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Academic analytics: Anatomy of an exploratory essay

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Abstract Investment in technological subsystems to support the activity of teaching and learning and the various areas of the life of Higher Education Institutions (HEI) is of increasing importance in the implementation of the policy and strategy of these organizations. Each of these subsystems collects a huge amount of data that, if properly organized, can provide useful information for decision making and informed action, which results in the need to articulate the strategic vision with Information Systems. This study aims to identify the technological requirements and understand the technical difficulties in accessing data sources of different technological subsystems in order to facilitate dialogue between the departments which hold the data to build a future Academic Analytics in a HEI. To achieve these goals a prototype was conceived which involved the aggregation, cleansing and standardization of data sources and resulted in a database that integrates records from three data sources—the LCMS (Learning Content Management System), academic management services and quality management services. This prototype allows reports and analysis to be made. Future studies for the development and implementation of Academic Analytics that can produce information to support decision making and control of the HEI's activity are also possible.

Keywords Academic Analytics · Design science · Higher education · Management

1 Introduction

HEIs are organizations recognized for their pedagogical and scientific functions, which are supported by a multitude of services, including administrative services, quality management or marketing. With the increasing penetration of technology in all socio-

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economic areas, the HEIs invest in the acquisition of technological subsystems to achieve their policy and strategy and to better manage their various activities. These technological subsystems gather and store a huge amount of data that, if properly analyzed and aggregated, can be valuable for the management and for informed decision making.

For several years businesses have been implementing technological systems for advanced analysis of the available data. These systems are increasingly vital in informing the decision-making process, fundamental requirement in effective management. The HEIs' interest in this new wave of how to use the data is only now beginning and they are timidly trying to implement their systems of Analytics: "More recently, institutions of higher education are starting to adapt these methods to target fund raising, inform enrollment decisions, target marketing efforts, improve student support processes, and to better understand retention/persistence patterns (p.1)" (Bach 2010).

The term Analytics is a neologism in Education and it is imported from other areas, especially in the field of management:

> «"Analytics" is a term used in business and science to refer to computational support for capturing digital data to help inform decision-making. With the growth of huge data sets and computational power, this extends to designing infrastructures that exploit rapid feedback, to inform more timely interventions, whose impact can in turn be monitored. Organisations have increasingly sensitive 'digital nervous system' providing real time feedback on the external environment and the effects of actions (p.1)» (Shum 2012).

In fact, Analytics in Education is an emerging theme, foreshadowing to its adoption by HEIs in the near future, according to the "Horizon Reports," within 2 or 3 years (Johnson et al. 2013). The interest shown by national and international organizations in the field of higher education, the organization of conferences to discuss this specific issue—e.g. three editions of the Conference "Learning Analytics and Knowledge", in 2011, 2012 and 2013 (SoLAR 2013)—and the increase of the number of scientific publications are indicators of the emergence of the topic and its relevance.

The top management of the Universidade Católica Portuguesa—Porto (Católica—Porto) has invested in several technologic subsystems to support the teaching and research activities, and also in administration and quality management (Ferreira and Andrade 2012a). From this context, this paper tries to identify the technological requirements, technical difficulties in accessing and integrating data sources and facilitate dialogue between the departments that hold the data through the design of a prototype that will facilitate the future implementation of a system of Academic Analytics, involving the different stakeholders. Specifically, a model is devised to operationalize the intersection of technological data from three subsystems: i) Teaching (*Campus Online*), ii) Administrative Management (*Sophia*); iii) Quality Management (*SIGIQ*).

The methodology followed in the development of this Academic Analytics' prototype was the Model *Design Science Research Process* (PRSP), proposed by Peffers et al. (2006), which predicts a sequence of six steps to conduct and control the entire process, from problem identification/motivation to making the prototype to the evaluation and reporting of results.

Taking into consideration this introductory section, this paper is divided into 6 sections. Section 2 focuses on the theme of Analytics in Education and it is divided into three subsections: in the first, remarkably conceptual, we explore the neologisms typical of an area still emerging with the aim of consolidating a speech not yet stabilized; in the other two subsections we discuss the uses, the potential and the difficulties of Analytics in Education. In Section 3 the methodological framework of the research is justified taking into consideration the objectives of the study. Section 4 presents the built prototype: a database that reads and aggregates records from multiple sources and allows the making of reports and analysis. In Section 5 the main conclusions of the study are presented and in Section 6 future work is discussed.

