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Data practices in quality evaluation and assessment: Two universities at a glance

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Abstract

As the debate on data in the society and in education grows the attention on data-trace as 'primary material' for governance, educational quality and innovation falls under the spotlights. In this context, HEIs have been put under pressure to adopt quantitative metrics and evaluation approaches enhancing the massive collection of trace data. Nonetheless, each university overall, and the academics specifically, might respond differently to this context of innovation. The present article aims to explore data practices in two higher education institutions. Two relevant areas for the imaginaries related to data and quantification were explored: (a) evaluation of quality in teaching and learning; (b) data to support assessment. The study is based on a survey distributed to the whole university teaching staff of two institutions. Descriptive and inferential statistics comparing multivariate sample means (MANOVA) were applied to 601 responses collected. The results indicated the prevalence of institutionally consolidated data practices relative to quality teaching evaluation, with fragmentation and isolation in some emerging data practices connected to decision-making and teaching and learning. Moreover, each of the universities revealed distinct institutional profiles which could be put in connection with the organisational culture. The results are discussed in light of the potential strategies at the institutional level, particularly regarding faculty development as means to build a visible, contextualised data culture.

A medida que aumenta el debate sobre los datos en la sociedad y en la educación, la atención sobre el rastreo de datos como 'material primario' para la gobernanza, la calidad educativa y la innovación recibe cada vez más atención. En este contexto, se ha presionado a las IES para que adopten métricas cuantitativas y enfoques de evaluación que potencien la recopilación masiva de datos de seguimiento. Sin embargo, cada universidad en general, y los académicos en particular, pueden responder de forma diferente a este contexto de innovación. El presente artículo pretende explorar las prácticas de datos en dos instituciones de educación superior. Se exploran dos áreas relevantes para los imaginarios relacionados con los datos y la cuantificación: (a) la evaluación de la calidad en la enseñanza y el aprendizaje; (b) los datos para apoyar la evaluación. El estudio se basa en una encuesta distribuida a todo el profesorado universitario de las dos instituciones. Se aplicaron estadísticas descriptivas e inferenciales de comparación de medias muestrales multivariadas (MANOVA) a 601 respuestas recogidas. Los resultados indicaron la prevalencia de prácticas de datos consolidadas institucionalmente en relación con la evaluación de la calidad de la enseñanza, con fragmentación y aislamiento en algunas prácticas de datos emergentes relacionadas con la toma de decisiones y la enseñanza y el aprendizaje. Además, cada una de las universidades reveló perfiles institucionales distintos que podrían ponerse en relación con la cultura organizativa. Los resultados se discuten a la luz de las posibles estrategias a nivel institucional, especialmente en lo que respecta al desarrollo del profesorado como medio para construir una cultura de datos visible y contextualizada.

1 | INTRODUCTION

The increasing digitalisation of human activity has led to the generation of massive digital data which can be processed, transformed and reused in several ways (Kitchin, 2014). This scenario has evolved rapidly, hand in hand with technological infrastructures computing digital data. However, despite an initial enthusiastic discourse relating the possibilities of data-driven practices in the society, more recently the criticalities of abuse, bias and ethical concerns emerged. The term 'datafication' was coined, indeed, to label such a situation, and it embeds a negative connotation overall (Van Dijck, 2014).

The problem has arrived to higher education institutions with all its implications. Educational data mining and techniques have developed in the last ten years to give place to data-driven feedback, recommendations and visualisations, as well as dashboards addressing the teachers and students' activities (Hoel & Mason, 2018). Allegedly, such developments have been connected to the personalisation of the learning experience and a better informed teaching practice (Nunn et al., 2016). Overall, the data-driven metrics adopted in the field of assessment to provide immediate feedback and/or calculate a summative final scores have been put in connection to quantitative indicators on the quality of teaching and learning. In time, these indicators have become sources of information for the university performance and position in international quality rankings (Siemens et al., 2013).

Nonetheless, human data interaction as driver of quality in education has been called into question, in search for striking a balance between the human pedagogical experience and the automated systems' responses (Fawns et al., 2021). Indeed, when coming to professional practices around the usage of data in higher education, there are numerous tensions to be solved with respect to technological possibilities and ethical concerns (Shum, 2019). Moreover, data and the connected practices should not be detached from the local and institutional contexts of practice. Data can be conceived indeed as form of complex representation of human knowledge, entailing assemblages of technical procedures with meaning making processes and power relationships (D'Ignazio & Klein, 2020; Ricaurte, 2019). Therefore, every university with their academics might be facing several technological, social and cultural problems at the time of using, elaborating and interpreting data to support teaching and learning (Selwyn & Gašević, 2020).

A relevant starting point is the characterisation of such practices, in order to understand the actual knowledge, the contexts of action and the needed literacies (Raffaghelli et al., 2020). Nonetheless, the problem is at its initial stages of exploration, since the phenomenon of datafication is also recent (Stewart & Lyons, 2021).

This article presents a multiple case study based on the analysis of data in two universities. The study introduces the results of a survey designed in the context of international research collaboration. Such collaboration emerged in the context of a project aimed at exploring differences and finding convergences amongst universities as local, organisational contexts of practice framing the faculty's response to datafication. From its inception, the project embraced the relevance of contextualising professional learning in relation to technological change, against an idea of context detachment and 'dematerialisation' of data-driven practices (boyd & Crawford, 2012; Crawford, 2021; D'Ignazio & Klein, 2020). Moreover, the idea of a professional practice as situated phenomenon, linked to organisational cultures and groups, is supported by a relevant corpus of literature (Chai & Kong, 2017; Felisatti & Serbati, 2019; Wenger, 1998; Za et al., 2014). In this regard, the organisations and their institutional cultures (narratives, instruments, practices, heroes) become crucial contexts which nurture or impede professional learning for the critical appropriation of technological innovations (Fenwick & Edwards, 2016). Universities as institutions develop cultures more or less prone to critically engage with technological innovations and their effects. Therefore, we will adopt the idea of universities 'data culture' as contexts framing practices which can span from naïve to critical and transformative approaches (Raffaghelli et al., 2020). In a context of increasing relevance of metrics and datafication in higher education, assessment and quality management are based on datafied practices (Sangrà et al., 2019; Williamson, 2018).

