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Faculty of Business Economics

Master of Management

Master's thesis

Data-driven analysis of curricula in higher education

Emmanuella Sirri Ntoh

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :
dr. Gert JANSSENSWILLEN

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Abstract

Data analytics is gaining popularity in higher education because it requires teachers to make high-quality decisions based on factual evidence and their knowledge. Previous studies indicate that data usage can improve school performance, particularly in terms of increased student achievement. This study looked at the relationship between data used for accountability, school growth, and instruction and key performance indicators (KPIs) for student performance outcomes, with a focus on students' satisfaction. However, the use of data analytics comes with obstacles such as ethical and privacy concerns, data loss, and ownership issues. This study employed a quantitative survey research technique and utilized a correlation matrix to examine and evaluate the hypothesis. Two distinct surveys were conducted, one targeting students (n=50) and the other targeting members of the education management team (n=31) in Flemish universities in Belgium. The result of the findings showed a non-significant (.621) and negative correlation (r=-.258). This study suggested that the slightly negative relationship may be due to the possibility of privacy invasion associated with large-scale data collection and analysis in education while the non-significant value might be due to small sample size. The geographical extent, anonymous replies, and short data collecting time limited the study. To understand data analytics' usage on student performance, future study should combine quantitative and qualitative methods. Also, to get more representative results, future research should examine technological infrastructure, other variables, and a bigger sample size. This study emphasized the need of taking into account data security, privacy, and ethical limits in education to improve the satisfaction of students and better meet their needs in this digital era.

Keywords

Data Analytics; Learning Analytics; Academic Analytics; Education Data Mining; Accountability; School Development; Instruction; Curriculum; Student Satisfaction; Data Privacy

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Abbreviations

LA	Learning Analytics
AA	Academic Analytics
EDM	Educational Data Mining
DAHE	Data Analytics in Higher Education
DDDM	Data Driven Decision Making
HEIs	Higher Education Institutions
EMT	Education Management Team
EFA	Exploratory Factor Analysis

1 Introduction

Recently, data-driven curriculum analysis in higher education has grown in importance because of technological advancements and the availability of massive amounts of data. Educational institutions may now use data analytics to acquire useful insights into their curriculum and make educated decisions to improve the quality of education they offer (Campbell & Levin, 2008). Historically, instructors and school districts have gathered and utilised data in a variety of ways, such as a grade book to monitor progress and determine final grades or standardised test results to measure district-wide success. However, as technology has advanced, it has become simpler to use data and analytics in the classroom. The advancements in information technology have resulted in a substantial revolution in the education sector (Chen, 2020). The traditional classroom education system is rapidly evolving into a modernized approach.

Analytics in education contains many levels of analysis, spanning from the micro level, which focuses on variables about the teaching and learning process, such as student growth or course design. Students and educators, who are more directly engaged, may find this material more intriguing. Additionally, the macro level encompasses broader concerns, such as administrative matters or quality management. The micro-scale is primarily associated with learning analytics, whereas the macro scale is closely linked to the subject of Academic Analytics. However, delineating the border between these two scales is a complex task (Ferreira & Andrade, 2016). There is a strong desire to increase and harness the value of rising data in the higher education setting, but there is limited research on academic analytics in higher education, says Mendez, Ochoa, Chiluiza, & De Wever (2014), and also limited research on analysing the learning process at the departmental or programme level to aid curriculum design and redesign, aside from studies on dropout (Wolff, Zdrahal, Nikolov, & Pantucek, 2013). Moreover, the adoption of learning analytics by higher education institutions (HEIs) would need many years to reach maturity. However, its influence is already apparent and warrants consideration (Picciano, 2012). This study will contribute to the field of academic analytics, and the results of the study aim to help education stakeholders in Flemish universities in Belgium understand the kinds of data, promoting or hindering factors, and purpose of data use in higher education. Furthermore, this study may serve as a blueprint for future research on data utilisation in other developed and developing nations and as a benchmark for the application of data-driven decision making.

This research aims to examine the relationship between data used for accountability purposes, school development purposes, and instruction purposes and student performance outcomes. By leveraging data-driven insights, institutions can identify areas of strength and weakness in their curricula and make informed decisions about how to improve student outcomes. To fully comprehend the context and significance of student performance with respect to the larger body of literature and on-going worries about the use of data analytics, one must understand the direct relationship between student satisfaction and the use of data analytics. This study expects that the use of data analytics in curriculum design and evaluation has the potential to significantly enhance student satisfaction in higher education.

This work is structured into six distinct sections. The first section is the introduction. The second section of this study centres on the topic of analytics in education. Section 3 of the research explains the methodological framework by considering the study's setting, explaining the survey questions, uses of data analytics and student satisfaction metrics, employing a predictive validity model, and ultimately, describing the data analysis approach. Section 4 summarizes the study's findings. Section 5 addresses the limitations and provides recommendations for further research, while part 6 presents the main conclusions of the study.

2 Literature review

This section is structured into five subsections. The first subsection looks into the conceptual aspects of data analytics in higher education. The subsequent subsections look into the concepts of the goals of data analytics, the challenges associated with data-driven analytics in the field of education, and student performance outcomes.

It is critical for educators to be able to make sound decisions on school practices as part of their decision-making processes. Schools' societal obligation, particularly social pressure to increase student success, is growing by the day, and accountability in education is becoming increasingly vital for school organizations (Anderson, Leithwood, & Strauss, 2010). However, without making evidence-based judgements, the accountability process cannot function effectively. Evidence-based decision-making necessitates the use of data relevant to the decision's nature. According to Schildkamp, Ehren, & Lai (2012), school organisations define data as all the information they gather to illustrate various aspects of their schools (Schildkamp, Ehren, & Lai, 2012). In addition, data comprise not only assessment data and other forms of student achievement data, but also any other form of structurally collected qualitative or quantitative data on the school's functioning, such as input data (e.g., student background data), process data (e.g., classroom observations and teacher interviews), context data (e.g., building information), and output data (e.g., student achievement data, student satisfaction questionnaire data). These data can be used to inform school-based decision-making, which is known as data-driven decision-making (Ikemoto & Marsh, 2007). The efficacy of data-driven decision-making in facilitating efficient decision-making cannot be guaranteed. The mere possession of data does not guarantee its use for decision-making or improvement generation. Data-driven decision-making in schools, often known as data utilisation, is gaining significant attention in nations worldwide. The primary rationale for this is that we anticipate instructors to make judgements of exceptional quality, hence requiring their conclusions to be grounded in both empirical facts and their own expertise and intuition. Multiple studies have shown that using data may result in improved school performance, specifically in terms of increased student achievement (Campbell & Levin, 2008).

Data analytics is divided into two forms of applied analytics: 'institutional analytics' and 'learning analytics.' (Dennehy Denis, Kieran Conboy, Jaganath Babu, 2021). Nguyen et al. (2020) identified three key domains within the realm of higher education that centre on the examination of data analytics: learning analytics (LA), academic analytics (AA), and educational data mining (EDM) (Nguyen, Gardner, & Sheridan, 2020).

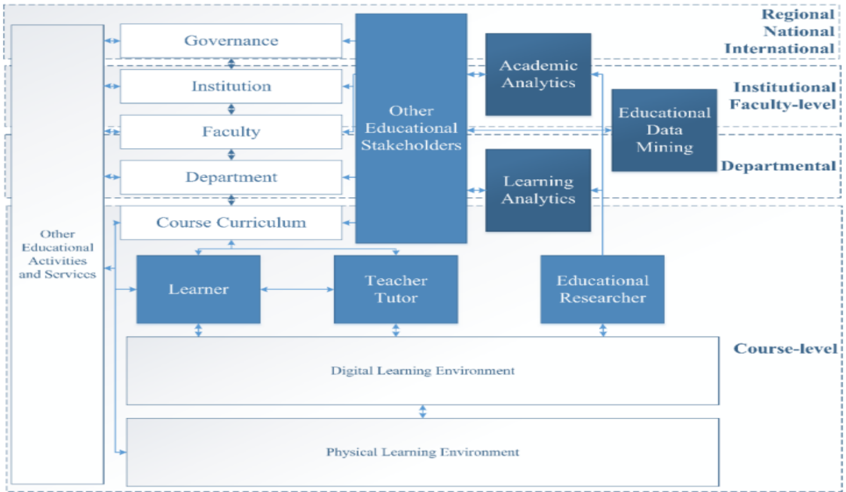


Fig. 1 An Integrated Framework for Data Analytics in Higher Education (DAHE) (Nguyen, Gardner, & Sheridan, 2020).

Freeman (1984) defines a stakeholder as any person or group of people who either influence the organization or have the ability to effect the attainment of its goals. This is the fundamental principle that supports stakeholder theory. This idea posits that the ultimate outcomes of any endeavour should include the benefits for all parties involved, rather than only focusing on the outcomes for owners or shareholders (Freeman, 1984). According to the DAHE framework, some of the stakeholders in HEIs include students, teachers, researchers, employers, alumni, funders, local communities, and the government. Also, Bridgestock (2021) states that; the other educational activities and services may include career counselling workshops, networking training and events, campus healthcare, student counselling, a language centre, a student gym, and study training and workshops that are being offered by the university to students (Bridgestock, 2021).

