10th European Quality Assurance Forum

19-21 November 2015

Quality Assurance Agency and UCL Institute of Education

London, UK

Taking stock and looking forward

Paper presented during EQAF 2015

Author(s)

Name: Anna Prades

Position: Project Manager

Organisation: AQU Catalunya

Country: Spain

Short bio:

Anna Prades is project manager in the Catalan University Quality Assurance Agency since 2000. She has a degree in Psychology (1996) and a PhD in Pedagogy (2005) from the Universitat of Barcelona. She coordinates the graduate, master and PhD placement surveys that the seven Catalan universities carry out every three years since 2000 (studies 2001, 2005, 2008, 2011 and 2014). She also has been active in designing quality assessment methodology, coordinating work-groups designing good-practices guidelines. She has been methodologist in several external assessments. She has participated as an expert in the feasibility study for the contextual strand of AHELO. She is actually involved in two European Projects: project ISLAH which wants to enhance quality and relevance of higher education in the partner countries and project IMPALA, which deals about the assessment of the impact of different External Quality Assurance procedures.

Author(s)

Name: Maribel Quirós

Position: Information systems

Organisation: AQU Catalunya

Country: Spain

Short bio:

Maribel Quirós has a degree in Computer Science Management Engineering (2002) from Universitat de Girona and actually studying a postgraduate in Business Intelligence (2015) from Universitat Oberta de Catalunya. She is analyst programmer in the Catalan University Quality Assurance Agency. She has developed a software for storage much data of several survey of labour market of Catalan's graduated, it has processed data to transform in KPI and export multiple reports which are sended to Catalan's Universities and they have published in AQU's web. An example of this reports can be looked at http://www.aqu.cat/uploads/insercio_laboral/enquesta2014/index.html)

Author(s)

Name: Maria Giné

Position: AQU's secretary

Organisation: AQU Catalunya

Country: Spain

Short bio:
Maria Giné is the secretary of the Board of Directors of the Catalan University Quality Assurance Agency since 2012. She has a degree in History (1997) from Universitat de Lleida, a Public Management Master (2000) from the Universitat Autònoma de Barcelona, Universitat Pompeu Fabra and ESADE Business School, and a MBA (2005) from ESADE Business School. She has held different responsibility positions in AQU Cataluña since 1998, related to Strategic Management, Planning, and Communication. Nowadays is working into AQU's Catalunya general management. In 2012 she assumed the general coordination of the team who is in charge of the labour market survey.

Author(s)

Name: Lorena Bernáldez

Position: Management assistant adviser

Organisation: AQU Catalunya

Country: Spain

Short bio:

Lorena Bernaldez has a degree in Statistical Science (2005) from the Universitat Politècnica de Barcelona. She is management assistant adviser in the Catalan University Quality Assurance Agency. Lorena Bernaldez has participated the graduate, master and PhD placement surveys that the Catalan universities carry out every three years – since 2005 (2005, 2008, 2011 and 2014). As data analyst, she has carried out a range of tasks: through data cleaning, integrating data bases; creation new variables; explorative and descriptive analysis; to advanced multivariate statistical methods. She is proficient in the management of SPSS, R-project, Matlab and Power-Pivot.

Proposal

Title: BIG (AND SMALL) DATA MEETS QUALITY ASSURANCE

Abstract:

Evidence, both quantitative and qualitative, is at the core of every assessment process. New technology has given us an unprecedented opportunity to tackle both structured and unstructured data, yet barriers remain that restrict our ability to take advantage of this scenario. As a result, data often falls short of triggering change. One reason for this is the over-abundance of information. In this paper, we present and discuss a case study for the assessment of research and teaching quality in university departments. The study illustrates how AQU Catalunya is changing the way it presents quantitative data, benchmarking clusters of indicators to foster debate about the results. Finally, we look to the future, discussing what resources will be required if we wish to explore every opportunity the new data era can offer to quality assurance.

Text of paper:

1. Data and quality assurance: love at first sight

In the nineties, the Dutch model of quality assessment (Vroeijenstijn, 1994; Westerheijden, 1996) became a clear reference for emerging models across continental Europe. Within this model, the quality assessment “spiral” (Westerheijden, 1996: 274) is a circular and cyclical process which begins with collecting and systematizing information relating to the unit to be assessed (i.e., programme or institution). This information comprises statistics, data management outcomes, and indicators on the inputs, processes and results of the studied unit through which to build a diagnosis of its strengths and weaknesses (Rodríguez, 2013:101).