Therefore, in this article we propose an exploratory study which results could contribute to understand and characterise emergent data practices in the area of assessment and quality management, as central expressions of datafied organisational cultures in higher education. In the reminder of the paper, we introduce briefly the background and constructs adopted in our study; therefore, we propose an appropriate methodology to deal with an emergent, new problem (data practices in a context of datafication). The results are presented and discussed in light of potential institutional strategies for professional development towards an integrated effective and ethically sustainable practice as driver supporting a reflective culture against datafication in higher education (Raffaghelli et al., 2020).

2 | BACKGROUND: QUALITY AND ASSESSMENT (DATA) PRACTICES IN THE CONTEXT OF A DATAFIED UNIVERSITY

In higher education, the idea of addressing better academic government and pedagogical practices through data-driven approaches emerged early and raised significant enthusiasm (Siemens et al., 2014). More recently this trend has been a matter of debate (Selwyn & Gašević, 2020). What has been contested is the embedded techno-determinism (possibility for the technologies to shape the human response) of the data-mining techniques. In fact, some studies have demonstrated the insufficient exploration of the adherence of data-driven practices to pedagogical constructs and educational values (Vuorikari et al., 2016; Williamson, 2018). Furthermore, data-driven practices might exacerbate the reductionisms embedded in the idea of universities' 'performance', measured through limited quantified indicators ending up in international rankings (Prinsloo, 2019; Sangrà et al., 2019). Ultimately, according to Williamson et al. (2020) the massive adoption of digital learning technologies in the context of the pandemic, has led to the monetisation of data tracked without consent or awareness of teachers and learners.

Therefore, each university could benefit from the exploration of their ongoing practices, discourses and myths relating data, aiming at a contextualised understanding of datafication and data usage (Selwyn & Gašević, 2020). Such an endeavour could go hand in hand with the reflection around the quality of higher education provision (Yang & Li, 2020). Nevertheless, as unique expression of organisational cultures, data practices might vary from one university to other. The availability of technological devices, the connectivity across networks and the data-processing performance with respect to volume and time; the attachment to national and international quality assurance approaches; the identity as research-based university or as teaching university, might have implications shaping discourses, stakeholders' motivations and practices. Indeed, as expressed by Yang and Li (2020) the actual stakeholders' literacies and reflection around the approaches to measurement, quantification and automation connected to data-trace and other forms of analogical data require specific institutional attention. In their project 'Data Culture' (https://databasic.io/en/culture/) Rahul Barghava and Caterine D'Ignazio referred to this central concept as shared and accepted knowledge around data practices, which also encompass the possibility to embrace transparent and negotiable strategies. Applying such a concept to higher education Raffaghelli et al. (2020) focused on the need of linking the technological skills and usage to the institutional values and particularly the existence of a shared ethical perspective on data to the academics' professional practice and development. This concept is also supported by Mortier et al. (n.d.) in their perspective on human data interaction. For this collective, the data infrastructures and services should become transparent and negotiable by means of participatory processes, from design to the control of the implications for end users. In time, this approach could support agentic practices.

Particularly, there are central connections between data-driven practices and assessment and quality in higher education, which require analysis and reflection to build higher education data culture as space of critical action taking, strategies and professional learning. As we will observe in the following paragraphs, the problem of quantification and the usage of metrics in such areas is not a new debate. Indeed, the too direct and enthusiastic connections between data and effective assessment and quality have been a matter of concern (Boud & Soler, 2016; Hazelkorn, 2016; Williams, 2016). If the practices are naïve, badly informed and or imposed, the results of data-driven approaches might be more harmful than beneficial, as demonstrated in other areas of human activity like social care and or employment (Eubanks, 2018).

The data practices of quality analysis and enhancement can be connected with the overall macro and meso context of the educational policies and the institutional strategies. In this area, Ghislandi and Raffaghelli have already considered (2014) that the evaluation of quality depends on a series of adjustments of interests, negotiation of meaning and institutional development objectives. As purported by these authors rather than evaluating an 'objective' phenomenology, quality in higher education is the resultant of a continuing process of evaluation, learning and adjustment. In recent research, Ghislandi et al. (2020) underlined the risks of excessive reliance on quantitative assessments, which are more concise and faster than qualitative investigations, to understand innovative and quality processes. Quantification and university rankings have also elicited an in-depth debate on what is being measured and for which purposes (Pozzi et al., 2019). Though it is not a new concern, the facilitating conditions for digital data extraction and the relating representations have exponentially increased attention on the validity and trust that society can deposit on such artefacts (Zuboff, 2019). Moreover, the analysis of quality in HEIs requires the development of quality literacy applied to the specific institutional context of quality assurance and quality enhancement (Ehlers, 2007). In the same vein, critical data literacies associated with educational quality are a requirement more than ever in a datafied university.

The data practices in assessment and evaluation can be connected with the micro-context of the classroom, supporting the analysis of teaching and learning effectiveness. In any case, these elements can be considered relevant (if not central) dimensions of quality evaluation. As Grion and Serbati pointed it out (2018, 2019), assessment at the university level can no longer be deemed merely an instrument to get a quantitative-based certification of the knowledge acquired by students. Instead, it must be considered a complex and fundamental process that requires students' engagement with the data produced in specific and holistic terms. Indeed, active engagement in assessment processes is a driver of fundamental skills, such as the calibration of judgement in various situations. In time, these abilities are a crucial component of lifelong learning for future professionalism (Boud et al., 2013).

Nonetheless, data literacy is embedded in the overall understanding of assessment and evaluation. This knowledge, based on many other transversal skills required in contexts, such as knowing how to make decisions, solve problems, and critical thinking, has been denominated ‘assessment literacy’ (Smith et al., 2013). However, little attention has been devoted to the formulation of a broader and complex vision to build such literacy (Grion & Serbati, 2018; Medland, 2019). In short, this means to be prepared to face analysis, evaluation and judgement applied to personal and professional life through available, more or less visible data. Nevertheless, assessing in a relevant and balanced way is not a competence that arises spontaneously. Still, it must be intentionally trained, considering it an indispensable training objective of every discipline (Boud et al., 2013). Graduates can engage in such an evaluative approach with autonomy and responsibility only if they are offered the opportunity to participate in evaluation and feedback processes (Serbati et al., 2019). Within the mentioned exercises, reading, analysing and interpreting data is crucial: not only from data manually collected, but also from dashboards and data tracked through smart technology systems.

Therefore, the ability to critically read data, even and above all beyond their numerical and quantitative form, cannot refer only to the teachers' skills, but it also profoundly concerns the students' data literacy at the crossover with their literacy as lifelong assessors (Boud & Soler, 2016). This competence might be transferrable to abilities to control and use personal data, as a requirement for critical data literacy (Pangrazio & Selwyn, 2019).