The DAHE framework shows that LA integrates with EDM at the departmental level, while AA integrates with EDM at the faculty and institutional level. Papamitsiou et al. (2014) provide a concise summary of the key distinction between LA and EDM in the discipline, stating that LA employs a comprehensive framework that aims to comprehend systems in their whole intricacy. In contrast, EDM takes a simplistic approach by examining individual elements, searching for novel patterns in data, and making adjustments to the corresponding algorithms. The focal object of AA, on the other hand, is institutional operation and decision making. Furthermore, an educational institution can utilize data analytics at all levels (Papamitsiou & Economides, 2014). Siemens and Long (2014) defined the five levels of analysis: course, departmental, institutional, regional, and national/international (Siemens & Long, 2014). Learning analytics primarily focuses on the first two levels, whereas the following three levels are often known as academic analytics (Siemens & Long, 2014) . In addition to the work of Siemens and Long (2014), learners and faculty benefit from learning analytics while financiers, administrators, marketers, the government and other educational institutes benefit from academic analytics.

2.1 Domains of data analytics in higher education

Researchers and developers in education are pursuing similar ways to obtain knowledge about online learners' and school activities. Currently, researchers have developed three areas to include and explore the use of data in education: learning analytics, educational data mining, and academic analytics.

2.1.1 Learning analytics

The field of learning analytics involves the systematic collection, analysis, and reporting of data pertaining to learners and their surroundings. The primary objective of this practice is to gain comprehensive knowledge of learning processes and the contexts in which they take place (Siemens G. , 2013). Alternative definitions are simpler and include terminology derived from the field of business intelligence: analytics is the systematic process of acquiring practical insights by defining problems and applying statistical models and analysis to current and/or projected data (Cooper, 2012). Ochoa Xavier states that the main objective of the learning analytics sector is to provide valuable information to anyone involved in the teaching process (students, instructors, and administrators) in order to help them make more informed choices about learning (Ochoa, 2015). In contrast, Kerr argues that the aforementioned description fails to include the whole of LA applications, including adaptive learning systems. Adaptive learning systems enhance learning by modifying the learning environment and content; instead of just providing data for actionable insights (Kerr, 2016).

"Curricular analytics" is a branch of learning analytics that seeks data and insights on the relationship between curriculum components and the achievement of curriculum outcomes. Curricular analytics can be helpful for higher education institutions in determining the strengths and shortcomings of their curricula as well as in supporting modifications to students' learning paths (Salazar-Fernandez, Munoz-Gama, Maldonado-Mahauad, Bustamante, & Sepúlveda, 2021). Furthermore, learning analytics focuses on assessing student performance (grades) and advancement. The focus is mostly on student learning, using ways to get a deeper understanding of students' achievements and outcomes in their courses. The tutors used a learning analytics report in order to provide students with comprehensive feedback about their academic progress. In contrast, students use learning analytics as a means of assessing their learning endeavours and achievements. Several educational institutions have used it to guide students on their academic performance (Greller & Drachsler, 2012).

2.1.2 Educational Data Mining (EDM)

In recent years, EDM has evolved as a study subject for scholars from a variety of relevant research disciplines throughout the world, including physical (offline) learning, digital learning, learning management systems, and blended learning. Learning management systems have rapidly become an essential component of higher education, particularly during the pandemic. As students utilized these tools, the log data generated has become increasingly accessible. Universities should enhance their ability to utilize this data for the purpose of predicting academic achievement and ensuring student advancement (Bernacki, Chavez, & Uesbeck, 2020). The topic of educational data mining (EDM) has been one of the first areas of study that aimed to effectively use quantitative analyses in the field of education (Baker & Yacef, 2009). According to Siemens and Baker (2012), educational data mining refers to the process of developing data mining techniques to analyze complex educational datasets and then using these techniques to get valuable insights on students and educational institutions (Siemens & Baker, 2012). The technique of Educational Data Mining (EDM) employs computational approaches to convert unprocessed data derived from educational systems into valuable insights that can be used to address educational challenges. Educational Data Mining, aims to use data repositories to get a deeper understanding of learners and their learning processes. It also aims to build computational methods that integrate data and theory to improve educational practices for the benefit of learners (Romero & Ventura, 2010). Further, there exists a wide array of data mining methodologies, with a predominant emphasis on clustering, classification, visualization, and association analysis within the realm of higher education (Castro, Vellido, Nebot, & Mugica, 2007; McGrath, 2008; Romero and Ventura, 2007). To add, this field is primarily exploratory (Baepler & Murdoch , 2010).

2.1.3 Academic analytics

Goldstein and Katz (2005) introduced the term Academic Analytics (AA) to describe the integration of technology, information, organisational culture, and data analytics in school administration. In addition, academic analytics integrates specific institutional data, statistical analysis, and predictive modelling to provide valuable insights that may be used by students, instructors, and administrators to impact academic conduct (Baepler & Murdoch , 2010). AA (a form of data-driven decision-making (DDDM)) as defined by Atkinson (2005), is a procedure for making decisions based on data or facts rather than observation, intuition, or any other type of subjectivity that may be biased. The usage of DDDM in the education sector is increasing in order to make informed improvements when educators use student data to affect curriculum decisions, strategies, and policies (Atkinson, 2015).

According to Chaurasia et al (2018), Academic Analytics, in essence, pertains to the use of business intelligence within the field of education. Specifically, it involves the systematic exploration of educational data to uncover significant patterns, enabling the identification of academic issues such as dropout rates. The ultimate goal is to facilitate informed strategic decision-making (Chaurasia, Kodwani, Lachhwani, & Ketkar, 2018). The primary focus of AA is to provide support to university administrators and educational policymakers. Students expect data analytics to predict and improve their learning outcomes, whereas institutional administrators see the use of academic analytics as a means to monitor and increase educational key performance indicators (KPIs) such student retention (Chaurasia, Kodwani, Lachhwani, & Ketkar, 2018). Student retention is widely recognised as a crucial key performance indicator (KPI) within the realm of higher education. Consequently, a significant number of faculty members exhibit a keen interest in the monitoring and prediction of student advancement. In addition, AA has the capability to derive valuable insights from educational data in order to identify the most efficient methods and enable instructors to make pedagogical adaptations in the curricula to fit the needs of the students (Nguyen, Gardner, & Sheridan, 2020). In the following paragraphs, we discuss curriculum development in more depth.

Curriculum development

Curriculum development encompasses the many stages of curriculum preparation, implementation, and assessment, alongside the intricate interplay of individuals, systems, and procedures involved in the creation and execution of the curriculum (Ornstein & Hunkins, 2009). Curriculum evaluation is one stage in the development process. To add to this, the process of designing and analysing curricula often takes the following methodical approach: exact identification of the requirements and limitations of the curriculum design (student outcomes, competencies, and learning objectives); deciding on a conceptual model for the curriculum (such as inquiry-based learning, problem-based learning, case-based learning, etc.); creating and evaluating the curriculum; and improving the curriculum based on input from stakeholders and students (Pukkila, DeCosmo, Swick, & Arnold, 2007). However, several textbooks on curriculum development outline the steps of the curriculum-creation process in the following manner: The process involves doing a needs analysis, establishing goals and objectives, organising the course, selecting and preparing teaching materials, and conducting an evaluation. In contrast to the conventional approach outlined in textbooks, Graves (1996) opted to adopt a reversed sequence of steps. Initially, principles for the course content were established, followed by an evaluation and revision of existing assignments to address the specific needs of identified students. Subsequently, the scope and sequence of the content were determined, and finally, objectives that students could attain were elicited. Consequently, curriculum developers should begin their work at any point and at any time they deem suitable given their particular circumstances (Graves, 1996).

Need analysis: Curriculum development aims to increase student learning by satisfying their requirements. Curriculum creators should acquire as much information as possible, regardless of the theory or model used. Important information for a high-quality programme includes targeted objectives, assessment role, current student accomplishment, and programme content. Information should include teacher, administration, parent, and student issues and attitudes (Kranthi, 2017)**.**

Setting goals and objectives: Goals and objectives are similar, yet there is a subtle difference. Goals are broad statements of the learner's knowledge, ability, or attitude and typically describe the key information from prior levels. In contrast, an objective is a quantifiable skill or attitude that the student will display after the educational activity. Goals help define the plan, while objectives are needed to evaluate your programme (Schneiderhan, Guetterman, & Dobson, 2019).

Designing the curriculum: After goals and objectives have been established, the curriculum is designed. This phase entails the creation of a comprehensive structure for the curriculum, including the subject matter, teaching approaches, evaluation techniques, and educational resources. The material must match with the aims and objectives of the curriculum and should be structured in a coherent and purposeful manner (Jain, 2023).

Implementation: Curriculum implementation is the process of putting the curriculum into action as an educational plan. Executing the curriculum necessitates the involvement of an implementing agent. Accordingly, the teacher is identified as the agent responsible for carrying out the curriculum implementation process (University of Zimbabwe, 1995).

Curriculum evaluation: The process of gathering data from which a programme's value and efficacy may be assessed is called curriculum evaluation. It involves making informed assessments to determine the future direction of the programme, such as whether to maintain it as is, make adjustments, or completely discard it (Afzaal , Ashiq , Muhammad , & Azra , 2011). After the evaluation, the curriculum is amended and updated based on the evaluation to increase its efficacy. Making modifications to the content, teaching methodologies, assessment methods, or materials is an example of revision. The redesigned curriculum should be connected with the curriculum's aims and objectives and tailored to fulfill the requirements of the learners and the community. Following the adjustments, the redesigned curriculum is implemented in the classroom (Suresh, 2015).

