PREDICTING STUDENTS' PERFORMANCE IN INTRODUCTORY PROGRAMMING COURSES: A LITERATURE REVIEW

Sónia Rolland Sobral, Catarina Félix Oliveira

REMIT, Universidade Portucalense (Portugal)

Abstract

The teaching-learning process in programming in university with freshmen is often associated with high failure and dropout rates. These outcomes frustrate both students and teachers and there is a need to verify the causes of these failures. By predicting the causes of these problems, we can try to control them, or at least try to plan the courses to try to avoid failure in the identified cases. The purpose of this paper is to analyze the scientific production concerning the prediction of students' performance in introductory programming courses. This analysis regards articles indexed in Clarivate Analytics' Web of Science and Elsevier's Scopus. The sample includes a total of 30 articles. The results obtained by bibliometric analysis show when and where those documents were published, who are the authors and what is the focus of said articles. We also analyzed the most cited documents. We made a summary of the articles. We were able to obtain a global overview of the theme, obtaining a strong analysis that is useful for teachers in the process of helping students achieve success in introductory programming courses at universities.

Index Terms— Educational data mining; CS1; programming courses; bibliometrics.

I. INTRODUCTION

Teaching and learning programming at the beginning of university courses worry many researchers and teachers [1] [2] [3] . The results reported are often disastrous: they tend to be associated with unwanted failure and dropout rates [4] [5] [6]. The propaedeutic character of courses such as introduction to programming causes the students' paths to be altered by their performance: if they manage to reach high levels of success, the rest of the course is facilitated; on the contrary, the failure in these curricular units makes students unmotivated, which often leads to drop out the course [7]. Are there students' characteristics that may indicate the level of success? Are there elements of the students' past career that make them tend to be more, or less, likely to drop out? What kind of motivation, habits and interests make students achieve lower or higher grades? These are just some examples of questions that can be asked, but there are many more [8]. By using students' characteristics (e.g. past career, motivation, habits, interests, among others) to predict their success or failure, we can foresee problems and try to guide the students' performance (and even the teachers' behaviour) in a better path [9].

It is possible to try to predict students' performance using data mining (the process of discovering patterns in data [10] and machine learning techniques that aim at analysing data to find meaningful patterns. There is a subfield of datamining, called Educational data mining, which consist of the application of data mining and machine learning techniques to educational data [11]. It has lately received increased attention by the scientific community [12], [13]. Surveys of educational data mining are presented in [11] and, more recently, in [14]. After that, several reviews have been published on the same subject [12] [15] [16] [17] [18] [19] [20].All these studies are important to give clues on how research in the area has been carried out and eventually to predict the future. The purpose of this paper is to analyse the scientific production that concerns the prediction of students' performance in higher education, specifically for introductory programming courses. We consider articles indexed in Clarivate Analytics' Web of Science and Elsevier's Scopus. The sample includes a total of 30 articles. The results obtained with the bibliometric analysis show when and where those documents are published, who are the authors and what is the focus of the research.

Bibliometric analysis [21] is the quantitative study of bibliographic material: it provides a general picture of a research field that can be classified by papers, authors and journals. Bibliometric methods employ a quantitative approach for the description, evaluation, and monitoring of published research. These methods have the potential to introduce a systematic, transparent and reproducible review process and thus improve the quality of reviews [22]. Bibliometric analysis provides objective criteria that can assess the research development in a field and act as a valuable tool for measuring scholarship quality and productivity [23]. Bibliometric methods offer systematization and replication processes that can improve understanding of the dissemination of knowledge in a field and can highlight gaps and opportunities that may contribute to the advancement of the discipline [24]. We also analysed the most cited documents and made a summary of the articles. This document is subdivided into several sections. First, on describe the research questions, followed by the methodology and the bibliometric results. Then we show the results of article content, ending with the discussion of results obtained, the conclusions and suggested future work.

II. THE RESEARCH QUESTIONS

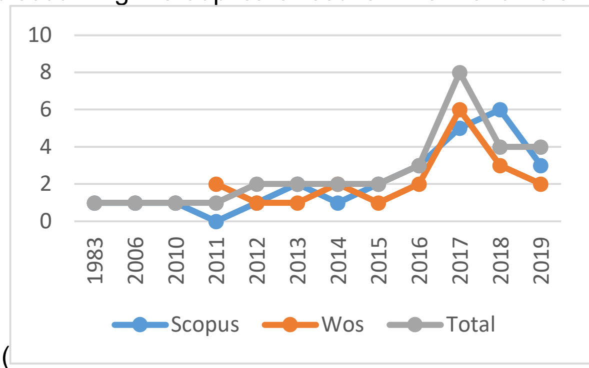
The research question, together with the purpose of the review, the intended deliverables and the intended audience, determines how the data is identified, collected and presented [25]. As already referred, we wish to study documents, concerning the prediction of students' performance on introductory programming courses in higher education, published in high quality journals. Regarding this, this work aims at answering bibliometric and content related questions.
The bibliometric questions considered are:
BQ1: When were the articles published?
BQ2: What is the type of these publications?
BQ3: Where were the articles published?
BQ4: What is the focus of the articles?
BQ5: Who publishes on the subject?
BQ6: Are there clusters of authors who publish together?
BQ7: What are the most cited articles?
As for the content related questions, the ones considered are:
CQ1: Which papers use machine learning as a technique? (The remaining content related questions refer only to the papers that use machine learning as a technique)
CQ2: What kind of data was used?
CQ3: What is the aim of the publication?
CQ4: Which machine learning task was considered?
CQ5: Which algorithms were considered?
CQ6: What were their findings?