Such complex and emerging panorama calls for faculty development to take action in to embrace or promote data practices in quality and assessment as part of a data culture. However, no systematic action could be implemented if there is no appropriate knowledge with regard to current data practices within situated institutional contexts, before exploring a broader situation. Therefore, the present study aims to contribute to the debate by exploring the informal universe of data practices within two universities placed in different technological, organisational and geographical contexts.

3 | METHOD

The research design was based on a multiple case approach, which refers to case study design in which several instrumental bounded cases are selected to develop a more in-depth understanding on an emergent phenomenon (Mills et al., 2010). Such an approach is based on at least two cases, as it is the case of our research design. Due to the exploratory and heuristic nature of the study, research questions were preferred to the formulation of a hypothesis. Research questions support an exploratory approach and can be used when there is little previous research on a subject, or a problem is seen as emergent (Doody & Bailey, 2016).

In our case, the analysis of the literature led to the formulation of two research questions. These were:

RQ1: What are the most common data practices based in relation to the activity of quality management and the assessment of learning, as expressions of the data culture in the two universities?

RQ2: Are there differences across the two cases with respect to the data practices under analysis, supporting the concept of data culture as a situated phenomenon?

3.1 | Instruments and data collection

This study is based on a survey conducted in two universities. The interuniversity approach originated from a collaboration within a national research project funded by the Ministry of Innovation and Research of Spain (Professional Learning Ecologies for Digital Scholarship: Modernising Higher Education by Supporting Professionalism: http://edulab.uoc.edu/en/projects/led-projects/professional-learning-ecologies-for-digital-scholarship-modernizing-higher-education-by-supporting-professionalism/). The project attempts to analyse academics' data practices in research and teaching in higher education, as part of their professional identity. Data practices have been defined upon the analysis of the literature. Specifically, data practices in Teaching and Learning have been based on the analysis 19 data literacy framework (Raffaghelli, 2019b) and include the following six scales: (1) Educational Data use for Management and Quality; (2) Data as resource for learning; (3) Data supporting teaching and learning processes; (4) Data for assessment; (5) Data to empower learners; (6) Developing learners' data literacy. Each scale was composed by a number of items which shaped the formal structure of the questionnaire (each question supported the exploration of an item). Overall, the six scales were based on 38 items. The questionnaire analysed the six areas of data practices and was complemented with questions relating the respondents' personal and professional profiles. Specifically, this study focused on two salient data practices: Data for professional development and quality management (1, 8 items) and Data for assessment (4, 10 items).

The questionnaire was subjected to two types of validation. The first, a Delphi study (Raffaghelli, 2019a), led to the instrument's theoretical consolidation. The feedback given by 8 experts participating in two phases of the Delphi study was analysed qualitatively and through quantitative procedures. The Kappa Fleiss index was used to measure the association and agreement between the experts' judgements (Agreement/Disagreement) in relation to the (a) conceptual introduction of the questionnaire (academics' data practices and data literacy); (b) alignment between the questions' formulation and the conceptual introduction, (c) the overall questionnaire structure; (d) the scales clearness and easiness. The value obtained applying the test on the mentioned areas of decision per 7 raters (the responses of the 8 expert were incomplete and were eliminated) was .79 ($z = 7.221$, p-value = <.001). According to Landis and Koch (1977), a value between 0.61 and 0.80 indicates substantial agreement.

Subsequently, the Cronbach test was carried out to analyse the constructs' reliability. The Cronbach Alpha was calculated for the dimensions of data practices studied in this article: Educational Data use for Management and Quality (EDMQ) and Data in Assessment (DA). Table 1 shows the scales with their items, and a complete version can be found at the aforementioned Delphi Study (Raffaghelli, 2019a). The first scale (EDMQ) got an $\alpha = .855$; and the second (DA), $\alpha = .906$. Such values are over the threshold of 0.70, considered good (Cortina, 1993).

3.2 | Participants

The study was carried out in two European universities located respectively in Italy and Spain, which remain pseudo-anonymised in this study according to the procedures authorised and agreed for the study with the

TABLE 1 Scales' description and items adopted in this study, included in the Survey 'Data Practices in Higher Education'

Data practices scales and description	*N* of items and description
EDMQ *(Educational Data use for Management and Quality)*	**8 items**
Use of data from different sources to inform institutional processes, collaboration and academic knowledge building to support teaching, including research	EDMQ1 I used processed data (national or institutional reports) to address institutional development and planning EDMQ2 I used data from institutional evaluation to support institutional development and planning EDMQ3 I used data from assessment and evaluation of my own course to engage in institutional development and planning EDMQ4 I used data from institutional assessment and evaluation for curriculum design EDMQ5 I used data from learning analytics of my own courses to support further learning design EDMQ6 I used data from learning analytics of my own courses to reflect on my own teaching effectiveness EDMQ7 I used data from social media integrated in my teaching activity to improve teaching effectiveness EDMQ8 I extracted and used data from social media where my students freely engage to address teaching effectiveness
DA *(Data supporting assessment)*	**10 items**
Teacher decision and analysis of teaching and learning process over the basis of data obtained/extracted through digital platforms	DA1 I used data from assessment activities to monitor learning DA2 I used data from assessment activities to monitor teaching effectiveness DA3 I used data from assessment activities to give feedback DA4 I used data from the overall course' evaluation to give formative feedback to my students DA5 I reflected with my students on the data collected from final assessments and evaluation. DA6 I used data students' logs to monitor/evaluate teaching DA7 I used data from teacher dashboards to monitor/evaluate teaching DA8 I used data from simple automated digital systems to analyse and score students' work (online quizzes) DA9 I used the learning management system (LMS) logs and dashboards to reflect with my students on the quality of learning and/or teaching DA10 I used simple automated digital systems to analyse jointly with my students' their opinions on the course (online final surveys)

participant institutions. The data characterising the overall institutions come from the Ministry of Education, University and Innovation in the Italian case: MIUR/USTAT 2017/2018 (http://ustat.miur.it/dati/didattica/italia/atenei-statali/); and from the Ministry of Science and Innovation of Spain: MICINN/Universidades/Estadísticas e Informes Universitarios (https://www.ciencia.gob.es/portal/site/MICINN/).

