"Prediction" in educational research: a bibliographic mapping of academic production over time

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Abstract

The article presents a Systematic Literature Review that analyzes a specific bibliographic corpus from Web of Science: papers about prediction published in the educational field from 1900 to 2019. Its objective is conducting a preliminary analysis over the academic production mapping considering not just its conceptual structure but also its scientific evolution. In doing so, text mining techniques on bibliographic material were used via SciMAT tool with the purpose of generating strategic, thematic, stability between periods, and evolution diagrams according to keywords indexed in the analyzed documents. The results obtained include…

Introduction

In the current scenario of data proliferation -or what some authors have called "datafication" (Breiter, 2016; Selwyn, 2015; Van Dijck, 2014)- new evaluative developments use algorithms to assess situations and make decisions that have an impact even at private individual level.

These automated systems are strongly present in business since it was there where the so-called "risk predictive analytics" first found applicability (Siegel, 2016). However, this kind of algorithms is also used to make decisions in the area of health, in justice, in urban design and its mapping, in government and bureaucratic systems (Batty, 2013; Jee and Kim, 2013; Kim, Trimi, Chung, 2014; Khel, Guo and Kessler, 2017) and, recently, in educational/pedagogical contexts (Danaher et al., 2017; Holmes, Bialik, and Fadel, 2019). Just to mention some examples, in this particular field, algorithms are usually aimed to predict performances, choose students and assess teachers, develop "Intelligent Mentoring Systems" or "Adaptive Learning Systems", among others (Aleven, et al. 2015; Baker, 2016; Daniel, 2017; Sclater, Peasgood and Mullan, 2016; Williamson, 2017).

In the case of the design and use of algorithms dedicated to the "prediction of students success", developments are increasingly frequent: the objective is generally identifying students "at risk" and customizing pedagogical interventions. These algorithms assume as a starting point that the prediction of learning is somehow a possible task (although there is no consensus about it) and that its measurement can be accurate as it is now feasible to apply certain statistical techniques on large volumes of data not previously available (Gandomi and Haider, 2015). In fact, according to Neresini (2018), this is the first time in human history that social scientists have available a vast amount of data produced "naturally" by the same actors involved in the phenomena. Moreover, it is broadly recognized that the generation of information "is more accurate, timely, and detailed than that gleaned from more traditional sources of data" (Schintler and Kulkarni, 2014: 344).

In this context, it is necessary to point out that prediction is not just a current concern and that certain approaches have worked for decades in that direction. Along this line, just to mention a case, Simpson already stated in 2006 that, finally, the statistical methods that involve logistic regression analysis are usually more useful and accurate as predictors than questionnaires or tutors' opinions about the students. Added to this is the apparently promising extra value of analyzing large volumes of data coming from educational settings. Anyway, despite this widespread optimism, it is still necessary to note some controversies and limitations related to the use of big data in Social Sciences (McNeely and Hahm, 2014; White and Breckenridge, 2014) and in educational contexts in particular (Siemens and Baker, 2012).

In concrete terms, there are several proposals for algorithms dedicated to prediction in education that has recently gained momentum at the university level (Arnold, Tanes and King, 2010; Harackiewicz, Barron, Tauer, and Elliot, 2002; Jayaprakash, Moody, Lauria, Ragan and Baron, 2014; Macfadyena and Dawson, 2010; Romero, López, Luna and Ventura, 2013; Sclater, Peasgood, and Mullan, 2016; Tanes, Arnold, King, and Remnet, 2011; You, 2016;). They are the so-called "probability of success algorithms" or "student success prediction algorithms" from which the "risk of falling behind" is calculated for each student in the cohort. It is even possible to track initiatives that consolidate institution networks that use predictive analytics in education and from this perspective (De Rosa, 2018).

These predictive models basically use student demographic data, previous academic history (scores from standardized tests such as SAT, etcetera), and data coming from the Learning Management Systems of the current course as well as test and assignment scores. With these data, universities contact their students and recommend activities in order to mitigate the risks of desertion and abandonment. It is a contact tailored to the needs of each student and addressed to certain groups with the objective of enhancing the quality of educational results and experiences.

However, it must be said that some applications put forward reasons other than assisting educators to better understand their students' learning process and improving students' performance in courses. For example, there are developments addressed to improve the decision-making process in university admissions, increase financial efficiency, elevate funds and university ranking positions, etcetera (see a comprehensive description in Jayaprakash, et al., 2014). In other words, these systems are used either in the framework of "academic analytics" where collected data is used for support operational and financial decisions or with an interest in providing feedback about teaching and learning performances in what is known as "learning analytics" (Siemens and Long, 2011; Ferguson 2012).

Having said that, some questions emerge: how has the topic of prediction been predominantly approached in educational research?; How does it fluctuate in conceptual terms across time?; what pedagogical approaches and ethical discussions are raised around it?; what is the treatment specificity of prediction in this specific field considering the current rediscovery and boost of Artificial Intelligence techniques?

With these questions in mind, after a meticulous search, little research in English with meta-analytical intentions over prediction studies in educational research has been found (Elliot and Murayama, 2008; Gardner, Brooks, and Baker, 2019; Howard, Meehan, and Parnell, 2018). Therefore, this paper comprises a preliminary analysis of predictive scientific production in education (1900-2019) taking into consideration not just its conceptual structure but also its scientific evolution.

In this context, this Systematic Literature Review uses text mining technics applied over bibliographic material and proposes to answer two specific questions: what are the main topics related to prediction investigated in the field of educational research from 1900 onwards?; and which is its thematic evolution during the period?

Following these objectives, our work herein is organized into three fragments. First, the methodological definitions are presented using SciMAT tool to apply text mining techniques on bibliographic material. Second, preliminary results are included using, initially, common measures to describe the main trends identified in predictive studies in the educational academic field. Subsequently, we analyze specific diagrams obtained with SciMAT to reconstruct the thematic evolution in the field as well as its thematic composition. Third and last, in the conclusions, we present theoretical discussions around the trends and findings detailed above.

Methodology

This exploratory study performs a Systematic Literature Review whereby are used systematic and explicit methods to find, select, and critically assess the relevant research starting from a question/problem, with the aim of mapping the field of knowledge in a particular moment or timelapse (Meca, 2010; Okoli and Schabram, 2010).