The collection of evidence is also at the core of Standard 1.7, on information management, in the European Standards and Guidelines (ESG, 2015), which states: “Institutions should ensure that they collect, analyse and use relevant information for the effective management of their programmes and other activities”. Indeed, one of the more significant and lasting impacts of the quality assessment movement has been the development of information systems capable of providing the evidence required for the different external quality assessment procedures.

Jeliazkova & Westerheijden (2001) stress that the ultimate goal of all quality policies is to foster “quality awareness” or a “quality culture” within higher education institutions (HEI) (2001), and it is difficult to imagine a quality culture that is not data-driven. “Data-driven decision making” can be defined as the use of data analysis to inform courses of action involving policy and procedures (Arnold & Pistilli, 2012:1), inherent to which is the development of reliable and timely information resources to collect, sort and analyse the data used in the decision-making process.

Corporations have long used data about consumers and their habits to determine marketing strategies, guide product development and predict sales on the basis of current buying habits. This practice is referred to as “business analytics”, which can be defined as the iterative, methodological exploration of an organization’s data with emphasis on statistical analysis. It is used by companies committed to data-driven decision-making (Rouse, 2010; cited by Pistilli et al., 2014).

Using data to drive decision-making processes is not new in higher education. Colleges and universities have begun to use data to better understand and begin to address areas such as student success, retention and graduation rates, course offerings, financial decisions, hiring and staffing needs, or admissions models of admits, yield, and matriculation (Pistilli et all 2014). Goldstein & Kats (2005) coined the term “academic analytics”, arguing that “business intelligence” was born in the private sector and that the concept of intelligence – competitive or otherwise – felt wrong in the context of the academy (2005:8). As in business analytics, in academic analytics it is crucial for data to be “actionable”, meaning that it must be converted into actionable insights that flag up issues and areas of concern and inform the necessary responses to plan for the future, what Arnold & Pistilli call “actionable intelligence” (2012).

Several HEIs have already harnessed big data to improve their efficiency. Course Signals at Purdue, for example, is a renowned program that uses learning analytics to increase student success (Arnold & Pistilli, 2012). Elsewhere, Cutter Consortium has developed an ambitious technology solution that uses big data analytics to obtain real-time feedback from students, enabling universities to improve classroom scheduling and building utilization through student retention or course recommendations (Kellen et al., 2013).

Data is necessary but not sufficient

According to Kellen et al. (2013): “Higher education is at the cusp of gathering an unprecedented amount of information using affordable tools and techniques.” Technology, therefore, may facilitate a greater degree of rationality in decision-making in higher education institutions (Picciano, 2012) and, consequently, help to build a quality culture.

However, data on its own is not sufficient, and the sheer amount of data can, in some cases, be a deterrent. Hebert Simon, Nobel Laureate in Economic Sciences (1978) for his research into the limits of rationality in organizations, stated “a wealth of information creates a poverty of attention” (cited by Picciano, 2012).

Davies et al. (2001) argue that organizations and workers will only be able to turn the massive influx of data into an advantage if they can learn to effectively filter and focus on what is important. This statement is expanded on in an honest and clear-sighted paper titled “Numbers Are Not Enough. Why e-Learning Analytics Failed to Inform an Institutional Strategic Plan” (Macfayden & Dawson, 2012). The authors acknowledge that the crux of the failure was focusing on technical systems and integration concerns, while failing to address the complexities and challenges of institutional culture and change. They propose that “greater attention is needed to the **accessibility and presentation of analytics** processes and findings so that learning analytics discoveries also have the capacity to surprise and compel, and thus motivate behavioural change” (2012:160).

2. Case study: assessment of university departments

2.1. AQU Catalunya and data

AQU Catalunya has a long history of data processing dating back to the year 2000, when it coordinated the first labour market survey of graduates from Catalan universities. The survey has since been carried out on a three-yearly basis (in 2005, 2008, 2011 and 2014) and now holds more than 80,000 entries, and encompasses the three cycles of higher education (bachelor’s degrees, master’s degrees and PhDs).

In 2012, AQU launched WINDDAT (http://winddat.aqu.cat/), a website containing a comprehensive series of teaching indicators for Catalan universities to allow analysis of the performance of each course organized by inputs, staff resources and outcomes indicators. The site takes its data, with the exception of those relating to graduate employment, from the UNEIX database[1].
As of 2014, AQU also carries out employer surveys and student satisfaction surveys.

