



## Article

# Big Data in Education: Perception of Training Advisors on Its Use in the Educational System

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**Abstract:** Big Data has revolutionized decision making in many fields, including education. The incorporation of information and communication technologies into education enables us to gather information about the teaching and learning process. As Big Data can help us improve it, it is paramount to integrate it into initial and continuous learning stages. This study therefore aims at finding out the perception of the training advisors of teacher training centers (N = 117) in Andalusia on the application of Big Data in education. The tool is an adaptation of the VABIDAE (Assessment of Big Data Applied to Education) scale, and the study of the descriptive statistics was carried out by using the analysis of variance (ANOVA) and Mann–Whitney U tests in order to check the existence of significant differences and correlations between the items that make up the scale. The results reflect the positive perception of training advisors on the use of Big Data in education. Significant differences were found in the competence level variable, whereby this tool was better rated by those advisors who feel that they have an advanced competence level. In conclusion, Big Data is valued for its ability to personalize educational processes and the consequent improvement in academic results, which shows the need to increase the level of knowledge about this tool.

**Keywords:** Big Data; education; innovation; training

## 1. Introduction

The technological revolution and the digitalization of the vast majority of processes have led to an exponential increase in data and information. In a context of different phenomena and factors that determine its evolution and progress, the analysis and interpretation of the massive data generated can facilitate decision-making and the implementation of proposals that could improve reality. It is with this purpose that Big Data or massive data (Rivas et al. 2019) was born. This is a set of technologies and tools that allows the management, analysis, interpretation, and evaluation of large amounts of data and information generated in different contexts (Bogarín et al. 2015; Mayer-Schönberger and Cukier 2013; Reyes 2015). Therefore, the value of Big Data lies in the possibility to analyze a larger amount of information that had not previously been considered. This leads to the discovery of new knowledge that should be taken into account in decision-making. In addition, this tool allows for the reduction of subjectivity in decisions, providing evidence and data that can refute, ratify, or reject them from a more objective perspective. It is therefore not only a question of the large amount of data to be considered, but also the types of links that can be established between them (Fosso et al. 2015). Big Data can be applied to many fields, such as medicine (Batton 2020; Galetsi et al. 2020), politics (Chen and Quan-Haase 2020; Ingrams 2019), or engineering (Xu et al. 2020). At the same time, the confidentiality,

ownership, the use that is made or can be made, or the economic valuation of the data generated are creating important social and legal debates ([Harari 2018](#); [Tirole 2017](#)).

However, the focus of this study is on the possibilities that Big Data can offer to the field of education. Considering the possibilities described above, it is worth asking if Big Data can revolutionize today's education. This is because, by implementing ICTs (Information and Communication Technology's) in the educational system, an environment is created in which everything that a student generates (tests, queries, submissions, grades, access, etc.) becomes information. Virtual platforms and technological tools are the main sources of information acquisition ([Elia et al. 2019](#); [Marín et al. 2019](#); [Thille et al. 2014](#)). Now, we can find out where students click, what resources they see, how much time they spend reading or studying, or how they interact with the information ([Franco et al. 2020](#); [Waller and Fawcett 2013](#)). By analyzing the information, we are able to understand what is happening and why it is happening, in order to forecast what can happen and how it can be improved. Thus, by applying Big Data, correlations can be found between the data and patterns can be detected. In this way, it will be possible to make predictions about the future of the teaching–learning process based on different educational theories. These will be the basis of relevant decisions of a pedagogical nature ([Puyol 2014](#)). Let us not forget that information without analysis is just information, but when analyzed, it can give us solutions. Given this reality, the challenge lies in the intelligent and responsible use of Big Data in the educational environment to improve training processes ([Crossley 2014](#); [Matas et al. 2020](#)) with the aim of optimizing performance. However, in an area such as education, conceived from an integral and holistic perspective, different questions arise around the applicability of Big Data from a human angle: How do we measure the intangible part of the educational process? What happens if the projection based on past data leads us towards a training in a specific area or level, without taking into account the potential and development that we could have achieved?