In order to accomplish this purpose, text mining techniques are here applied. Specifically, a bibliometric analysis was carried out with SciMAT, a science mapping analysis software developed by Cobo, López-Herrera, Herrera-Viedma, and Herrera (Cobo et al. 2011; 2012; Martinez et al. 2015). This software application is based on co-word analysis and quality measures that enable longitudinal examination with the purpose of detecting the evolution of different themes treated in a specific research field across given time periods.

Particularly, this research design has included several steps.

First, a search engine in the Web of Science Core Collection (ISI WoS) was established containing classic keywords related to predictive uses in the educational field published in English and considering articles from all years included in educational categories.

This search yielded a result of N=3996 documents downloaded by the end of May 2020. At the same time, since we observed an accumulation of articles from 1990 and none until the 20s, it was determined to break up periods every 10 years from 1920 until 1989 and every 5 years from 1990 to 2019. Accordingly, a more interesting evolution diagram was generated especially detailed in the last periods.

Second, the keyword was defined as the item to analyze. This included authors' keywords, journals' keywords, and indexing keywords presented in the selected documents.

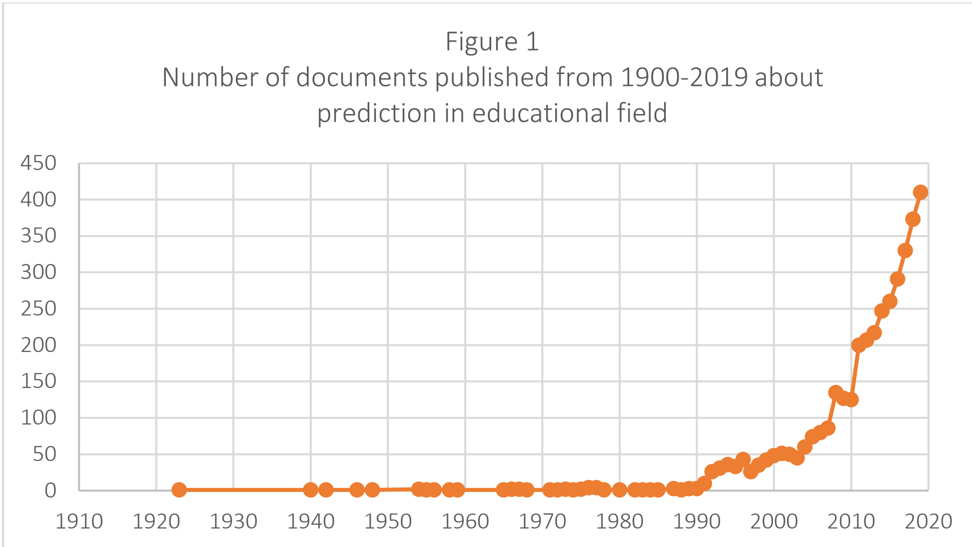
For its normalization, keywords were chosen in the plural rather than in the singular form and with hyphen/s rather than without them. In this way, the terms were joined in groups automatically. After this operation, a manual process of location was conducted with the keywords that did not were classified by the software.

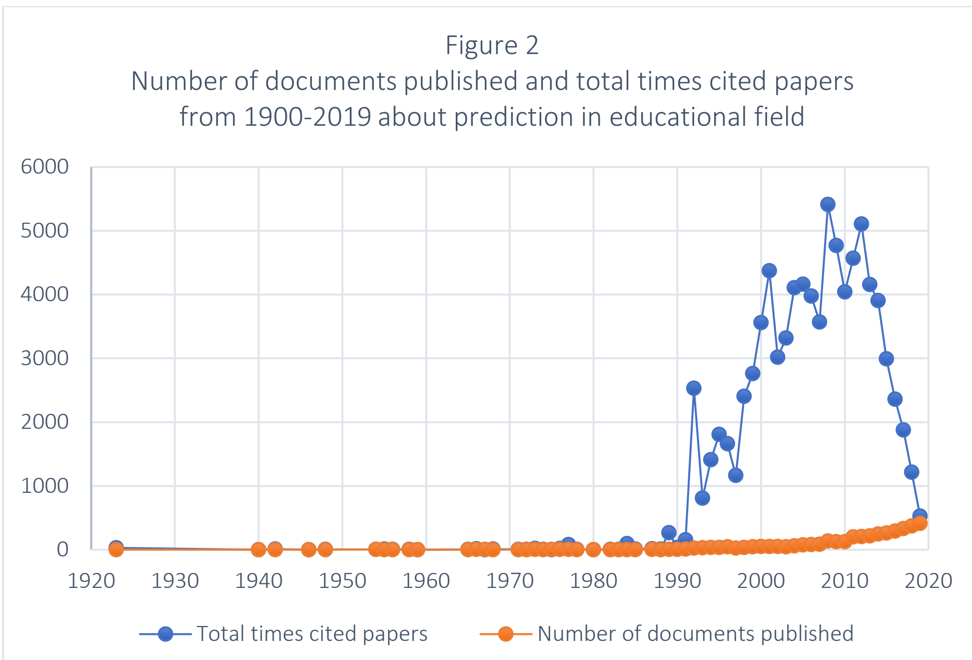
Third, keywords co-occurrence frequencies and similarities between items were calculated. The measure of similarity used to normalize the network was Equivalence Index. Posteriorly, the clustering process was carried out. Through this technique, it was possible to locate subgroups of terms that are solidly linked and that correspond to centers of interest in educational research about prediction. In doing so, SciMAT uses Simple Centers Algorithm to obtain automatically labeled clusters. Additionally, the quality measures selected were h-index and sum of citations as well as Jaccard Index and Inclusion Index were defined as similarity measures used to build the evolution diagram.

Finally, in addition to performance analysis measures (such as the number of documents, authors, journals, received citations, h-index or measure of scientific research impact, among others), four types of diagrams were built and interpreted according to the framework provided by SciMAT: thematic diagrams, strategic diagrams, the stability between periods diagram, and the evolution diagram. Additionally, other pertinent graphics were constructed to complement the interpretation of the results obtained in this study.

