MUSICOLOGÍA Y TICs

LEARNING ANALYTICS AND HIGHER MUSIC EDUCATION: PERSPECTIVES AND CHALLENGES

LEARNING ANALYTICS Y EDUCACIÓN MUSICAL SUPERIOR: PERSPECTIVAS Y DESAFÍOS

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ABSTRACT

Continually monitoring student learning, improving tutoring, predicting academic risks such as performance drops or dropouts, assessing more objectively or understanding the behavior of student groups are some of the tasks that have been beyond the reach of music teachers. The current technology of massive data processing (Big Data) and its analysis (*Learning Analytics*-LA) allows to achieve these goals with relative ease. The possibility of extracting individual behavior patterns facilitates attention to diversity, reduces school dropout and failure, and opens the possibility of implementing new educational strategies. The phenomenon of data-based education has led to different types of studies. This paper reflects on three trends or fundamental perspectives in the use of the collection of massive information applied to learning and teaching. We offer an overview of research and applications of Learning Analytics specifically in the field of music education, as well as a reflection on its possible practical uses in higher music education in conservatories. For this purpose, we discuss some practical examples of how this technological methodology could be incorporated into music and music education research, and its influence on possible new educational paradigms that lead to innovation on teaching-learning process through new technological resources.

KEYWORDS

Learning Analytics; Big Data; Educational Data Mining; Higher Music Education; Music Education Research; Self-Regulated Learning

RESUMEN

Monitorizar continuamente el aprendizaje de los alumnos, mejorar las tutorías, predecir riesgos académicos como caídas o abandonos en el rendimiento, evaluar de forma más objetiva o comprender el comportamiento de los grupos de alumnos son algunas de las tareas que han estado fuera del alcance del profesorado de música. La tecnología actual de procesamiento masivo de datos (*Big Data*) y su análisis (*Learning Analytics-LA*) permite alcanzar estos objetivos con relativa facilidad. La posibilidad de extraer patrones de comportamiento individuales facilita la atención a la diversidad, reduce la deserción y el fracaso escolar y abre la posibilidad de implementar nuevas estrategias educativas. El fenómeno de la educación basada en datos ha dado lugar a diferentes tipos de estudios. Este trabajo reflexiona sobre tres tendencias o perspectivas fundamentales en el uso de la recopilación masiva de información aplicada al aprendizaje y la enseñanza. Ofrecemos una visión general de la investigación y las aplicaciones de *Learning Analytics* específicamente en el campo de la educación musical, así como una reflexión sobre sus posibles usos prácticos en la educación musical superior en los conservatorios. Para ello, discutimos algunos ejemplos prácticos de cómo esta metodología tecnológica podría incorporarse a la investigación musical y en educación musical, y su influencia en posibles nuevos paradigmas educativos que lleven a la innovación en el proceso de enseñanza-aprendizaje a través de nuevos recursos tecnológicos.

PALABRAS CLAVE

Analíticas para el aprendizaje; Big Data; Minería de datos educativa; Educación musical superior; Investigación educativa musical; Aprendizaje autorregulado

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INTRODUCTION

The increasing use of digital mediation systems in educational spaces, whether face-to-face or not, and at all educational levels, has accelerated the advance of the so-called *Learning Analytics* and led to an exponential increase in research that takes the information collected as a reference of the activity of the students in said educational digital spaces. Domínguez, Reich and Ruipérez (2020) postulate that the interaction between students, teachers and learning resources through digital educational tools "continuously generate a remarkable volume of data that can be analyzed by applying a variety of methodologies" (p. 33).

The phenomenon of data-based education has originated three types of studies. On the one hand, there is a large amount of research based on the mining of educational data, which seeks to analyze the behavior patterns of students and establish relationships between the variables involved in the learning process. A second trend refers to studies with a marked pedagogical approach, which use the aggregate information resulting from the analysis of the data in order to improve instructional design, enrich teaching methods and better understand the role of educational agents. Finally, there is also a significant number of research that focuses on the institutional derivatives of the use of data and aims to develop frameworks to improve strategic decision making, organizational design and curricular policies (Domínguez, Reich and Ruipérez, 2020: 34).