In light of these questions, it should be stressed that meta-analyses focus on evidence, data, and objective information. For questions more closely linked to personal and axiological development, the role of the teacher and the development of social and emotional skills will continue to be fundamental, as [Clayton and Halliday \(2017\)](#) point out. For these reasons, the interest of Big Data in education must be placed around the ability to understand the objective decisions that are made in the pedagogical field by investigating what we do with the students and what we intend to achieve in terms of academic results ([Blanken 2017](#)), while the social development dimension will be left out of the quantifiable evidence of this tool.

There are many opportunities that Big Data can provide to present and future education. On this subject, various authors and studies have focused their attention on analyzing the benefits and challenges linked to the implementation of Big Data in education ([Anshari et al. 2016](#); [Chen et al. 2012](#); [Cope and Kalantzis 2016](#); [Daniel 2014](#); [Domínguez et al. 2016](#); [Hilbert 2016](#); [Macfadyen et al. 2014](#); [Williamson 2017](#)). Below, we highlight some of the main contributions and the way in which Big Data can help us in the educational process:

- Improve the learning process ([Reidenberg and Schaub 2018](#); [Zheng et al. 2019](#)). The information obtained from the Big Data analyses enables us to find repetitive patterns of failure or success, thus making it possible to: Act both to solve the former and to promote the latter; optimize the selection of resources and tools by incorporating, modifying, or eliminating ideas and materials, depending on the results obtained; detect areas of improvement in terms of content or skills by identifying those that need more attention as they are difficult to learn, from those that students find easy. Moreover, this information allows us to carry out more objective training processes, free from the subjectivity of the teachers who now make fewer decisions, since these are now the results of patterns and predictions derived from data analyses ([Crawford 2016](#)).
- The possibility of obtaining real-time feedback and acting on the information collected ([Franco et al. 2020](#)). The collection of data allows us to know how students interact with the virtual learning environment, with a record of the places where they click and view on the Internet, as well as their participation in chats and forums (number of participations, accesses, time online, etc.). In

addition, in virtual learning environments that incorporate identity detection programs, even the facial and visual reactions of the students are recorded (for example, during the performance of a test or exam) (Bousbia and Belamri 2014; Khan et al. 2018). This is also crucial in areas such as early detection of possible school dropouts so that preventive measures can be taken. Thus, Big Data provides us with a continuous analysis that can help us decide the action plans that we can develop for students.

- Personalizing education (Chen et al. 2014). We start from the concept that each student learns in a different way. Therefore, if we know what they ask, what they look for, what doubts they have, the deadlines they meet or do not meet, their normal delivery format, the way they present the information, or their learning style when working with information (visual, auditory, reading–writing, or kinesthetic), the process can be tailored to them (Ghani et al. 2018). In addition, personalized learning paths can be put forward, where students, depending on their interests, priorities, results, and degrees of knowledge acquisition, can delve deeper into the subject with more relevant and effective learning methods (Bienkowski et al. 2012; Zapata-Ros 2015). Big Data information can help us in different areas of the personalization process, from taking into account cognitive, social, and motor aspects, such as the state of mind, the student’s satisfaction with the resources, or the time slots in which they normally work at optimum performance, to selecting training options according to their personal interests, encouraging a specialization within their study area with the implementation of specific resources such as Massive Open Online Courses [MOOCs] (Sánchez Rivas et al. 2018). The aim is to be able to choose from a wide range of resources that will help students improve their education by acquiring skills and achieving the required results and criteria, without losing sight of their interests.
- Improvement of digital skills. This is achieved by increasing interaction with learning technologies as a regular resource. To this end, teachers must improve their own abilities if they wish to provide enriching and positive support during the learning process (Gertrudis et al. 2016). However, different studies (Fernández et al. 2018; Fuentes et al. 2019; Menon et al. 2017) show that, in the midst of the technological era, teachers have not yet acquired the necessary skills to carry out their work adequately.
- Analysis of the employability rates of graduates to detect which areas of training could be improved. In this regard, Big Data simplifies the meta-analysis of the graduate surveys, finding patterns that explain the difficulties in accessing the labor market and their relationship with the training received. Hence, changes in the structure or organization of the curricula could reverse the situation or could include specific improvement areas.
- Avoiding plagiarism. Big Data is the basis of anti-plagiarism programs, since its function is to crosscheck the information between new documents and existing ones in search of possible coincidences. The exponential proliferation of written material that has resulted from the spread of the Internet and databases makes it impossible to carry out this kind of detection work manually; therefore, this tool becomes necessary to verify the authenticity of a text and ensure compliance with ethical codes in the scientific field.