2 Analytics in Education

2.1 The emergence of the topic and the need to clarify the conceptual framework

As with any new area of research, Analytics in Education has imported from other fields of knowledge a variety of terms and expressions to describe concepts and processes, often with significant conceptual and functional differences, and the use of different terms for the same conceptual definitions and functions has also occurred.

In this context, in order to ensure the accuracy of any communication on the topic, it is imperative to clarify the conceptual framework. Figure 1 shows schematically the work of systematization of the concepts used in Analytics in Education, presented in a "white paper" from *Educause*, published in 2012 (Barneveld et al. 2012) which establishes parallels between the conceptual framework of the field of Management and Education.

> **Analytics**—Comprehensive concept that has associated the idea of informed decision making based on data. Both in the field of Management as in Education, the definition is consistent. Norris et al. (Norris et al. 2009) present a definition of Analytics that integrates the main ideas associated with the concept: "[The] processes of data assessment and analysis that enable us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and/or entire industrie (p.1)" (Norris et al. 2009).

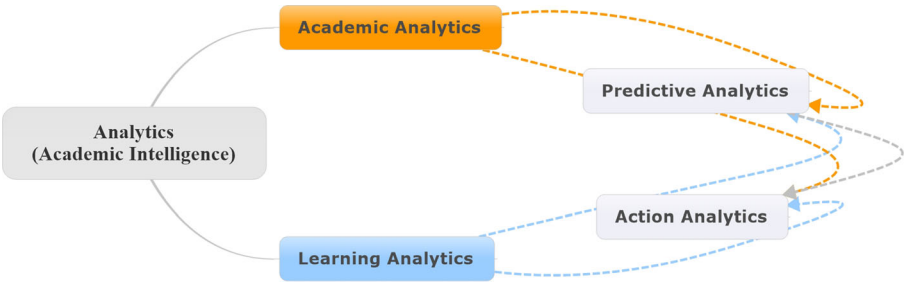

Fig. 1 Semantic field of Analytics in Education

Academic Analytics—The expression "Academic Analytics" in Education is a concept with many meanings. In literature this concept acquires different scope in terms of materials and scales of the analysis. In its broadest meaning, the Academic Analytics is equivalent to the term Business Analytics, which relies on the use of data to support the management of the activity of the HEIs, in its various forms (e.g. financial, educational, marketing, etc.). In the strictest sense, it focuses on monitoring issues related to the academic success of individual students (e.g. students at risk of retention). In this line, Analytics allows the HEIs' managers to access historical indicators, or in real-time, on various aspects of the institution and its organizational units (faculty/schools and departments). Goldstein's definition reflects the association for the concept of "Business Intelligence": "The term Academic Analytics is our imperfect equivalent term for Business Intelligence. We use it to describe the intersection of technology, information, management culture, and the application of information to manage the academic enterprise. Our use of the term academic is in no means intended to exclude the application of information to support decision making in the financial and business functions of the academy. We were very much interested in these areas as well (p.2)" (Goldstein 2005).

Learning Analytics—It focuses on issues of teaching and learning activity. The scale of analysis varies between the institutional level (e.g. evaluation of curriculum and institutions) and the monitoring of individual students, confusing itself with the *Academic Analytics* in its strictest sense. The Learning Analytics is the point of divergence in establishing the conceptual parallels between the worlds of Management/Business and Education. This concept Analytics can be viewed from two perspectives: one focusing on metrics that provide information to the departments on aspects related to the organization and operation of the courses; the other geared specifically for students and their learning activities. Bach's definition of "Learning Analytics", shows the semantic breadth of the concept: "Learning analytics involves the use of advanced modeling techniques integrated with learning outcomes assessment to better understand student learning and more efficiently and meaningfully target instruction, curricula and support" (Bach 2010).

Predictive Analytics—Once the data is collected, the reports are prepared and the information is analyzed, the next step is to use this data to anticipate scenarios ("Predictive Analytics") and make decisions based on the information ("Action Analytics"). This predictive analysis serves all levels of higher education.

Predictive Analytics—interventions, definition of policy and practices supported by the data collected by Analytics systems.

2.2 Uses and potential of Analytics in Education

The potential of the huge volume of data of the technological subsystems to feed the Analytics subsystems of the HEIs has an interest and applicability at various levels and dimensions. HEIs are organized according to a hierarchical structure, an organization type can be: University/Faculty/Department/Course/CU (Curricular Unit). These structures and the various actors of the organizations need systems of Analytics with different scales and granularities. Figure 2, adapted from the work of George

Siemens (2012) summarizes the use of Analytics at macro and micro scales, highlighting the complementary relationship between them.