The first case is represented by a traditional and ancient Italian state university, with most undergraduates entering the university from the schooling system. With nearly 60,000 students, it counts almost 4500 teaching staff members, from which nearly 35% are tenured and divide their time between research and teaching duties.

The university can be considered amongst one of the largest Italian universities, which in average enrols 21.994 students and provides nearly 1250 academic jobs. The university is well-known at regional and national level. International students are about 2500, but in a good number can be considered mostly residents (second generations of immigrants in Italy).

As for the second case, it is represented by a young, private Spanish University with a focus on distance learning and lifelong learning. With nearly 80.000 students, it counts over nearly 5000 teaching staff members. Within this workforce, nearly 10% is devoted to research activities and half of them as full-time researchers. The university is recognised worldwide for its flexible and international educational model, serving about 6500 international students from nearly 145 countries. As a private university, it covers almost half of the enrolled students in such a branch of HEIs (in total, 199.706). This figure represents nearly 6% of the total enrolled students in Spanish institutions, which in the average enrolment is 15,500 students. Therefore, with structural differences in staff and educational models, the second university can also be considered a medium-large dimension case.

Data collection was carried out through an online questionnaire sent via each of the universities mailing list to all tenured academics, researchers, research fellows and teaching assistants. The two universities sent an invitation by email to respond to the survey to their whole professoriate, between January 2020 and March 2020. Overall, the first university invited 4464 professors, and the second, 4028 professors. The answer rate was 17% in the first case (800 responses) and 9% in the second case (374 responses). The final processed number of records for the two cases was 601 (Italy = 244, Spain = 377), after polishing and eliminating incomplete responses. As expressed by Holbrook et al. (2008) low response rates (around 5%) in large samples have a negligible effect on the demographic representativeness. Our sample covered the whole population in relation to the two cases studied.

The calculated margin of error (MOE) for a sample of 601 and the overall population of 84,111 academics in the Italian context (USTAT 2017/2018) and of 122,910 academics in Spain (*Ministerio de Universidades* 2017/2018) was of ±3.992%

Even if the two cases were sampled on a voluntary, non-probabilistic basis, they reflect two types of diversified profiles of teaching models (public, traditional face-to-face or b-learning model versus private, flexible, fully online model). Moreover, the two cases present medium-large size universities which can be deemed institutional instances for their cultural, regional and national contexts. In no case our study can be generalised to the whole population under statistical principles.

3.3 | Data analysis

To answer the research questions, two types of data analysis were carried out. Firstly, each case (case A, Italy and case B, Spain) was explored through multivariate descriptive statistics. The characteristics of each case with respect to age, gender and scientific-disciplinary field, and scales of data practices in HEIs (see Table 1) were investigated. The categorical variables were represented with respect to frequencies and percentages (Table 2). The set of variables connected to the data practices' scales (EDMQ and DA) were explored through a Likert scale based on the frequency of data practices (range 1–6 expressing no experience to total agreement with the daily frequency of a practice). This ordinal type of scale was converted to discrete numeric type to proceed with inferential statistics, as accepted procedure in the literature (Sullivan & Artino, 2013). In addition, the characteristics of the distributions for categorical variables were analysed using Pearson's Chi-Square (Table 2). As for the numeric variables, measures of central tendency (mean, median) and dispersion (standard deviation, quartiles) were adopted (Table 3). Kurtosis and asymmetry for numerical variables were not included in the table, but overall, each variable falls within the values of a normal distribution (2 and −2). Graphical representations were added to show the differences between the two universities at a glance. Ultimately, in order to explore the possible differences in data practices according to the diversified characteristics found in each case, an inferential test of multivariate analysis of variances (MANOVA) was performed, comparing the differences in response to data practices for each

TABLE 2 Bivariate descriptive statistics characterising the two cases

Categories	Total N	Total %	Case A N	Case A %	Case B N	Case B %
GENDER						
Fisher Exact Test [Gender × Case]. *df* = 2, *p*-value = <.05*						
Female	288	47.92%	91	40.63%	197	52.25%
Male	304	50.58%	131	58.48%	173	45.89%
NA	9	1.50%	2	0.89%	7	1.86%
TOTAL	601	100.00%	224	100.00%	377	100.00%
SCIENTIFIC DOMAIN						
Fisher Exact Test. *df* = 6. *p*-value = <.001***						
Formal Sciences	32	5.32%	13	5.80%	19	5.04%
Humanities	42	6.99%	15	6.70%	27	7.16%
Linguistics	28	4.66%	5	2.23%	23	6.10%
Medical Sciences	33	5.49%	17	7.59%	16	4.24%
Natural Sciences	63	10.48%	51	22.77%	12	3.18%
Social Sciences	296	49.25%	77	34.38%	219	58.09%
Technology	107	17.80%	46	20.54%	61	16.18%
TOTAL	601	100.00%	224	100.00%	377	100.00%
AGE						
Fisher Exact Test. *df* = 4, *p*-value = <0***						
Less than 25	1	0.17%	1	0.45%	0	0.00%
25–34	42	6.99%	8	3.57%	34	9.02%
35–44	180	29.95%	55	24.55%	125	33.16%
45–54	235	39.10%	71	31.70%	164	43.50%
More than 55	143	23.79%	89	39.73%	54	14.32%
TOTAL	601	100.00%	224	100.00%	377	100.00%
TEACHING EXPERIENCE						
Fisher Exact Test = 31.458. *df* = 5, *p*-value = <0***						
Less than 3 yrs	79	13.14%	14	6.25%	65	17.24%
3–4 yrs	60	9.98%	14	6.25%	46	12.20%
5–10 yrs	88	14.64%	28	12.50%	60	15.92%
10–15 yrs	105	17.47%	42	18.75%	63	16.71%
More than 15 yrs	264	43.93%	125	55.80%	139	36.87%
NA	5	0.83%	1	0.45%	4	1.06%
TOTAL	601	100.00%	224	100.00%	377	100.00%
RESEARCH EXPERIENCE						
Fisher Exact Test = 200.27. *df* = 6, *p*-value = <0***						
No experience	91	15.14%	0	0.00%	91	24.14%
Less than 3 yrs	48	7.99%	2	0.89%	46	12.20%
3–4 yrs	46	7.65%	1	0.45%	45	11.94%

(Continues)

TABLE 2 (Continued)

	Total		Case A		Case B	
Categories	*N*	%	*N*	%	*N*	%
5–10 yrs	82	13.64%	22	9.82%	60	15.92%
10–15 yrs	72	11.98%	38	16.96%	34	9.02%
More than 15 yrs	243	40.43%	159	70.98%	84	22.28%
NA	19	3.16%	2	0.89%	17	4.51%
TOTAL	601	100.00%	224	100.00%	377	100.00%

Note: Signif. codes: *** = 0; ** = .001; * = .01; . = .05; = .1; *p*-Values have been adjusted using the Benjamini and Hochberg (1995) correction [https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/p.adjust].

of the two cases. All calculations were made using RStudio and referring to R documentation (https://www.rdocumentation.org/).

