic and behavioral dimensions. Such solutions also allowed working on another problem emerging from the dropout risk: the time to complete higher education (EAB, 2019). Advances continued, and the development of software capable of generating, storing, and processing massive amounts of data allowed some universities to test sophisticated statistical predictive analysis techniques. These techniques were recognized as promising tools to identify and classify patterns, offering valuable data to address problems related to student retention and academic success (Campbell et al., 2007), as observed in some experiences reported in the literature.

One of these experiences that stands out is the pioneering *Predictive Analytics Reporting Framework* (PAR) initiative, conducted between 2010 and 2014 with the participation of 20 institutions associated with the Western Cooperative for Educational Technology (WCET) and funded by the Bill & Melinda Gates Foundation. The PAR project was a joint effort to use predictive analytics to improve students' retention and completion rates in online distance learning programs (Wagner & Longanecker, 2016). Each institution offered anonymized academic data from its students and programs to form an extensive database maintained by WCET, the organization responsible for building predictive models, data management, and operationalizing the project goals and activities (Ice et al., 2012).

In 2012, another initiative using predictive models was started by the Georgia State University (GSU). This experience is possibly the most successful in the United States. That year, GSU decided to transform its student counseling and guidance service, making it proactive rather than reactive. The institution analyzed ten years of academic data, creating the Graduation and Progression System (GPS) — a software based on predictive techniques that send preventive alerts to counseling office staff indicating students who are at high risk of dropping out or risk of not completing their respective programs on time (GSU, 2017). The GPS contains more than 800 risk alert indicators and provides, through a sophisticated dashboard, analyses of students' academic progress that allow the counselor to identify potential obstacles to student success and trigger early interventions to overcome them (Kurzweil & Wu, 2015).

GSU also uses predictive data to support first-year students even before the year begins. The predictive model identifies incoming students at higher academic risk and asks them to attend the Summer Success Academy — a 7-credit summer course program (Kurzweil & Wu, 2015). During this period, the institution offers tutoring, academic guidance, and academic development and financial training programs (GSU, 2021).

In 2014, not only GSU but Arizona State University (ASU) and the University of Texas at Austin (UT Austin) were already recognized as leaders in the use of predictive techniques in the United States (Paterson, 2019). These three universities that same year joined with eight other institutions[4] to form the University Innovation Alliance (UIA), a consortium of public research

[4] Iowa State University, Michigan State University, Ohio State University, Oregon State University, Purdue University, University of California – Riverside, University of Central Florida, and University of Kansas. Currently, the *University of Kansas* and the *University of Texas – Austin* are no longer part of UIA, while four other universities have joined the consortium: North Carolina A&T State University, University of Illinois Chicago, UMBC, and Virginia Commonwealth University.

universities committed to increasing the number and diversity of graduate students in the United States through shared innovation and collaborative learning (UIA, 2021a).

In 2015, based on successful experiences at GSU, ASU, and UT Austin, and with funding from the Bill and Melinda Gates Foundation, the UIA was launched to promote the scale-up of predictive tools for the other institutions forming the consortium (UIA, 2021b). The initiative's main objective was to increase student retention and graduation rates — particularly for low-income, black, and first-generation students[5] — by analyzing institutional data, identifying early signs of dropout behavior, and creating preventive interventions (UIA, 2020). The project was designed so that the three universities with more experience in this field mentored the others (Paterson, 2019).

The three experiences presented (PAR, Georgia State University, and University Innovation Alliance) — two of them conducted collectively — show that predictive modeling applied to student success management (including management of dropout behavior and student retention) has been a practice in the US for at least ten years. This technology has been increasingly adopted by higher education institutions in that country, getting the attention of New America, a non-profit organization based in Washington, D.C., which has published studies to analyze the potential of predictive tools and identify best and bad practices related to these instruments. New America published three reports on the subject in 2016, 2017, and 2018.

The first was dedicated to examining how higher education institutions were using predictive models and outlined the challenges of doing so ethically (Ekowo & Palmer, 2016). The ethical use of this tool was discussed again in the second report, and five guiding practices were suggested to university managers: 1) having a vision and a plan; 2) building a support structure; 3) ensuring the proper use of data; 4) developing predictive models and unbiased algorithms; 5) meeting institutional goals and improving student performance through careful intervention (Ekowo & Palmer, 2017). The third report had a more practical objective. It offered tools so educational institutions could decide whether it is better to develop prediction systems in-house or to hire specialized external providers — in this case, suggesting the steps to choose the best and most ethical ones (Palmer, 2018).

This section presented so far the developments and advances regarding predictive tools in the US, showing how higher education institutions in the country have been testing and using, for at least one decade, the approach of students' success prediction to guide management practices. This does not mean that there are no other international experiences in progress, but apparently, these are still concentrated in experimental and academic studies, not reaching the scale and degree of dissemination observed in the United States. Even if only academic studies on predictive techniques in higher education are considered, the broad US hegemony in comparison to other countries and continents is proven — at least regarding predictors and early warning systems for students at risk of dropping out — as demonstrated by the literature review carried out by Liz-Domínguez et al. (2019).