The upper part of Fig. 2 reflects the role of a macro scale Analytics—HEI as a whole or its basic units—being associated with the concept of Academic Analytics. At this scale, the Analytics reflects a top-down view, in the sense that the analysis is done on a global scale through the integration of data sources of various technological subsystems of the HEI in an analysis tool, which should allow access to indicators, historical or in real time, on the various dimensions of the HEI and its organizational units.

The data sources used to power the Academic Analytics can be limited to pedagogical aspects, being in this case nearest to the concept of Learning Analytics: "Learning Analytics is more specific than Academic Analytics: the focus of the former is exclusively on the learning process. Academic Analytics reflects the role of data analysis at an institutional level, whereas Learning Analytics concentrates on the learning process (which includes analyzing the relationship between learner, content, institution, and educator) (p.34)" (Long and Siemens 2011); or they can integrate data from a variety of sources (e.g. pedagogical activity data, but also administrative sources, financial and others, allowing the HEI to manage the different dimensions underlying its operation), having in this case a concept parallel to *Business* Analytics: "Data is the foundation of all Analytics efforts. Academic Analytics can be based on data from multiple sources (such as an SIS [Student Information Systems], a CMS [Course Management System], or financial systems) and in multiple formats (such as

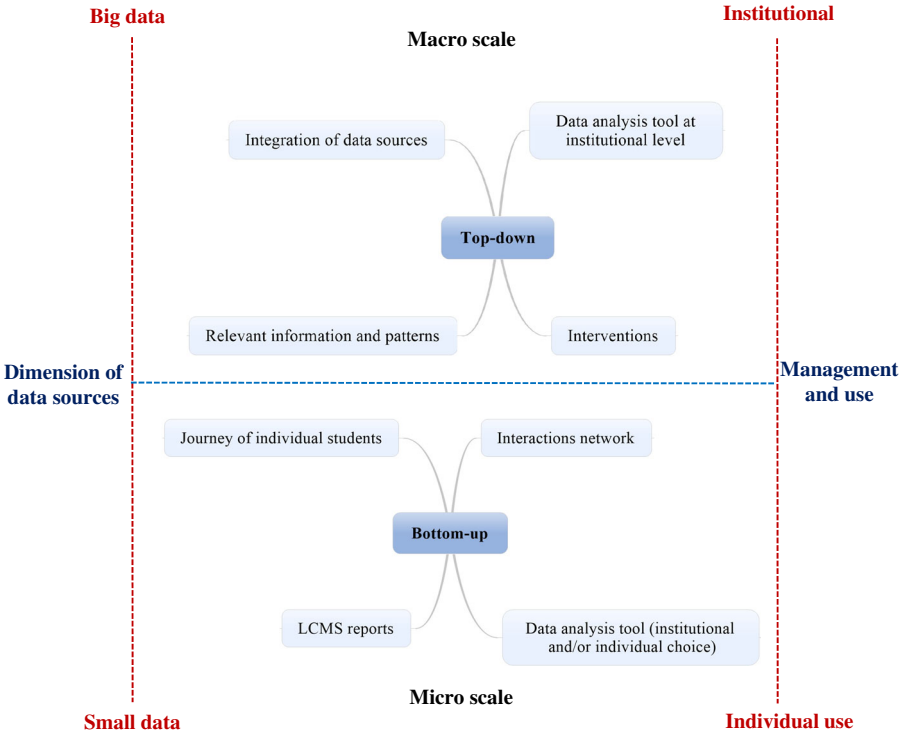

Fig. 2 Use of scales of analytics in HEIs

spreadsheets, enterprise financial system reports, or paper records) (p.3)" (Campbell and Oblinger 2007).

At the institutional level, these systems are used by administrators, quality control services, marketing and financing of HEIs to support decision making and an action guide (Campbell and Oblinger 2007; Long and Siemens 2011; Campbell et al. 2007), and it is possible to identify five steps in its use: data capture → production of reports based on the collected data → identification of relevant information/patterns/forecasts → intervention → redefinition of actions (Campbell and Oblinger 2007).

The lower part of Fig. 2 focuses on a micro scale and the approach is the *bottom-up* type in which the smallest elements of the system are specified in great detail. The data (*small data*) are used by a user or a small group of users (e.g., course coordinator, teachers who teach a specific CU, etc.), seeking information filtered to the course, CU or student's scale.