2.2 Goals of data analytics

Educational institutions of all grades in Europe and the United States are increasingly emphasizing the "culture of evidence," where data can guide solutions, as demonstrated by Bouwma-Gearhart and Collins (2015). The role of quantitative data and evaluation in this line is becoming increasingly important (Bouwma-Gearhart & Collins, 2015). Institutions invest millions in purchasing, implementing, and supporting e-learning platforms like Moodle or Blackboard, which use data mining and academic analytics to inform curriculum and instruction decisions (Lonn and Teasley, 2009; Morris, Wu, and Finnegan, 2005). (Lonn & Teasley, 2009; Morris, Finnegan, & Wu, 2005). Moreover, several data-driven models of action exist (Boudett et al., 2005; Earl & Katz, 2006; Lai & Schildkamp, 2013; Mandinach et al., 2008; Marsh, 2012; Schildkamp & Poortman, 2015). Schildkamp et al. (2017) suggest using data for accountability, school improvement, and instruction objectives (Schildkamp, Poortman, Luyten, & Ebbeler, 2017).

2.2.1 Data used for instructional improvement

Using data to improve instruction is a persuasive argument based on excellent teaching principles. (Schildkamp, Lai, & Earl, 2013). Effective teaching should be reflective and data-driven rather than relying on unscientific assumptions (Timperley & Phillips, 2003). According to Salpeter (2004) and Sulser (2006), it is important to assess student learning on a regular basis, such as quarterly, monthly, weekly, or daily. Longitudinal data is crucial for data-driven decision-making, in addition to examining student learning over the school year. Longitudinal data helps schools monitor trends. Tracking student growth over time can reveal the effectiveness of intervention measures and curriculum programs. Longitudinal data can help classroom teachers' measure student progress and predict future outcomes (Sulser, 2006; Salpeter, 2004). Besides, when teachers use data, they may make better decisions about which curriculum areas require more attention for exams, which groups of students want special attention for further academic support, and what kind of instructional arrangement best meets the needs of certain groups of students (Young, 2006).

In the field of instructional improvement, data plays a crucial role in determining the effectiveness of students' learning in the school system, including their understanding of the general expectations and purposes of the curriculum, their preparation for future study and life, the presence of unique strengths and weaknesses in their knowledge and abilities, the performance of certain subgroups in the population, the variables associated with student success, and the changes in student accomplishments over time (Greaney & Kellaghan, 2008). The quality of the data, its use, and the provision of appropriate assistance for school development determine whether the consequences of using data for educational purposes are beneficial or bad (Darling-Hammond & Rustique-Forrester, 2005).

2.2.2 Educational data used for the advancement of schools

Data plays a key role in the iterative process of school improvement. This highlights the idea that data utilization does not begin with data. Rather, data is merely one of the instruments that schools may utilize to enhance their operations and this implies that data utilization must begin with specific aims, frequently related to increasing the quality of teaching and learning. These objectives must be concrete and quantifiable (Schildkamp, 2019). Further, educators frequently find themselves on unfamiliar ground as they strive to raise their students' expectations to world-class levels of success. The path might be either complex or unpleasant, or it can be straightforward and fulfilling. It is best to complete this school improvement process collectively and reflectively. Collaboration invites members of a school community to participate in ongoing problem-solving activities, sharing their knowledge, abilities, and ideas, while reflection, a component of cooperation, encourages students to consider and alter their actions based on available knowledge. Put together, reflective collaboration is a strong practice between staff and school community members (Shively, 2004).

Globally, there is a growing trend towards using data to promote school development and evaluate teacher performance (Jerrim & Sims, 2021). Besides, this is partially driven by the fast advancements in data-related technologies and the increased accessibility of these tools in educational institutions. Many people have a very optimistic view of the potential of educational data to contribute to educational reform. They believe that using data may lead to excellent results for the education system, schools, and individual students. This positive outlook is supported by research conducted by Luckin et al. in 2016 (Luckin & Wayne, 2016). To add to that, data utilization for school development entails the use of data by educational institutions to improve their schools. Educational assessments, such as student satisfaction surveys and test results, may assist school administrators and educators in evaluating progress towards objectives (Schildkamp, Poortman, Luyten, & Ebbeler, 2017). The process involves the collection and examination of qualitative and quantitative data to ascertain the needs, strengths, and weaknesses of students and then customise educational interventions to meet these specific requirements. Student achievement statistics may serve several purposes, including assessing the school's performance and informing curricular choices. Higher education institutions may enhance results for students, teachers, staff, and the institution as a whole by using data in a deliberate and strategic manner (Young, 2006).

2.2.3 Data used for accountability

The use of data for accountability in higher education institutions may be attributed to the primary objective of accreditation (Nuffic). Furthermore, data may be used to satisfy accountability obligations, adhere to regulations, and validate programs and policy choices (Coburn & Talbert, 2006). With the rise of globalization and a more competitive economy, there is a growing need for governments to oversee public sector operations, such as education systems, in many countries. In recent decades, there has been a worldwide emergence of educational evidence-based policymaking and outcomes-based accountability. Evidence-based policymaking involves using data, such as the success of programs or the varying academic performance of various student groups, to guide policy-making. In the realm of evidence-based policymaking, outcomes-based accountability is a distinct approach that relies on data pertaining to the efficacy of individual units within a particular system, such as individual schools within a school system (Loeb & Byun , 2022). For example, the Accreditation Organization of the Netherlands and Flanders (NVAO) oversees the quality of higher education programs offered in the Flemish Community. Recognized higher education institutions are held accountable for the quality of their academic offerings. Again, Global university rankings are 21st-century phenomena that impact how higher education institutions are regarded and respond to these impressions. According to Hazelkorn et al, certain institutions' posture falls short of expectations, prompting a call to action (Hazekorn, Loukkola, & Zhang, 2014). Rankings have raised awareness about accountability, openness, and quality across institutions. However, at a meso-level, institutions implement macro-level policies by prioritizing curricula that are practical and economically useful; creating a climate of performance in which engagement and success are measured; and adhering to an accountability regime that monitors and publicizes how well performance standards are met (Zepke, 2017).

2.2.4 Data used for curriculum evaluation

Curriculum evaluation pertains to the systematic gathering of data that enables the assessment of the value and efficacy of a certain educational curriculum. It involves making judgements to determine the future of the programme, whether to keep it as it is, make modifications, or completely eliminate it (Hussain, Dogar, Azeem, & Shakoor, 2011). Evaluation is both a phase and a specific stage in the curriculum development paradigm. The primary objective of the evaluation phase is to assess the degree of student achievement and ascertain the influence of the course design on student performance. Assessment is a continuous process that takes place throughout the course, including several aspects such as student performance, internal analysis of lessons and assessments, and feedback from students, Learning Coaches, and instructors (Tremblay, Lalancette, & Roseveare, 2012). During evaluation, data can be obtained from sources like current students, alumni, faculty heads and professionals.

2.2.5 Enhancing overall institutional performance

Universities may improve their institutional performance by utilising data analy tics to get valuable insights into resource allocation, financial performance, and other critical areas. Universities can use data analysis of budgetary trends, enrolment patterns, and student results to make well-informed decisions on resource allocation and strategic planning (Bichsel, 2012).

2.3 Challenges Associated with Data-Driven Analysis

However, there are a number of challenges associated with the use of data analytics in higher education.

Data quality

A data set's ability to fulfil its intended function is a measure of its data quality. Data quality indicators include correctness, completeness, consistency, validity, uniqueness, and timeliness. However, the collection of data from multiple systems and departments typically comes in different types and formats, generating interoperability issues, while there is a danger of data loss throughout the data cleansing and data integration process, thereby reducing the quality of the data. (Daniel, 2017).

Ethical and privacy issues

Data privacy is another major difficulty with data analytics in education. According to Ifenthaler and Schumacher (2016), ethics is defined as a set of fundamental rules and universal standards of right. Privacy may be broadly defined as the state of being free from any form of disturbance or intrusion. The legal definition of privacy encompasses an individual's entitlement to regulate the accessibility of their personal information. Privacy may be defined as the amalgamation of control and restrictions, wherein individuals have the ability to exert influence over the dissemination of their personal information and hinder unauthorised access by others (Ifenthaler & Schumacher, 2016). Also, Ifenthaler & Schumacher (2016) found that learners have a desire to maintain the privacy of their information due to both competitive and personal motivations. However, in order to identify more extensive learning processes, a greater amount of data is required. This data, which tracks students' private information and learning data, could be exploited and harm students in the long run as they go through the educational system and reach the job (Wang Y., 2016).

Data ownership

Within the institution, the issue of data ownership does emerge. Because of the ownership issue, the institution must find a balance between data protection and data use for institutional purposes. Furthermore, the institution must guarantee that they adhere to the rules regarding ethical and legal consent for data usage. Clear communication with personnel is crucial for protecting sensitive information and adhering to regular processes (West, 2012).

A high initial cost

Data analytics necessitates the digitization of educational and institutional processes. This digitalization necessitates the availability of various software and hardware, which comes at a high initial cost. There is also a considerable cost because the process of gathering, storing, and analysing the data produced requires access to a high-speed computational infrastructure that can handle a vast volume of data (Daniel, 2017). Also, Marsh et al. (2006)**,** state that the process of transforming data into information, knowledge, choices, and actions is a laborious and time-intensive endeavour. Practitioners must carefully consider the advantages and disadvantages of spending time on data collection and analysis, as well as the expenses associated with providing the required support and infrastructure to facilitate data utilisation (Marsh, Pane, & Hamilton, 2006).