2.2. Objective of the assessment

AQU Catalunya was commissioned by the executive branch of the Government of Catalonia to design a method for analysing the research and teaching activities of departments[2] in the Catalan university system, using quantitative research and teaching data available in UNEIX. The main strength of the resulting project it is use of consolidated, reliable and comparable data on the Catalan university system, while the main weakness is the restriction to the available, rather than the “necessary”, data. The objective of the study was to harness – and to clearly delimit – the full potential of the available data for the task entrusted to us.

---

[1] UNEIX is an information system that, since 2000, has compiled and collated the management data of all universities in Catalonia (7 public and 5 private). It contains microdata on every student (socio-demographic information, enrolled credits, completed credits, etc.), data on teaching staff (category, age, credits taught), and data on research, grouped by department.

[2] In Spain, university teaching is organized at faculty level, while research is organized by departments, which are attached to specific knowledge areas.

2.3. The project

The working group

The project group was formed by Dr Martí Casadesús, an academic and the current director of AQU Catalunya; Dr Sebastián Rodríguez, a leading academic in the field of institutional assessment; Joan Bravo, a statistics expert specializing in the Catalan university System and creator of UNEIX, and the database specialist Maribel Quirós. The skills and expertise of the working group were one of the main strengths in the development of the project.

Method

The analysis focused on the last year for which data were available, 2012, with the exception of financial data, which were taken from the period 2009-2012.

The working group chose subject sub-areas, rather than institutions, as the reference units for the study, as no relevant conclusions could be drawn from comparing, for example, data on the funding of a humanities department and a biomedicine department. The 287 departments that existed in 2012 were therefore grouped according to the following classification:

Table 1. Departmental classification: subject areas and sub-areas

Subject area	Sub-area	Nº Departments
Humanities	Fine Arts	6
	Philology	22
	Philosophy	5
	Geography and History	21
Social Sciences	Political Sciences and Sociology	5
	Law	17
	Economics and Business	20
	Education	19
	Journalism and Communication and Library Science	7
	Psychology	11
Experimental Sciences	Biology	6
	Geology	8
	Mathematics and Physics	19
	Chemistry	10
Health Sciences	Biomedicine	21
	Pharmacy	4
	Nursing	7
	Medicine and Surgery	16
	Veterinary Science	4
Engineering & Architecture	Architecture and Civil Engineering	12
	Mechanical and Production Engineering	28
	Agricultural Engineering	5
	ICT Engineering	14
Total		287

The indicators

An exhaustive search of UNEIX was conducted to determine the indicators that would give the most reliable picture of teaching and research quality across the 287 departments. Twenty-five indicators were selected, as shown below:

Table 2. Research and teaching indicators

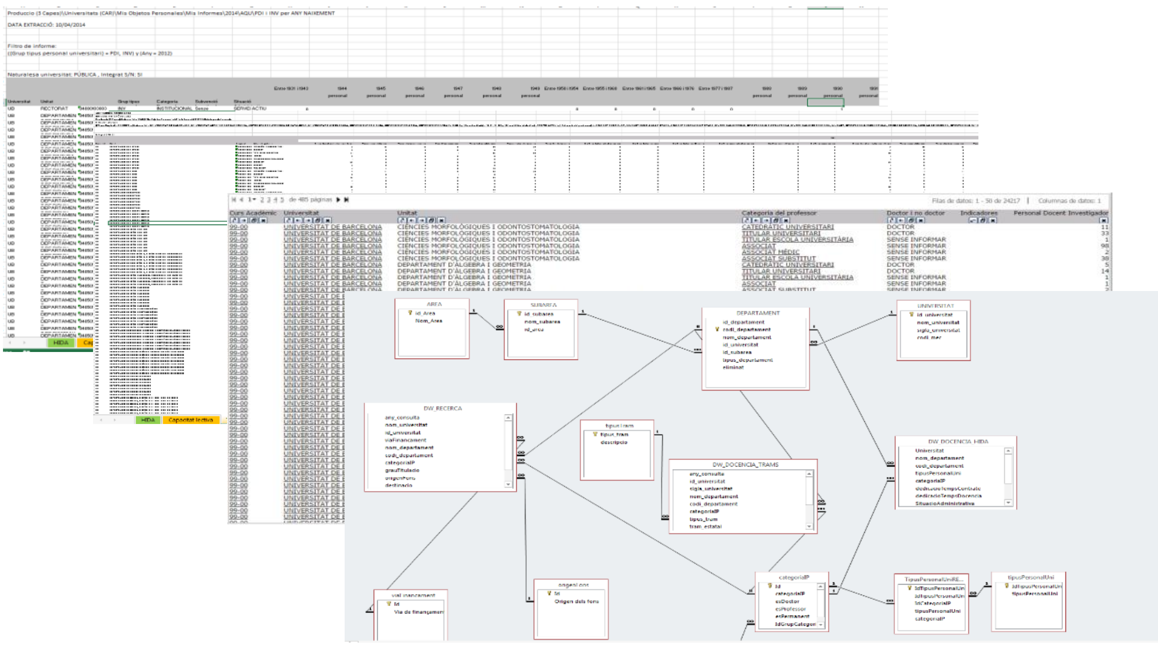
Research	**RIND01**	Sum of TOTAL income generated in 4 years by PhD-holders / number of PhD-holders
	RIND02	Sum of income from EUROPEAN SOURCES generated in 4 years by PhD-holders / number of PhD-holders
	RIND03	Sum of income from STATE SOURCES generated in 4 years by PhD-holders / number of PhD-holders
	RIND04	Sum of income from CATALAN SOURCES generated in 4 years by PhD-holders / number of PhD-holders
	RIND05	Sum of income from CONTRACTS AND AGREEMENTS generated in 4 years by PhD-holders / number of PhD-holders
	RIND06	Sum of income from COMPETITIVE FUNDING SOURCES generated in 4 years by PhD-holders / number of PhD-holders
	RIND07	Sum of income from NON-COMPETITIVE FUNDING SOURCES generated in 4 years by PhD-holders / number of PhD-holders
	RIND08	Current research premiums from regional government / no. people with current research premiums in the category Principal Investigator
	RIND09	Sum of **TOTAL income** generated in 4 years by: 2-FULL PROFESSOR, 3-SENIOR LECTURER, 16-UNIVERSITY SCHOOL FULL PROFESSOR
	RIND10	Sum of **TOTAL income** generated in 4 years by ALL OTHER TEACHING STAFF (not categories 2,3 or,16, above)
Teaching	**PIND01**	Permanent teaching staff / teaching staff (permanent + adjunct) * 100
	PIND02	Full-time teaching staff (A+B) with net teaching capacity > 0 / teaching staff (permanent + adjunct) * 100
	PIND03	Part-time teaching staff (A+B) with net teaching capacity > 0 / teaching staff (permanent + adjunct) * 100
	PIND05	Permanent teaching staff >= 60 years / total permanent teaching staff * 100
	PIND06	Permanent teaching staff >= 45 years and < 60 years / total permanent teaching staff * 100
	PIND07	Permanent teaching staff >= 35 years and 45 < years / total permanent teaching staff * 100
	PIND08	Permanent teaching staff < 35 years / total permanent teaching staff * 100
	PIND10	Six-yearly research premiums from regional government * 6 / five-yearly teaching premiums from regional government * 5
	PIND11	Total teaching and research staff + International researchers / Total teaching staff * 100
	PIND12	Total teaching and research staff + EU researchers - 15 + USA & CANADA / Total international * 100
	PIND14	% permanent teaching staff in (23 Special Services and 22 Services) / teaching staff (permanent + adjunct)
	PIND15	% net teaching capacity of permanent teaching staff / potential teaching capacity of permanent teaching staff
	PIND17	% PhD-holders / total teaching staff
	PIND18	Age indicator (sum of all groups - over-60) / over 60
	PIND19	Distribution of classroom teaching hours; % according to teaching staff category

Methodology and data processing

The tools used to process the data were: Microsoft Excel (macros and PowerPivot), Microsoft Access and Micro Strategy (UNEIX). Figure 1 illustrates the complex integration of data across these three tools.

In total, the analysis required us to process some 82,000 entries, making it impossible to analyse the data and interpret the results using conventional list or table formats.

Figure 1. Data processing tools



The solution arrived at to "make sense" of this vast amount of data was to benchmark clusters of indicators. The steps for obtaining the final report are outlined below using an example indicator:

Step 1: Define and calculate the indicators for each department.

Step 2: Within each sub-area, place the indicator in quartiles (25%, 50%[3], 75% and 100%). This step consists in comparing the value of the indicator for one department with the values of the indicators for the other departments in the same sub-area. So, for example, indicators in the top 25% are classified in quartile 1 (Q1) and are the most favourable indicators relative to the other departments in the sub-area. This process is repeated for each indicator.