2.3 Challenges of Analytics in Education

The use of Learning Analytics by HEIs will take a few years to mature, however, its presence is already felt and should not be ignored (Picciano 2012). According to the report "The State of Learning Analytics in 2012: A Review and Future Challenges" (Ferguson 2012), the development and use of Analytics systems by HEIs faces two main challenges: the technological challenge and educational challenge.

The technological challenge is related to the ability of HEIs to develop software that enables deeper ways of extraction, aggregation and visualization of data and different ways of making reports, which establishes them as Analytics. This challenge is enhanced when the data sources are spread over multiple platforms.

The educational challenge is related to the ability of HEIs to optimize the use of information in the management of learning environments rich in technology and to enhance the effectiveness of the teaching-learning process (Ferguson 2012).

Related to these two challenges are the six barriers that institutions must take into account in developing their Analytics systems, which are mentioned in the Report "Predictive Analytics—Extending the Value of Your Data Warehousing Investment", of "The Warehousing Institute" (Eckerson 2007):

- *Complexity*—To develop models of Analytics in Education is a slow, complex and labor intensive work that requires the involvement of different people from the university and multidisciplinary teams;
- *Data*—Most of the HEIs' databases are full of errors and inconsistencies which have to be cleaned and standardized so that they can be used;
- *Processing*—Complex analyzes of data require efficient processors and intelligent software, requirements that are still not met in many HEIs;
- *Experts*—Difficulty in hiring experts in the development of Analytics computer systems;
- *Interoperability*—Analytics systems involve accessing and integrating data sources from multiple platforms and applications that require interoperable software.
- *Price*—The development of Analytics systems can have significant costs to midsize organizations, as are most of the HEIs.

Following these barriers, in the same report it can be read "Fortunately, these barriers are beginning to fall, thanks to advances in software, computing, and database technology (p.20)" (Eckerson 2007).

3 Methodological framework

The model *Design Science Research Process* (DSRP), suggested by Peffers et al. (2006), is the result of an effort to systematize the theoretical and practical knowledge in *design science*, and it has served as a guide in the construction of the prototype of Academic Analytics. The proposed model satisfies three requirements: i) it is consistent with the theoretical and practical knowledge produced under the paradigm of *design science*; ii) it presents a diagram with various stages of the *design science* process; iii) it defines a mental outline with the characteristics of the research's *output*. Figure 3 shows the PRSP model in a schematic way, where we can identify six steps in conducting research.

- *Problem identification and motivation*—The Academic Analytics is an emerging theme in the literature and its potential for the management of the different aspects of the HEIs' lives is recognized. The Católica—Porto has several technological subsystems that store data of interest for management, particularly in the field of teaching activity. In the current situation, these technological subsystems do not communicate with each other, and it is not possible to cross data from different sources. The approach is centered on this problem and its motivation is to aggregate data from various sources and cross them with each other, in order to extract useful information, which can be translated into gains in the management of the teaching activity.
- *Objectives of the solution*—Using the data that the institution already has, the aim is to present an architecture of an Academic Analytics system and to develop a prototype to demonstrate the mode of operation and its utility for the management of the teaching activity.
- *Design and development*—Mobilization of knowledge of the literature review in the area of Analytics to define the conceptual basis of the architecture of the Academic Analytics system. Delivering a prototype of an Academic Analytics system that includes three types of data sources originating from technological subsystems used in the institution—i) Teaching (*Campus Online*), ii) Administration (*Sophia*); iii) Quality (*SIGIQ*);
- *Demonstration*—The demonstration of the effectiveness of the solution was held through experimentation and simulation of cases, focusing on the verification of effectiveness of the crossing between the three data sources and on the interest and relevance for the management of the information *output*;
- *Evaluation*—Observation and successive testing; presentation of top management progress, with the aim of adjusting the model to the needs of the institution's

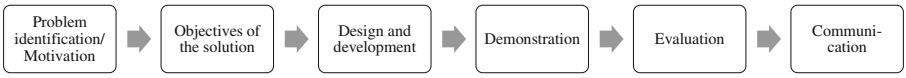

Fig. 3 Process of design science to the Academic Analytics of Católica - Porto

information; submission of the research done to journals and conferences with referees for validation by the scientific community;
- *Communication*—Information on the top management results of the Católica—Porto and submission to refereed journals and conferences.