A lack of trained workers

Fifth, one of the factors contributing to the gap between demands and solutions in the implementation of data-driven analysis has been recognised as a lack of trained workers (Norris & Baer, 2013). For example, a pilot study that investigated preparation for learning analytics across nine institutions in the United States discovered that one of the primary concerns is a lack of analytics capability among staff (Kimberly et al., 2014). The skill scarcity makes it difficult to use learning analytics on an institutional scale.

Security concern

Finally, data security include measures used to safeguard data from unauthorised access, use, alteration, disclosure, or destruction, hence influencing the confidentiality, integrity, and availability of the data. Besides, the storage of large amounts of data in a single database creates a security concern, despite the fact that it enables data analytics. Data analytics necessitates the use of a distinct security technology, as typical security solutions are ineffective in dealing with massive volumes of dynamic data. Inadequate data security can result in data breaches, cyber-attacks, legal complications, and harm to one's reputation. (Wang Y., 2016).

2.4 Student Performance Outcome

The use of student performance to assess the impact of data-driven maturity is critical because it gives concrete proof of the success of data-driven activities in education. Educators may determine if the use of data-driven techniques has resulted in improved academic results, such as higher test scores, graduation rates, and overall student accomplishment, by analysing student performance data. This assessment enables schools and educational institutions to recognise their strengths and weaknesses, adapt their procedures appropriately, and make educated choices to improve student learning and success. Furthermore, assessing student performance over time gives important insights into the long-term influence of data-driven maturity on educational results, allowing educators to measure progress, create objectives, and constantly improve their teaching approaches (SRI International , 2010).

Apart from this, current educational establishments function under a highly competitive and intricate milieu. Nowadays universities have challenges such as assessing performance, providing top-notch education, establishing assessment mechanisms, and acknowledging future requirements. Universities use student intervention programmes to assist students in overcoming challenges encountered during their academic journey. The ability to forecast student performance throughout the first and subsequent periods may assist institutions in formulating and refining intervention strategies that provide advantages for both administration and instructors (Albreiki, Zaki, & Alashwal, 2021).

Additionally, predictive models can be developed by examining past data on student performance, including grades, attendance, and demographic information, to predict student outcomes such as graduation rates, academic success, and retention rates. Higher education institutions are interested in student academic achievement and graduation rates. The investigation of issues connected to university students' academic success has grown in popularity in the higher education community (Vaitsis, Hervatis, & Zary, 2016). The variables used to measure student performance in this research are graduation rate, retention rate and student Satisfaction. The former two are difficult to measure quantitatively, thus in this research, we only measured the later which can easily be quantified. Surveys may quickly collect input on satisfaction from a large number of students, since satisfaction is a subjective evaluation that does not need long-term monitoring or validation against official data. Graduation rates on the other hand, need the systematic monitoring of individual students to see if they successfully finish their degree programmes within a designated timeframe. Surveys may inadequately capture longitudinal data, resulting in mistakes in the stated rates. In addition, retention rates pertain to the tracking of students who persist in their studies at the same educational institution from one academic year to the next. This might provide difficulties when relying only on surveys for assessment.

2.4.1 Graduation rate

Higher education plays a pivotal role in fostering the development of highly qualified persons and facilitating the progress of a nation's economic expansion. The student graduation rate serves as an indicator of the performance of higher education, presenting a challenge in improving the quality of higher education. A high rate of graduation serves as an indicator of the efficacy of the educational programme, while a low rate of graduation may suggest issues within the learning process or academic administration, thereby diminishing the effectiveness and efficiency of the educational process and hindering the attainment of the educational institution's objectives (Rohmawan, 2018). High graduation rates are related with beneficial outcomes such as greater graduate earnings, improved university reputation and ranking, informed policy decisions based on educational outcomes, and a better educated workforce contributing to economic growth. Indeed, the prediction of timely graduation among students may be anticipated from the first semester with the application of established data mining methodologies used by scholars. These methodologies include the utilisation of Decision Tree (DT), Neural Network (NN), and Support Vector Machine (SVM) techniques to forecast the graduation of students (Riyanto, Hamid, & Ridwansyah, 2019).

Although graduation rates have remained a prominent indication of institutional achievement, other studies have examined college graduation rates using different variables than this one. In a study of eight cohorts of undergraduate college students from the 1990s, Zhang (2009) found a positive association between state funding and college graduation rates. Increasing state financing by 10% resulted in a 0.64% improvement in graduation rates for full-time students. The author came to the conclusion that "it is the interaction between student characteristics (including commitments to their educational goals and institutions and the academic and social contexts of the institutions that ultimately determines students' college persistence and graduation" (Zhang, 2009).

2.4.2 Retention rate

Recent advances in technology have enabled LA researchers to collect digital traces of students' learning activity in Virtual Learning Environments. This comprehensive and fine-grained data on real learner behaviours provide educators with potentially significant insights into how students respond to alternative learning schemes and how 'at-risk' students might be encouraged to finish their studies (Pulker, 2019). Besides, student retention is easier to define than success. It is defined as students finishing or continuing a course of study after passing through milestones such as examinations or enrolment periods. According to Tinto (2017), retention is primarily linked to institutional performance: the percentage of students who complete their courses and the rate at which they are retained. In contrast, limiting the number of dropouts is one of the most difficult issues that any manager or educational institution faces. Student retention on the other hand can be increased by introducing proper processes such as carefully monitoring and scrutinising existing activities and rectifying or removing faults when identified (Leathwood & O'connell, 2003).

The primary goal of retention research is to determine what institutions may do to enhance retention rates (Tinto, 2017). Early detection of accurate student dropout rates helps eliminate underlying issues via the creation and use of prompt and reliable intervention strategies (Albreiki, Zaki, & Alashwal , 2021). Similarly, student retention is crucial for higher education success. If students are dissatisfied with their institution, they are less likely to continue their studies year after year. Predictive learning analytics tool such as Machine Learning (ML) algorithms have been used to predict dropout and discover students at risk in higher education, and they play an important role in enhancing students' performance (Albreiki, Zaki, & Alashwal, 2021). Although universities often have access to student personal data through their student information systems and can readily monitor academic achievement, they frequently lack a simple method for measuring students' more profound involvement with the system (Matz et al. 2023).

2.4.3 Student Satisfaction

In the UK, Higher Education (HE) students are regarded the "primary customers" of a university, even before paying "up-front" tuition costs (Crawford, 1991). Students directly benefit from the three-year degree program, which includes modules at each level. The Higher Education Funding Council for England launched a National Student Survey, confirming the "student as customer" position. The survey aimed to gather feedback from final-year students on their experiences with teaching, assessment, and support at their university. The results were utilized by government and funding bodies to create league tables of university performance. A university's ranking in league tables impacts its image. Image in return has a tremendous impact on retaining current students and attracting future students (James, Baldwin, & McInnis, 1999).

Even so, satisfaction is commonly used by businesses to evaluate customer service, trends, appreciation, and expectations. According to Kotler and Clarke (1986), satisfaction refers to the feeling of fulfilment or dissatisfaction with an event or outcome based on expectations and perceived performance (Kotler & Clarke, 1986). Colleges and universities on the other hand describe student satisfaction as meeting their needs and goals through campus activities and learning environments (Lin, Lin, & Laffey, 2008). In this research, we divided student satisfaction into service feature satisfaction, ethical and privacy satisfaction and explicit student satisfaction.

Service feature satisfaction

According to Checa et al (2020), Student satisfaction gives an insight into how students feel a service supplied is regarded as a crucial indicator of service quality in the teaching-learning process, which is why it has become one of the fundamental goals of universities (Checa , De-Pablos-Heredero, Torres, Montes-Botella, Barba, & García , 2020). Besides, according to Roberts et al. (2016), students do not expect LA services to hinder their capacity to learn independently. Roberts et al. found that autonomous learning is a crucial necessity for university students. Therefore, LA services should not encourage reliance on measurements (Roberts, Howell, Seaman, & Gibson, 2016).

Ethical and privacy satisfaction

Research indicates that students have high expectations for data management methods when it comes to LA services ethics. Students expect institutions to obtain informed consent or provide opt-out options for the LA procedure (Prinsloo & Slade, 2014). Similar statements were made in the work of Roberts et al. (2016), who discovered that students expect the institution to protect their privacy, seek informed consent, and be transparent at all times (Roberts, Howell, Seaman, & Gibson, 2016) . Learning analytics will become more widely used in higher education in the next years. Educational data informs support services for student learning, including early alert systems, personalised learning environments, and enhanced feedback processes (Whitelock Wainwright, Gašević, Tejeiro, Tsai, & Bennett, 2019).

Explicit service satisfaction

The explicit service encompasses staff knowledge, teaching ability, consistency of teaching quality, ease of scheduling appointments, subject content difficulty and workload, staff treatment of students, including friendliness and approachability, concern for problems, respect for feelings and opinions, availability, and competence. The university's environment should provide students with a sense of comfort, competence, confidence, and professionalism during lectures and tutorials. Students should also feel that their best interests are being served and that rewards are commensurate with their efforts in coursework and exams. Everything above is predicated on how students view the different components of the service (Douglas, Douglas, & Barnes, 2006).

3 Methodology

In conducting this research study on data-driven analysis of curricula in higher education, the research objectives were defined and the research question was formulated to guide the study which can be seen below. Hypothesis was stated and tested and the results can be seen in the result analysis section.

Research Objectives

To analyze the relationship between use of data analytics in curricula design and student engagement and success (graduation rates, retention rate, student satisfaction.

