Available online at http://www.journalijdr.com

IJDR

ISSN: 2230-9926

International Journal of Development Research
Vol. 09, Issue, 11, pp. 31710-31716, November, 2019

REVIEW ARTICLE

OPEN ACCESS

ACADEMIC ANALYTICS: A SYSTEMATIC REVIEW OF LITERATURE

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ARTICLE INFO

Article History:
Received 03rd August, 2019
Received in revised form
21st September, 2019
Accepted 06th October, 2019
Published online 30th November, 2019

Key Words:
Academic analytics,
Academic Management, Education.

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ABSTRACT

The educational environment is increasingly complex and competitive, a large quantity of data is generated that needs to be treated and interpreted competently. One area that emerges for this purpose is known as Academic Analytics. The objective of this article is to present the state of the art of the Academic Analytics research, and identify computational tools and indicators focused on academic management. For such, we carried out a systematic review of the literature, using all the databases included in the *Portal de Periódicos da Capes* (Web Portal of Academic Journals of the Coordination for the Improvement of Higher Education Personnel - CAPES). The search retrieved 177 academic articles, of which, after applying the exclusion/inclusion and quality criteria, 10 articles were selected for an in-depth analysis. Among the main results, we highlight some Educational Data Mining tools and Learning Analytics that were used to aid the academic analysis, in addition to presenting several indicators such as focus on the students, professors and academic management. In summary, it is likely that this review will provide researchers with an overview of the subject matter under study, and that it highlights research trends that could be the focus of future research.

Citation: Fábio Josende Paz and Silvio Cesar Cazella. 2019. "Academic analytics: a systematic review of literature", *International Journal of Development Research*, 09, (11), 31710-31716.

INTRODUCTION

In the information age, one of the most important and influential areas is education. The environment of the Higher Education Institutions (HEI) has become more complex and competitive than ever. According to Andrade and Ferreira (2016), Higher Education Institutions (HEI) have identified that it is essential to adopt technological platforms that provide support for the pedagogical transformation and management of the several dimensions of teaching. However, these platforms generate a significant amount of data that must be analyzed. In this way, several studies are performed applying Learning Analytics (LA) tools and Educational Data Mining (EDM) techniques converging into Academic Analytics. These expressions are often used and can be defined as: Educational Data Mining (EDM) according to Baker *et al*. (2011) aims to explore data sets collected in educational environments, making it possible to effectively understand students, how they learn, how learning takes place, in addition to other factors that influence learning. EDM techniques have already been applied in several studies (PRABHA, SHANAVAS, 2014, COSTA *et al*., 2015, PAZ, and CAZELLA, 2017) with satisfactory results, generating information to support educational managers.

Learning Analytics (LA) consists of measuring, collecting, analyzing, and interpreting the data generated in educational environments, allowing us to evaluate academic progress, predict the future, and identify possible problems (LONG e SIEMENS, 2011; JOHNSON *et al*., 2011). In turn, Rigo *et al*. (2014), stated that LA could aid in monitoring and visualizing several fundamental aspects of the teaching and learning process. Within this context, some studies used an automated data analysis technique known as Learning Analytics (ARNOLD, 2010; RIGO *et al*., 2014). The term Academic Analytics has been known for a little over a decade (CAMPBELL, DEBLOIS & OBLINGER, 2007; CAMPBELL & OBLINGER, 2007). Being a relatively new area, many terms are confused in the literature, in this sense Barneveld, Arnold and Campbell (2012) conducted a thorough study and proposed a conceptual framework that defines Academic Analytics as a process that provides the HEI with the data needed to support operational and financial decision making, and a guide to strategic actions. The authors argue that its use allows educational managers to access real-time indicators and historical data through dashboards about the institution's performance, its colleges, centers or departments, expanding to its courses (CAMPBELL & OBLINGER, 2007).