In line with the increase in research around educational data and data-based algorithms, concern has arisen about how to handle all this information because educational algorithms are very intrusive: they directly influence the practices of educational agents and determine the student learning (Hartong and Förschler 2019). In addition, in the development of data-driven education it is essential to consider aspects such as cognitive biases, cultural variables and questions related to the skills of users. Shibani, Knight, and Buckingham Shum (2020) warn of the importance of exploring not only what can be done with data, but also if it should be done, how it should be done, and how it fits into existing learning ecosystems.

Other emerging aspects in relation to *Learning Analytics* (LA hereinafter) are the political and ethical questions that can be raised in data-driven educational practices. Domínguez, Reich and Ruipérez (2020) warn of the existence of a growing concern about ethics and the misuse of data. Faced with these fears, which were also experienced during the beginnings of the use of artificial intelligence and which now focus on digitally mediated education, Barocas and Boyd (2017) suggest the need to rely on comprehensive analytical approaches, considering all the planes that are part of an educational process.

It is interesting to observe how there has been a departure from the main topics on which the learning analytics initially focused (enrollment rates, drop-out rates, evaluation follow-up, etc.), and which were closely related to the aggregation of large volumes of data from learning situations (Domínguez, Reich & Ruipérez, 2020). Currently, learning analytics are advancing towards other educational topics that did not have a prominent role in the field of data-based education and that are now fundamental pieces, as will be shown in the following sections.

SOME PREVIOUS DEFINITIONS

Current technology resources seek to improve and optimize students' learning experiences by adapting or intelligently using the information gathered about students, their environment, and their interactions. The use of mass information collection applied to learning and teaching has been approached from three different perspectives (Atkinson, 2015):

Academic Analytics (AA) aimed primarily at the use of information to improve organizational efficiency; Aspects such as the way in which teachers use the teaching space, the popularity or impact of a certain program, the individualization in the offer of instructional modules, etc., contribute to improving the training offer of the institutions. For example, Louisiana State University (LSU, 2019) uses AA for departmental and programmatic evaluation and expansion, departmental peer comparisons and benchmarking or the evaluation of new program proposals.

Academic analytics refers to "analytics used to help run the business of the higher education institution" (Oblinger, 2012, p.10). It is used to describe the intersection of technology, information, management culture, and the application of information to manage the academic enterprise (Goldstein & Katz, 2005).

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Educational Data Mining (EDM) uses the knowledge of machine learning and the way in which they predict events or behaviors to predict student behaviors in different circumstances, which in turn will influence the way in which teachers organize o design teaching and evaluation. Baker (2010) suggests that EDM can be useful to improve knowledge of the learning models that characterize students, organize the pedagogical support offered by software for learning, and inspire scientific research on learning and learners.

Castro, Vellido, Nebot and Mugica (2007) propose that EDM is applicable to the evaluation of student learning, evaluation of online course materials, management of feedback from students and teachers of online courses and models for the detection of student learning behaviors. The most frequently used analysis methods are (Algarni, 2016): prediction, clustering, relationship mining, distillation of data for human judgment, discovery with models and Social Network Analysis (SNA).

Big Data are also used to understand the effectiveness of administrative decisions and educational interventions. Big Data models can predict *when* actions need to be taken for students, such as identifying when students are disengaging from online courses (Le, Pardos, Meyer & Thorp, 2018). For instance, Whitehill et al. (2015) analyzed more than 2 million data points generated by more than 200,000 students taking 10 MOOC courses from *HarvardX* to develop detectors of whether a student would stop course work. These detectors were then used as the basis of interventions that improved student engagement.