To evaluate the use of data-driven approaches in identifying gaps and areas for improvement in the curricula.

To investigate the potential challenges associated with implementing data-driven analysis in curricula development.

Research Question

What is the correlation between the use of data driven analysis in curricula and student performance outcomes (Student satisfaction)?

Research Hypothesis

Null Hypothesis (H0): The use of data analytics of curricula in higher education does not have a significant impact on student performance outcome.

Alternative Hypothesis (H1): The use of data analytics of curricula in higher education has a significant impact on student performance outcome.

Furthermore, this study used a survey research methodology, using a quantitative approach. It included a correlation matrix to test hypotheses and the Statistical Package for Social Sciences (SPSS) was used for data analysis. Two different surveys were developed and these surveys were administered in a large sample to current students and also current members of the Education Management Team (EMT) in Flemish universities in Belgium. Questionnaires were sent to EMT members and students in Belgium with the use of Google Forms via email and LinkedIn.

3.1 Context

This study took place in Flemish universities in Belgium. The Flemish Community has one of the most evolved education systems in the OECD, with schools enjoying great autonomy and the local government (Provincial and Municipal) playing a small role (OECD, 2015). Modelling the intricate relationship between student learning and tools to aid decision-making is crucial for improving student learning experience.

3.2 Survey

The survey was developed based on the theoretical framework and on existing valid and reliable instruments of the works of Schildkamp & Kuiper (2010), Whitelock Wainwright et al (2019) and

Douglas et al (2006). Before the survey, the participants were provided with information about the study and guaranteed their information would be kept anonymous. They were also informed that completing the questionnaire would take about 10 minutes. 197 questionnaires were sent from February to April 2024 through email and 8 through LinkedIn to EMT members and from the 205 questionnaires sent, 31 was received making a response rate of 15%. Also, questionnaires were sent to students using email and Whatsapp group chats and a total of 50 questionnaires were received. The study subjects were EMT members across all departments and business students at Flemish higher institutions.

For students

Part one of the questionnaire consisted of demographic, educational level, and name of higher institution and current studies program information about the respondent. Section two and three of the questionnaire consisted of student satisfaction scale developed by Whitelock-Wainwright et al (2019)). These questions were answered on a 5-point Likert scale, with "1" denoting "strongly disagree", "2" representing "disagree", "3" representing "neither agree nor disagree", "4" denoting "agree" and "5" denoting "strongly agree." Section two of the questionnaire contained six questions related to Learning Analytics feature satisfaction. The respondents were asked to indicate to what extent they agreed or disagreed with the following statements. Part three consisted of five questions was based on ethical and privacy satisfaction. These questions were answered on a 5-point Likert scale, with "1" denoting "very low level of trust", "2" denoting "low level of trust", "3" denoting "neither high nor low level of trust", "4" denoting "high level of trust" and "5" denoting "very high level of trust." Lastly, section four of the questionnaire consisted of implicit service satisfaction scale developed by Douglas et al (2006). These questions were also answered on a 5-point Likert scale, with "1" denoting "Very low" and "5" denoting "very high."

For EMT members

Part one of the questionnaire consisted name of current institution employed and EMT program(s), years of experience and highest level of education obtained. Section two, three and four of the questionnaire consisted of use of data analytics scale developed by (Schildkamp, Lai, & Earl, 2013). Section two of the questionnaire contained five questions related to data use for accountability purpose and these questions were answered on a 5-point Likert scale, with "1" representing "strongly disagree", "2" representing "disgree, "3" representing "I do not know, "4" representing "agree'' and "5" representing "strongly agree." The "I don't know" option was included to recognise and respect the fact that not all EMT members may have a clear view or understanding on the subject. Part three consisted of seven questions based on data use for school development. These questions were answered on a 5-point Likert scale, with "1" representing denoting "stongly disagree" and "5" denoting representing "strongly agree." Lastly, section four of the questionnaire consisted of data use for instruction (ad-hoc analysis). These questions were also answered on a 5-point Likert scale, with "1" denoting "Almost never", "2" denoting "once a month", "3" denoting "quarterly", "4" denoting "twice a year" and "5" denoting “once a year."

To avoid social desirability bias and hallo effects and to ensure data quality, only active EMT members and students of Flemish universities in Belgium were chosen as respondents to the questionnaire. (DeVellis, 1991), suggests that experts examine the scale for content validity. An Information system department professor (my supervisor) with professional backgrounds and education in Data analytics served as an expert and reviewed the scale items for relevance and classification. After the review, some information was added to make the questionnaire more interactive and valid.

3.3 Predictive Validity Model

Figure 2 shows the predictive validity model. This kind of model was developed by Libby, Bloomfield, and Nelson (2002). Link 1 illustrates how the use of data analytics and student satisfaction are conceptually related. Link 2 relates the operationalized independent variable(s) to the antecedent theoretical idea A, capturing the independent variable in operational A with three variables. Link 3 connects concept B to the study's operationalized dependent variable, capturing it in operational B with three variables. Link 4 evaluates the relationship between operational independent and dependent variables.

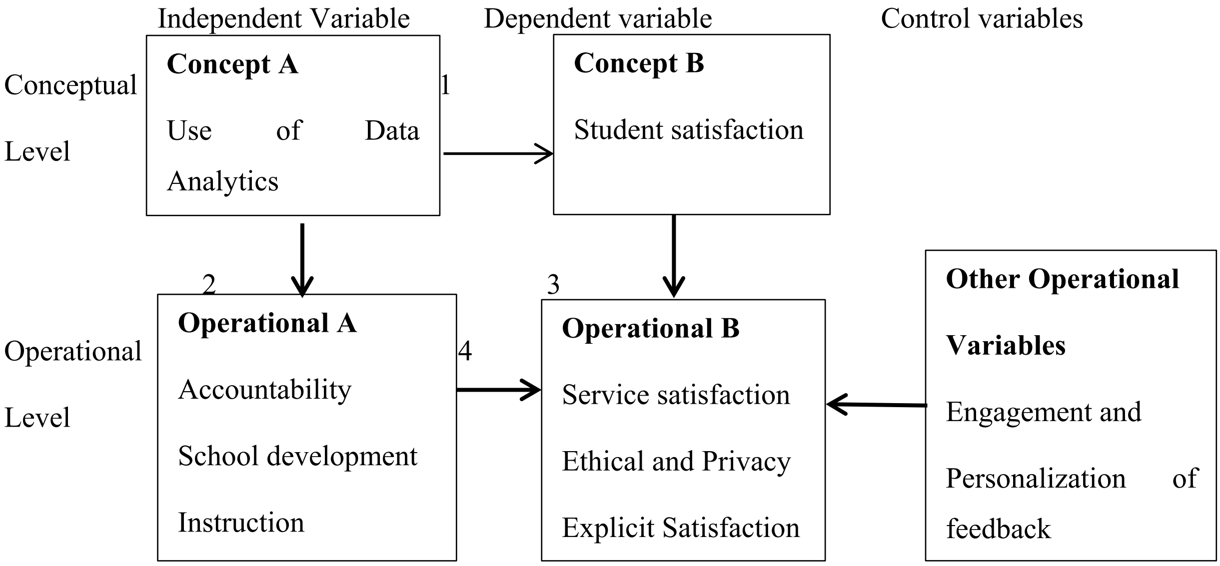


Fig. 2 The Predictive validity model (Libby, Bloomfield, & Nelson, 2002)

All constructs, ideas, concepts, and variables that can be conceptualized but not fully measured are considered conceptual variables. The idea or construct is given meaning by the specification of operational variables, which define the necessary operations for measuring or manipulating the concept. The data obtained during research is based on observable occurrences. Operational definitions play a crucial role in research as they enable researchers to quantify abstract notions and constructions, facilitating the transition from theoretical conceptions to empirical observations. On the other hand, Control variables are parameters that are kept constant or limited in a research study so that they do not influence the study's results. These factors are not the primary subject of the investigation, but they are controlled since they may influence the results. By controlling these factors, researchers hope to improve the study's internal validity by lowering the effect of confounding and extraneous variables, allowing for a more precise link between the variables under consideration. (Ary, Jacobs, & Razavieh, 1985).

In this study, one hypothesis was generated based on the research question by developing a link between some of the goals/uses of data analytics and student satisfaction to assess whether or not these goals and student satisfaction are significantly related.

3.4 Data Analysis Methods

Validity test: The processes for determining validity in this study made use of exploratory factor analysis (EFA) to analyse the relationships between observed variables and underlying theoretical constructs, which are frequently referred to as factors. Since its invention a century ago by Spearman & Galton (1904), EFA has been widely applied to a range of behavioural research (Spearman, 1904).

Reliability test: The reliability test evaluates the level of consistency shown when a measurement is repeated under the same circumstances (Porta, Greenland , Hernán, Santos SI, & JM, 2008). This study made use of Cronbach's alpha to check the internal consistency of the factors.

Statistical analysis: Statistical analysis, often known as statistics, is the act of gathering and analysing data in order to find patterns and trends, remove bias, and make informed decisions. It is a subset of business intelligence that includes gathering and analysing company data, as well as reporting on trends. Some of the statistical analysis methods used were the mean, standard deviation and hypothesis testing.