The different stages of the DSRP model are intrinsically related and contain three fundamental cycles identified in the work of Hevner et al. (2004). In fact, the "Three-cycle view of design science research" (Hevner et al. 2004), which inspired the DSRP model (Peffers et al. 2006) is a landmark in terms of conceptualization and definition of guide lines to understand, implement and evaluate the design science applied to Information Systems.

In Fig. 4 the three cycles of the design science research are present, schematically, (Hevner et al. 2004):

- The **cycle of relevance** is measured by the response that the produced artifact offers to concrete problems and how it can contribute to the improvement of organizations.
- The **cycle of design and development** is the core of the process and that is where the artifacts are subject of evaluation, which feedback is the basis for the redefinition of the design and future developments.
- The **cycle of rigor** integrates scientific knowledge and methods in the construction and development of the system. At this stage, the assessment of the work done by the leaders of the educational institution and the submission of articles to specialized conferences and peer-review journals are fundamental in ensuring that rigor.

4 Results

Figure 5 reflects the architecture of the ongoing work in the field of Analytics in Católica—Porto. At this stage, the analysis was limited to three technological

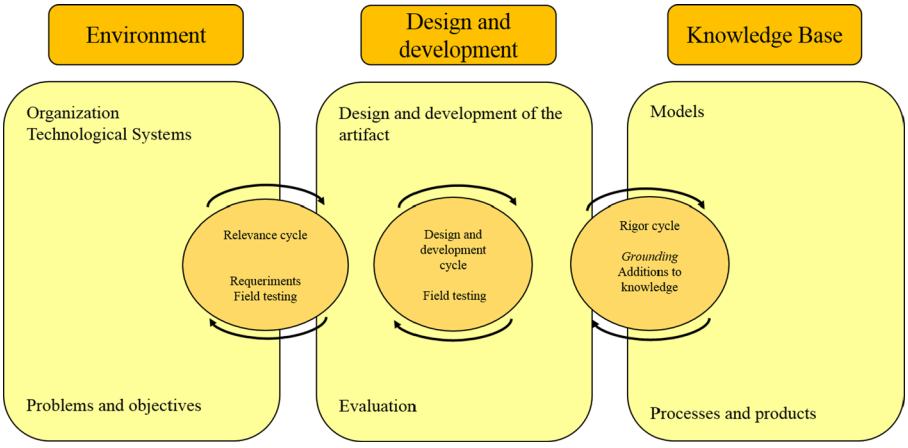

Fig. 4 Cycles of *Design Science*, according to Hevner et al. (2004)

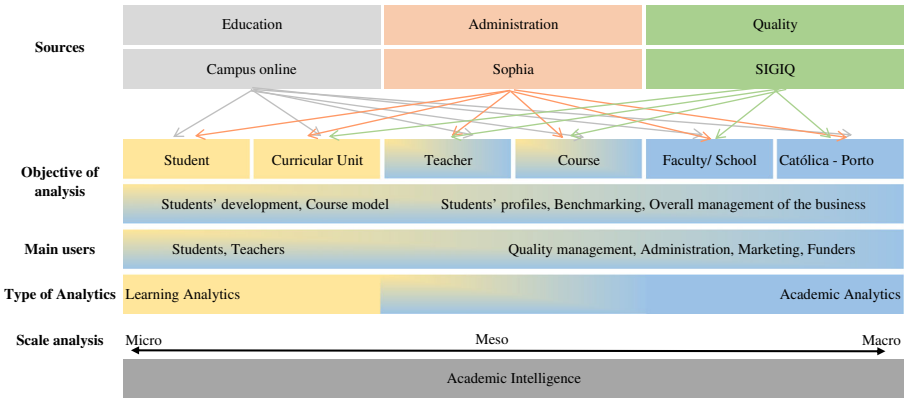

Fig. 5 Architecture of the Academic Analytics with data sources of teaching activity

subsystems that stores relevant data to the management of the teaching activity: *Campus Online* (LCMS), Administrative Management (*Sophia*) and Quality Management (*SIGIQ*).

In line with the theoretical framework presented in Section 2, the Analytics in Education can have multiple scales of analysis, ranging from the micro level (focused on aspects related to the process of teaching and learning, for example the development of the students or the course model. This information is potentially more interesting to teachers and students (more directly involved) and the macro level (which includes more general aspects, such as administrative issues or quality management). The micro scale is mainly related with the Learning Analytics and the macro scale with the field of Academic Analytics, although the boundary between the two is not easy to define.