Results and preliminary analysis

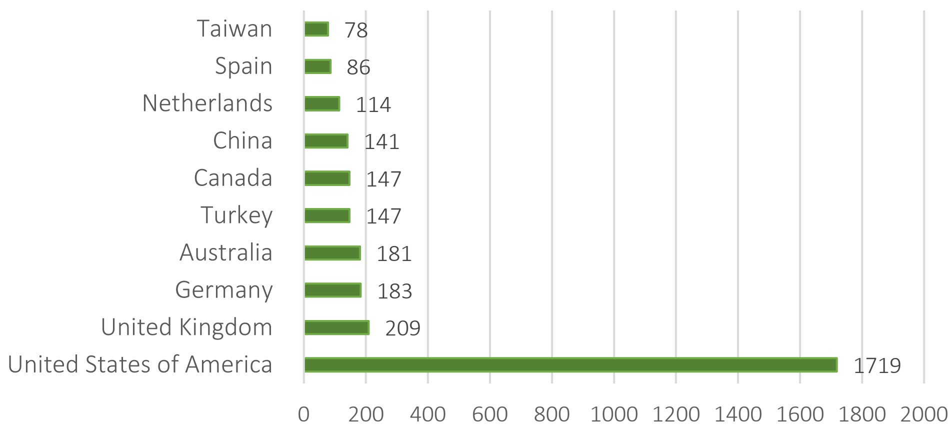
According to Figure 1, the explosion of documents on prediction published in the educational field has been recorded since 2010 with sustained growth until the date of database downloading. Furthermore, Figure 2 shows the strong impact of the publications according to the number of citations received especially since 2000 onwards. Expectably, the recent reception of the latest papers explains the recorded impact drop.





From the geographical point of view (Figure 3) the main publisher country is undoubtedly the United States of America (57% of the material published by the top ten countries), followed by the United Kingdom (7%), Germany (7%), and Australia (6%).

Figure 3
Top 10 publisher countries about prediction in educational field



Regarding the predominant publications (Table 1), despite having a great dispersion, the main journal is Learning and Individual Differences indicating that predictive studies prevail about phenomena linked to the learning carried out by individual agents. This publication is followed by the Journal of Educational Psychology and Child Development, showing that the topic of prediction is also considered in scientific magazines with interest in educational psychology, evolutionary approaches, and psychometry. Next, Computers & Education is registered as a leading publication mean, indicating the extensive production on prediction covered in the field of Educational Technology. Additionally, it is worth mentioning journals that address particular study objects whose research on prediction is considerable in number (such is the case of Reading and Writing and the Journal of Counseling Psychology). Further, the topic of prediction is equally present in specialized magazines about Higher Education.

Table 1
Top 10 publications about prediction and education (1900-2019)

Name of The Publication	Number of documents
Learning and Individual Differences	156
Journal of Educational Psychology	114
Child Development	89
Computers & Education	68
Educational and Psychological Measurement	67
Contemporary Educational Psychology	62
British Journal of Educational Psychology	59
Reading and Writing	53
Journal of Counseling Psychology	52
Research in Higher Education	47

Now, if the focus is put on the strategic diagrams (Table 2), the evolution of prominent topics about prediction in educational research can be examined. In the table, each one of the diagrams stands for a lustrum from 1990 until 2019. Worth mentioning that although we have considered publications from 1900 onwards, only from 1990 did we obtain the minimum frequencies and co-occurrence required by this analysis. It is for this reason that strategic diagrams were solely obtained since 1990.

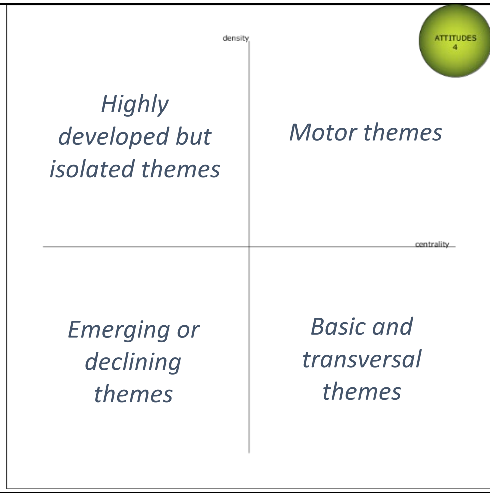
Basically, each one of these diagrams locates “themes” -actually, networks composed by keywords- according to two parameters: their centrality and density measures (Cobo, López-Herrera, Herrera-Viedma and Herrera, 2011). As a result, themes can be located in the four quadrants of the cartesian plane according to centrality and density network indexes: motor themes, basic and transversal themes, emerging or disappearing themes, and highly developed but isolated themes (as indicated in the strategic diagram for 1990-1994 period in Table 2). Besides, the volume of the node is, in this case, proportional to the number of documents corresponding to each theme undergone analysis.

Considering Table 2, thematic proliferation about prediction prevails in the last three decades, with sustained growth. Particularly, a drastic thematic diversification is well-observed since 2005 with a few established core themes. This result is endorsed by the evolution diagram (see Addendum Figure 1) which shows wide thematic diversification in the most recent periods but with few consolidated lines of research: the thematic continuities of

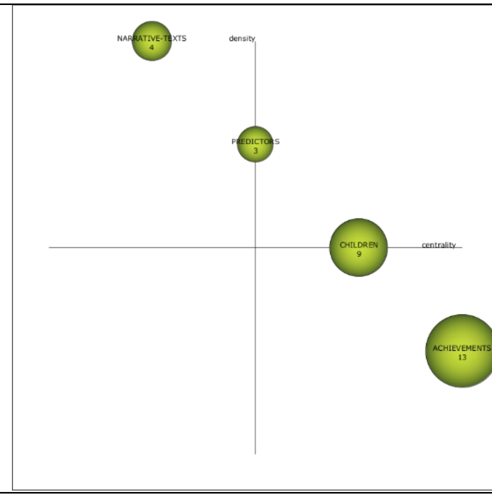
Table 2: Strategic Diagrams (1990-1919): core documents count

[*volumes of nodes are proportional to the number of core documents for each theme]