Hence, from the pedagogical perspective, Big Data can offer us endless possibilities to improve the educational processes. However, it is also important to point out the problem that derives from the teachers’ level of knowledge when managing and analyzing Big Data. This is an operational knowledge that most teachers lack. It would therefore be interesting not only to develop training programs in this area, but also to consider the possibility of incorporating specialized staff to do this from a pedagogical perspective (Williamson 2016).

In light of this, if Big Data is to be incorporated into education, both initial and continuous training of future teachers must be reformulated. For this study, our emphasis will be on the ongoing training of teachers and on the role of advisors as key elements to reach this goal. Advisors are teachers who, after a professional career in the educational field, offer their knowledge and experience to their colleagues through the design, planning, and development of a permanent training scheme that meets

the different needs of the teaching staff. Therefore, they are the agents responsible, at the administrative level, for the offer of continuous teacher training. In this way, if we want Big Data to become a reality in continuous training, we must initially see how teacher training advisors perceive it, taking into account all of the variables that can influence such conceptions, to work on those aspects that are precise. The focus of our study will be the advisors in teaching centers (CEPs) in Andalusia (Spain). Within the framework of the Andalusian Continuous Teacher Training System, Teacher Training Centers are responsible for the assessment programs of local schools and for the ongoing training of the teaching staff. CEPs are institutionalized permanent training centers for teachers. Based on the concept of cooperative work and on principles such as quality, excellence, transparency, and willingness to serve, the goal is to implement a continuous training that will develop teaching skills. To achieve this, the CEP team is made up of a group of advisors under the leadership of the management team, and it is divided into educational stages (pre-school, primary, secondary, and professional training) or by specialty (special education, continuous education, artistic education, or Catholic religion), so they can meet the needs of and give advice to both schools and teachers in a targeted and specialized way. Therefore, the role and importance of advisors is fundamental for incorporating new resources and tools into continuous training. In this sense, the teacher training advisors have not received explicit training on Big Data in order to assess its possibilities, but we start from the previous knowledge they had. In this way, the possible differences in perceptions according to level will be an argument in favor of the need to initially implement training processes in teacher training advisors before they propose the design and development of continuous training without adequate command of said tool. If we start from the conception that we cannot train or propose training in what we do not know or do not master with adequate competition, the different levels become a real handicap for efficient decision-making. Therefore, knowing their perception regarding the opportunities and possibilities offered by the use of Big Data in education can be a starting point both to become aware of the need for training in this regard by many advisers, and an argument to bet on the promotion and implementation of this resource in the continuous training of teachers.

## 2. Material and Methods

### 2.1. Objectives

This study aims at finding out the perception of training advisors of the teacher training centers in Andalusia on the application of Big Data in education. The objectives are as follows:

- Analyzing the advisors' assessments of the benefits offered by the use of Big Data in education.
- Checking if there are significant differences in their perceptions, according to the variables of gender, educational stage that they gave advice to, and level of knowledge about the use of Big Data in education.
- Determining if there are any correlations in the assessments of the benefits that Big Data offers to the educational environment.

### 2.2. Methodological Approach

This is a quantitative study of a descriptive nature. A questionnaire adapted to the sample will be used in order to statistically quantify and analyze the perception of teacher training advisors on the implementation of Big Data to education.