Table 3. Calculated value and classification of each department in a sub-area by indicator

RIND01: *Sum of **TOTAL** income generated in 4 years by PhD-holders / number of PhD-holders*

[3] Equivalent to the average.

Area: Eng. i Arquitectura
Subarea: Enginyeria TIC

University	Department	Numerator	Denominator	Quartile	The value of the indicator
Uni 1	TELECOMUNICACIÓ I D'ENGINYERIA DE SISTEMES	3.641.954 €	24		151.748 €
Uni 1	ARQUITECTURA DE COMPUTADORS I SISTEMES OPERATIUS	1.261.764 €	19		66.409 €
Uni 1	CIÈNCIES DE LA COMPUTACIÓ	604.981 €	29		20.861 €
Uni 1	ENGINYERIA DE LA INFORMACIÓ I DE LES COMUNICACIONS	2.536.556 €	16		158.535 €
Uni 2	ARQUITECTURA DE COMPUTADORS	13.895.444 €	67		207.395 €
Uni 2	ENGINYERIA DE SISTEMES, AUTOMATICA I INFORMATICA INDUSTRIAL	5.452.522 €	41		132.988 €
Uni 2	LLENGUATGES I SISTEMES INFORMATICS	6.666.972 €	77		86.584 €
Uni 2	TEORIA DEL SENYAL I COMUNICACIONS	21.515.083 €	108		199.214 €
Uni 2	ENGINYERIA TELEMATICA	5.405.242 €	39		138.596 €
Uni 2	ENGINYERIA DE SERVEIS I SISTEMES D'INFORMACIÓ	991.360 €	16		61.960 €
Uni 3	DEPARTAMENT DE TECNOLOGIES DE LA INFORMACÓ I LES COMUNICACIONS	43.364.398 €	113		383.756 €
Uni 4	DEPARTAMENT D'INFORMÀTICA I MATEMÀTICA APLICADA	749.672 €	35		21.419 €
Uni 4	DEPARTAMENT D'ARQUITECTURA I TECNOLOGIA DE COMPUTADORS	3.748.370 €	27		138.829 €
Uni 5	ENGINYERIA INFORMÀTICA I MATEMÀTIQUES	6.109.317 €	42		145.460 €

Step 3: Calculate the total number of indicators in each quartile by sub-area or by university, according to the level of analysis.

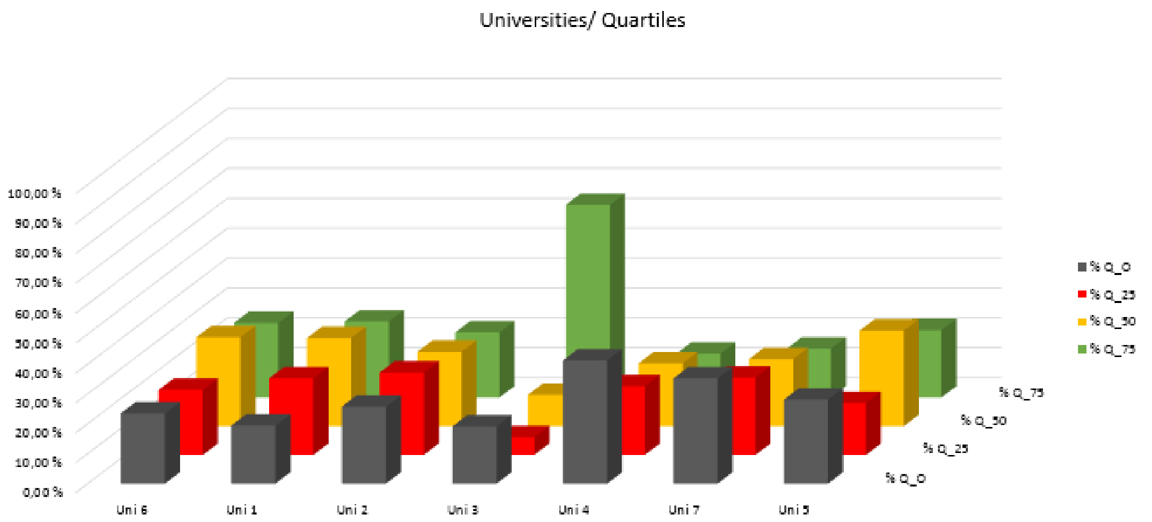
Table 4. Final breakdown by university of the total number of indicators in each quartile