3.5 Student Satisfaction Measures

To measure student satisfaction the works of Whitelock Wainwright et al (2019) and Douglas et al (2006) were used. On the scale of Whitelock Wainwright et al (2019), Service feature satisfaction and ethical and privacy satisfaction are measured using ten and nine items respectively. Student satisfaction was measured using three dimensions on a scale, consisting of a total of 19 items. However, this research used the two-dimensional method, with service feature satisfaction measured using seven questions and ethical and privacy satisfaction measured using six items. Also, the scale of Douglas et al (2006) was used to measure explicit satisfaction. Satisfaction was measured using two dimensions with 30 items, but one dimension was used in this research with eleven items. The questions were shortened to mitigate the potential response bias or increase in the questionnaire's dropout rate that may arise from employing all 19 items from the former or 30 items from the later. Out of the 24 items used in this study, we considered only fourteen items and deleted ten items due to poor loading (less than 0.5) or cross loading with other items.

The fourteen items in this research loaded into the three theoretical factors with item factor loadings that were typically 0.60 or higher; factor loadings greater than 0.50 are deemed acceptable in the exploratory factor analysis (DeVellis, 1991). The Cronbach's alpha coefficients for service and feature satisfaction (4 items), ethical and privacy satisfaction (5 items), and explicit satisfaction (5 items) are .764, .898, and .845, respectively. These values imply that the scales have high internal consistency. In theory, Cronbach's alpha values should range from 0 to 1, with a value of 1.0 indicating the maximum degree of internal consistency for the components of the scale. The recommendations offered by George and Mallery (2001) are as follows: "If α is greater than 0.9, it is considered excellent. If α is greater than 0.8, it is considered good. If α is greater than 0.7, it is considered acceptable. If α is greater than 0.6, it is considered questionable. If α is greater than 0.5, it is considered poor. If α is less than 0.5, it is considered unacceptable" (George & Mallery, 2016).

The findings of the exploratory component analysis using Principal Component Analysis (Varimax with Kaiser Normalisation) are shown in Table 1.

Table 1 Exploratory factor analyses (n = 50)

Items		**Cronbach's alpha**	**Factor Loading**
Service and feature satisfaction		.764	
Item 1	The use of data analytics will promote academic and professional skill development for future employability		.771
Item 2	Encourage me to adjust and set learning goals based on feedback provided		.851
Item 3	Support me if the analytics show that I am at risk of failing		.645
Item 5	Present me with a complete profile of my learning across every module		.768
Ethical and privacy Satisfaction		.898	
Item 1	Ask my consent before my educational data are outsourced for analysis by third parties		.867
Item 2	Ask my consent to collect, use and analyse my grades, attendance and virtual learning environment		.798
Item 3	Ensure that my data will be kept confidentially		.775
Item 4	Ask my idea before using any identifiable data about my ethnicity, age and gender		.892
Item 5	Request further consent if my educational data are used for a different purpose		.853
Explicit service satisfaction		.845	
Item 4	The feeling that rewards gained are consistent with the effort you put in assessment		.642
Item 6	Concern shown when you have a problem		.806
Item 7	Respect for your feelings, opinions and concerns		.768
Item 8	Friendliness of teaching staffs		.854
Item 9	Approachability of teaching staffs		.851

3.6 Use of Data Analytics Measures

The study conducted by Schildkamp, Kuiper, and Wilmad (2010) aimed to produce a measure that identifies the specific data used and the purpose for which it is used as the basis for the construction of a scale. This research used three aspects to assess data analytics goals: Accountability (5 questions), School Development (7 items), and Instruction (10 items). Participants answered these questions on a 5-point Likert scale, with "1" representing "strongly disagree" and "5" representing "strongly agree" for the first two constructs and "1" representing "Almost never" and "5" representing "once a year" for the last construct. All 7 school development items, accountability item 3 and instruction items 1, 2, 5, 7, and 9 were deleted because of non-significant factor loadings and significant cross-loadings between some of the items.

The findings of the exploratory component analysis using Principal Component Analysis (Varimax with Kaiser Normalisation) are shown in Table 2.

Table 2 Exploratory factor analyses (n = 31)

Items		Cronbach's alpha	Factor Loading
Accountability		.764	
Item 1	My institution provide data for institution improvement to inspectors		.871
Item 2	The data use for accountability purposes represents the reality at the institution		.741
Item 4	Grant of institution facilities are based on data provided by the institution to Government		.578
Item 5	Data are used to present evidence to auditors.		.869
Instruction		.715	
Item 3	Make or adapt teaching to individual students' needs		.593
Item 4	Give student feedback on their learning process		.710
Item 6	Form small groups of students for targeted teaching and learning		.840
Item 8	Determine which topics and skills students do and do not possess		.725
Item 10	Make changes to your instructional practices based on data analysis		.564

4 Results

4.1 Descriptive Statistics

The survey included 31 education management team members and 50 business students from six Flemish higher education institutions who volunteered to participate via email, Whatsapp, and LinkedIn. Moreover, 62% of student responds are female, whereas 38% are male. Over 60% of students have been at the same university for 1-3 years, whereas over 50% of EMT members have more than 5 years of experience, indicating their appropriateness as knowledgeable respondents (Patton, 2002). These findings indicate that the respondents are well-qualified and the greatest match for this study. Figures 3 and 4 summarise the demographic features of responses for EMT members and business students, respectively.

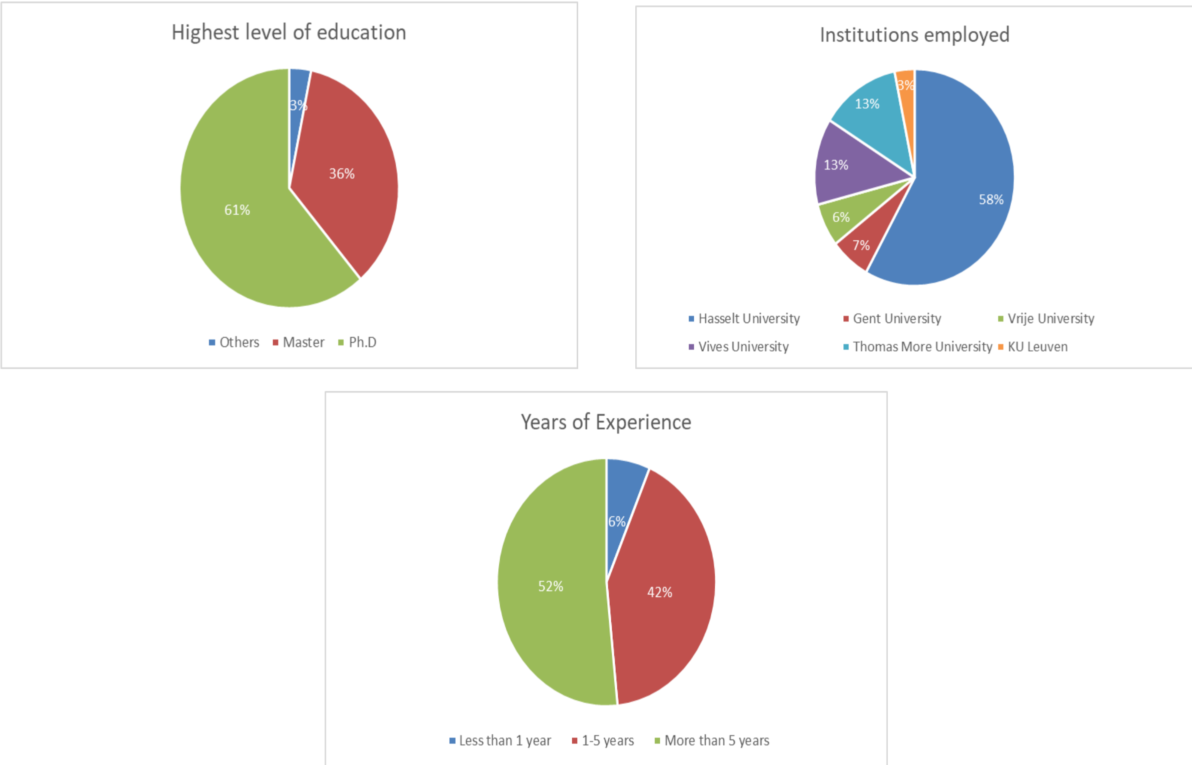
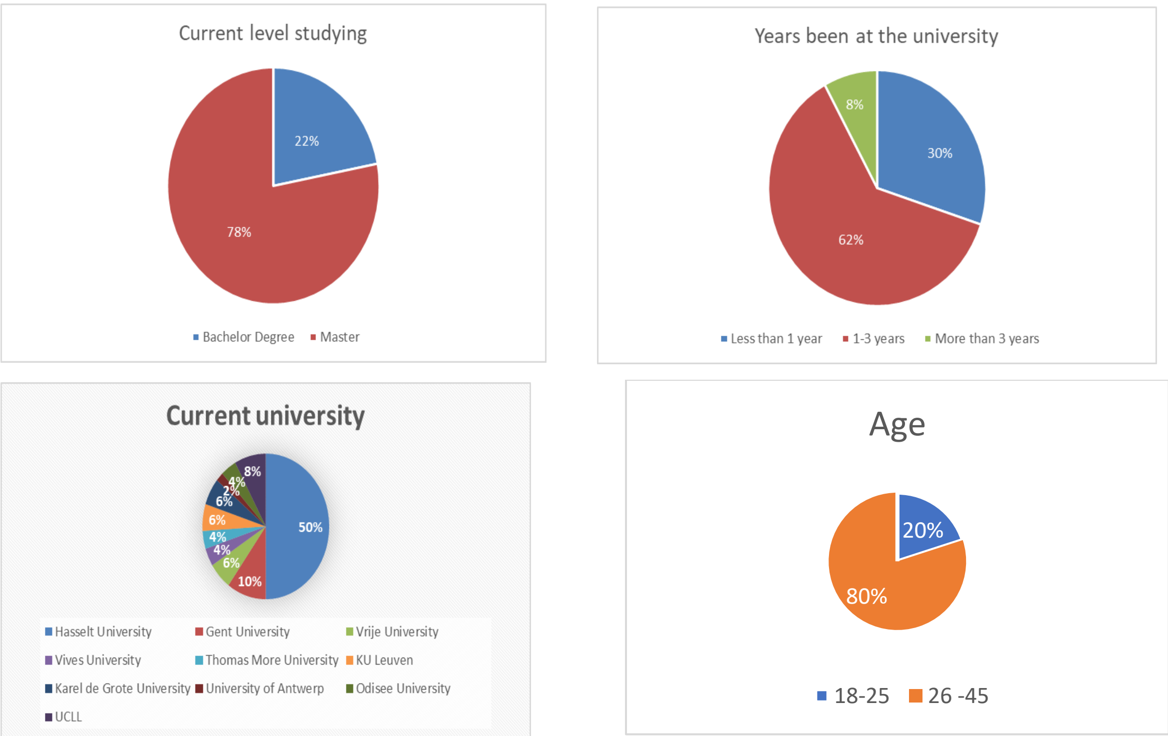