Corroborating this idea, Baepler and Murdoch (2010), and Siemens (2011) argue that the term emerged in higher education to organize the widespread use of EDM and LA practices, focusing on Business Intelligence (BI) tools for operational purposes at the university or college level. Long and Siemens (2011), Shum (2012), and Ifenthaler (2014) belong to a large group of authors that distinguish LA from Academic Analytics, the latter concept being more related to the institutional and supra-institutional level, connected to the concept of BI that for Chen *et al*. (2012) is the process of collecting, organizing, analyzing, sharing and monitoring information that support business management. Its objective is to allow an easy interpretation of vast amounts of data through dashboards, ad hoc queries, OLAP, indicators table, predictive modeling and data mining. According to Siemens (2011), LA benefits the students and professors, and Academic Analytics benefits the educational managers and administrators. In light of this scenario, this review article aims to present the state of the art in Academic Analytics research and to identify computational tools and indicators focused on academic management. This article is structured in five sections, including the introduction and the theoretical studies that ground this research. In section 2, materials and methods are presented, in section 3, follows the analysis of the results and discussion. To conclude, the final considerations and the references used in this study are presented.

MATERIALS AND METHODS

This study is characterized as a systematic literature review, which according to Dresch *et al*. (2015) serves to map, find, evaluate, and identify gaps to be filled, resulting in a coherent report or synthesis, providing a comprehensive and robust view, thus allowing researchers to keep informed of what has been studied in their areas of interest. In this sense, the focus of this systematic literature review was to present the state of the art on Academic Analytics research and to identify computational tools and indicators focused on academic management. For that end, the following steps were defined, according to Figure 1. Below, we present the steps of conceptualization and execution of the research, considering the adopted methodology.

Source: Adapted from Kitchenham, (2004) Gough et al., (2012), and Dresch et al., (2015).

Figure 1. Steps of the systematic literature review

In the first step we identified the central topic of this research study, which is Academic Analytics with Learning Analytics (LA), and we defined the main research question (RQ) that this study seeks to answer, which can be stated in the following way: "How the tools and methodologies of Learning Analytics are contributing to the University Academic Management within the context of Academic Analytics?". From this question, we identified four other questions of relevance, which are shown in Table 1.

Table 1. Guiding questions

Code	Question
Q1	Which tools and methodologies based on LA or MDE are being applied within the context of Academic Analytics?
Q2	Are there any specific tools for course coordinators?
Q3	What indicators are used for academic management?
Q4	How are these tools and methodologies contributing to Academic Management in HEIs?

Next, we defined the search strategy, identified keywords, and defined the terms of a search string:"academic analytics" OR ("academic management" AND ("Learning analytics" or "Educational Data mining")). We have chosen to perform the search of both terms, since Academic Management and Academic Analytics usually complement each other in the articles of the field. In the same sense, Learning Analytics (LA) is directly related to Educational Data Mining (EDM). Some authors consider LA as a fundamental part of EDM (Romero and Ventura, 2010), while others consider that LA goes beyond EDM since it is centered on human judgment (SIEMENS AND BAKER, 2012). These terms could appear in any part of the document, in addition, the period defined was from 2008 to April 2019 and only peer-reviewed articles in the English language and open for free consultation were considered. These rules were applied to search the databases of the *Portal de Periódicos da Capes*, which returned 177 academic scientific articles, distributed as presented in Table 2.

Table 2. Databases for retrieval of articles

Database searched	Articles
SpringerLink	26
Emerald	13
Springer (crossref)	21
Web of Science	24
Scopus	3
Other databases	90

We read the abstracts of the articles and applied the inclusion and exclusion criteria presented in Table 3, resulting in 18 articles to be read entirely.

Table 3. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Original article	Review article
Articles published since 2008	Duplicate articles
English language articles	Articles lacking open access
Peer reviewed articles	This is not an article although it is classified as such.
Articles focused on academic management	Articles lacking the keywords in the title or abstract
	Articles whose focus is not higher education

After reading the articles, we proceed to step 4, when we evaluated the quality and relevance of the studies judiciously, after which 8 articles were excluded, leaving 10 (ten) potential studies to answer the questions of this research. Figure 2 shows a summary of the article selection processes. A summary of the results will presented next.