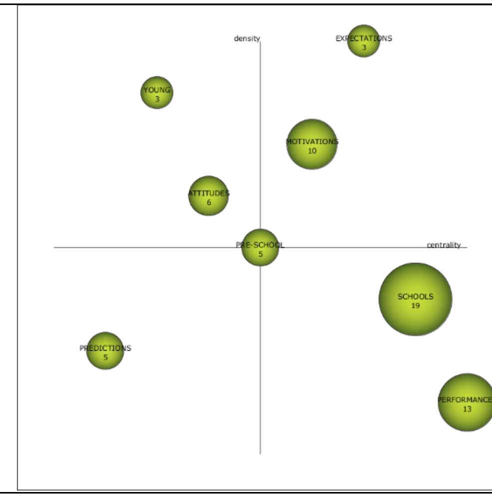
1990-1994



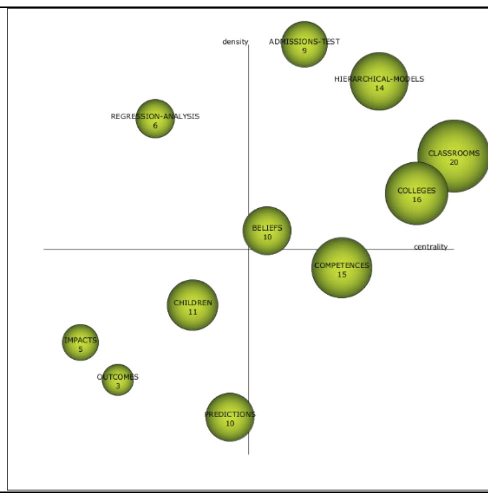
1995-1999



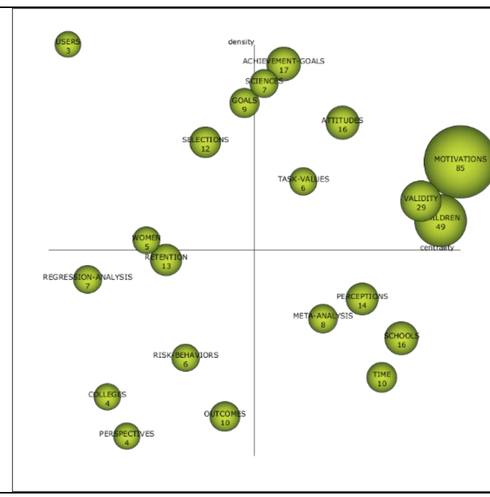
2000-2004



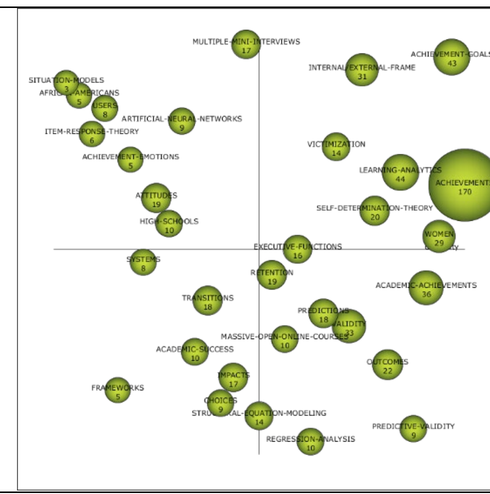
2005-2009



2010-2014



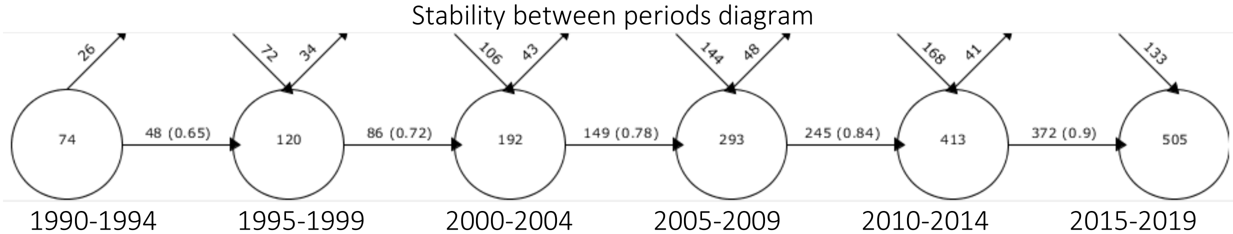
2015-2019



dotted lines abound, indicating that the continuity is not that strong because the themes tend to diversify into new ones. This evidence allows to sustain that scientific production about prediction in educational research implies mainly thematic proliferation but with still weak maintenance of interest over specific themes (especially during the last three analyzed periods). Only a few exceptions are identified around the thematic continuity of studies on motivation and achievements, attitudes, and retention.

At the same time, the stability diagram (Figure 4) shows a clear increase in the number of keywords submitted to analysis: from 74 in the period 1990-1994 to 505 in the period 2015-2019. Furthermore, the similarity index (shown in brackets) rises from 0.65 to 0.9 indicating a considerable overlapping between sets and, therefore, that the terminology about prediction in education is shared and maintained over time. Nevertheless, it should be mentioned here that this finding in terms of terminological uses does not mean that there is a thematic continuity in the sense of the aforementioned consolidated lines of research.