This study takes the same view of the Academic Analytics' perspective (macro analysis) and it tests the organization and aggregation of existing data from different technological subsystems used in the institution to inform, first the management and service quality management on relevant aspects of the university's teaching activity. In Fig. 6, the results are represented under the form of a database structure.

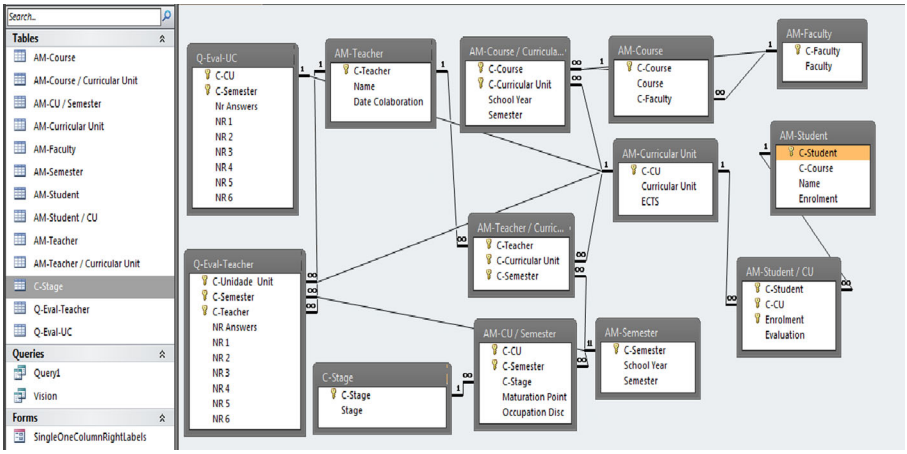

Fig. 6 Database structure with the aggregation of sources of technological subsystems relevant to the management of teaching activity

The development of this database, that and reads and aggregates records from multiple sources and allows reports and analysis to be made, assumed the completion of a set of steps that includes the aggregation of sources, cleaning and data standardization. In Fig. 6 three technological subsystems are aggregated:

- *C* (*Campus Online*)—The data source is the LCMS. The available data are the *output* of a Learning Analytics system developed at LCMS' *backoffice*, at an earlier stage of this process. This Learning Analytics system allows the positioning of each CU in a matrix with five levels of integration of this technological platform in the process of teaching and learning—introduction, adoption, adaptation, immersion, transformation—(Ferreira and Andrade 2012a, b);
- *AM* (*Administrative Management*)—The data source is *Sophia*. The data provided enables the association of administrative dimensions (faculty, CU, teachers, students, number of enrolments, ETCS, …);
- *Q* (*Quality Management*)—The data source is the *SIGIQ*. The data provided by this subsystem are the result of questionnaires given to students at the end of each CU, where one can extract information on the overall evaluation of CU the teacher.

In Table 1 the aggregation of data from the three technological subsystems: AM—the data obtained has the name of the CU, the number of students and average ratings of academic students enrolled; C—provided data with the stage and the point of maturation of each CU regarding the use and integration of the LCMS in the process of teaching and learning (Ferreira and Andrade 2012a, b); Q—has provided data on the overall assessment of the CU made by the students at the end of the activities by completing a questionnaire (the six columns that appear in the table refer to the six levels of positioning, ranging from "Quest_1"—evaluation less favorable—and "Quest_6" - evaluation more favorable.

Figure 7 illustrates the potential that this Academic Analytics system can have in the following plans: i—integrating data from different technological subsystems in use in the educational institution, in this case: C—Campus, AM—Administrative Management; Q—Quality Management; ii—organization and multidimensional data analysis by levels of detail (university, college, CU, teacher, student); iii possibility of selection of variables to be considered at a given time.