### 2.3. Sample

The target group for this research was a total of 282 teacher training advisors of the pre-school, primary, and secondary stages who met our criteria, from the eight provinces of the Autonomous Community of Andalusia (Spain). The final sample, selected incidentally (not probabilistically), following Mantilla (2015), is made up of 117 training advisors ( $N = 117$ ) from teacher training centers (CEPs), who were working during the 2019–2020 academic year and who replied to the researchers'

request for collaboration. This represents 41.49% of the total population under study. Among the participants, 42.74% were women (50) and 57.26% men (67), with a mean age of 47.15 years. They were asked to specify the province of the CEP where they worked: 22 participants were from the province of Malaga (18.80%), 26 from Seville (22.22%), 13 from Granada (11.11%), 11 from Almeria (9.40%), 18 from Cadiz (15.38%), 10 from Cordoba (8.55%), 12 from Jaen (10.27%), and 5 from Huelva (4.27%). They were also asked in which educational stage they give advice, with 11.11% in pre-school (13), 36.75% in primary (43), and the remaining 52.14% in secondary (61), as well as the number of years of experience performing the tasks of advisor, grouping the data into three ranges: 1 to 3 years of experience (43 teacher training advisors, representing 36.75%), 3 to 7 years of experience (58 teacher training advisors, 49.57% of the total), and more than 7 years of experience (16 teacher training advisors, representing 13.68% of the sample). Finally, they were asked which level of knowledge about Big Data they thought they had: 6.84% (8) of those surveyed rated themselves at an advanced level, 36.75% (43) at a medium level, and 56.41% (66) at a basic level.

#### 2.4. Tool

Together with a set of sociodemographic and informational questions, including gender, age, CEP where they worked, the educational stage they give advice to, and level of self-perceived competence on the use of Big Data, an adaptation of the [Borrego et al. \(2019\)](#) scale of the Assessment of Big Data Applied to Education (VABIDAE) was also used. The original scale has a total of 31 items, organized in three blocks or dimensions: Opportunities, challenges, and feelings caused by the use of Big Data (positive and negative). For this study, only the opportunity block was applied, consisting of a total of 11 items (Table 1). Perceptions of the items are made using a Likert-type assessment scale, with scores ranging from 1 to 5 points (not at all = 1; I do not think so = 2; I do not know = 3; I think it is = 4; I totally agree = 5).

**Table 1.** Assessment of Big Data Applied to Education (VABIDAE) scale.

Dimension	Item	Code
Benefits	Improving attention to students' needs	O1
	Improving academic results	O2
	Personalizing education	O3
	Improving employability	O4
	Avoiding plagiarism	O5
	Improving school organization	O6
	Improving the selection of teachers	O7
	Creating educational resources tailored to students	O8
	Facilitating decision-making at a political level	O9
	Promoting the quality of education in general	O10
	Help preventing academic failure	O11

Source: Adaptation of [Borrego et al. \(2019\)](#).

As for the quality criteria of the tool, we considered the content validity parameter—the implementation of which was guaranteed in the scientific field by a previous research ([Matas et al. 2020](#))—and the reliability parameter, obtaining a Cronbach's alpha coefficient of 0.897, which indicates a high reliability.

#### 2.5. Procedure

The questionnaire was conducted in January 2020 through a link to Google Forms, which was chosen for the time and space flexibility offered by the online set-up. Participation was requested by the CEP in Malaga to the other CEPs in Andalusia via e-mail by providing the link to the form. Once the responses were collected, they were analyzed with the SPSS statistics v.25 by carrying out different tests depending on the established objectives: Analysis of descriptive statistics of the set of



responses by item, Mann–Whitney U or analysis of variance (ANOVA) tests to check if there were significant differences depending on the variables of gender, educational stage they gave advice to, years of experience as consultants or teacher training advisors, and level of knowledge about the use of Big Data in education, and correlation tests to determine if there are significant relationships between the established items in order to assess the benefits that Big Data can offer to education.