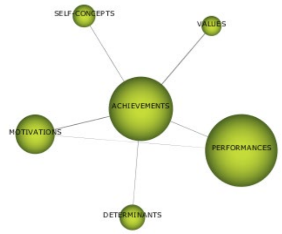
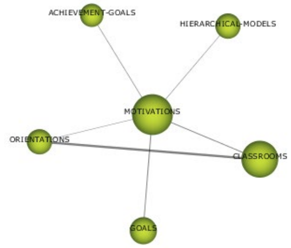
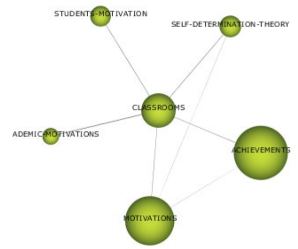
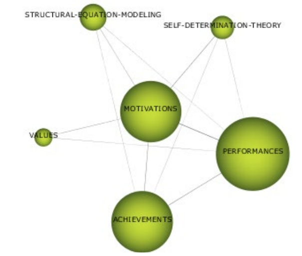
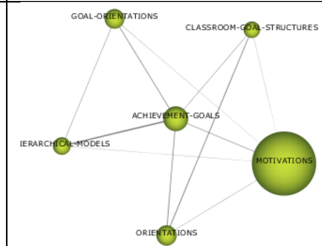
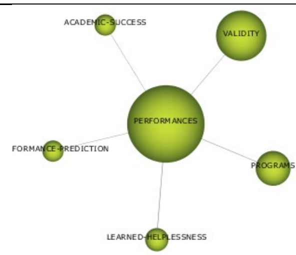
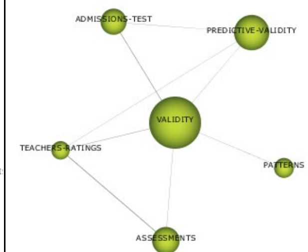
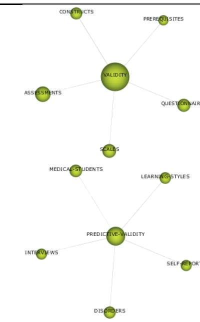
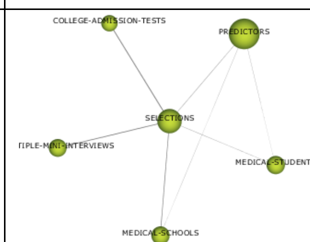
Figure 4
Stability between periods diagram



With this said, thematic contents and their evolution can be analyzed in more detail. Regarding predominant topics, four main results should be highlighted according to the analysis of thematic diagrams (Table 3 and 4). Following our interpretative framework coming from SciMAT tool, each one of the themes located in the previous strategic diagrams (Table 2) is (actually) a network or cluster of keywords with specific centrality and density indexes.

First, “motivation” emerges constantly as a theme of interest from 1995 onwards, most of the time appearing as a motor theme, that is, with high centrality as well as network density. The theoretical reason for this phenomenon is that motivation is often considered a habitual if not a “star” predictor of student learning and success. In the sequence, motivation keyword is initially present composing the transversal “achievement” topic in 1995-1999. Then, motivation appears as a motor theme in 2000-2004 with strong inner development (density of 11.97), and posteriorly takes part in “classroom” motor theme in 2005-2009. Next, motivation turns up as a motor theme by itself again in 2010-2014 with not just 85 documents referring to it but also with an outstanding centrality of 25.64 which means a valuable measure of its importance in the research field. Finally, motivation appears integrating the motor theme “achievements-goals” in 2015-2019. In light of these findings, motivation (especially its approach in its intrinsic version) seems to be well established as an ever-present phenomenon in performance prediction studies.

Table 3
Main themes composition

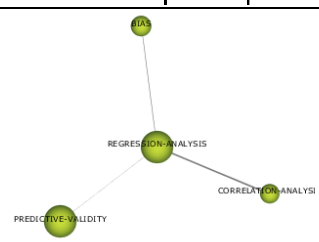
Continued topic	1995-1999	2000-2004	2005-2009	2010-2014	2015-2019
Motivation	 Transversal theme Name: **Achievements** Density: 7.11 / Centrality: 8.22	 Motor theme Name: **Motivations** Density: 11.97 / Centrality: 7.85	 Motor theme Name: **Classrooms** Density: 6.33 / Centrality: 22.26	 Motor theme Name: **Motivations** Density: 6.37 / Centrality: 25.64	 Motor theme Name: **Achievements-Goals** Density: 12.23 / Centrality: 15.89
Validity	*	 Transversal theme Name: **Performances** Density: 4.12 / Centrality: 14.32	 Well-developed & isolated theme Name: **Regression-analysis** Density: 7.11 / Centrality: 3.00	 Motor theme Name: **Validity** Density: 4.83 / Centrality: 9.00	 Basic & transversal **Validity** & **Predictive-Validity** Density: 1.81 &0.7 / Centrality: 8.05 &10.92
Selection of Students	*	*	 Motor theme Name: **Admissions-Test** Density: 16.99 / Centrality: 10.82	 Well-developed & isolated theme Name: **Selections** Density: 6.99 / Centrality: 4.7	 Transition to motor theme Name: **Multiple-Mini-Interviews** Density: 16.31 / Centrality: 6.43

Second, the mention of “validity” discussions about prediction in pedagogical research shows a persistent presence since 2000. As can be seen in Table 3, in period 2000-2004 the transversal theme "performances" is formed by a group of keywords among which is present "validity". Then, between 2005 and 2009, the highly developed but isolated theme "regression analysis" is constructed by keywords such as "predictive validity" and "bias". Subsequently, in the period 2010-2014, "validity" constitutes itself as a motor theme referred by 29 documents with well inner development (density index of 4.83) as well as maintains interesting relationships with other themes (according to high centrality of 9.00). In this case, validity discussions are specifically related to predictive validity for students' assessments and admissions. In the last period (2015-2019) the validity concern about predictive power goes to the basic and transversal quadrant and appears diversified into, on the one hand, "validity" theme (mainly linked to instruments) and, on the other hand, "predictive-validity" theme. In this period, both themes present increases in its centrality measures (with indexes of 8.05 and 10.92 respectively) which can be suggestive of the rising importance given to discussions not only on the possibility of predicting in educational settings but also on the ways of achieving it. In any case, it must also be said that, in this last period, the depth in the treatment of these issues is minimal (densities of 1.81 and 0.7 respectively) which could constitute a vacant area for future developments given the aforementioned recognition of its importance.

Third, the “selection of students” is shown as a recurrent educational research topic for prediction studies in the last 15 years. The link between educational prediction and students' selection is suggestive and mainly mentioned in Higher Education studies. In the period 2005-2009, “admissions-test” appears as a motor theme with formidable inner development (density equals to 16.99). Specifically, it includes keywords referring to medical admissions and concerns about selection validity. Then, from 2010 to 2014, “selections” theme is recognized as a well-developed topic (density of 6.99) but still shows weak relationships with others (centrality measure of 4.7). In this case, the network of "selections" is constituted by keywords that also focus on college admissions and medical students. In the next period (2015-2019) “multiple-mini-interviews” is a topic in transition from developed and isolated themes to motor themes with exceptional conceptual development (16.31 for density). In the same line, it is composed of a continued preoccupation with student admissions in medical schools.