In Brazil, the literature on predictive models applied to higher education is still incipient, mostly published in congresses in the area of computing, and, in general, it is immersed in the field of data mining, as demonstrated by the works of Colpo et al. (2020) and Maschio et al. (2018). This scenario may change with more research on the subject, either to report and analyze case studies or to conduct systematic studies such as the research presented in this article, following the steps of other authors who have worked to identify factors that influence the students' dropout behavior in higher education (Agrusti et al., 2019; Alturki et al., 2020; Proaño & Villamar, 2018).

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[5] Students who are the first in their families to access higher education.

Methods

This study is a systematic literature review (SLR) seeking to discuss the evidence (Kitchenham et al., 2009) on higher education dropout based on predictive methods. The review followed rigorous protocol based on the literature and was carried out in three main phases: i) planning; ii) development; and iii) dissemination/publication of results.

Three research questions (RQs) were prepared according to the criterion of PICOC systematic studies (Scannavino et al., 2017), which stands for *P* – population (full scientific articles evaluated by peers in a database of scientific articles of high academic reputation on university dropout); *I* – intervention (bibliometric research); *C* – comparison (applications in the Brazilian and international context, differences in variables and methods); *O* – outcomes (recent literature and construction of a research agenda for studies on higher education dropout); and *C* – context (scenario of the application at the country level).

The research questions are:

- RQ1 – What are the methodological and contextual characteristics of the recent literature on predicting dropout of higher education students?
- RQ2 – What determinant variables explain and predict dropout of higher education students?
- RQ3 – According to the literature studied, what actions have the HEIs developed to address students' dropout behavior, in addition to applying predictive models?

Thus, the search string used terms in English that correspond to the research scope to increase the number of articles found. After carrying out a pilot search by title, keywords, and abstract, conducting successive refinements, and searching relevant terminology, the final string obtained was:

(dropout OR "drop out" OR "student desertion" OR "academic success") AND ("higher education") AND ("predictor models" OR "dropout prediction" OR "educational data")*

In this work, a broad automatic search strategy was applied in six databases and search engines in a 10-year temporal filter: ACM Digital Library, IEEE Xplore, Scielo, Science Direct, Scopus, and Spell. For the Brazilian database Scielo, the string was also executed in Portuguese, but the result was irrelevant since no article was found. The search took place on October, 2020, exclusively using the outlined strategy.

Thus, to select the relevant studies, inclusion criteria (IC) and exclusion criteria (EC) were defined in this SLR, as follows:

Inclusion

IC1: The study reports the determinants of school dropout in higher education using techniques and predictive models applied to school dropout.

Exclusion

EC1: The article was not published in the last ten years;

EC2: The article does not deal with undergraduate student dropout;

EC3: The article does not deal with predictive models for dropout;

EC4: The study is an older version of another study already selected;

EC5: The full article is not available;

EC6: The work is not a full article published in conference annals or in a journal;

EC7: The work is not a primary study.

Following the established criteria, the selection process went through two stages: i) reading the metadata (title and abstract) and ii) reading the full text. Each article was framed in one of the IC or EC for selection or exclusion. Thus, the articles selected fit into a data extraction form aiming to answer the research question (Table 1):

Table 1

Data extraction form

Fields of Extraction		
Means of publication	Context	Sample
Year of publication	Modality	Main dropout determinant variables
Authors' affiliation	Technique/method	Main results
Number of authors	Research nature	Forms of addressing the issue beyond prediction
Type of publication	Data sources	Suggested gaps

Note. Elaborated by the authors.

The online platform Parsif.al[6] was used to support the SLR. It is a support software to carry out systematic studies, from the protocol documentation to data extraction of the selected articles. In addition, the Google Sheets tool was used to organize data and generate graphs of the results found.

Results and Discussion

The application of the search string in the databases using advanced search resulted in 119 articles, four from ACM Digital Library, 14 from IEEE Xplore, 34 from Scielo, five from Science Direct, 61 from Scopus, and one from Spell. Of the total, 18 were duplicated, leaving 101 for metadata analysis. Of these, 57 were pre-selected after reading the title and abstract and, at the end of the complete reading, 48 works represented the final sample, as shown in Figure 1.

[6] https://parsif.al/

Figure 1

Flow of information about the process of selecting the articles

Note. Elaborated by the authors.

Table 2 lists the articles eliminated according to the exclusion criteria applied, as defined by the SLR research protocol.