This clever and versatile data presentation, inspired by the OLAP philosophy—Online Analytical Processing—(OLAP.COM 2010), has a huge potential because: i—through filtering variables, reduces the entropy associated with high volumes of information; ii—enables development of custom reports, satisfying the information

Table 1 Report with analysis of data originating from the three technological subsystems

CU	C - Stage	C - Point of Maturation	Q-Quest1	Q-Quest2	Q-Quest3	Q-Quest4	Q-Quest5	Q-Quest6	AM - Nr students	AM - Average
A	Introduction	15	0	1	3	3	1	1	10	14
B	Introduction	3	0	0	0	0	0	2	5	17
C	Introduction	3	0	0	0	0	1	14	20	14
D	Introduction	10	0	3	5	9	6	2	31	10

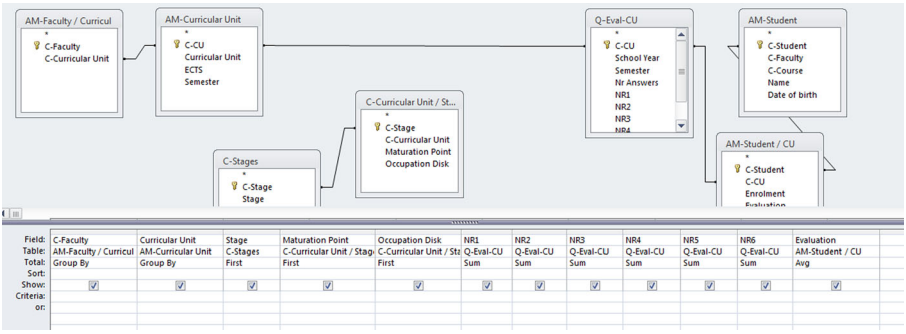

Fig. 7 Example of customized reports with integration of sources and definition of dimensions and scale of analysis

needs of each specific group; iii—enables conditioning access to information, ensuring the confidentiality of the most sensitive information.

The design of the Academic Analytics prototype followed the different methodological stages set out by the DRSP model (Peffers et al. 2006) and fulfilled the three cycles of Hevner et al. (2004), which ensured the relevance, appropriateness and accuracy of the system.

- The cycle of relevance was ensured in two ways: i) demonstration, based on published papers, of the potential of Academic Analytics systems for managing the activity of HEIs; ii) answer to a management information problem of Católica—Porto, which resulted from the use of different technological subsystems that do not communicate with each other (Phase of DRSP model: problem identification and motivation).
- In the design and development cycle, a prototype of Academic Analytics was made, which aggregates data from the three subsystems in use in the educational institution—the LCMS, the academic management services and the quality management services (Phase of DRSP model: Objectives of the solution). To implement this prototype we needed an intense work of aggregation, cleansing and standardization of the data from the three subsystems (Phase of DRSP model: Design and development). In this cycle the operation of the system has been demonstrated through its operationalization (cf. Table 1 and Fig. 6) and the stages of evaluation and reporting of results of the DRSP model were fulfilled. To this end, successive tests were performed and the progress was presented to the top level of the university management and quality management services.
- The cycle of rigor is strongly linked to the two cycles and it is guaranteed by communication actions, which allowed the procedural evaluation by the people in charge of the educational institution and peers in the scientific community (as in the case of the submission of this article).

5 Conclusions

In several sectors of activity (e.g. Marketing and Management) they have already been implemented for several years, technological systems that allow us to analyze the huge

volume of existing data relevant to the management, being essential for informed decision making.

> In the Education sector, specifically in higher education, such Analytics systems which could be used to inform the university and serve as a guide to more informed action and which are so technologically robust so they would enable the aggregation and the processing of HEIs already existing data do not yet exist: "Although (…) generic software features, the depth of extraction and aggregation, reporting and visualisation functionality of these built-in Analytics has often been basic or non-existent (p.4)" (Ferguson 2012).

The result of this study, which falls within this context, manifests itself in the creation of the theoretical framework of the Analytics thematic in Education and in the presentation of a prototype of Academic Analytics system whose main contributions were:

- Articulation of policy and strategy defined by HEI with Information Systems. The demonstration of the integrated use of data already available in the technological subsystems can help open new avenues in the field of management, particularly in the process of decision making based on the information.
- Identification of the technological requirements and the technical difficulties in accessing the different databases, particularly in: i) Understanding of data: collection, description, exploration and verification of data quality. The prototype showed the kind of data that the institution already has in the different technological subsystems. This information is important in the development of future Academic Analytics model and in the adaptation of the information *output* from the different subsystems to the information needs of HEI; ii) Preparation of data: data from the three subsystems had errors, redundancies and different codes to designate the same object of analysis (e.g. the code of CU is different in the subsystems Sophia or Blackboard), which required a great deal of data normalization. In the prototype a response to the problem of aggregating different sources of data on occurrences in the same time period has been given. Data were properly normalized and identified through an appropriate encoding iii) Integration of data sources from different technological subsystems that did not communicate: Campus, Sophia and SIGIQ.
- Facilitating dialogue between department holders of data that favors future implementation through the creation of the involving the different *stakeholders*.
- Innovation of the methodological procedures, which do not follow the traditional paradigms used in educational sciences, which still are the descriptive or explanatory studies, and more recently, interpretive studies (Peffers et al. 2006; Sampiere et al. 2006)—proved to be very appropriate, ensuring accuracy in the various dimensions of the prototype development process and may constitute a methodological alternative to other studies, where the goal of the research is the development of a technological artifact in response to a practical problem.