Universities routinely collect reams of course-taking and student performance data, but until recently these data were rarely used for institutional reforms or to improve student decision making. By analyzing these data, and making data and analyses available to students, schools can meaningfully improve outcomes. Importantly, public access to these data may also improve equity. Whereas course-taking information was historically available only through social networks, such as fraternities and sororities, more open access may have a democratizing effect by giving all students equal access.

Learning Analytics (LA) shares with EDM the quest to improve student learning experiences and individualized adaptations, but LA focuses more on knowing how students learn -which are the most successful behavior patterns-, how those patterns relate to social variables and predicting future behaviors in relation to learning. Atkinson (2015) and Siemens, (2012) define *Learning Analytics*: is the process of collecting, measuring, analyzing and reporting data on the context of the learner and the learner's engagement with learning with a view to optimizing both. LA emphasizes the social dimension in the search for patterns and models of student behavior. Since learning has a social dimension that currently tends to be channeled through distributed learning platforms, a wide possibility of means and ways of participating with its social characteristics and potential to be used pedagogically opens up.

It is worth noting cases such as that of the Stanford University (USA) that creates personalized itineraries based on the results obtained through LA techniques, or that of the University of Michigan (USA), with its *Gradecraft* project, uses analytics both to guide students in the course they are taking and to inform teachers of their progress. In the European sphere, *LACE* is a project where different partners investigate and implement LA applications. Learning platforms are no strangers to the use of these techniques: *Blackboard* incorporates tools of this type and *Moodle Watchdog* has created the *Moodog project* to incorporate a tool for monitoring student activity by analyzing the logs of their activities (Zhang & Almeroth, 2010).

LA has been used in various educational settings: identifying students at risk of dropping out or underperforming (Foster & Siddle, 2020), assisting students to improve their vocational choices (Gedrimiene, Silvola, Pursiainen, Rusanen & Muukkonen, 2019), prediction of student performance (Huang, Lu, Huang, Yin & Yang, 2019), patterns in collective problem solving (Hwang & Chen, 2019), change in teachers' beliefs in training (Sun, Hu, Wan, Fu & Wu, 2019), the analysis of Personal Learning Environments (Casquero, Ovelar, Romo, Benito & Alberdi, 2016) or the dropout of students in distance education (García-Tinizaray , Ordoñez-Briceno & Torres-Díaz, 2014). Kumar and Kumar (2018) review different uses of LA in the academic field.

THE CHALLENGES OF BIG DATA APPLIED TO EDUCATION AND EDUCATIONAL RESEARCH

In the last decade the analysis of educational data has grown remarkably, but the transfer of such research to the practices of educators in the classroom or its impact on institutional policies has been quite limited (Domínguez, Reich & Ruipérez, 2020). In this sense, during the past decade, rather than finding solutions, challenges have been identified, organized fundamentally into three areas: research, educational practices and institutions.

Fischer et al. (2020) outline current challenges of accessing, analyzing, and using Big Data. Such challenges include balancing data privacy and protection with data sharing and research, training researchers in educational data science methodologies, and navigating the tensions between explanation and prediction. The challenges in the field of educational practice focus specifically on solving the problem of the lack of sufficiently validated results and the strong theoretical base of the studies that has led to a low transfer of research to practice (Domínguez, Reich & Ruipérez, 2020). It is not yet common to find educators applying learning analytics in their classrooms. As Mandinach and Gummer (2016) emphasize, the main challenge that arises is the training of teachers in management skills and interpretation of digital data.

Accessing Big Data

Educational data exist in a wide array of formats across an even wider variety of platforms. In almost all cases, these platforms were developed for other purposes, such as instruction or educational administration, rather than for research. Many commercial platform providers, such as educational software companies, have no interest in making their data available publicly. Other companies make their data available in a limited way but have not invested resources to facilitate access to data for research. Only a small number of platforms, such as *Cognitive Tutor* and *ASSISTments*, have made high-quality data broadly available. Parents, educators, and others are rightly concerned about companies' ability to mine large amounts of sensitive student data and fears have been raised that student data that are inappropriately shared or sold could be used to stereotype or profile children, contribute to tailored marketing campaigns, or lead to identity theft (Strauss, 2019).