Fig. 3 Demographic characteristics for EMT members



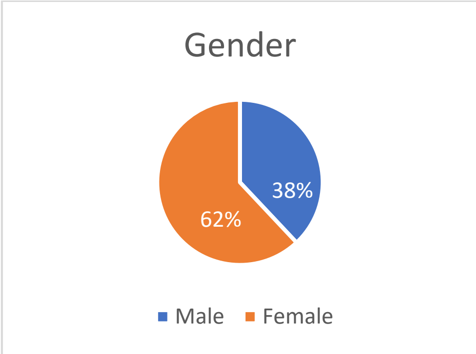


Fig. 4 Demographic characteristics for students

Table 3 shows that, the data use for accountability (ACC) variable has 4 questions with a mean of 3.9113 and a standard deviation of 0.58291. The use of data for instruction (INS) variable has a mean of 2.8968 and a standard deviation of 0.94920 with 5 questions. The next variable is the service feature satisfaction. The mean of the service feature satisfaction (SFS) is 4.2200, the standard deviation is 0.64807, and there were a total of 4 questions. Ethical and privacy satisfaction (EPS) has a mean of 4.1920 and a standard deviation of 0.79894, with a total of 5 questions. Explicit service satisfaction (ESS) has a mean of 4.0520 and a standard deviation of 0.60852 with a total of 5 questions. Finally, Student satisfaction (SS) has a mean of 4.1547 and a standard deviation of 0.45914 with a total of 15 questions. When the mean and standard deviation of each variable are considered, the replies of the respondents vary greatly.

Table 3 Descriptive statistics table

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error
ACC	31	2.50	2.50	5.00	3.9113	.10469	.58291	-.146	.421
INS	31	3.40	1.00	4.40	2.8968	.17048	.94920	-.285	.421
SFS	50	2.67	2.33	5.00	4.2200	.09165	.64807	-.642	.337
EPS	50	3.40	1.60	5.00	4.1920	.11299	.79894	-1.062	.337
ESS	50	2.40	2.60	5.00	4.0520	.08606	.60852	-.281	.337
SS	50	1.80	3.20	5.00	4.1547	.06493	.45914	-.022	.337
Valid N (listwise)	31								

The figures 5,6,7,8 and 9 below visualises the various constructs per universities.

Accountability (ACC)

On average, it showed all six universities somewhat agree to the fact that they satisfy accountability obligations, adhere to regulations, and validate programs and policy choices and also accountable for the quality of their academic offerings.

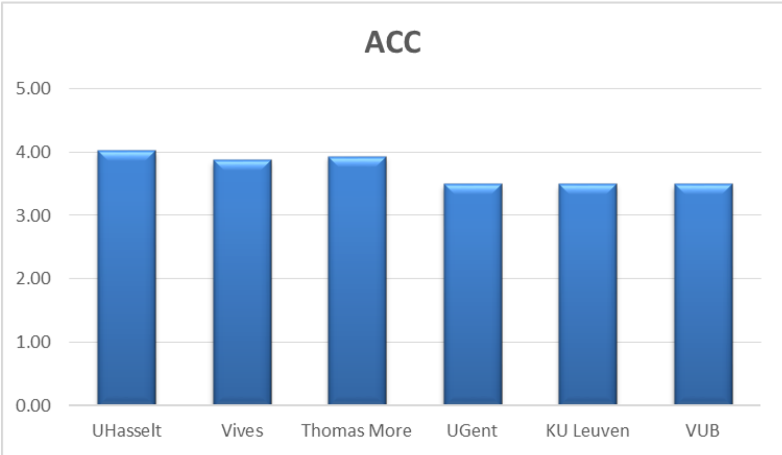


Fig. 5 Visualization of Instruction construct

Instruction (INS)

It showed on average that four of the universities make decisions about which curriculum areas require more attention for exams, which groups of students want special attention for further academic support, and what kind of instructional arrangement best meets the needs of certain groups of students at least quarterly or semi-annually, while the other two almost never make the same decisions for certain groups of students.

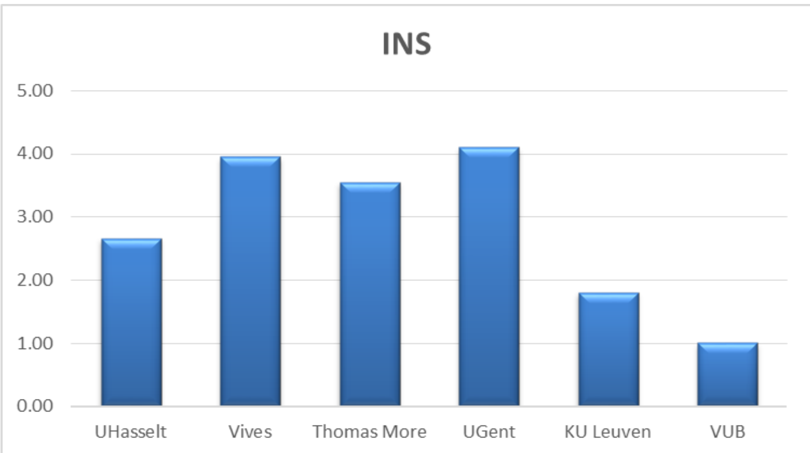


Fig. 6 Visualization of Instruction construct

We only considered student responses from six out of ten universities for the dependent variable, student satisfaction. We excluded the responses of students from four universities due to the absence of responses from the EMT members at those institutions.

Service feature satisfaction (SFS)

Students believed and agreed that the use of LA will help set learning goals based on feedback, detect if they are at risk of failure and also help provide skills for future employability.

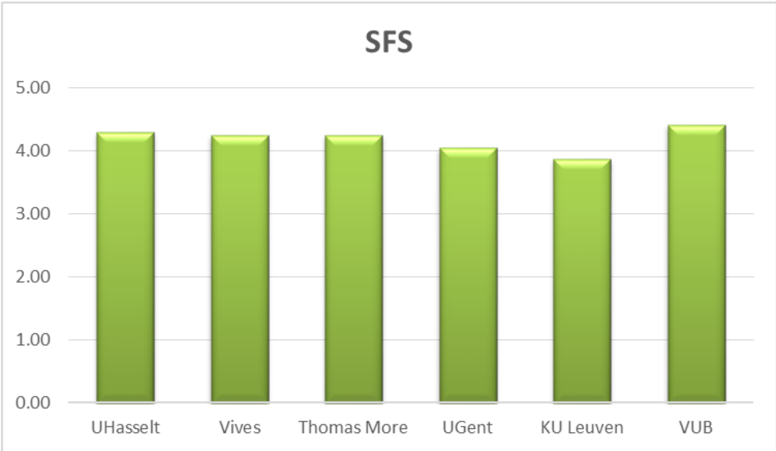


Fig. 7 Visualization of service feature satisfaction construct

Ethical and privacy satisfaction (EPS)

Students from all six institutions hoped and believed high that the institution will look into data privacy issue and seek their concern before their data is being shared especially to third parties.

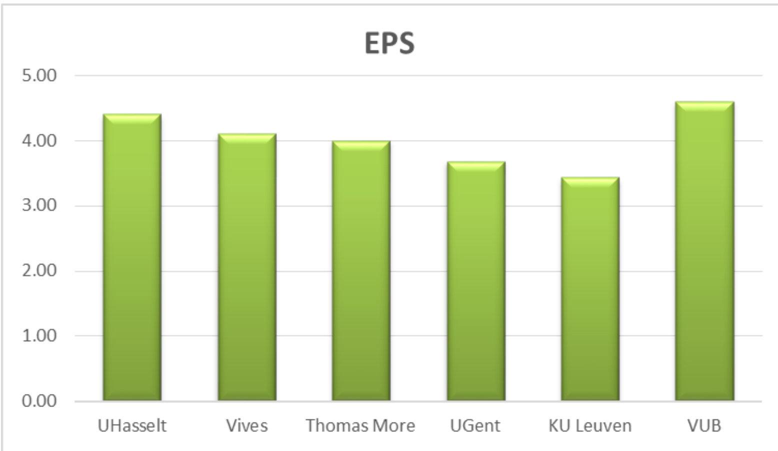


Fig. 8 Visualization of ethical and privacy satisfaction construct

Explicit Feature Satisfaction (ESS)

Students have high level of trust that the university's setting fosters a sense of ease, proficiency, self-assurance, and professionalism during lectures. Students also believed that their utmost concerns are being addressed and that the rewards they receive are in proportion to their accomplishments in school work and exams.