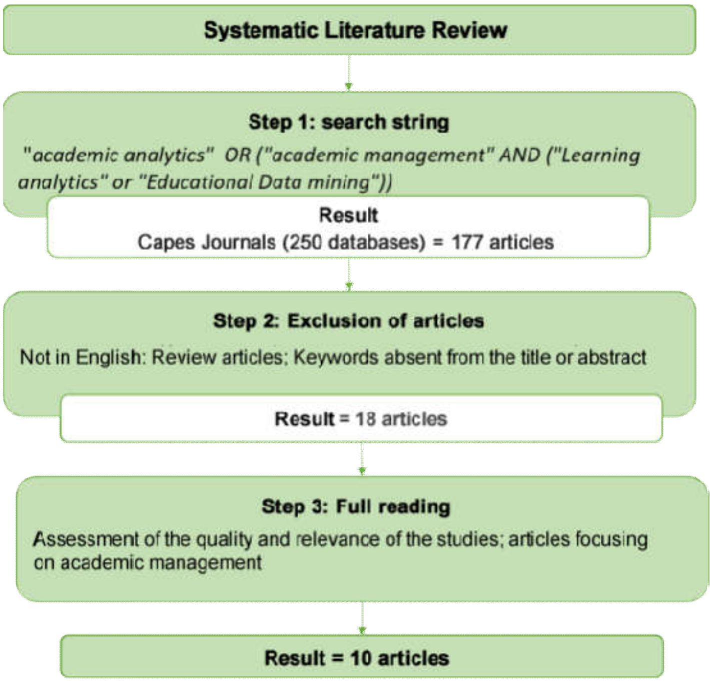

Figure 2. Summary of the article selection process

Table 4. Elements extracted from the articles

Terms/expressions	Description
Academic analytics	Verify what type of academic analysis the article has (students, professors, coordinators, academic management)
Dashboard	Indicates whether the article has used Dashboard indicators
Application	Indicate if it has any application
Database	Indicates the database used in the application
Computational tool	Indicates the computational tool used or created
LA or MDE tool	Indicates which LA or MDE tool was used
Focus of the article	Indicates the focus of analysis of the article
Method	Indicates the method used
Place of study	Indicates the HEI where the study was performed

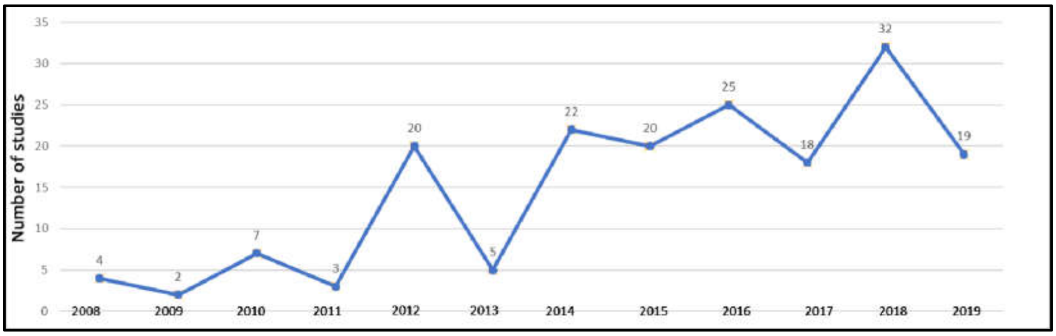

Figure 3. Number of articles by year of publication

After selecting the articles, we created a table for the evaluation and extraction of relevant data that would be useful to answer the guiding questions of the project. We have previously defined the elements to be verified, which are presented in Table 4. Section 3 presents an analysis of the selected articles.

RESULTS AND DISCUSSIONS

In this section we discuss the results of the extraction and synthesis of information and the data analysis of this systematic review, in order to answer the specific research questions presented in Table 1. Figure 3 shows the number of papers selected by year of publication. We can see that the number of publications on the subject is rising.

Although in 2019 there are fewer studies, we must take into account that this research was conducted in April 2019, therefore it does not consider the whole year. In order to begin summarizing the results found, in Table 5 we show the studies found along with an analysis and categorization.

General analysis of the collected data

Table 5 shows the publications that were analyzed. Only one application (system) was found in the article by Gutiérrez et al. (2019), which presents LADA, a system that has a dashboard focused on students and professors for academic counseling. The most used method was the case study.