Fourth, the presence of the topic "regression analysis" implies that more sophisticated technical definitions about educational prediction are being incorporated more recently in the research field (particularly from 2010) (Table 4). As mentioned before, in 2005-2009, regression analysis is mostly involved in discussions regarding validity and prediction; it is a well-developed theme with high density (7.11) but, at the same time, is not referring to specific technics about regression models. Anyway, if we look explicitly for specific prediction techniques in this period, there is an initial mention of neural networks composing the emergent theme "predictors". Progressively, the diversification of technical languages appears in between 2010 and 2014 with regression analysis as an emerging theme composed by keywords such as artificial neural networks, decision trees, classification trees, and neural networks to study public schools. Finally, in the period 2015-2019, regression analysis is already a transversal theme linked, among others, to biases. Even so, the mention of other techniques is multiplied around other themes such as “Item Response Theory” (compound by “Bayesian analysis”) and "Artificial Neural Networks" (that includes “machine learning” in time-series analysis). In other words, it seems that, in the last decade, data mining techniques are beginning to openly establish itself beyond traditional and widespread predictive techniques in this field of scientific production. In addition, it can be clearly observed that these themes -generally well developed conceptually in other fields of knowledge- are recently emerging as recurrent topics in the field of educational research although they are still isolated in their relationship with others.

Table 4
Techniques in prediction studies at educational research field (2005-2019)

<table>
<tr>
<td>2005
-
2009</td>
<td>
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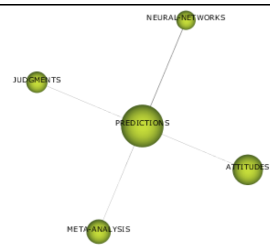
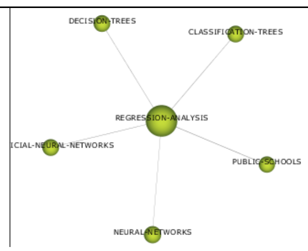
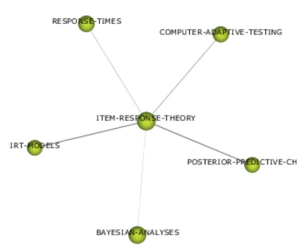
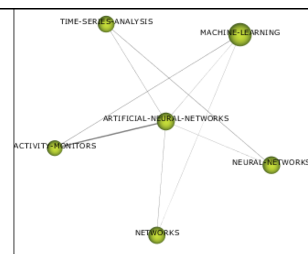
<td>
</td>
<td>Well-developed & isolated theme
Name: Regression-analysis
Density: 7.11 / Centrality: 3.00

Emerging theme
Name: Predictions
Density: 3.35 / Centrality: 5.35</td>
</tr>
<tr>
<td>2010
-
2014</td>
<td>
</td>
<td>Emerging theme
Name: Regression-analysis
Density: 3.54 / Centrality: 1.29</td>
<td></td>
</tr>
<tr>
<td>2015
-
2019</td>
<td>

Transversal or basic theme
Name: Regression-analysis
Density: 0.41 / Centrality: 7.52</td>
<td>

Highly developed but isolated
Name: Item-response-theory
Density: 6.7 / Centrality: 0.80</td>
<td>

Highly developed but isolated
Name: Artificial-neural-networks
Density: 7.00 / Centrality: 5.23</td>
</tr>
</table>

Discussions and conclusions

This exploratory study has presented a preliminary analysis from a Systematic Review of Literature on a specific bibliographic *corpus* obtained from the Web of Science. The explicit purpose was to construct a bibliographic mapping aimed at identifying the salient topics related to prediction investigated in the educational field from 1900 to 2019.

In general terms, the main results observed in the analyzed material are: a) an explosion of documents on prediction published since 2010 with prolonged increase until the date of data downloading; b) a strong academic impact of the documents measured by number of citations received, especially since 2000 onwards; c) the United States of America is the main publisher country, followed by the United Kingdom, Germany, and Australia; d) the main journals that publish works on prediction in education are especially focused on learning/s, particular objects of study (such as literacy processes, counseling, etcetera), methodologies typical of Psychometrics, developments of Educational Technology, and the level of higher education; e) the thematic proliferation about prediction prevails in the last three decades, with sustained diversification but with still weak continuity over specific themes (with only the exception of thematic lines such as studies on motivation and achievements, attitudes, and retention); f) in the last decade, more sophisticated data mining techniques have been incorporated beyond the usual predictive techniques used in this particular academic field.

From the point of view of the predominant themes, other observations and comments that deserve to be mentioned, even if not briefly, can be presented as the following.

First. Studies dedicated to identifying and measuring predictive variables of educational phenomena dominate in a sustained manner over time. A well-known example of this is the predictive studies about literacy practices enrolled in the line of Psycholinguistics that uses predominantly quantitative methodologies and causal mechanisms of explanation.

For future explorations, a concern around deductive strategies in methodology could be maintained especially in the context of "big data" academic production. Indeed, it could be asked what degree of theoretical work and conceptual interchanges these studies present beyond the frequent use of factoring techniques that rest primarily on inductive strategies of knowledge production. In other words, what power of orientation educational theories have in the production, management, and analysis of data about pedagogical phenomena? In this context, we recognize that the mere extraction of factors and patterns defending certain blind confidence in the data can be problematic due to the diverse biases that the databases can carry (O'Neil, 2016; Saracino, 2018).

Second. An important set of studies referring to individual attitudes as predictors of academic success is recognized. Just to mention one case, exemplary works from this perspective cover epistemological beliefs that affect students' success. Many of these investigations are characterized by predominantly approaching the individual as unit of analysis and highlighting the self-determinacy and self-regulating character of practices. Given this presentation of the issues, a series of criticisms of traditional cognitive science could be considered if situational-type approaches are pondered (Lave, 2001).