Table 2

Number of articles eliminated based on the exlusion criteria

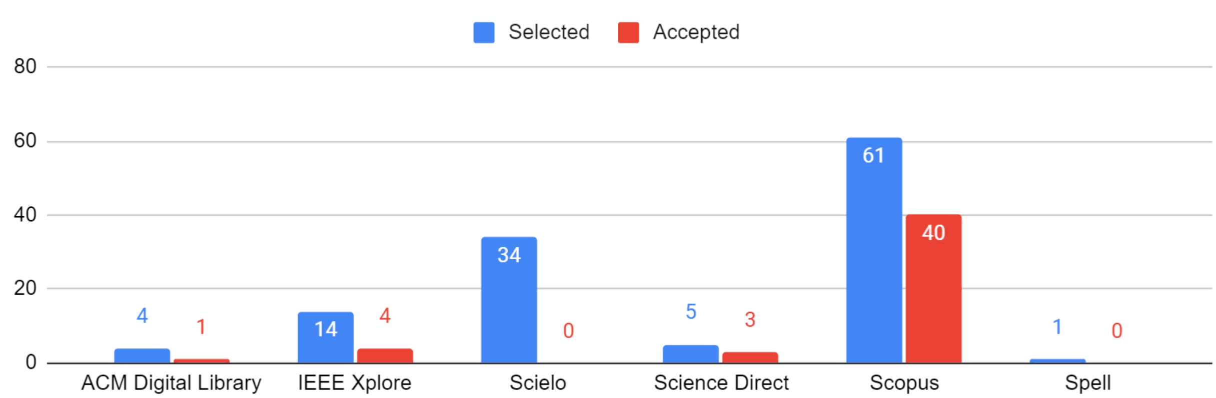
Exclusion Criteria (EC)							
EC1	EC2	EC3	EC4	EC5	EC6	EC7	Total
10	16	14	1	6	6	0	53 excluded

Note. Elaborated by the authors.

Therefore, 83.3% of the 48 selected articles were derived from a single search engine. The Scopus digital library was the most relevant database for this systematic study (Figure 2).

Figure 2

Articles found and selected per database

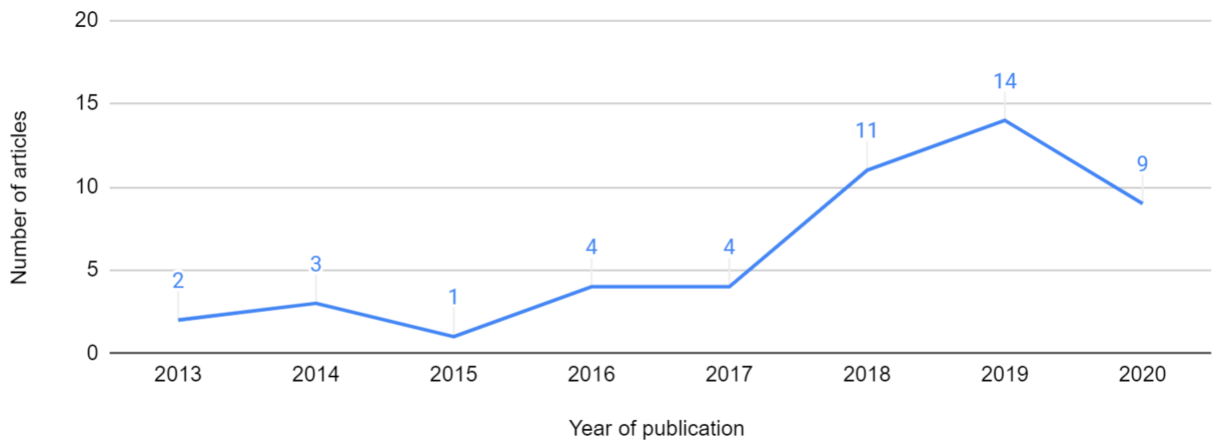


Note. Elaborated by the authors.

Although the search retrieved articles published in the last ten years, the first studies of the 48 selected articles were published only in 2013. A trend toward an increase in publications from 2015 is also noticeable (Figure 3), which highlights that this field of study has been increasing in recent years, corroborating the literature (Agrusti et al., 2019). It is noteworthy that the number of articles published in 2020 is not the total for the year. Data collection was conducted in October 2020, and other articles may have been published after this date.