Universities

	Nº Dept.	Nº Ind.	% Q4	% Q3	% Q2	% Q1
Uni 6	106	2014	23,44 %	21,80 %	29,79 %	24,98 %
Uni 1	57	1073	19,38 %	25,63 %	29,54 %	25,44 %
Uni 2	42	798	25,69 %	27,57 %	24,94 %	21,80 %
Uni 3	8	152	19,08 %	5,92 %	10,53 %	64,47 %
Uni 4	24	456	41,23 %	23,03 %	21,05 %	14,69 %
Uni 7	26	494	35,22 %	25,91 %	22,47 %	16,40 %
Uni 5	24	456	28,07 %	17,32 %	32,02 %	22,59 %
Total	**287**	**5443**	**25,79 %**	**23,06 %**	**27,28 %**	**23,87 %**

Step 4: Present the results graphically.

Figure 2. Visualization of results by university



2.4. Discussion

The graphic displayed in Figure 2 is a global summary of departments' performance. The data is displayed in a way that leaves nobody indifferent, stimulates the analyst, and, hopefully, encourages the search for further information that could explain the current diagnosis. This is, according to Conesa and Curto (2010), the objective of scorecards and dashboards, to offer a display with relevant data, organized in a single screen, so that the information can be perceived and understood quickly (Conesa & Curto, 2010).

Despite the robustness of the data presented in this report, we are aware that our approach is a preliminary one and must be tested further, giving due consideration to the complex and diverse situations of the different departments. This document should be understood for what it is: a first approach using the data available to us**. The analysis has enabled us to detect the need to incorporate new indicators**, with a view to making a more accurate diagnosis of teaching and research quality.

It could be argued that this case study in fact ranks departments. It is also true that the study offers information "relative to others", i.e. comparative indicators, yet this is the definition of benchmarking: the continuous, systematic processes involving internal and external measurement of products, services and processes which lead to better practice and improved performance (Appleby, 1999:55). The criteria of the EFQM and Malcolm Baldrige (USA) models require organizations to demonstrate that their processes are measured and compared, both internally and externally, through benchmarking (Rodríguez, 2002).

We hope that this report invites reflection, helping department heads and university directors to plan improvements that will drive the Catalan university quality system forward.

Beyond the scope of this case study, the new indicator methodology is being extrapolated to other studies coordinated by AQU Catalunya, such as labour market surveys, with a view to its ongoing use in the future.

3. The future

We believe that one of our roles as a quality assurance agency is to help HEIs take advantage of the opportunities provided by big and small data. To do this, three ingredients are needed: leadership and business sense, data infrastructure, and staff with the necessary skills.

3.1. Big data/small data: what are they for?

According to the GovLoop guide *The Big Data Playbook for Government* (2015), the first step is to define the problem you need to solve and the outcomes you want to achieve. This is related to proving the business value of the project.
Data can help to address information needs in the following areas:

a) *Graduate surveys (bachelor's degrees, master's degrees and PhDs):*
An integrated database, containing all of the bachelor's degree, master's degree and PhD surveys carried out since 2001, would allow us to conduct temporal analyses, construct predictive models of professional success, conduct cluster analyses to improve training effectiveness (good practices), predict enrolment trends, taking into account the economic situation[4], etc..

[4] Blom et al. (2015) discovered changes in enrolment strategies during recessions, for example.

b) *Institutional data:*

- Real-time teaching staff "replacement" in the event of upcoming retirements.
- Identification of at-risk students, via socio-demographic characteristics, access grades in certain subjects, and first-semester success rate.
- Institutional KPI for teaching and research (using date aggregated by degree programme, sub-area, subject area and institution).

c) Quality assurance procedures:

- Design of a predictive model of accreditation results, a self-assessment tool applicable prior to external assessment.
- Possible use of existing data to simplify the assessment procedures.
- Use of teaching staff and learning outcome indicators as the basis for risk assessment procedures.