Moreover, concerns of this type could be applied to some of the motor themes identified here. As noticed, it has been found that motivation is a strong motor theme from 1995 onward because of its high centrality and network density and, conceptually, because it is usually considered as a prominent predictor of student learning and success. Now, what senses and approaches are attributed to the concept of motivation? In accordance with a preliminary reading of the most cited papers in each analyzed period (see Table 1 at Addendum), a hypothesis can be drawn for future research. In this sense, we could suppose that predominant approaches to motivation in these prediction studies focus mainly on intrinsic motivations, leaving aside situational perspectives that involve more complex constitutive dimensions and communal compromises of motives (Engestrom, 2015). As a promising clue, mentions about extrinsic motivations appear more recently in the *corpus* analyzed.

Third. In the last 10 years, the topic “retention” emerges and consolidates as a transversal one. Its link with predictive interest is, at least, suggestive. Studies of student retention (especially at higher education level) and discussions about variables that affect it have considerable representation in the bibliographic material. A certain need for efficiency seems to have gained momentum thanks to predictive studies that try to guarantee social inclusion and equity, minimize dropouts, often reduce the de-funding of universities as well as the drop in rankings.

Having said that, in addition to the predictive interests applied to the problem of student retention, a group of studies dedicated to the use of prediction with the aim of selecting students is also clearly identified.

A purpose like this raises big discussions about whether prediction should be used to select students or whether it should be used for anti-dropout support systems. Until now, it is known that the so-called "elite universities" are reluctant to use this kind of systems to select students, mainly because of ethical foundations, but also due to theoretical reasons linked to specific characteristics of learning as object of study (for example, the fact that learnings can be reconstructed *a posteriori* but never predicted, among others).

Right here, the problem of false positives arises as a nodal discussion point when trying to align prediction systems with the perspective of the right to access to education. The wrong decision to reject a student who actually meets the admission requirements poses an ethical problem and requires that the decision-making process be carefully reviewed.

As De Rosa (2018) highlights in a reference to Ellen Wagner, Chief Strategy Officer for Predictive Analytics Reporting (PAR) Framework, it is necessary to avoid the naive and harmful uses of educational data since they are intended to restrict access or punish students. Indeed, social inequalities should not be reproduced or legitimized through the implementation of predictive systems of academic success.

Fourth. The reference to “validity” concerns about prediction in the educational research shows an important presence since 2000 not just as a many times transversal theme but also specifically linked to predictive validity for students' assessments and admissions.

In this case, situational validity concerns about the applicability of prediction in education are at least promising. It is argued in this regard that conceptual and methodological difficulties would arise around the generalization of predictive systems of academic performance.

In concrete, the reason that discourages the predictive possibility in educational settings is given by the type of systemic or contextual model that needs to be used when addressing a social phenomenon as complex as that of successful learning. These types of approaches are characterized by recognizing the specific situation of each learning case that can hardly be generalizable to other cases.

As we know, the disadvantage of a linear conception of causality applied to education implies that such complex problems do not allow to quickly derive a result from the background conditions. It is necessary, then, to think of other ways of approaching the idea of causality in Social Sciences that lead to more precise predictive possibilities.

In fact, a paper with this thematic authored by Dragan Gašević and his team in 2016 is one of the most cited in the last analyzed period (see Table 1 in Addendum). In this study on the validity of predictive models applied to educational contexts is questioned the possibility of scalability, that is, the predictive model generalization beyond their first application context. Among its main results, the authors indicate that the prediction of academic success is affected by disciplinary differences (even with variations) and by the technologies used in each specific course. Definitely, they call attention to the importance of making a careful interpretation of the results obtained with these predictive model implementations, especially, "if these models do not incorporate instructional conditions. In such cases, several threats to the validity of the results may emerge such as overestimation or underestimation of certain predictors" (Gašević et al., 2016: 79).

As social phenomena are characterized by such complexity, the possibility of finding valid and generalizable models is drastically reduced. Consequently, specialists should recognize the limits imposed by the study problems. As Sedkaoui suggests, scientists "need to understand not only the limits of the data but also the limits of the questions that it can answer to, as well as the range of possible appropriate interpretations" (2018: 121).

Last but not least, some final comments need to be made in this preliminary study aimed at exploring hypotheses around the bibliographic mapping constructed.

On the one hand, future inquiries should also include some interesting topics detected in the last period (2015-2019) but not analyzed deeply in this occasion: Learning Analytics and its link with predictive models, the auspicious concern about situational models to think about prediction in education, the link between MOOC's and Adaptive Learning Systems and recommendation systems based on predictive activity, the appreciable thematic diversification observed in the evolution diagram, among others. On the other hand, mixed designs that incorporate qualitative analyzes (for example over material most cited in each period) to the quantitative analyzes already performed in this study will shed light to deepen and adjust the interpretation of the academic production mapping here presented. At the same time, exploring academic production in languages other than English remains an unfinished and certainly challenging task of comparison from the point of view of the various traditions that have (or have not) engaged in addressing the issue of prediction in education.