In the perspective of H. C. Lucas, a system is "an organized set of procedures which, when executed, produce information to support decision making and control of

organizations (p.10)" (Lucas 1987). It was this goal that was pursued in the development of the prototype of the Academic Analytics system. Creating this prototype involved a set of procedures that involved the aggregation, cleansing and standardization of data sources and resulted in a database that aggregates records from multiple sources and allows reporting and analysis.

6 Future work

The development of a model of an Analytics system that responds to the real needs of the institution for information and that allows for organization and presentation of data in a versatile way, in order to provide relevant information for decision making, in relation to the different aspects of the HEI's life assumes: i) the definition, by decision-makers and other HEI's stakeholders, of the dimensions and data to be included in the Academic Analytics model; ii) development of a technologically-based system that allows the aggregation of multiple sources and feeds the database in order to meet the information requirements defined in i). Data filtering by size, time period and scale of analysis is a fundamental requirement for the effectiveness of Academic Analytics in the management of the different dimensions and at different levels of the institution's life.

The technological solution may require the construction in the server of an application of data source aggregation and the development of a system of analysis (classical *web* application) or to apply a tool of OLAP cubes that replicates the model and enables pre-formatted analysis (reports pre-defined)

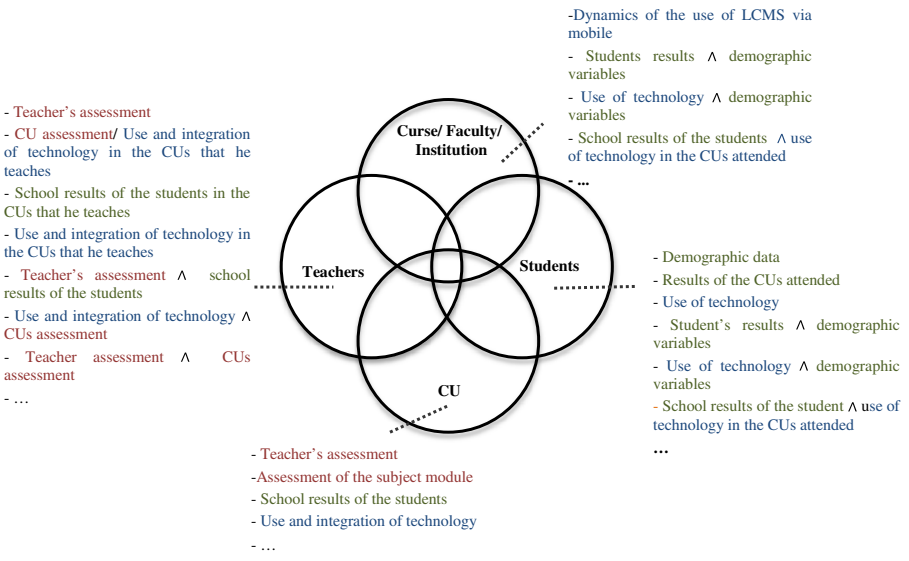

Fig. 8 Examples of indicators that can be part of the future *Academic Analytics*

and allows flexibility to define new reports, depending on the HEI's information needs, adding versatility.

Figure 8 presents examples of indicators which can be built by crossing data from different sources with several levels of detail. This data can be used to inform, anticipate scenarios (*Predictive* Analytics) and make decisions based on the information (*Action* Analytics).

Some examples:

- Cross-reading the academic results of students and the demographic variables may enable the identification of profiles of students at risk, which is important information for the definition of pedagogical intervention plans;
- The relationship between the use/integration of technology and appreciation of CUs can give indications about the acceptance of technology in several CUs;
- The dynamics of access to the subsystems via mobile may affect the decision on possible investments by the institution in software applications or *Learning Objects* for those platforms.

Therefore, there is a whole world that opens up to management—in the definition of policy, practices, interventions and actions—based on the power of Analytics systems in giving meaning to information.

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