Figure 3

Studies selected, per year of publication

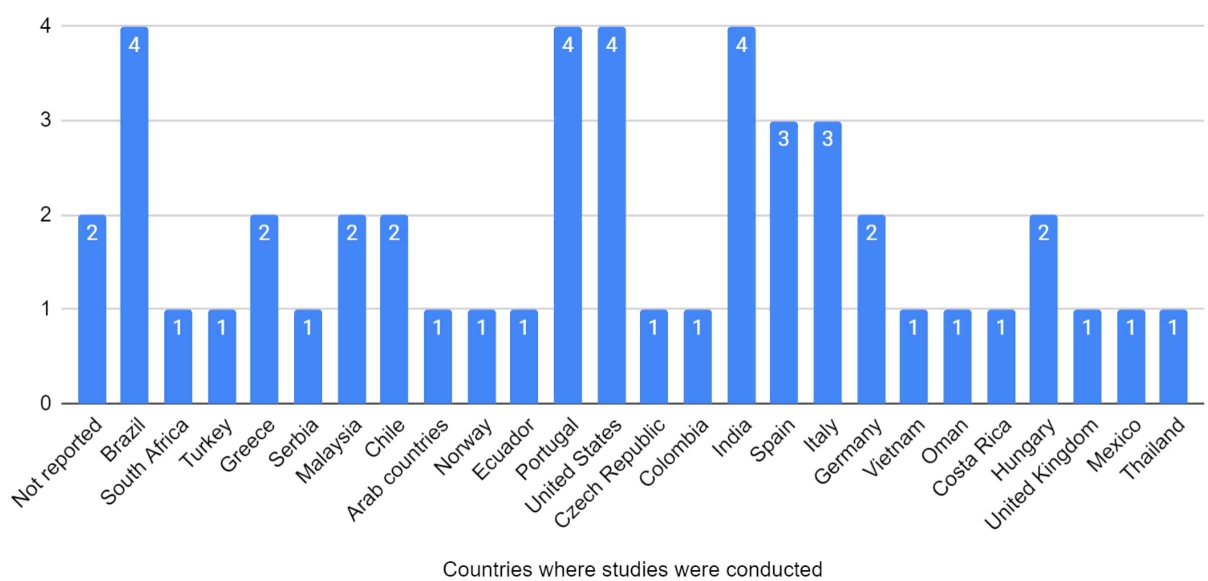


Note. Elaborated by the authors.

Among the 25 countries where the studies were conducted, four countries stand out with four articles each: Brazil, India, Portugal, and the United States.

Figure 4

Number of articles per country where studies were conducted

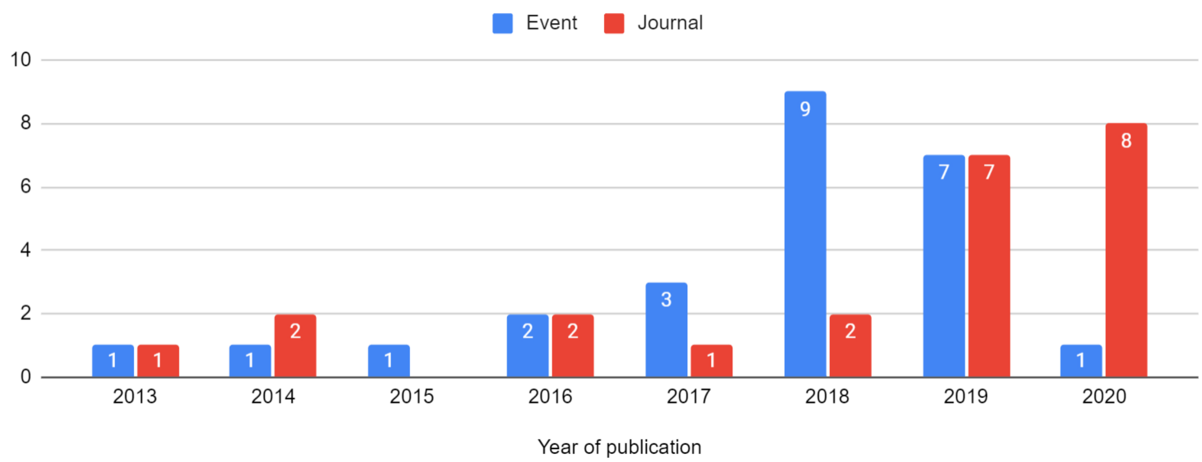


Note. Elaborated by the authors.

When verifying the type of publication, if published in journals or presented in academic events, in general, the highest number of articles (52.1%) were presented in events. However, the evolution through time shows that recent articles (published in 2020) were published in high-impact journals. In 2019, 2016, and 2013, the same number of articles were published in journals and presented in events, while in 2018, they were predominantly presented in events (Figure 5).

Figure 5

Means of publication per year



Note. Elaborated by the authors.

It is important to stress that the field of computing in Brazil recognizes presentation in events evaluated by peers as a practice as relevant as the publication in journals[7], given the existence of Qualis-Capes (Brazilian classification system) indicators for events in the field.

Among the methods used in models to predict student dropout, there is a growing interest in and application of approaches that involve computing techniques, such as educational data mining[8]. These involve knowledge discovery in databases (KDD) to obtain significant information and relationships among variables that may contribute to predicting school dropout (Agrusti et al., 2019).

Thus, regarding the predictive techniques adopted in the articles, those using data mining and machine learning algorithms stand out. Decision trees, Bayesian networks, logistic regression, and neural networks were the most mentioned techniques. Decision trees represent a hierarchical model in a tree structure with directed roots (Agrusti et al., 2019) that can be seen as a flowchart with rules, facilitating data interpretation.