3.2. Team requirements

In order to carry out a data project you need a data team. Taking as a reference GovLoop suggestions for an "all-star team" (2015), in our experience, at least the following roles must be covered:

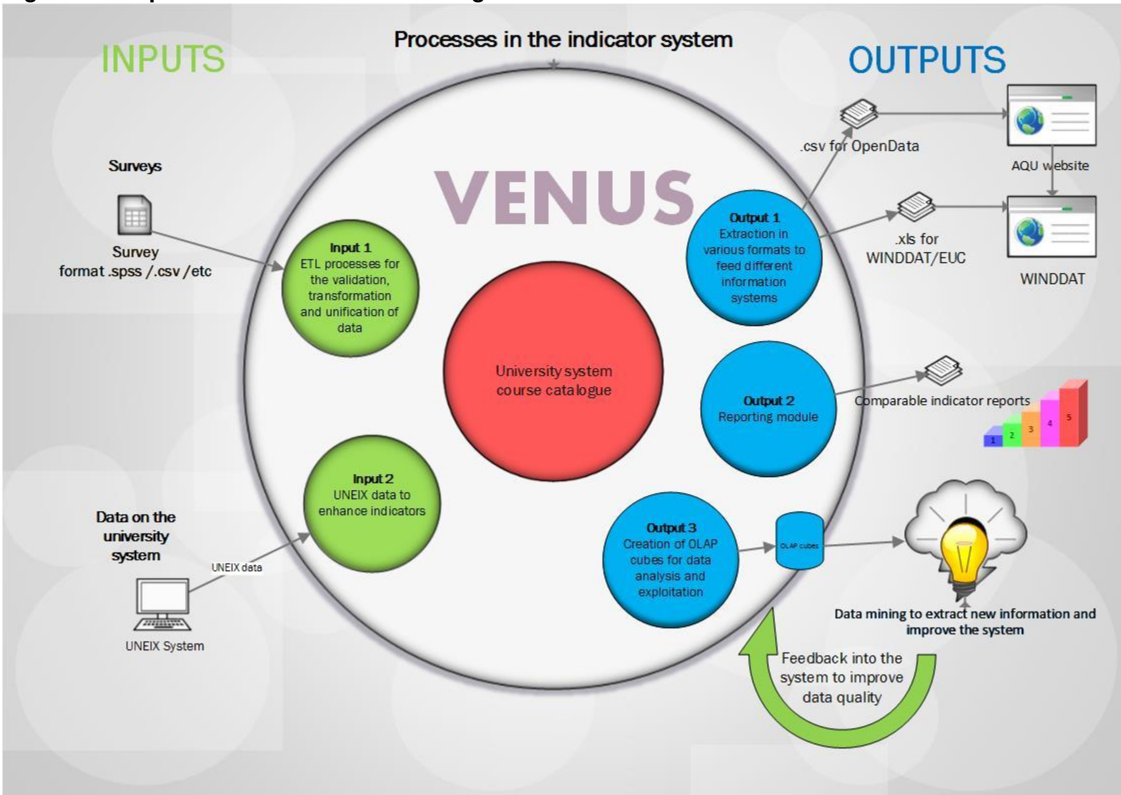
- The data project manager, i.e., the person who brings the team together and makes sure work is completed on time and within budget.
- An institutional researcher/big data analyst, or researcher, who understands how data impacts university policy decisions; the relevance and suitability of data projects are reliant on this vision. This person must be able to derive value from multiple data sets.
- The data scientist, i.e., an expert in databases querying and statistical analysis who must be able to create, manage and operate databases.
- The programmer/engineer, who can build prototypes of the proposed big data solution.

3.3. Technical requirements

As we have seen in the case study, although it is possible to perform complex analysis with common software products, it is far from an ideal solution. Our engineer has conducted an analysis that shows the need to create a data warehouse[5]; the inputs and outputs are shown in Figure 3.

[5] A data warehouse is a data repository that provides a global, common and integrated vision of data organization, irrespective of its intended use (Conesa & Curto, 2010).

Figure 3. Proposed data warehouse configuration



The first phase of the project implementation will be the creation of a survey repository.

The core of this system is formed by the degree and centre catalogues, which will enable us to analyse data at the level of different units of aggregation: from degree course to university and the Catalan university system as a whole.

The proposed solution would allow us to unify the different surveys and apply data validation tools (ETL processes[6]) to improve the reliability of our data, as well as creating a reporting module for automatic reporting. One of the most promising features of this project is the use of OLAP cubes, which are subsets of variables that can be harnessed for specific analyses and could therefore be used to optimize the database system.

To sum up, we envision a data warehouse that allows for reliable reporting; this, in turn, will make our institutions more accessible and provide assessors with succinct and accurate information to gauge *what* is happening, triggering the analytics process to discern *why* it is happening (self-evaluation process) and to determine the necessary courses of action.
Several challenges remain. First, a good academic analytics system does not merely exploit available data; it also collects and analyses the data required to make decisions. Second, to construct such a system, extensive human and material resources are needed. Despite these challenges, the enormous potential of the approach might be well worth the effort.