Table 5. Analysis and categorization of the studies found

Analyzed Publications	Academic Analytics for				Dashboard (indicators)	Application	Database (LMS, GIS)	Computational Tool	LA or MDE tool	Focus of the Articles	Method
	Students	Professors	Coordinators	Acad. Management							
Baepler and Murdoch 2010	No	No	No	No	No	No	No	No	No	Conceptualize EDM and Academic Analytics	Theoretical
Olmos, M. & Corrin, L. (2012)	Yes	Yes	Yes	Yes	Yes	No	Not informed	No	Google's interactive Motion Chart tool, Excel	Curriculum building and review	Case study
McNaughton et al. (2017)	No	No	No	Yes	Yes	No	Not informed	No	Excel	Academic management	Case study
Cantabella et al. (2019)	Yes	Yes	No	No	No	No	Sakai LMS	QlikView, Tableau	MapReduce	Students' LMS use	Case study
Dziuban et al. (2012)	No	No	No	Yes	No	No	Not informed	Executive Information System (EIS)	Executive Information System (EIS)	Academic Management TOP - DOWN	Case study
Bharara et al. (2018)	No	Yes	No	No	No	No	LMS	Rapid Miner	Rapid Miner	Students' LMS use	Case study
Ndukwe et al. (2018)	No	Yes	No	No	Yes	No	Not informed	Splunk	Splunk	Academic achievement	Case study
Ferreira & Andrade (2016)	No	Yes	No	Yes	No	No	LMS, Academic System and Services	prototype	prototype	Academic management	prototyping
Chaurasia & Rosin (2017)	No	No	No	No	No	No	No	No	No	Big date in university	theoretical
Gutiérrez et al. (2019)	Yes	Yes	No	No	Yes	Yes (LADA)	Academic system	Analytics Dashboard for Advisers	Python API	Academic counseling	case study

Whereas regarding the type of academic analysis used in the articles, we noticed that the target audience of the projects varies, focusing on professors, managers, students and coordinators, the first two being more predominant. However, only one article includes tools for coordinators, specifically, curriculum construction and review by Olmos, M. & Corrin, L. (2012).

We found several indicators in the articles, however, few refer to dashboards (n = 4) for their visualization, which suggest that the indicators are generally used in isolation, corroborating the study by Siemens and Long (2011) who state that Higher Education Institutions (HEIs) generate and store a large amounts of data, but lack systems that provide quick, predictive and specific information to the administrative and academic reality, thus reducing the number of opportunities for real-time interventions.

Q1: Which tools and methodologies based on LA or MDE are being applied in the context of Academic Analytics?

The following LA and MDE tools were found in the studies: Google's interactive Motion Chart tool, MapReduce, Executive Information System (EIS), Rapid Miner, and Splunk. In addition, a prototype and a Python API were found using the following MDE algorithms: Apriori, decision and regression trees, cluster (K-mens and C-mens). In addition to the computational tools: QlikView, Tableau and Analytics Dashboard for Advisers.

Q2: Are there any specific tools for course coordinators?

Only one tool for course coordinators was found, in the article by Olmos, M. & Corrin, L. (2012), in which indicators are presented on a dashboard with the computational tools Google's Interactive Motion Chart and Microsoft Excel. However, the process is not automated but rather built individually for each course, thus requiring a lot hard work by those responsible. Even though it does not present a specific tool for course coordinators, the prototype developed by Ferreira and Andrade (2016) has a lot of potential for this purpose. Their prototype accesses the LMS Moodle, the academic system and the HEI services databases in an automated way, but it does not have a dashboard to better present the results.

Q3: What academic management indicators are used?

To answer this question, we elaborated Table 6 to identify the indicators, their focus and provide a brief explanation.

Table 6 shows that the indicators are more focused on management and students. In figure 4 it is possible to visualize the possibilities that these indicators generate in order to improve decision-making. According to Dziuban et al. (2012) the Management of HEIs can use these indicators when meeting with colleges and departments to shape strategic conversations about how to allocate resources to explore opportunities that could have been unknown to them because they lacked the data.