As for the other types mentioned, Bayesian networks are probabilistic graphical classification models, which denote a representation of the joint probability distribution of the model variables (Agrusti et al., 2019).

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[7] https://www.gov.br/capes/pt-br/centrais-de-conteudo/CienciaComputacao20132015.pdf

[8] Data mining can use machine learning algorithms so the process of obtaining patterns is automated and based on a massive amount of data. This area of study adopts computational elements that allow computers to "learn" and recognize complex patterns based on data, and depending on the type of learning, making decisions considering such data (Han et al., 2011).

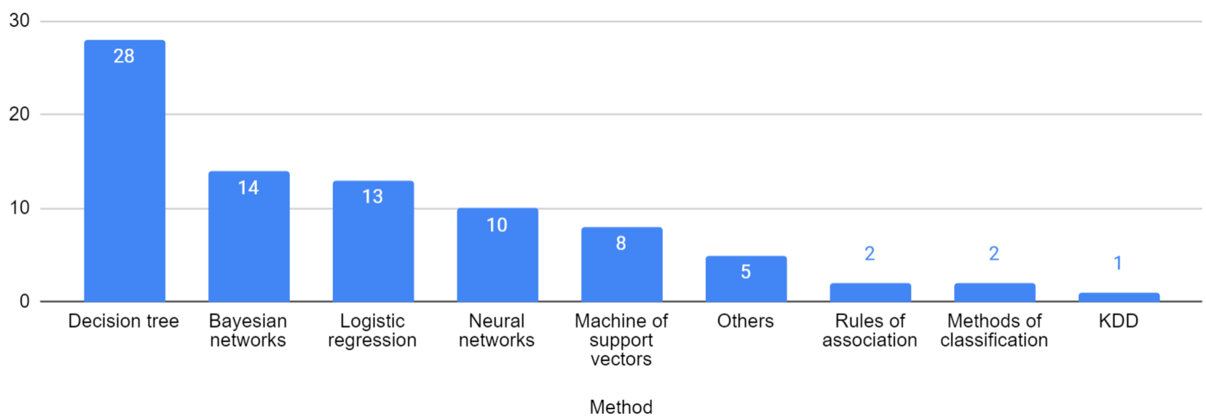
Logistic regression concerns the use of a statistical method to find patterns in the data through the relationship between two sets, such as X and Y, and in this case, allows the calculation of probabilities of the occurrence of a certain phenomenon (Silva et al., 2020).

Neural networks are computational models or mathematical objects inspired by the neural circuits of the human brain. Unlike the classical programming paradigm that requires the programmer to have prior knowledge of the problem to be solved, the implementation of neural networks is premised on the black box approach — it is not necessary for the programmer to understand a priori the mechanism underlying the classified phenomenon to create the correct algorithm (Agrusti et al., 2019).

The various techniques identified in the SLR were grouped considering the division of Agrusti et al. (2019), presented in Figure 6. Decision trees were adopted in 28 articles, while Bayesian networks were found in 14. These two classification methods have been considered the most popular in studies that address issues of student performance (Khasanah & Harwati, 2017), mainly due to the accuracy and precision of the models in relation to other algorithms.

Figure 6

Frequence of the use of classification techniques



Note. Elaborated by the authors.

Dias et al. (2008) consider decision trees advantageous in the educational context because they enable reaching decisions considering the most representative attributes. The decision rules represented in the form of a tree help understand a phenomenon based on the perspective of the vast majority of individuals, observing which factors are more influential when explaining a topic, in this case, the student's behavior of dropping out.

The second most discussed item was the Bayesian networks that verify, through establishing causal relationships, for example, a relationship of dependence between teaching-learning actions and the students' performance (Dias et al., 2008).

Although both predictive techniques can be quickly classified, they belong to different operational profiles. In this sense, decision trees perform the prediction based on splitting criteria of the training data and, at the same time, have a lower tolerance to noisy data than the Bayesian network. Thus, the selection of one or the other must consider the scenario in which they will be applied (Sharma et al., 2013).

Khasanah and Harwati (2017) established a comparison between the two techniques and suggested that, depending on the factors evaluated, the accuracy rate of these methods can be increased, demonstrating the importance of selecting the attributes of the most significant impact to improve the predictive models' assertiveness. Due to the advantages and disadvantages of each of the approaches, most of the articles combined techniques to predict dropout such as decision trees and logistic regression, or decision trees and Bayesian networks.

Regarding the education modality, most articles focused on regular education (~81% of the sample), while distance learning attracted attention from 2018 onward. As for the data source, only two studies used secondary data, which indicates the difficulty of accessing public and consolidated databases. Also, studies analyzing only one institution dominate the selected articles, limiting the models' predictive power, accuracy, and generalization.