Analyzing Big Data

As with accessing Big Data, analyzing Big Data also poses challenges regarding researchers' skills. Few education researchers know key programming languages used for data science, such as Python. Education research graduate programs seldom offer instruction in the data-clustering, -modeling, and prediction techniques used to analyze Big Data (Fischer et al., 2020) but, in general, there is a lack of training in Big Data analysis for educational research in general and in music education in particular.

On the other hand, numerous investigations develop systems without considering the target user as part of the design, and end up implementing prototypes that do not meet the requirements or interests of the people who are going to use them (Domínguez, Reich & Ruipérez, 2020). To solve this, Dollinger and Lodge (2018) propose the implementation of systems and applications of learning analytics whose design is focused on the user, as well as the involvement of that user -teachers, for example- in co-design sessions.

A very interesting initiative is the one carried out by the *Sloan Equity and Inclusion* in STEM Introductory Courses, launched by the University of Michigan, exemplifies the value of open science for new kinds of education research. Faculty at 10 large research universities connect through parallel and combined data analyzes and continuous exchange of speakers and graduate student researchers to explore and improve instructional practices and outcomes in foundational STEM (science, technology, engineering, and mathematics) courses reaching hundreds of thousands of students. Open sharing of data and team science will be hallmarks of this important research initiative.

Using LA

Finally, even if we successfully access and analyze Big Data, additional issues arise related to how such data are used. One of them is that the applications of learning analytics can be systematically integrated within the infrastructure of educational institutions (Tsai & Gavesic, 2017). These infrastructures must incorporate options to ensure privacy so that data can be shared by students and teachers in a transparent way. Leitner et al. (2019) point to the need to create work units or teams focused on learning analytics, within the departments or institutional units dedicated to educational

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innovation. In this way, the different points of view of the multiple actors that participate in the learning analytics process (researchers, teachers, students, educational technologists and administrators, among others) could be channeled, facilitating synergies between all of them.

Curricula in graduate schools of education overwhelmingly favor research methods that fall within one of two major paradigms: quantitative measurement and hypothesis testing or interpretive qualitative research. Analyzing Big Data draws on an alternate research paradigm to those used in computational social sciences. Only a handful of doctoral programs in education offer the kinds of research training necessary to develop the educational data sciences of the future, and even fewer offer instruction related to the ethical, moral, and privacy dimensions of working with Big Data. There is too little interdisciplinary training across these fields and education.

Traditional models of education research privilege the sole author. In contrast, research projects that involve data mining typically privilege team science, with junior and senior scholars, and open science, so that large data sets can be combined and reused for new analyses and replication.

Examples of use of LA in teaching–learning music

1. Using LA to investigate Self–Regulated Learning (SRL) in Music Teacher Education

Montgomery, Mousavi, Carbonaro, Hayward and Dunn (2019) report research on how four-year undergraduates use SRL in a Blended Learning (BL) environment. Self-regulation is especially important when learning in virtual and face-to-face (BL) environments. Determining when to connect, for how long, how to explore the materials, etc., are personal decisions of the student that must be self-regulated to achieve their learning objectives. In the aforementioned experience, the authors tried to investigate SRL patterns in a music teacher training course and also whether these patterns had any relationship to the performance of participating students. The analyzed group consisted of 157 participants in the 4th course of a Bachelor of Education in the BL modality with a distribution of Face to face (F2F) activities (50%) and online (50%). The online activity was carried out through the Moodle platform. The information collected consisted of eight variables: seven that describe the activity within the platform and one that collects the performance of the course:

- Activity: Location, day of the week of connection to the platform, time of connection
- Sustainability: number of connections and modules visited
- Structure: Regularity, pattern of test revisions
- Course performance

2. The Objective Ear: assessing the progress of a music task

Burrows and Kumar (2018) have developed a tool called *Objective Ear*; Starting with a couple of performances of a piece of music returns an accurate and reliable assessment of progress between performances. The system consists of two components: an evaluator and a classifier. The performances of the piece are entered into the evaluator in MIDI format through a keyboard. The evaluation component tackles an analysis of the piece and each analysis provides a measurement that can be compared with other measurements of that piece executed at a different time. In the reported case, the authors focused their work on western classical music (from 1700 to early 1800). The analysis of each piece was based on the following parameters:

- Tempo: The pace of the music.
- Pitch: The rate of likely pitch errors.
- Rhythm: The rate of likely rhythm errors.
- Flex-Rhythm: The rate of likely rhythm errors, allowing the tempo to slow at the end of sections.
- Ornaments: The rate of ornaments performed, weighted by their complexity.
- Error Groups: The rate of errors after combining errors close in time as a single error.

The result of the comparison (subtraction between measures) is the input of the classifier that provides a result in terms of worse, equal

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or better. The precision (reliability) of the system when compared with other sources of assessment was in the range 0.81-0.86, which indicates the feasibility of the proposal.

MUSIX

Guillot, Guillot, Kumar and Kinshuk (2015) present a learning analytics tool for music: *MUSIX*. Basically MUSIX is a music self-learning tool that allows students to learn at their own pace and monitor their progress; this makes it easier for students to detect their learning difficulties and solve them in an individualized way. As students monitor their progress and grow in autonomy, their self-confidence and motivation to learn increases. Based on the information collected, MUSIX forms study patterns, identifies what skills are present in the student's activity, predicts the growth / development of the skills and competencies involved in learning, and measures the students' self-regulation efforts regarding their learnings.

One of the multiple applications of this tool is to inform students and teachers on a daily basis of the pace of student progress in order to avoid possible delays as well as to reinforce the feeling of not being alone, as a way of preventing unwanted dropouts. MUSIX currently collects data from the following three activities: music theory study, vocal training, and learning an instrument.

• **Music theory**. MUSIX offers instruction in music theory (musical language, musical writing and interpretation of music in different contexts). Instruction is organized by mastery levels. MUSIX continuously monitors the interactions of the students with the platform in which the training activities are implemented, collecting, for example: response time to questions, number of initiatives taken by the students, time to read a page, games in which the student participates and activities derived from them.

• **Vocal training**. MUSIX collects the audio recorded by the students and analyzes the recordings to determine the skills exhibited in them. It offers two alternatives: sight singing and vocal techniques.

- For sight singing, the tool presents a melody on the student's computer screen and, in addition, an audio file that reproduces the notes of the melody and allows different options such as listening to each note, the measure of the rhythm and other alternatives. The student must sing the melody and record it as many times as they want. The recordings are analyzed by the tool to determine the precision of the notes, the adjustment of the rhythm and the pitch.
- For vocal techniques, the system registers and records physiological responses from different parts of the body: breathing, position of the mouth, muscular tension, etc., and other complementary data such as delays before breathing, pitch of each note, duration of each note , etc.

• **Learning an instrument**. The tool collects data such as instrumental practice time, breaks between practices, the sequence of practice, the way the student works on their mistakes, how much mastery of the specific concepts of each lesson the student exhibits in their performance, and the amount of notes played correctly. MUSIX collects information regarding time, the precision of notes and rhythms and other important data that is sent to the tool in MusicXML format. The recording of the information is done in MIDI format.