Table 6. Indicators found

Author	focus of the indicator	Indicator	explanation of the indicator
Olmos, M. & Corrin, L. (2012)	Student	Student attendance	Verify attendance
Olmos, M. & Corrin, L. (2012)	Student	Guidance	Student-advisor relationship
McNaughton el al., (2017)	Student	Time spent on the platform	Content exposure time
McNaughton el al., (2017)	Student	content viewed	content viewed
McNaughton el al., (2017)	Student	Login	How long the student is logged out of the system
McNaughton el al., (2017)	Management	Time since entering university	Identify average student years (courses)
McNaughton el al., (2017)	Management	Enrolled	Number of students enrolled
McNaughton el al., (2017)	Management	Applicants	students taking entrance exams
McNaughton el al., (2017)	Management	retention rate per year	Student retention rate per year
McNaughton el al., (2017)	Management	completion rate	Students who graduate
McNaughton el al., (2017)	Management	non-completion rate	Identify courses from which less students graduate
McNaughton el al., (2017)	Management	entrance exam conversion rate	Identify the conversion of students who took the entrance exam
McNaughton el al., (2017)	Management	Students	Identify growth by period (years 1, 2, and 3)
Cantabella et al. (2019)	Coordinators	Use of LMS services (modalities)	line plot of LMS services (forum, videos, chat, activities, visits, downloads) - Evolution of services
Cantabella et al. (2019)	Professors	Student profiles by services (LMS)	Group students who use the same LMS services
Cantabella et al. (2019)	Management	Use trend	LMS connection trend by modality (forum, videos, texts, etc.)
Dziuban et al. (2012)	Management	Course's DE percentage	Check the course's DE percentage
Dziuban et al. (2012)	Management	Student success by modality	Students' success percentage by modality (DE...)
Dziuban et al. (2012)	Management	Dropout percentage per course	Dropout by course
Dziuban et al. (2012)	Management	Satisfaction level	Identify student satisfaction level
Dziuban et al. (2012)	Management	Dropout prediction	prediction of student dropout
Dziuban et al. (2012)	Management	Dropout prediction by course	Prediction of student dropout by course and year
Bharara et al. (2018)	Professors	Student absenteeism	Student groups by absence
Bharara et al. (2018)	Professors	Grouping by grade	Student groups by grade
Bharara et al. (2018)	Professors	Grouping by interaction	Student groups by interaction in Moodle
Ndukwe et al. (2018)	Professors	Student performance	Student performance by discipline and semester
Ndukwe et al. (2018)	Professors	Student performance	Student performance by course and semester
Ferreira & Andrade (2016)	Management	Professor performance	Professor evaluation
Ferreira & Andrade (2016)	Professors	Student performance	Individual student results
Ferreira & Andrade (2016)	Management	Technologies used	use of technologies by students (define platforms)
Ferreira & Andrade (2016)	Management	Grouping by demographic data	Student groups by demographic data
Ferreira & Andrade (2016)	Management	Identify ICT use patterns	Demographic data crossing using ICT
Ferreira & Andrade (2016)	Management	Academic results	Academic results by course and semester
Ferreira & Andrade (2016)	Management	Dropout Risk	Student at risk of dropout
Gutiérrez et al. (2019)	Student	Passing rate	Identify student passing rate (disciplines passed)
Gutiérrez et al. (2019)	Student	Student's academic evolution	Average student grades per semester
Gutiérrez et al. (2019)	Student	English level of student	Check student's English level
Gutiérrez et al. (2019)	Professors	Dropout Risk	Predict the dropout risk
Gutiérrez et al. (2019)	Professors	Student grouping by performance	group students with similar academic profiles
Gutiérrez et al. (2019)	Student	Student's likelihood of success	predict the student's likelihood of success
Gutiérrez et al. (2019)	Student	Student x student average	Compare the student to the class grade average
Gutiérrez et al. (2019)	Student	Course completion rate	Course completion percentage
Gutiérrez et al. (2019)	Student	Accomplishment rate	Percentage of accomplishment (disciplines taught and failed)
Gutiérrez et al. (2019)	Student	Performance rate	Compare student grades with previous semesters
Gutiérrez et al. (2019)	Student	Skill analysis	analyze students' area skills (mathematics, humanities, basic and advanced) – radar chart

Figure 4. Indicator focus overview

Some indicators can be used with a different focus from the one presented in the studied articles. However, we noticed that there are almost no indicators for course coordinators, and furthermore, that the management indicators are mostly focused on the students. In Figure 5, the percentage of the type of indicator found in the articles studied is shown. We highlight the fact that although the articles are focused on academic management, financial indicators were not found, and the main focus is on pedagogical indicators that support professors and students in the teaching and learning process. The operational indicators comprise: number of new students/graduates (alumni), dropouts, leaves of absence, withdrawals, transfers, enrollment of students, attendance of professors, etc.