Regarding the determinants of dropout, in a non-exhaustive way, the studies evaluate the following dimensions of variables or attributes:

- **Socioeconomic:** in this dimension, variables (also called attributes) refer to gender, ethnicity, age, income, marital status, type of transportation, number of children, if the student works, the status of work, if the student has a computer, and the level of computational knowledge. Level of education and occupation of parents, distance from school to student's residence, type of secondary school, use of student financing and other mechanisms to facilitate completing higher education, among others;

- **Academic:** variables/attributes such as attendance, hours of study, partial grades, overall average grade, passed and failed courses, library consultations, data on the student's academic success in high school, participation in tutoring and monitoring are used in this dimension. , other activities carried out by the student (extension, languages, sports, cultural, etc.);

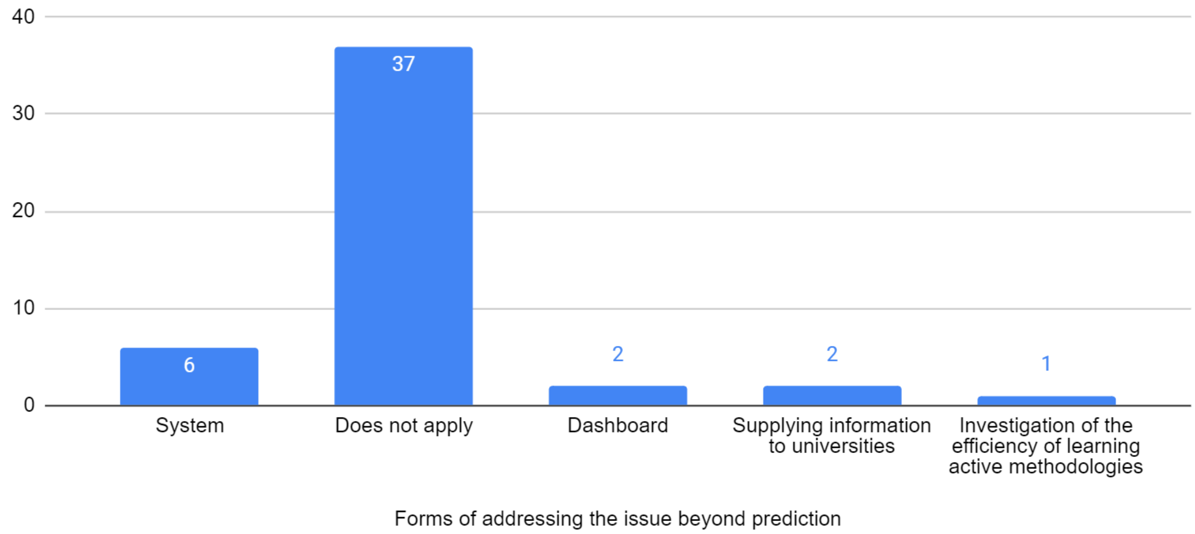
- **Psychologic and Health:** more recently, variables/attributes related to psychological and health aspects such as learning and memory difficulties, academic resilience, satisfaction with the method and with the class, degree of satisfaction with academic spaces; degree of satisfaction with tutoring, student well-being, health problems, social media, number of friends and time spent with them, university integration, community involvement, alcohol and cigarette consumption, level of motivation to entering the higher education program, indulging in bad habits;

- **Access:** studies that evaluate distance learning tend to develop predictive models based on variables/attributes related to access, such as logs performed in online environments and learning environments, access to videos, blogs, questionnaires, and different available resources.

An important gap verified in the sample of articles selected is that, for the most part, the studies do not carry out or propose coping actions beyond the prediction of students' dropout behavior (Figure 7). In Brazil, only one study proposed actions to address the issue. It was a study by researchers from the Federal Institute of Ceará (Freitas et al. , 2020) in which the authors created a platform for predicting dropout based on socioeconomic information.

Figure 7

Actions to face dropout, beyond predictive models



Note. Elaborated by the authors.

Of the 11 studies that went beyond predicting students' dropout behavior, the development of systems stands out (reported in six articles), as well as applications focused on business intelligence, dashboards, and providing information to universities (warning systems). In the context of the educational institution, only one of the articles explored the effect of active learning methodologies in addressing the issue of students dropping out.

Figure 8 presents a cross-reference of the dimensions of attributes and variables, teaching modality, country of research, and articles.

Figure 8

Dimension, modality, country of research, and articles

Dimension	Modality	Country	Articles
Socioeconomic	**Regular**	Brazil	(Martinho et al., 2013) (Freitas et al., 2020)
		Serbia	(Išljamović et al., 2016)
		Chile	(Hasbun et al., 2016) (Olaya et al., 2020)
		Ecuador	(Noboa et al., 2018)
		Czech Republic	(Vaclavek et al., 2018)
		Colombia	(Hernandez et al., 2018)

Figure 8 (Cont.)