### 3. Results

Considering the objectives set for the research, the main results are as follows (Table 2):

**Table 2.** Descriptive statistics.

Items	N	Min.	Max.	Mean	SD	Skewness	Kurtosis
O1: Improving attention to students' needs	117	3	5	4.15	0.72	−0.235	−1.006
O2: Improving academic results	117	1	5	4.03	0.83	−0.433	−0.105
O3: Personalizing education	117	3	5	4.01	0.80	−0.016	−1.450
O4: Improving employability	117	1	5	3.38	0.76	0.398	0.526
O5: Avoiding plagiarism	117	2	5	3.29	0.82	0.746	0.142
O6: Improving school organization	117	1	5	2.87	1.10	−0.262	−0.508
O7: Improving the selection of teachers	117	1	5	2.81	0.98	−0.112	−0.043
O8: Creating educational resources tailored to students	117	1	5	3.40	1.19	−0.513	−0.416
O9: Facilitating decision-making at a political level	117	1	5	3.59	0.76	−0.372	1.191
O10: Promoting the quality of education in general	117	1	5	3.44	0.83	0.697	0.155
O11: Help preventing academic failure	117	1	5	3.74	0.77	−0.223	0.397

Source: Own research.

By working with a single-dimension analysis in the adaptation of VABIDAE, all items were valued based on the benefits that Big Data can offer to education. In this respect, we found that every item has a maximum score of 5, which means that at least one participant fully agreed with all of the proposed statements. As for the minimum scores, we found that many of the items were rated with the lowest score (1), which means that at least one respondent totally disagreed with the specific statement regarding Big Data's potential in education. However, it would be interesting to focus on items O1 and O3, where none of participants' scores were less than three points. Before delving into the mean scores, it should be noted that none of the items analyzed found symmetric data with a normal distribution. As for the asymmetry, we found both positives (O4, O5, and O10) and negatives (O1, O2, O3, O6, O7, O8, O9, and O11), just by bringing element O3 closer to a symmetric distribution. If we look at the distribution, we find leptokurtic distributions (O4, O5, O9, O10, and O11) and platykurtic distributions (O1, O2, O3, O6, O7, and O8). In this case, item O7 is closest to a normal distribution. If we look at the mean scores, the worst-perceived items are "O6: Improving school organization" (2.87 points and the second-highest dispersion with 1.10) and "O7: improving the selection of teachers" (2.81), rated lower than three points, which reflects the participants' doubts regarding the potential of Big Data in improving the organization of schools and the selection of teaching staff. On the other hand, items "O1: Improving attention to students' needs" (4.15 points and the most homogenous answers from the participants with 0.72), "O2: Improving academic results" (4.03), and "O3: Personalizing education" (4.01) are above the four-point mark, reaching the "I think so" rating, which highlights the positive perception about the personalization of the training processes and the improvement of results. The other items range between three and four points, a score that means that implementing Big Data could possibly benefit education. As for the standard deviation, the greatest heterogeneity in the participants' responses can be found in item "O8: Creating educational resources tailored to

students" (1.19), despite its position in the middle of the rating scale. In contrast, the least dispersion, apart from item O1, is found in "O4: Improving employability" and "O9: Facilitating decision-making at a political level" (both with 0.76), as they are two items that rank at intermediate positions in the advisors' ratings.

After presenting the main descriptive statistics, we went on to analyze whether there are significant differences in the participants' perceptions, considering the variables of gender, educational stage, and level of self-perceived competence of Big Data.

With regard to the gender variable, the Mann–Whitney U test shows that there are no significant differences ( $p \geq 0.05$ ) in any of the items analyzed. As for the stage variable, the Wilks'  $\Lambda$  test ( $p = 0.315$ ) shows that there are no significant differences ( $p \geq 0.05$ ). Despite this, we applied the one-way analysis of variance to know if differences had been found in some of the items. This occurred with item "O2: Improving academic results" (Table 3), where secondary-school advisors scored significantly higher than primary-school ones.

**Table 3.** Items with significant differences depending on the advisory stage variable.

Item	STAGE	N	Mean	SD	F	Sig.
O2	Pre-school	13	4.08	0.64	3.152	0.047 *
	Primary school	43	3.79	0.89		
	Secondary school	61	4.20	0.79		

Source: Own research. \* =  $p \leq 0.05$ .