4 | RESULTS

4.1 | Descriptive statistics

Initial differences relating age, gender, scientific domain, teaching and research experience between the two cases can be observed at the Table 2. As for the gender, case A (Italian HEI) shows a larger male presence where the opposite is true for case B (Spanish HEI). As for the scientific domains, it is plausible that each university can be specialised in knowledge areas, which is demonstrated in our sample. Social sciences are overwhelmingly represented in case B, whereas Natural Sciences are more relevant in case A. In both cases there is a relatively balanced situation insofar as technology is concerned, and a similar distribution for Humanities, Linguistics, Formal and Medical Sciences.

As for the age, case A shows an older population in comparison with case B. Even though, the central categories of 35–44 and 45–54 contribute very relevantly in the two cases. When coming to teaching experience, the two universities show a consolidated situation with most cases falling in the category 'more than 15 yrs' (56%, 139 respondents in case A; and 37%, 139 respondents for case B). The second university shows a more balanced situation amongst categories and a broader participation of staff with lower experience, which are plausibly younger scholars devoted to teaching duties (17%, 65 respondents). Finally, concerning the research experience, the traditional career pathway followed at the first institution (case A) is characterised by the broader representation of respondents in the category 'more than 15 yrs' (71%, 159). This is also an indicator of an aging staff, which can also be connected to a slow career advancement. Instead, the second case shows a flatter distribution and a diversified presence of younger staff with less research experience (nearly 30%, 111 respondents have less than 10 years of experience) and an increasing group of senior scholars (31%, 118 respondents show more than 10 years). However, there is also a 24%, 91 respondents who declare no research experience, which points to the diversified career pathways in such university, where the entrance level to the academic career can also be based on teaching activities.

The Table 3 reports the descriptive statistics by case and data practice scales. The Figures 1 and 2 represent scores' distributions per scale item (EDMQ, DA) and case (Italian University, Spanish University). As for the Figures 3 and 4, they report a radar chart visualisation that facilitates the comparisons between the two cases for each of the scales. Within the radar chart, also the lower and upper scores of the confidence intervals have been added for the reader to inspect the scores where the difference was negligible (falling within the same CI band). It can be noticed that, overall, the EDMQ scale reports higher values than the scale DA, as if the data practices were more frequent for the first area (management & quality) than for the second (assessment). However, it should

TABLE 3 Distribution analysis: Central tendency measures, dispersion, min and max datapoints

	Total					Case A—N = 224					Case B—N = 377				
Scales	Min	Median	Max	Mean	*SD*	Min	Median	Max	Mean	*SD*	Min	Median	Max	Mean	*SD*
Educational data for quality management															
EDMQ1	1	2	6	2.705	1.53	1	2	6	2.75	1.44	1	2	6	2.66	1.62
EDMQ2	1	3	6	3.02	1.56	1	3	6	3.42	1.57	1	2	6	2.62	1.55
EDMQ3	1	4	6	3.87	1.63	1	5	6	4.37	1.61	1	3	6	3.37	1.65
EDMQ4	1	4	6	3.78	1.535	1	5	6	4.65	1.47	1	3	6	2.91	1.6
EDMQ5	1	4	6	3.965	1.54	1	5	6	4.78	1.43	1	3	6	3.15	1.65
EDMQ6	1	4	6	4.255	1.68	1	3	6	3.82	1.7	2	5	6	4.69	1.66
EDMQ7	1	3	6	3.53	1.52	1	3	6	3.38	1.48	2	3	6	3.68	1.56
EDMQ8	1	3	6	3.11	1.235	1	3	6	2.99	1.1	2	3	6	3.23	1.37
Data in assessment															
DA1	1	4	6	3.74	1.65	1	4	6	3.94	1.63	1	4	6	3.55	1.66
DA2	1	4	6	3.81	1.62	1	4	6	4.08	1.63	1	4	6	3.54	1.61
DA3	1	4	6	3.95	1.68	1	4	6	3.95	1.66	1	4	6	3.95	1.69
DA4	1	4	6	3.80	1.66	1	4	6	3.71	1.65	1	4	6	3.89	1.67
DA5	1	3	6	3.39	1.64	1	3	6	3.38	1.61	1	3	6	3.40	1.67
DA6	1	3	6	3.25	1.61	1	2	6	2.74	1.52	1	4	6	3.77	1.69
DA7	1	2	6	2.70	1.51	1	2	6	2.21	1.25	1	3	6	3.19	1.76
DA8	1	2	6	2.81	1.65	1	2	6	2.69	1.60	1	2	6	2.93	1.70
DA9	1	2	6	2.44	1.37	1	2	6	2.18	1.16	1	2	6	2.71	1.58
DA10	1	2	6	2.61	1.58	1	2	6	2.52	1.58	1	2	6	2.69	1.58

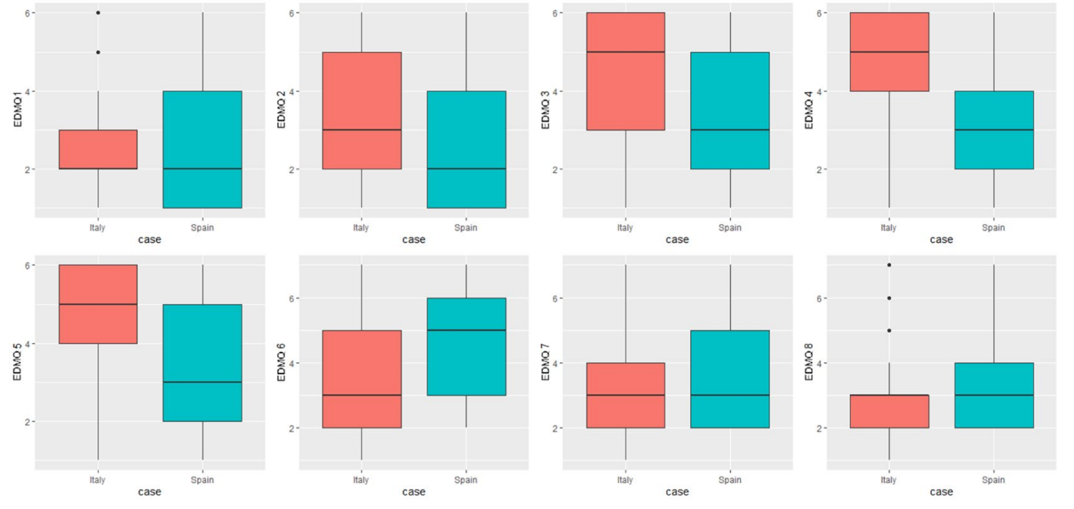

FIGURE 1 Boxplots per item scale (EDMQ) and case (Italy, Spain)