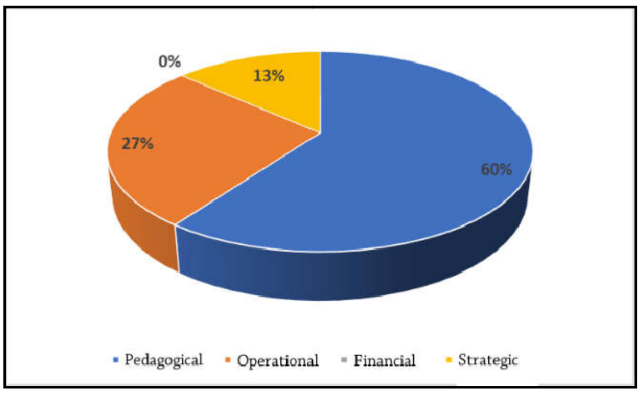

Figure 5. Types of indicators used

The strategic indicators (satisfaction level, technologies used, identification of Information and Communication Technology standards, grouping of profiles by demographic data, course's DE percentage) comprise only 13% of the total indicators. Figure 6 illustrates the target users of the indicators. Based on the 10 articles studied, only 8 included indicators, none of them for all types of users. Four articles have only one focus user. Our search indicated a lack of solutions and more complete studies that support the academic processes of HEIs.

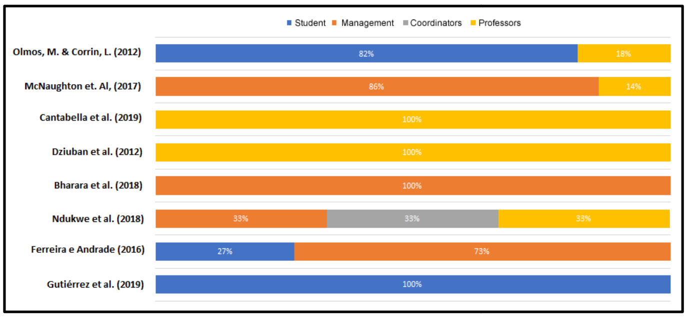

Figure 6. Individual focus of the articles

Q4: How are these tools and methodologies contributing to Academic Management in HEIs?

The importance of the tools and indicators for academic management became clear from the articles. According to Olmos, M. & Corrin, L. (2012), just presenting the data in a more organized way is already of help to the management. Dashboards help the managers to organize the information. Along these lines, Analytics allows HEI managers to access historical or real-time indicators on various aspects of the institution and its organizational units (faculty, schools, and departments) (FERREIRA & ANDRADE, 2016). Cantabella et al. (2019), adds that in order to have a stronger impact, the results from the indicators should be presented in a way that is intuitive and easy to understand, since these data are usually discussed by people who are not data science experts. In this sense, McNaughton et al. (2017) states that data quality is critical to the success of the analysis. In all the articles studied, the authors show the improvements generated by the application of Academic Analytics with excellent results. If we analyze Table 6, we can see that there are many possibilities to help the management of HEIs. The indicators used together can allow a more precise, fast and systemic management of an HEI.

Final Considerations

In this article we presented the results of a systematic review of the literature on Academic Analytics that comprised an analysis of 10 international studies published in the period from 2008 to 2019 in the *Portal de Periódicos da Capes*. Regarding the guiding questions of the study, we observed that the most explored aspect in the publications were tools to help professors and students. We were able to identify the computational tools and MDE and LA techniques used, in addition to the indicators, of which many are educational management indicators. These indicators, however, still focus more on students, and give secondary importance to the financial aspects of an HEI. We would like to highlight the importance and prominence that this field will have in the near future, due to the assistance it provides to treat the generated data, thus enabling a more precise, fast and systemic management of an HEI. Considering the results of this study, we identify a research niche in the field of Academic Analytics, specially in relation to course coordinators, which offer many possibilities for improvement. In summary, it is possible that this mapping will provide researchers with an overview of Academic Analytics, and it points out research trends that could be the focus of future studies. This study is not free from the classic limitation of systematic literature reviews, related to the execution of the whole process, and other relevant studies or data may not have been considered in the process of analysis. In future studies, we intend to create a prototype of a system based on Academic Analytics focused on academic management and course coordinators of Higher Education Institutions.

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