[6] ETL stands for “Extract, Transform and Load”; ETL systems commonly integrate data from multiple applications (systems). These processes are closely linked to the management of metadata and quality management data (Wixom & Watson, 2010).

References:

Appleby, A (1999). Benchmarking Theory – A framework for the business world as a context for its application in higher education. In: Smith, H; Armstrong, M; Brown, S (Eds). *Benchmarking and Threshold Standards in Higher Education*. Lodnon: Kogan Page (53-69).

Arnold, K. E., & Pistilli, M. D. (2012). Course Signals at Purdue: Using Learning Analytics to Increase Student Success. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, (May), 267–270. doi:10.1145/2330601.2330666

Blom, E., Cadena, B. C., & Keys, B. J. (2015). *Investment over the Business Cycle : Investment over the Business Cycle : Insights from College Major Choice*. Bonn. Retrieved from http://ftp.iza.org/dp9167.pdf

Conesa Caralt, J.; Curto Díaz, J*. (2010). Introducción al Business Intelligence. Barcelona: Editorial UOC.*

Davies, Anna; Fidler, Devin; Gorbins, Marina(2001). *Future Work Skills.* Institute for the Future for University of Phoenix Research Institute.

Govloop(2015). *The big data play book for government.* Washington, D.C: GovLoop. Available at: http://www.govtech.com/library/papers/The-Big-Data-Playbook-for-Government-1379.html

Dowling, D. A. (2015). *The Dowling Review of Business- University Research Collaborations*. Department for Business, Innovation and Skills. Retrieved from https://www.timeshighereducation.co.uk/sites/default/files/breaking_news_files/dowling-report-final.pdf

Dziuban, C., Moskal, P., Cavanagh, T., & Watts, A. (2012). Analytics that inform the university: using data you already have. *Journal of Asynchronous Learning Networks*, *16*(3), 21–38. Retrieved from http://files.eric.ed.gov/fulltext/EJ982670.pdf

Jeliazkova, Margarita; Westerheijden, Don F (2001). *A next generation of quality assurance models. On phases, levels and circles in policy development.* Paper for the CHER 14th Annual Conference "Higher Education and its Clients: Institutional Responses to Changes in Demand and in Environment", Dijon, 2-4 September, 2001.

Kellen, V., Recktenwald, A., & Burr, S. (2013). *Applying Big Data in Higher Education : A Case Study Herding Cats* (Vol. 13). Retrieved from https://www.sap.com/bin/sapcom/no_no/downloadasset.2014-01-jan-29-18.applying-big-data-in-higher-education-a-case-study-pdf.html

Macfadyen, L. P., & Dawson, S. (2012). Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan. *Educational Technology and Society*, *15*(3), 149–163. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.441.9712&rep=rep1&type=pdf

Picciano, a G. (2012). The Evolution of Big Data and Learning Analytics in American Higher Education. *Journal of Asynchronous Learning Networks*, *16*(3), 9–20. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=19395256&AN=85626774&h=RbmYHo0CbdCmUcqcNhaOwpVLqATms92q1tMlMRI26mkstBBHH63OVEbyrFRDYCcgGyP44QjKxZqzhw8H6jSDxw==&crl=c\npapers3://publication/uuid/49E87BBA-1C

Pistilli, Mattheru D; Willis III, James E; Cambell, John P. Chapter 5 Analytics Through and Institutional Lens: Definition, Theory, Design and Impact. In: Larusson, Johann Ary; White, Brandon (2014). Analytics Through and Institutional Lens: Definition, Theory, Design, and Impact. Pp 79-102 DOI: 10.1007/978-1-4614-3305-7_5

Rodríguez Espinar, S (2013). La evaluación de la calidad en la educación superior. Madrid: Editorial Síntesis.

Rodríguez Espinar, S (2002). La evaluación de la calidad de la enseñanza universitaria o la “conquista del oeste”. Revista Qurriculum, 15, 11-33.

Westerheijden, D.F (1996). Use of Quality Assessment in Dutch Universities. In: P.M.A Maassen & F.A. van Vught (Ed). Inside Academica. New challenges for the academic profession. Ensechede: C.H.E.P.S (p 269-289).

Wixom, B.; Watson, H. (2010). “The BI-based organization”. International Journal of Business Intelligence Research (vol. 1, p 13-21).

Vroeijenstijn, Ton (1995). Improvement and accountability: navigating between Scylla and Charybdis