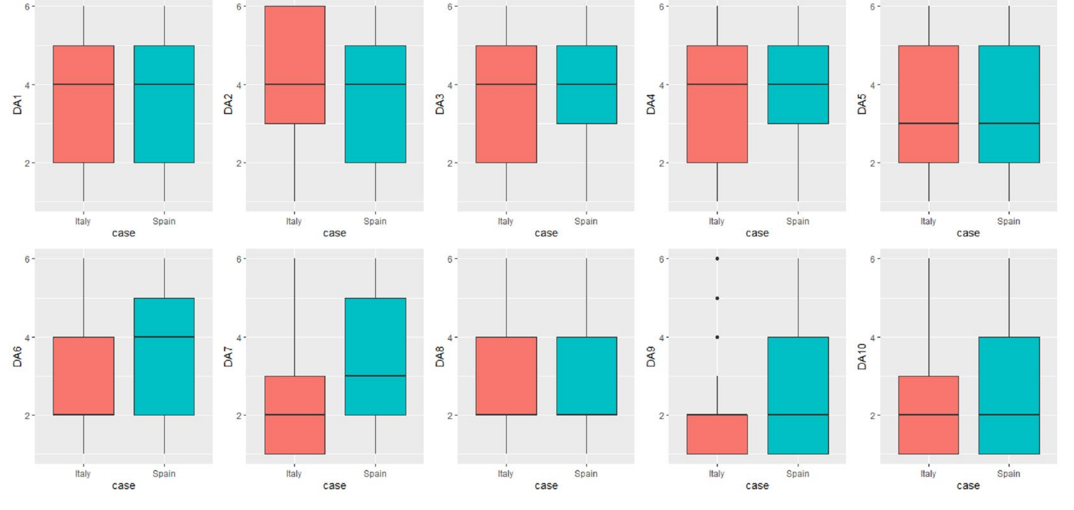

FIGURE 2 Boxplots per item scale (DA) and case (Italy, Spain)

also be discerned that the areas of 'best performance' are also diversified across the two cases. As a matter of fact, EDMQ4, dealing with the usage of data from institutional assessment and evaluation for curriculum design (4.65), and EDMQ5, connected to the use of data from learning analytics at the courses taught to support further learning design (4.78), get the upper scores in the first case. Conversely, in the second case the best scores are shown at EDMQ 6, dealing with the use of learning analytics of courses taught to reflect on teaching effectiveness (4.69). The item EDQM7 also gets a relevant score (3.68) in the second case (data usage from social media integrated in my teaching activity to improve teaching effectiveness), but it is one score point below the other cases. Overall, items 5 and 6 are higher than the rest. In other items the mean score is similar (EDQM1, 7.8) but with evident outliers in the first case and higher variance in the second case: this could be pointing at the presence of advanced users and innovators in these areas, with regard to the general behaviour. On the whole, it appears that the respondents in case A (Italian) engage more frequently in the usage of metrics of quality evaluation to design

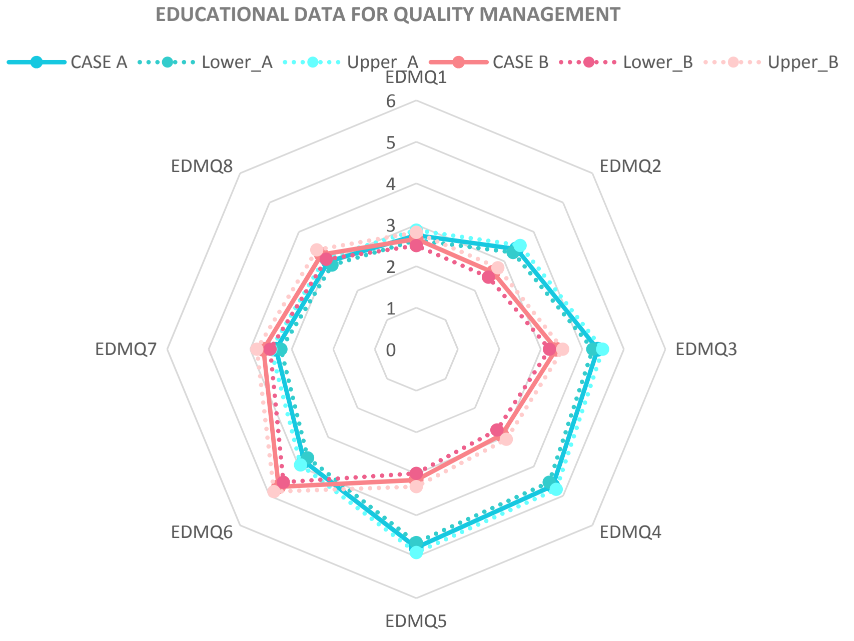

FIGURE 3 Radar chart representing the mean values of the EDMQ scale per case

FIGURE 4 Radar chart representing the mean values of DA scale per case

for learning. In contrast, in case B (Spanish), there is a more robust approach to using technology-enhanced tools supporting teaching effectiveness.

When coming to the second scale (DA), one notices a more similar approach in appraising data practices in this area. The higher scores are yielded at the scales 2 (use of data from assessment activities to monitor teaching effectiveness), 3 (use of data from assessment to provide feedback) and 4 (use of data from the overall course evaluation to give formative feedback).

The items DA2 and 3 are higher for case A, and the items DA3 and DA4 for case B. Mean scores in other scales are similar, though the radar chart shows that also DA6 (use of data of students' logs to monitor/evaluate teaching), DA7 (use of data from teacher dashboards to monitor/evaluate teaching) and DA8 (use of data from simple automated digital systems to analyse and score students' work) yield higher scores, in comparison with the first case. Nonetheless, the scores are low (under 4, the score indicates that the practices are rare).