Dimension, modality, country of research, and articles

Dimension	Modality	Country	Articles
Socioeconomic	**Regular**	India	(Hussain et al., 2018) (Hegde & Prageeth, 2018) (Kamal & Ahuja, 2019) (Devasia et al., 2016)
		United States	(Jayaraman, Gerber, & Garcia, 2019)
		Italy	(Perchinunno, Bilancia, & Vitale, 2019) (Agrusti & Mezzini, 2020)
		Oman	(Krishnan, Begum, & Sherinon, 2019)
		Costa Rica	(Fernández-Martín et al., 2018)
		Hungary	(Kiss et al., 2019) (Baranyi, Nagy, & Molontay, 2020)
		Mexico	(Urbina-Nájera, Camino-Hampshire, & Barbosa, 2020)
		Portugal	(Miguéis et al., 2018) (Martins et al., 2020)
	Distance Learning	Greece	(Kostopoulos, Kotsiantis, & Pintelas, 2015) (Kostopoulos et al., 2017)
		United States	(Kang & Wang, 2018) (Kashyap & Nayak, 2018)
Academic	**Regular**	Brazil	(Martinho, Nunes, & Minussi, 2013) (Manrique et al., 2019) (Costa et al., 2019)
		South Africa	(Mashiloane & Mchunu, 2013)
		Turkey	(Tekin, 2014)
		Serbia	(Išljamović, Jeremić, & Lalić, 2016)
		Malaysia	(Badr et al., 2016) (Yaacob et al., 2019)
		Chile	(Hasbun, Araya, & Villalon, 2016) (Olaya et al., 2020)
		Not Identified	(Moscoso-Zea, Mayra, & Luján-Mora, 2017)

Figure 8 (Cont.)

Dimension, modality, country of research, and articles

Dimension	Modality	Country	Articles
Academic	**Regular**	Bahrain, Egypt, Jordan, Kuwait, Lebanon, Oman, Palestine, Saudi Arabia, Sudan	(Hussein & Khan, 2017)
		Ecuador	(Noboa, Ordóñez, & Magalhanes, 2018)
		Portugal	(Lima et al., 2018) (Martins et al., 2019) (Miguéis et al., 2018) (Martins et al., 2020)
		United States	(Zhang & Rangwala, 2018) (Jayaraman, Gerber, & Garcia, 2019)
		Czech Republic	(Vaclavek et al., 2018)
		Colombia	(Hernandez et al., 2018)
		India	(Hegde & Prageeth, 2018) (Kamal & Ahuja, 2019) (Devasia, Vinushree, & Hegde, 2016)
		Italy	(Perchinunno, Bilancia, & Vitale, 2019) (Sarra, Fontanella, & Di Zio, 2019) (Agrusti & Mezzini, 2020)
		Germany	(Askinadze & Conrad, 2016) (Behr et al., 2020)
		Vietnam	(Mai et al., 2019)
		Oman	(Krishnan, Begum, & Sherinon, 2019)
		Costa Rica	(Fernández-Martín et al., 2018)
		Hungary	(Kiss et al., 2019) (Baranyi, Nagy, & Molontay, 2020)
		Mexico	(Urbina-Nájera, Camino-Hampshire, & Barbosa, 2020)
		Thailand	(Lam-On & Boongoen, 2014)

Figure 8 (Cont.)

Dimension, modality, country of research, and articles

Dimension	Modality	Country	Articles
Academic	**Distance Learning**	Greece	(Kostopoulos, Kotsiantis, & Pintelas, 2015) (Kostopoulos et al., 2017)
		United States	(Kang & Wang, 2018) (Kashyap & Nayak, 2018)
		Spain	(Figueroa-Cañas & Sancho-Vinuesa, 2020)
Psychological and Health	**Regular**	Norway	(Giannakos et al., 2017)
		India	(Hegde & Prageeth, 2018) (Kamal & Ahuja, 2019) (Devasia, Vinushree, & Hegde, 2016)
		Italy	(Sarra, Fontanella, & Di Zio, 2019)
		Mexico	(Urbina-Nájera, Camino-Hampshire, & Barbosa, 2020)
Access	**Distance Learning**	Not identified	(Mishra & Mishra, 2018)
		Greece	(Kostopoulos, Kotsiantis, & Pintelas, 2015)
		Spain	(Figueroa-Cañas & Sancho-Vinuesa, 2019) (Lara et al., 2014) (Figueroa-Cañas & Sancho-Vinuesa, 2020)
		United Kingdom	(Mubarak, Cao, & Zhang, 2020)
		United States	(Kashyap & Nayak, 2018)

Note. Elaborated by the authors.

Final Considerations

This study carried out a systematic literature review (SLR) on dropout prediction in higher education from 2010 to 2020. The results indicate a recent evolution in studies on this issue, pointing out the geographical context where predictive techniques have been employed, the main variables and dimensions classified by teaching modality (regular or distance learning), and identifying the main gaps in the reviewed studies. In addition, the study highlighted the actions to address higher education dropout observed in the articles selected, especially in the United States, constituting a theoretical-empirical survey of successful practices that can inspire interventions in Brazilian higher education.