Reflections on possible applications of Learning Analytics in Higher Music Education

An initial approach to the potential in Music Education of Learning Analytics leads us to imagine its possible practical applications in different fields and levels. It is not difficult to think about the usefulness of the Big Data collection in harmony, composition, conducting, analysis, instrument, virtual classes, teacher training and its influence on possible new educational paradigms that make a greater impact on self-regulated and reflective learning, Long Life Learning, improve tutoring, improve student monitoring, self-assessment, imitation of models, enhance creativity, etc.

Some concrete proposals for the application of LA in the learning process of music students, and aimed at strengthening autonomy in study and self-assessment, could be, for example:

1. Chamber music rehearsals to test the degree of progress when they rehearse in groups without a teacher, as well as the relational structure within the group and

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planning within the rehearsal (when, where, frequency, duration, etc.)

2. Individual study of the instrument

3. To carry out exercises of stylistic harmony or historical composition where the tool allows to identify harmonic and musical gestures inside or outside a certain style. Also for self-assessment of traditional harmony exercises and scholastic counterpoint.

4. The imitation of sound models (quality, projection, acoustic characteristics, etc.) with comparative analyzes between the real sound and the previously stored sound to be imitated (introduced by the teacher, or by a specific recording)

5. Individual and collective work with exercises designed to practice tuning, interval intonation, rhythmic pulse accuracy, transposition, sight reading, and a long list of learning and improving training in multiple musical parameters.

The collection of data from all these experiences would allow teachers and music institutions to investigate the learning methodologies, the ways in which students learn and the frequency of work, among many other things. The results of the application of the analysis of this data would allow to improve tutoring and follow-up of music students. In this context, LA can also be a valuable tool for self-assessment and peer-assessment.

In relation to music research, LA has great potential as a tool in artistic research where the subject and its learning is the object of study. LA could endorse the perceived improvements - or not - in the results of artistic research, thus avoiding the subjectivity inherent in this research paradigm, increasingly on the rise in music and other arts. The use of Big Data and its analysis in the field of higher music education could help shed light on issues related to the music profession. Understanding the demands of the music market; identifying the possible job niches, not too explored until now; being aware of some of the keys to the success or failure of graduated students, or having the knowledge of the real difficulties they face in their work as musicians of the XXI century, for example, could have a great impact on the design of conservatory training programs and the adaptation of them to authentic needs of future professionals.

In the field of music teacher training, research based on Big Data and LA is also seen as an innovative technological incorporation that can promote an updating of the training curriculum, especially at a methodological level.

CONCLUSIONS

The availability of Big Data offers exciting new threads of research and the opportunity to add additional perspective to existing threads in education, in general, and particularly, in music education. All types of Big Data in education offer affordances and challenges.

On the one hand, the ubiquity of Big Data and LA suggests an increased emphasis on preparing students in educational graduate music programs to utilize data science methods, as well as a committed push toward open science and research structures that favor collaborative teams, to improve our field's capacity for mining Big Data for education research. On the other hand, to achieve the above, it is necessary that conservatories implement the mechanisms to be able to access this data, and instruct the educational community how to use them, as well as promote the design of tools that allow them to personalize data searches and applications.

There is no doubt that, given the potential benefits of mining Big Data in music education, it is worth our effort to begin addressing these challenges. There is still a long way to go before LA can be used in higher music education research as a common research paradigm, but the first steps have already been taken and we should rethink the use of new technologies, and more specifically Big Data mining, in its application to educational improvement, specifically in the arts.

The limitations of each of these types of use of Big Data can be minimized, and the benefits amplified, if future research is triangulated either with the remaining types of Big Data or with more traditional forms of quantitative or qualitative analysis.

In summary, the use of LA in the educational process concerns all the actors involved, and to ensure the synergy of all of them is essential, on the one hand, the training of teachers in data analysis and the design of tools designed for users and, on the other hand, the creation of specific work units or departments to jointly

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address the use of digitally obtained data. It is important for higher music conservatories to be up to date by incorporating new data collection strategies for research and taking advantage of technology to improve the educational process.

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