Overall, the radar chart is showing similar patterns of practice. Most data practices are based on data collected via forms or generated by the teacher while grading. The usage of such data is mostly devoted to self-informing decision making about the course. However, the second case shows that the participants devote some attention to a basic data-driven analysis by consulting students' logs and adopting automatised data collection processes. On the whole, the score for opening data systems to students to discuss with them about the quality of the teaching and learning experience points at inexistent practices in this area in both cases.

4.2 | MANOVA

As a second step in the data analysis, the inferential test MANOVA detected relevant differences across the several items for the two cases. As we can observe from Table 4, overall significant differences between the two cases with respect to data practices were found, supporting the concept of situated approaches to data. The post hoc comparisons were made using one-way ANOVA and multivariate eta-square to measure effect size. This last indeed is a recommended measure to understand the dimension of the differences once tested the significance (Kline, 2004). The multivariate eta-squares can be interpreted as follows: .01 is to be considered low; .06 is medium; .14 is high, though this is a rule of thumb and the results have to be considered contextually and taking into consideration whether the study is causal—experiments—or correlational—surveys as the present study—(Bakker et al., 2019). We observe that the items EDMQ2,3,4,5,6 get highly significant scores, and the items EDMQ7 and 8 get significance at the cut-off value of .05, which is also acceptable in social research. This points at configured pedagogical practice identities, which ends up in a different adoption of data within the institution for planning and design purposes. It appears that in case A there is more attention to strategical institutional data-documenting processes. In contrast, in case B, there is more attention to innovative ways of extracting data to inform quality teaching as the single endeavour. As for the eta-squares, EDMQ2 gets .06; EDMQ3, .08; EDMQ4, .23; EDMQ5, .20; EDMQ6, .06, with all the remaining scales getting values considered low. Therefore, the most relevant dimension of the effect between the two cases is observed with regard to the way teachers adopt data to design their courses and the overall curriculum.

When coming to the scale DA, the MANOVA analysis yields a significant result which support the null hypothesis that there is no difference between the two universities for data practices. However, the post hoc analysis on the items contributing to the significant value shows that the items more solidly supporting significance are the DA1 (cut-off p-value = .001) and the DA6, 7, 9, where the scores were low. This output highlights the presence of academic educators who carry out advanced data-driven practices in assessment in the second university. Specifically, the use of data from the students' logs to monitor/evaluate teaching (DA6) appears to be a widely disseminated practice in the second institution. Moreover, data usage to build dashboards could be an emerging trend. Though the use of *LMS' logs and dashboards to reflect with students about their learning progress* yields a significant difference, the low mean scores support the assumption of being in front of a little common and widespread innovation at the second institution. As for the eta-squares, DA6 gets .09; DA7, .08; DA9, .03. Therefore,

TABLE 4 MANOVA results (cases for scale items)

General EDMQ	Df	Pillai	*F*	No Df	den Df	Pr (>*F*)
Case	1	0.47202	66.157	8	592	<2.2e−16***
Residuals	599					
Scale	Df	Residuals	Sum Sq	Mean Sq	*F* value	Pr (>*F*)
EDMQ1	1	599	1.06	10.604	0.438	0.5084
EDMQ2			90.7	90.698	37.481	<.001***
EDMQ3			143.55	143.554	53.794	<.001***
EDMQ4			424.2	424.20	176.2	<.001***
EDMQ5			374.57	374.57	151.81	<.001***
EDMQ6			105.48	105.479	37.597	<.001***
EDMQ7			12.68	126.817	53.859	<.05*
EDMQ8			8.20	81.957	50.437	<.05*
General DA	Df	Pillai	F	No Df	den Df	Pr (>*F*)
Case	1	0.23048	17.671	10	590	<2.2e−16***
Residuals	599					
Scale	Df	Residuals	Sum Sq	Mean Sq	*F* value	Pr (>*F*)
DA1	1	599	21.49	214.906	79.141	<.001**
DA2			41.54	41.538	15.798	<.001***
DA3			0.0	0.00023	1.00e0.4	0.9927
DA4			4.53	45.331	16.343	0.2016
DA5			0.03	0.03491	0.0129	0.9098
DA6			149.06	149.061	55.983	<.001***
DA7			136.5	136.502	54.192	<.001***
DA8			8.33	8.3337	3.0138	<.01.
DA9			39.42	39.418	19.122	<.001***
DA10			4.06	4.0602	14.974	0.2216

Note: Signif. codes: *** = 0; ** = .001; * = .01; . = .05; = .1; *p*-Values have been adjusted using the Benjamini and Hochberg (1995) correction [https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/p.adjust].

the most relevant dimension of the effect between the two cases can be seen in relation to the way teachers use both the data from the LMS to monitor/assess teaching and the data-driven dashboards to inform teaching. Needless to say, these innovations require a strong technical support and development which goes beyond the educator's willingness to adopt such systems.

5 | DISCUSSION

Our study, contextualised in broader research on data practices and the underlying institutional cultures, attempted to answer two research questions:

> RQ1: What are the most common data practices based in relation to the activity of quality management and the assessment of learning, as expressions of the data culture in the two universities?

RQ2: Are there differences across the two cases with respect to the data practices under analysis, supporting the concept of data culture as a situated phenomenon?

Considering the two scales under analysis, it is shown that there are common practices across the two universities, but also differences which characterise specific institutional cultures in the way digital data and data overall is conceived and used. We demonstrated that in the most traditional university (Case A), data practices stick to the idea of adjusting learning design and teaching under the light of national and institutional reports. In contrast, in the youngest university (Case B), the drivers of attention fall under the more individual perceptions of innovation and quality. This finding does not imply that there are single innovators in each university. Still, in the second case, it appears that the attention is turned over the micro-spaces (teaching).

Conversely, in the second case, the focus is on the relationship between the micro-spaces and the macro-spaces (the institutional metrics). Our results do not cater any information on data practices for different subgroups (younger academics, gender, different scientific domains, the levels of experience in teaching and research, etc.). Therefore, further research is needed to understand if patterns or differences are characterising data practices.