As described in the methods section, three research questions (RQ) guided the SLR. RQ1 sought to identify the methodological and contextual characteristics of the recent literature on predicting dropout of higher education students. RQ2 asks about the determinant variables that explain and predict dropout of higher education students. Finally, RQ3 seeks to know what actions the higher education institutions (HEIs) have developed to address the students' dropout behavior, in addition to applying predictive models.

When observing RQ1, the reviewed articles show the use of probabilistic predictive models related to data mining techniques to predict dropout, especially decision trees, which are applied even in combination with other methods. When addressing RQ2, variables related to the socioeconomic, academic, psychological and health, and access dimensions are most used in research carried out in different countries. It is noteworthy that studies predominantly focus on only one HEI. Finally, the results obtained in response to RQ3 showed that the vast majority of the studies analyzed are limited to exploring dropout prediction without advancing in actions to address the issue after gathering the data from the predictive models.

However, the results for RQ3 deserve some additional consideration since the availability and use of predictive models, per se, are not enough to mitigate the student's dropout behavior. It is necessary to develop management actions within HEIs and public policies in higher education systems, supporting students and adopting a preventive approach.

In HEIs, actions of retaining students and promoting academic success by applying predictive models, such as tutoring centers focused on welcoming and teaching-learning (Gutierrez et al., 2018), and the evaluation of other educational management actions aimed at improving academic performance can be developed. Also noteworthy is the role of the professor in motivating the student to overcome difficulties, prioritize studying, and progress with quality (Costa & Dias, 2015). In addition to early detection of the risk of dropout, educational institutions can contribute to reducing the asymmetry of information by offering vocational guidance to the student before choosing a higher education program (Bernárdez-Gómez & Belmonte, 2020; Cabral, 2018) by providing clear information about the courses, the profession (Bernárdez-Gómez & Belmonte, 2020), and about the job market.

In addition to the internal actions carried out by each HEI, public policies play a relevant role in dealing with the phenomenon of dropout, and this is clear in the Brazilian case of the National Student Assistance Plan (PNAES), created in 2010 by the Ministry of Education (MEC). This is considered a milestone in a policy to combat dropout, focusing on the permanence and completion of higher education within the scope of federal public education (Cabral, 2018; Santos Junior et al., 2020). In the sphere of private higher education institutions, public policy prioritizes student financing through the Student Financing Fund (FIES) and the program Universidade para Todos (PROUNI), which is a way of supporting the student's permanence in higher education, although this is not explicit in these instruments.

The existing public policies to support student permanence or student financing in Brazil address only part of the factors leading to students' dropout behavior. However, there are structural issues that can accentuate the situation of dropout of minority and vulnerable groups, political and economic factors such as the "increasing concentration of income and property; the extinction of jobs; unemployment; the transformation of universal rights into services offered on the market" (Azevedo et al., 2010, p. 3, our translation). These aspects associated with the COVID-19 pandemic can further increase dropout and accentuate inequalities (Nunes, 2021).

With these considerations, this work contributes to assessing how dropout prediction has been faced from the viewpoint of methodology, determining variables, and post-prediction (or the intervention actions adopted based on data gathered). The results can contribute to the field of computing by presenting the recent literature on predictive techniques. They also dialogue with educational management through the understanding of how research has unfolded the theme for preventive intervention actions aimed at students' retention and success. In other words, the early detection of dropout risk is essential to equip information managers, but it is only a first step. Based on the prediction, managers face the challenge of defining institutionalized actions to deal with dropout, planning and executing welcoming actions, pedagogical intervention, and others, depending on the main factors present in calculating the student's risk of dropping out.

Another contribution of this work is in public policies, because accurate knowledge of the factors determinant for higher education dropout facilitates the design of policies to assertively retain students and lead them to academic success. Comprehensive pilot projects involving multiple institutions to develop predictive solutions for dropout risk and intervention methodologies and pedagogical monitoring can provide evidence and help design these policies.

It is necessary to emphasize that this systematic literature review presents the limitation inherent to the choice of databases and the definition of search strings. Although relevant databases have been used in the field of research on dropout prediction, choices and definitions of different strings could result in other articles.

Thus, future studies using the same approach could include more scientific databases, encompassing the application of other strategies such as manual search in renowned national and international events that have not been indexed by the databases used in this study. Additionally, future literature reviews or theoretical-empirical research should dedicate to the following agenda: (i) proposition and application of actions to combat the dropout behavior and not a mere prediction; (ii) inclusion of variables that have not yet been explored, such as high school data, student's health, and extracurricular activities; (iii) creation of public databases to expand research, as is already the case with the Nilo Peçanha Platform, created by the Brazilian Federal Network for Professional, Scientific and Technological Education; and, (iv) evaluation of the impacts of educational management actions on dropout, both through qualitative and quantitative approaches.

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