A similar situation occurred when considering the variable years of experience, where the  $\Lambda$  test of Wilks ( $p = 0.401$ ) indicates that there are no significant differences ( $p \geq 0.05$ ). However, when applying the ANOVA, we found significant differences in the item "O8: Produce educational resources adapted to the students" (Table 4), where both new and older teacher training advisors scored significantly higher than intermediate advisers.

**Table 4.** Items with significant differences depending on the years of experience variable.

Item	Years of Experience	N	Mean	SD	F	Sig.
O8	1–3	43	3.70	1.08	3.790	0.025 *
	3–7	58	3.10	1.22		
	+7	16	3.69	1.14		

Source: Own research. \* =  $p \leq 0.05$ .

The last variable to consider is the level of self-perceived competence when using Big Data, where significant differences between the advisors ( $p \geq 0.05$ ) were recorded by means of Wilks'  $\Lambda$  ( $p = 0.00$ ). In this variable (Table 5), the ANOVA shows significant differences in all of the items that make up the tool.

**Table 5.** Items with significant differences depending on the Big Data competence variable.

Item	Competence Level	No.	Mean	SD	F	Sig.
O1	Basic	66	3.68	0.50	78.212	0.000 *
	Medium	43	4.72	0.45		
	Advanced	8	5.00	0.00		
O2	Basic	66	3.48	0.61	78.666	0.000 *
	Medium	43	4.70	0.47		
	Advanced	8	5.00	0.00		
O3	Basic	66	3.45	0.53	96.729	0.000 *
	Medium	43	4.67	0.47		
	Advanced	8	5.00	0.00		
O4	Basic	66	3.18	0.65	30.499	0.000 *
	Medium	43	3.40	0.62		
	Advanced	8	5.00	0.00		
O5	Basic	66	2.97	0.61	38.478	0.008 *
	Medium	43	3.47	0.74		
	Advanced	8	5.00	0.00		
O6	Basic	66	2.29	0.99	48.005	0.000 *
	Medium	43	3.42	0.50		
	Advanced	8	4.75	0.46		
O7	Basic	66	2.24	0.79	66.179	0.000 *
	Medium	43	3.35	0.48		
	Advanced	8	4.63	0.52		
O8	Basic	66	2.67	0.98	66.305	0.000
	Medium	43	4.26	0.62		
	Advanced	8	4.88	0.35		
O9	Basic	66	3.36	0.62	16.498	0.000 *
	Medium	43	3.72	0.77		
	Advanced	8	4.75	0.46		
O10	Basic	66	2.92	0.32	81.474	0.000 *
	Medium	43	3.98	0.77		
	Advanced	8	4.88	0.35		
O11	Basic	66	3.42	0.63	24.161	0.000 *
	Medium	43	4.02	0.71		
	Advanced	8	4.88	0.35		

Source: Own research. \* =  $p \leq 0.05$ .

If we look at the results, the advisors who believe they have a basic level of competence in the use of Big Data give less value to the opportunities that will be created by its implementation in education than those who claim to have a medium or advanced level. This fact becomes a constant in all items. It is also interesting to point out that there are significative differences between the medium and advanced levels in all items except “O1: Improving attention to students’ needs”, “O2: Improving academic results”, “O3: Personalizing education”, and “O8: Creating educational resources tailored to students”, which coincide with three of the best-rated items and whose content is centered on the personalization of the processes (attention to needs and production of materials) and on the improvement of students’ results; this is where the participants of both levels agree on Big Data’s potential. It should be noted that the means of the participants with an advanced level of competence do not fall below 4.63 points, which is why they are close to the “totally agree” option in all of the ratings. This fact reflects the relationship between the level of competence and a positive perspective on the opportunities that Big Data can bring to the educational arena, thus underlining the need for explicit training for teacher training advisors.



Finally, we wanted to determine if there are significant relationships between the items that focus on the opportunities that Big Data can bring to the educational field (Table 6). To this end, a correlation analysis has been carried out, the results of which are set out below.