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Addendum

Figure 1: Evolution diagram

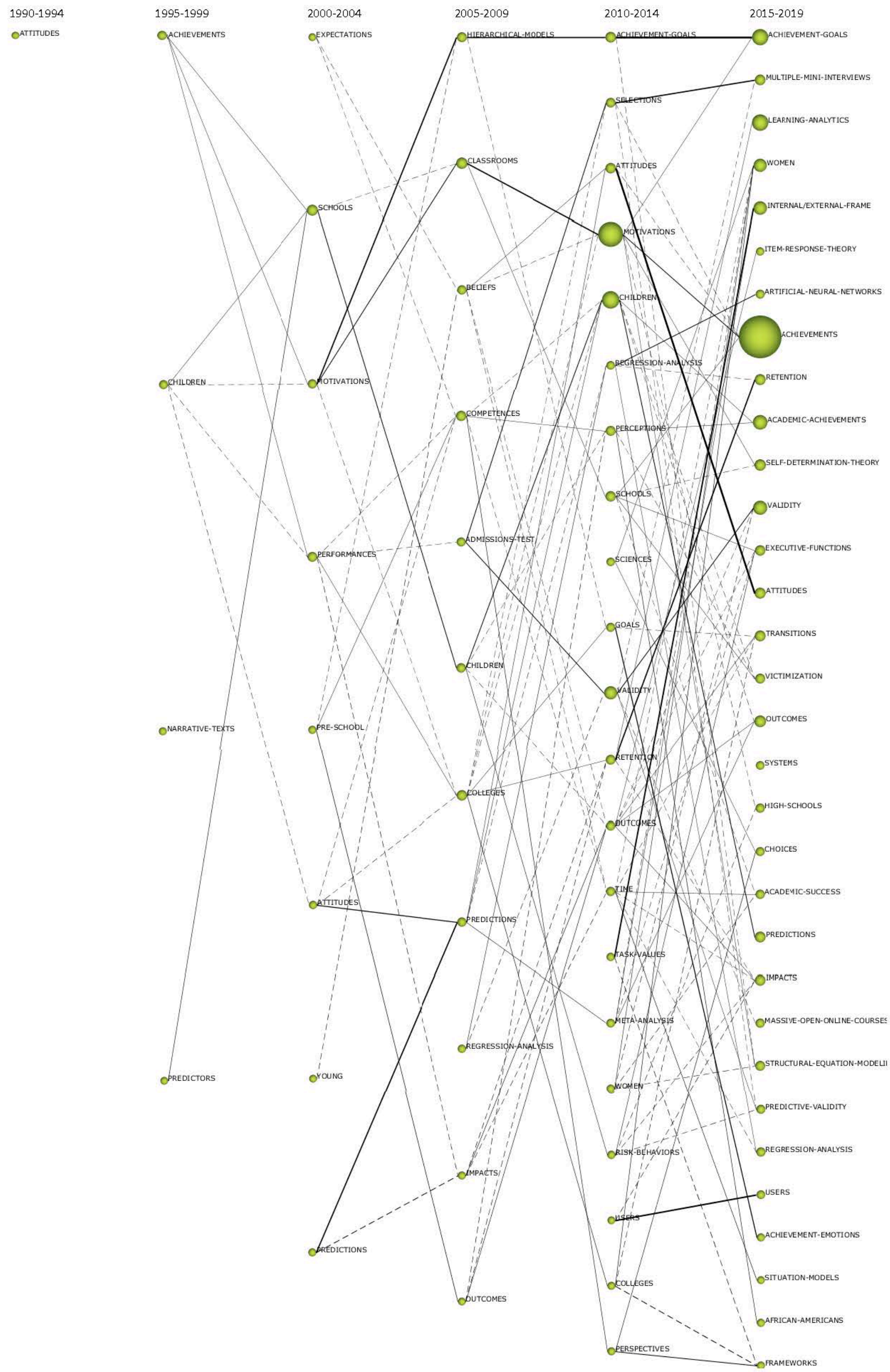

Table 1
Papers on prediction in the educational field most cited in each period (1990-2020)

#	Paper Title	Author/s	Publication Name	Country	Year of pub.	Total times cited
1	Predicting Academic Success	May, Ma	Journal of Educational Psychology	United States of America	1923	28
2	Predicting Success of Graduate Students in a College of Education	Cook, Ww	School and Society		1942	11
3	Predicting Academic Success through Achievement and Aptitude Tests	Watson, Ri	Journal of Medical Education		1955	10
4	Relative Usefulness in Predicting Academic Success of Act, Sat, and Some	Lins, Lj	Journal of Experimental Education	United States of America	1966	12
5	Predicting Success of Black, Chicano, Oriental And White	Goldman, Rd	Journal of Educational Measurement	United States of America	1976	16
6	Noncognitive Variables in Predicting Academic-Success by Race	Tracey, Tj	Measurement and Evaluation in Guidance	United States of America	1984	94
7	Self-Motivation for Academic Attainment - The Role of Self-Efficacy	Zimmerman, Bj	American Educational Research Journal	United States of America	1992	907
8	A Prospective-Study of Life Stress, Social Support, And Adaptation In	Dubois, Dl	Child Development		1992	260
9	Individual-Differences in the Effects of Educational Transitions on	Harter, S	American Educational Research Journal		1992	171
10	Academic Motivation and School Performance - Toward A Structural Model	Fortier, Ms	Contemporary Educational Psychology	Canada	1995	213
11	Mathematics Self-Efficacy and Mathematics Performances - The Need for	Pajares, F	Journal of Counseling Psychology	United States of America	1995	211
12	Self-Efficacy Beliefs and Mathematical Problem-Solving of Gifted	Pajares, F	Contemporary Educational Psychology		1996	210
13	The Causal Ordering of Academic Achievement and Self-Concept of Ability	Helmke, A	Journal of Educational Psychology	Netherlands	1995	189
14	A Model of Contextual Motivation in Physical Education: Using Constructs	Standage, M	Journal of Educational Psychology	United Kingdom	2003	443
15	Short-Term and Long-Term Consequences of Achievement Goals: Predicting	Harackiewicz, Jm	Journal of Educational Psychology	United States of America	2000	433
16	Predicting Success in College: A Longitudinal Study of Achievement Goals	Harackiewicz, Jm	Journal of Educational Psychology	United States of America	2002	416
17	On the Measurement of Achievement Goals: Critique, Illustration, And	Elliot, Aj	Journal of Educational Psychology	United States of America	2008	501
18	A Test of Self-Determination Theory in School Physical Education	Standage, M	British Journal of Educational Psychology	United Kingdom	2005	461
19	Developing a Learning Progression for Scientific Modeling: Making	Schwarz, Cv	Journal of Research in Science Teaching	United States of America	2009	400
20	Mining LMS Data to Develop an "Early Warning System" for Educators: a	Macfadyen, Lp	Computers & Education	Canada	2010	331
21	Boredom in Achievement Settings: Exploring Control-Value Antecedents and	Pekrun, R	Journal of Educational Psychology	Germany	2010	329

22	Personality Psychology and Economics	Almlund, M	Handbook of the Economics of Education	United States of America	2011	319
23	Learning Analytics Should not Promote One Size Fits All: the Effects of	Gasevic, D	Internet and Higher Education	United Kingdom	2016	119
24	A Multivariate Approach to Predicting Student Outcomes in Web-Enabled	Zacharis, Nz	Internet and Higher Education	Greece	2015	77
25	Identifying Significant Indicators Using LMS Data to Predict Course	You, Jw	Internet and Higher Education	South Korea	2016	67