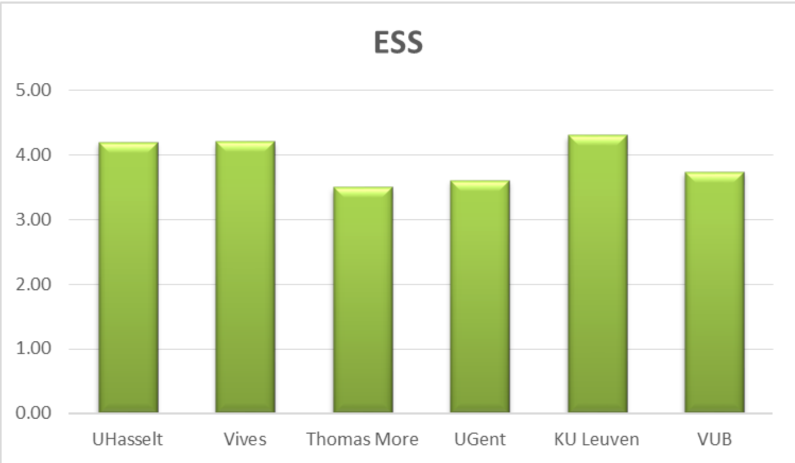


Fig. 9 Visualization of service feature satisfaction construct

4.2 Correlation Tables

Table 4 Independent Variable correlation table

		ACC	INS
ACC	Pearson Correlation	1	
	Sig. (2-tailed)		
	N	31	
INS	Pearson Correlation	.049	1
	Sig. (2-tailed)	.793	
	N	31	31

Table 4 above shows the correlation matrix investigating the direct relationship between the

Independent variables (Data used for accountability and instruction purposes).

The correlation findings reveal that there are no significant correlations between the variables Accountability (ACC) and instruction (INS). This was done to test for discriminant validity and multicollinearity. Also, the independent variables have no obvious relationship with one another and have correlation coefficients less than 0.5, so multicollinearity is not an issue in this model (Rönkkö & Cho, 2020).

Further, correlation was measured between EMT members and students at the corresponding universities. A total of six Flemish universities mean were used as shown on table 5. The correlation measurement did not include the responses of 10 students from Karel de Grote, the University of Antwerp, UCLL, and Odisee University because those higher institutions did not have the corresponding EMT members. Table 8 below shows the correction matrix for the six institutions.

Table 5 Mean value of each variable per institution

Institution	ACC	INS	SFS	EPS	ESS	Data analytics	Student satisfaction
UHasselt	4,03	2,66	4,30	4,40	4,19	3,34	4,30
Vives	3,88	3,95	4,25	4,10	4,20	3,91	4,18
Thomas More	3,94	3,55	4,25	4,00	3,50	3,74	3,92
UGent	3,50	4,10	4,05	3,68	3,60	3,80	3,78
KU Leuven	3,50	1,80	3,88	3,43	4,30	2,65	3,87
VUB	3,50	1,00	4,42	4,60	3,73	2,25	4,25

Table 6 Correlation table

Correlations

		Mean data analytics	Mean Student satisfaction
Mean data analytics	Pearson Correlation	1	-.258
	Sig. (2-tailed)		.621
	N	6	6
Mean Student satisfaction	Pearson Correlation	-.258	1
	Sig. (2-tailed)	.621	
	N	6	6

This research finding suggests that one of the key reasons for the slightly negative association shown on table 6 might be the risk of privacy invasion associated with substantial data gathering and analysis in educational settings. When schools gather large amounts of data on students, such as academic achievement, attendance records, behavioral trends, and personal information, they risk violating their privacy rights. This interference can cause emotions of discomfort, suspicion, and discontent among students, who may see such methods as invasive or immoral (Wang Y. , 2016).

Furthermore, an overreliance on data analytics in decision-making processes inside educational institutions can often obscure the human aspect in student relationships. While data might provide important insights and trends, it may not fully reflect the complexities of student experiences or emotions. Students are more than simply numbers or data points; they are persons with distinct needs, goals, and difficulties that cannot always be appropriately reflected by quantitative indicators alone. As a result, a heavy emphasis on data-driven techniques at the expense of personalised assistance and understanding might lead to lower student satisfaction levels (Bryant & Bryant, 2015).

4.3 Testing the Hypothesis

The study hypothesis was evaluated by analysing the correlation matrix between the independent and dependent variables for the six universities. Table 7 displays the significant coefficient for the hypothesis, the standardised coefficient of the path linking it, and the test results at the 0.05 significance level. It is safe to conclude with 95% confidence based on the dataset that there is a non-significant and slightly negative relationship between the use of data analytics and student satisfaction which might be due to privacy and ethical reasons explained in the previous sub heading. The non-significance correlation could be as a result of the smaller sample size.

Table 7 Hypothesis testing

Test results	Significant level	Correlation coefficient	Relationship between research variables	Hypothesis
Non-Significant and negative relation	.621	r=-.258	The use of data analytics of curricula in higher education has a significant impact on student performance outcome.	H1

5 Limitations And Further Research

This research recognizes some constraints. The study's geographic reach was limited since it focused just on EMT members and business students at Flemish institutions in Belgium. Expanding the application to other cultural and geographical situations would be a logical progression. Also, the presence of within-institution replies in the sample is expected due to the distribution of questionnaires to specific respondents inside a particular organisation (Van der Hauwaert, Hoozée, Maussen, & Bruggeman, 2022). Despite the fact that each respondent's answers to the questions implied their own separate observations (Govindarajan & Fisher, 1990). Because the answers were gathered anonymously, it could not account for within-institution differences. Also, the short timeframe of data collection may have contributed to the low response rate.

It is necessary to consider if the results of this research can be applied to a broader population, since the variables employed to assess both the independent and dependent variables may have a significant impact compared to other factors. Future research could explore the relationship between the use of data analytics and student performance by considering technological infrastructure as a mediating factor, rather than solely focusing on a direct relationship and also look at other variables that might impact student performance. This means that a variable that influences or moderates the relationship between data analytics and student performance could be the technological infrastructure. Secondly, advanced data analytics tools, such as machine learning and predictive modelling, may give more comprehensive insights into the link between curriculum and student performance results. Future study should look at the effectiveness of these technologies in optimising instructional practices. Also, I will advise future researchers to do a mixed method since this topic is exploratory. Mixed methods (surveys and interview/focus group) provide a thorough investigation of the issue by capitalising on the advantages of both quantitative and qualitative procedures. Quantitative data enables the identification of statistical patterns and the capacity to make generalisations, whereas qualitative data provides a more comprehensive understanding by offering depth, context, and nuanced insights. By combining these methodologies, one may get a deeper understanding and a more comprehensive understanding of how data analytics can inform the curriculum and improve student performance. Finally, future researchers can carry out the research on a larger sample size since it improves the capacity to apply the results of the research to a wider population. By increasing the size and diversity of the sample, researchers may more effectively capture the range of differences and subtle distinctions that exist within the population. This leads to findings that are more representative and relevant to a broader spectrum of people. Furthermore, bigger samples enhance the statistical power of a study, enabling researchers to identify minor effects or disparities between groups with increased accuracy and certainty. The increased statistical power decreases the probability of false-negative findings, which occur when actual effects are not discovered owing to a sample size that is too small.

6 Conclusion

Numerous studies have explored the use of business models for knowledge management in education. Petrides and Guiney (2002) demonstrated how knowledge management may help educators create an effective learning environment. In education, like in business, data transformation into knowledge informs school development plans and initiatives (Petrides & Guiney, 2002). This research quantified the use of data analytics by measuring three variables: accountability, school development, and instruction. The result of student performance was assessed by measuring three variables: Graduation rate, retention rate, and student satisfaction. The research focused only on measuring student satisfaction using three quantitative variables: contentment with service features, ethical and privacy satisfaction, and explicit satisfaction.

Ultimately, a survey was carried out, and information was gathered from 31 participants who are currently involved as EMT members and 50 business students at six Flemish higher institutions in Belgium. Student satisfaction was quantitatively assessed using scales derived from the research of Whitelock Wainwright et al (2019) and Douglas et al (2006). Data used and the purpose for which it is used scale development by Schildkamp, Kuiper, and Wilmad (2010) was used to measure goals of data analytics. Reliability, validity and statistical tests were used as data analysis methods. The fourteen items in the student satisafction research loaded into the three theoretical factors with item factor loadings that were typically 0.64 or higher while the nine items of data analytics uses/goals loaded into the two theoretical factors with item factor loadings that were typically 0.58 or higher. Also, the findings of the exploratory component analysis made use of Principal Component Analysis (Varimax with Kaiser Normalisation). The cronbach alpha for all items were above 0.7 which indicated that the scale has an acceptable consistency. Statistical methods of mean, standard deviation and correlations were used to analyze the data. The correction for the six universities analyzed showed a non-significant and slightly negative correlation. The fact that the measurement of satisfaction relied on LA satisfaction rather than learner outcomes may account for the negative relationship. Privacy and ethical considerations are associated with this LA-based satisfaction. However, only a limited amount of research has investigated the relationship between these data analytics goals and uses and student satisfaction.

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