**Table 6.** Correlations between the items on the questionnaire.

	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11
O1											
O2	0.703 **										
O3	0.688 **	0.607 **									
O4	0.301 **	0.305 **	0.289 **								
O5	0.438 **	0.428 **	0.453 **	0.370 **							
O6	0.488 **	0.413 **	0.540 **	0.286 **	0.531 **						
O7	0.582 **	0.526 **	0.482 **	0.385 **	0.432 **	0.531 **					
O8	0.586 **	0.501 **	0.600 **	0.341 **	0.339 **	0.655 **	0.589 **				
O9	0.277 **	0.256 **	0.318 **	0.335 **	0.291 **	0.227 *	0.418 **	0.281 **			
O10	0.585 **	0.582 **	0.540 **	0.356 **	0.521 **	0.598 **	0.626 **	0.563 **	0.378 **		
O11	0.403 **	0.569 **	0.437 **	0.361 **	0.434 **	0.412 **	0.347 **	0.303 **	0.278 **	0.468 **	

Source: Own research. \*\* =  $p \leq 0.01$ .

The results show that there are positive correlations between practically all items. Therefore, we are going to focus only on those whose relationship is considered moderately positive and highly positive (between 0.600 and 0.703).

Firstly, we highlight how items O1, O2, and O3 have a significant moderately positive and highly positive relationship, as they are the areas that were rated the best by the participants due to their relationship with the personalization of the educational process and the improvement of results. It is also relevant to see how item O3 correlates with O8, so that the personalization of the educational process goes hand in hand with the production of resources tailored to each student. Item O8 itself also correlates with O6, meaning that the creation of personalized resources has an impact on the best organization of schools. Finally, we highlight the correlation between items O7 and O10, where participants indicate that, if Big Data helps in improving the selection of teachers, this should ameliorate the quality of education, as reflected in the relationship between the two items.

#### 4. Discussion and Conclusions

Considering the results achieved, we can state that the use of Big Data in education, as per the perception of advisors in teacher training centers in Andalusia (Spain), offers a wide range of opportunities to improve the academic and organizational processes in education, which confirms the results of other investigations (Daniel 2014; Dishon 2017; Wang 2016).

Big Data is particularly useful in personalizing education processes and improving academic results. The possibility of collecting extensive information on students, both in real time and retrospectively, enables teachers to implement changes in pedagogical approaches, as well as to select the most suitable resources. Salazar's conclusions (Salazar 2016) were also running along these lines, as he highlighted that the use of Big Data enables teachers to develop training processes that attend to and satisfy the needs of their students. In short, it is a question of personalizing a process in which each student learns in a different way, shows different levels of competence, has specific interests, and recognizes that their cognitive process works differently from those of their peers. To achieve this, according to the study of Merceron et al. (2015), Big Data offers information that allows us to deal with each one of these situations in the best possible way. This coincides with the positive evaluation of the advisers of the teaching centers of Andalusia. The result of the personalization and enhancement of the educational process means an actual improvement in academic results, as stated by López et al. (2019), as attention tailored to the cognitive, social, and affective characteristics of students should result in an improved development of competencies linked to the teaching process. Thus, the data provided by the use of Big Data in education have a direct effect on the improvement of the pedagogical design and on the teaching approach.

If we consider the worst-valued items, we find that, for the advisors, both the school organization and the selection of teachers are not aspects that can be improved by implementing Big Data. In this sense, we are faced with realities that are largely subordinate to the subjective perspectives of the participants. We assume that all of the information analyzed can contribute to the formulation of conclusions on different fields, which, although not explicitly linked, are nevertheless related. This occurs when, by implementing changes in areas such as the personalization of processes, the results are also felt in other areas, such as school organization. However, there are centers whose vision and mission shape their structure and functioning in such a way that their identity and procedures are above the evidence that can be obtained from implementing changes in their organization. Something similar occurs with the selection of teachers, with two types of access to the system (Spanish public examination for state schools and selection for subsidized and private schools); here, Big Data can provide further evidence on top of the above-mentioned ones, although it is not a main factor (at least for the time being) in the selection processes. Additionally, there is the problem of the concept of what makes a good teacher, with multiple views and studies (Colomo and Aguilar 2019; Colomo and Gabarda 2019; Esteban and Mellen 2016; Jordán and Codana 2019) that reveal a lack of agreement in this respect. Here, Big Data becomes a resource that can provide valuable information, albeit always conditioned to the subjective perception about teachers.