As for the DA situation (Data uses in assessment), traditional approaches linked to the cultures of analogue data in evaluation prevail in both cases and show alignments or patterns of practice. However, the more frequent usage of digital environments in case B seems to support increased attention to the adoption of trace data to generate dashboards supporting teaching and learning. It appears that the potential of digital data as a dynamic structure to support feedback discussion with and amongst students is an emergent, though sporadic, element. A concern that requires attention and might puzzle most academics to embrace such systems relates to the possible ethical risks of operations. The ethical concerns of using data were not fully explored with the two scales presented but only considered as part of an integrated critical analysis of assessment and quality evaluation. Data not only are to be displayed and read, but they must be used to trigger reflection for the curriculum and design for learning, or just used in a traditional vein. However, in the second case, the trend is accompanied by practices like discussion and transparency in the design of dashboards. Reflecting critically on the learning processes by using technological and visual tools like dashboards might be an expression of how the problem is being worked out. As Pangrazio and Selwyn (2019) note, data do not communicate an existing reality but as a starting point for meaning-making processes. At this point, data can be considered not only as simple means of representation, but also as powerful synthetic tools.

Having worked with a non-probabilistic sample, our study has heuristic value, which cannot be transferred at the national level. The limitations in the sample related the difficulties in analysing techno-organisational innovations and the relating professional practices in higher education (Steinert et al., 2016). Indeed, in our questionnaire, nearly 10% of respondents complained about the difficulty of interpreting some of the items. Despite our study being limited to two specific cases, the results support a preliminary reflection on data practices and data culture in higher education. Such a reflection can become relevant to address recommendations for faculty development and institutional strategies to analyse and improve a data culture.

As the debate on data in the society and in education grows (Williamson, 2018) the attention on data-trace as 'primary material' for governance, educational quality and innovation falls under the spotlights. The university could not step aside from these trends: actually, HEIs have been put under pressure to adopt quantitative metrics and evaluation approaches enhancing the massive collection of trace data. Nonetheless, these practices have different effects and a critical perspective is also increasing against 'datafication' as a negatively connoted phenomenon. Our study supports the idea that there are diversified and concurrent data practices as the resultant of the context of increasing attention on data in our societies. Nonetheless, we brought some evidence on the uniqueness of each institutional contexts, and the fragmentation, to some extent, of the data approaches in each institutional context, a fact which could entail difficulties in planning institutional strategies and staff development (Yang & Li, 2020). Our study can be placed at a preliminary level of institutional analysis. Yet, there is abundant literature pointing out the need of disentangling the material/technological and social systems to support transformational and empowering practices around data, beyond the mere institutional productivity (D'Ignazio & Klein, 2020; Gray et al., 2018; Lehtiniemi & Ruckenstein, 2019) In this sense an accurate self-analysis and awareness might be a base to promote transparency and possibility of negotiation around the meanings attributed to data, the technical infrastructures supporting data-driven practices, and the ethical problems.

6 | CONCLUSIONS

The literature analysed in this paper supports the idea that the universities can no longer escape a critical reflection on the use of data produced through administration, quality assessment and teaching. Our study has attempted to spot the diversity of situations around most common data practices in teaching and learning. Ultimately, our findings could address the need to deepen on the institutional contexts of intervention as unique spaces of practice, before intervening to develop data literacy.

As we observed in our study, the rapid technological advancement places some groups in an advantageous position concerning the pragmatic use of such data-driven innovations. Though we need further exploring, the contribution of the scientific domain, gender, experience, and so on, it was evident in our study that there are innovators pushing towards data-practices. Presumably, such practices could be more intuitive than connected to an institutional vision and ethical reflection of students' data. Moreover, some stakeholders' lack of involvement could also respond to emerging critical perspectives on technology issues, imagining negative ethical and social consequences. The excessive 'metrics' of the university system, needless to say, has led to a series of imbalances, pushing academics to practices aimed only at focusing on the results under evaluation in the system (Hazelkorn, 2016). For instance, in the context of digital scholarship linked to research, the use of bibliometric indicators in scientific production has already been criticised (with 'lighter' cases of ethically neighbouring behaviour such as 'slicing' and self-citation; or data frauds). In the areas of digital scholarship linked to teaching portrayed in our study, there is raising concern on the shortage of discussions related to the use of algorithms and 'nudge' systems for students; as well as the problems concerning the automation of graded correction systems (Selwyn & Gašević, 2020). Currently, no one could deny the potential of learning analytics systems when working with large numbers of students or assistive technologies (Essa, 2019). However, as we observed in our survey, the lack of adequate shared reflection (also and above all at the institutional level) on technology and its purpose creates a situation of fragmentation in data practices.

Bringing the problem of digital data back to the fore can be part of a strategy bridging data practices to an institutional culture of quality and evaluation. As for the future research, our work set the basis to think about staff development in higher education. Doubtless, our results spot very general trends and requires in depth interviews and focus groups in order to dig into the meanings, the narratives and motivations driving data practices in the overall context of a data culture. Most importantly, such analysis could address organisational and professional development. It must be recalled that the development of advanced literacies to participate in a data culture includes both technical (how to engage with data practices) and critical positioning (what for engage with data practice) against naïve practices and discourse around data in higher education (Raffaghelli & Stewart, 2020). In this regard, Felisatti and Serbati (2019) purport that faculty development requires complex structures and articulated projects, where the training objectives are clear, supported by collaborative, interdisciplinary engagement into institutional projects. In the same vein, the development of a data culture, stemming from similar analysis as the portrayed in our study, might provide institutional basis to develop situated, critical literacies and practices around data in higher education.

According to our results, some institutions could have less advanced technologies and the relating practices might be the expression of individual engagement and willingness to explore new technologies in education. Faculty development could take advantage of such practices, promoting a reflection over them as sources of inspiration through such as workshops and educational hackathons. Across these relatively informal spaces, the scholars might explore what exists and discuss what can turn into mainstream. Moreover, they could engage in activism when a transformation is needed. Nonetheless, we also observed data practices that are widespread but require further development. In this regard, structured training activity, where consolidated practices and digital tools can be introduced as drivers of professional learning, could be an approach. In both spaces, however, the technological dimension of data practices should be investigated further, hand-in-hand with the exploration of data transparency, negotiability and agency, as needed drivers of fair data cultures in HEIs. Each university, as a holder of a unique organisational identity, is called to formulate their own questions for reflection and debate, and hence, to develop their own data culture (Raffaghelli et al., 2020). By no means does this imply to be out of a global debate; it entails critical understanding of social and cultural conditions shaping practices against an evolving, international panorama.

CONFLICT OF INTEREST

The signing authors of the article have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available and can be cited as: Raffaghelli, J. E. (2021). Dataset for the exploration of data practices in Higher Education [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5153142

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