Focusing on the differences in the variables, no significant differences have been found in the gender variable in terms of the score given to the opportunities offered by Big Data to the educational system, which is in line with the research by Klasen and Lamanna (2009). However, other studies, such as Tapasco and Giraldo (2017), do find significant differences between genders; in this case, it is women who are keener to incorporate ICT resources or tools to help improve teaching processes. In our case, the evaluation of Big Data is not related to gender, but is linked to the level of knowledge about its possibilities. On the other hand, the educational stage variable only reflected significant differences between primary and secondary school advisors, in favor of the latter, in relation to the improvement of academic results when implementing Big Data. The fact that there are no other significant differences in the other items enables us to state that providing advice, at one stage or another, does not change the perspective on the impact of this tool in education. A similar circumstance occurs with the variable of years of experience. In this case, the teacher training advisors with the fewest years of experience and those with the most scored higher than those who were in an intermediate position regarding the capacity of Big Data to produce resources adapted to the needs of the students. Therefore, it is the level of knowledge that really makes the difference in the perceptions of the teacher training advisors. As for the variable of self-perceived competence level, the results of the basic level denote that there is still a wide lack of knowledge about the real potential of this tool in the educational sphere, in line with Daniel's study (Daniel 2019). This situation has led to significant differences in all of the items at the basic level of competence, as opposed to the medium and advanced levels, with differences also occurring between these two levels in 63.6% of the items, where participants with a self-perceived advanced level of competence have a better perception. This means that we are faced with a resource whose strengths and potential we can see; however, in order to use it, specific training is required on different tools to be able to perform the different meta-analyses. Thus, knowing how to use the programs and software provides a real vision of its application possibilities, thereby increasing the positive perception of it. Therefore, these results underscore that, beyond seeing possibilities in Big Data by teacher training advisors, it is necessary to develop ad hoc training for them on this tool. In this way, the decision to bet on Big Data will be pedagogically based and will not, to some extent, be based on predictions of its usefulness and potential without the adequate knowledge for its realization.

As for correlations, the results reflect the belief that the implementation of Big Data helps personalize educational processes with the consequent improvement in academic results, in line with the study by Matas et al. (2020). There is also a significant relationship between the selection of teachers based on Big Data's information and the improvement of educational quality in general.

As limitations, the size of the sample ( $N = 117$ ), as well as the poor knowledge about Big Data (56.41% basic level), makes it difficult to extrapolate and generalize the results. To overcome this issue and link it to future lines of research, it would be interesting to apply the scale to a broad sample of participants with a higher level of knowledge about Big Data (increase the number of participants with advanced competence). This would yield a more realistic picture of the educational possibilities of Big Data through the voices of professionals with more experience in this field. As we have reiterated, knowing the perception of teacher training advisors on Big Data showed us the scenario on which decisions would be made for inclusion in continuous training. The results highlight that we are facing a pro-active situation for its incorporation, that is, there are agreements and a general positive vision about what Big Data can contribute to education. However, the differences depending on the level of knowledge confirm the need for prior training on this resource for teacher training advisors, so that their assessment of the possibilities and opportunities has a greater pedagogical foundation and, thus, the commitment for the design and development of continuous training in Big Data for teachers will decidedly become the object of study of the following research. Based on the above, we believe it is crucial to implement training courses on the use of Big Data in education so that it can be used both in initial and continuous teaching–learning processes. In continuous training, the role to be played by teachers’ advisors is key, as they become the facilitators for the incorporation of this educational tool through the design and planning of the ongoing training for teachers. In short, the question is not ignoring a reality that can improve the educational system. Thus, there is a need to incorporate this tool in training programs in order to make the best out of it.

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