III. METHODOLOGY

The term bibliometrics was first used in 1969 by Alan Pritchard, hoping that the term would be used explicitly in all studies which seek to quantify the processes of written communication and quickly gain acceptance in the field of information science [26]. Moed mentioned the possibilities of this type of study that reveal the enormous potential of quantitative, bibliometric analysis of the scholarly literature for a deeper understanding of its activity and performance, and highlights their policy relevance. [27] In scientific research, it is important to get a wider perspective of research already being conducted concerning a relevant subject matter [28] and a bibliometric analysis profile on the research trajectory and dynamics of the research activities across the globe [29]. This is a bibliometric study that systematically analyses the literature using articles indexed at Elsevier's Scopus (Scopus) and Clarivate Analytics' Web of Science (WoS) databases. This study conducts a bibliometric analysis of international journal papers that we expect provides a useful reference for future research.
The search strategy was
TITLE-ABS-KEY (predict*) AND
TITLE-ABS-KEY ("learn to program" OR "learning programming" OR "introductory programming" OR "novice programming" OR "introduction to programming") AND
TITLE-ABS-KEY (university* OR "higher education")
PUBYEAR: < 2020.

IV. BIBLIOMETRIC RESULTS

A set of 20 published papers were collected from WoS and 26 from SCOPUS. The search returned a total of 30 documents after discounting the duplicate results. The first article in Scopus was published



in 1986 and second in 2006 (

Fig. 1. Annual evolution published documents.).

20 (67%) of the documents are conference papers and 10 (33%) of them are journal articles, as we can see in Fig.2. The next table (**Erro! A origem da referência não foi encontrada.**) shows the conferences where the papers were published, including number of publications (n), h-index (H), Scientific Journal Ranking (SJR 2018), and Country where the conference was held.

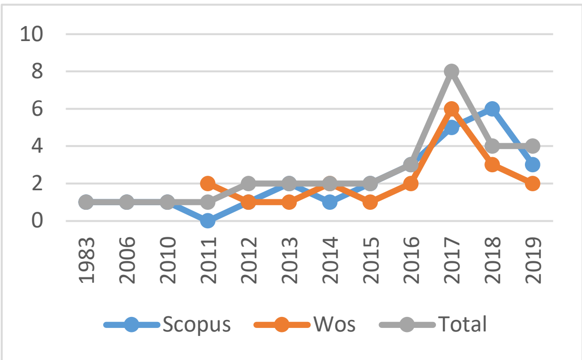


Fig. 1. Annual evolution published documents.

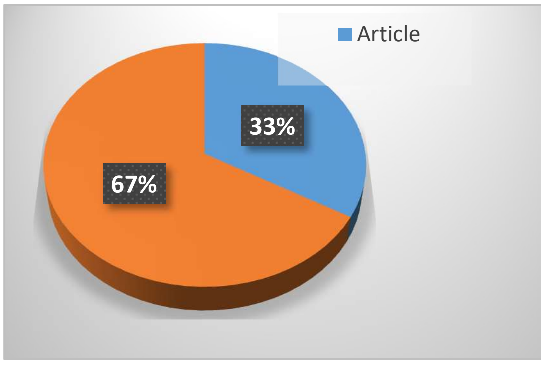


Fig. 2. Document type

Table 1. Conference papers.

Conference	n	H	SJR 2018	Country
ACM Technical Symposium on Computer Science Education	3	13	0.18	United States
Frontiers in Education Conference	3	35	0.16	United States
ACM International Conference Proceeding Series	2	98	0.17	United States
Efficiency and Responsibility in Education	2			Czech Republic
ASEE Annual Conference and Exposition	1	25	0.22	United States
CEUR Workshop Proceedings	1	42	0.17	United States
Computers and People Research Conference	1	2	0.11	United States
IEEE International Conference on Advanced Learning Technologies	1	5	0.18	United States
International Conference on Computer Science and Engineering	1			EAI

International Conference on Education and New Learning Technologies	1			Spain
International Conference on Educational Data Mining	1	12	0	United States
International Conference on Inventive Computing and Informatics	1			India
International Conference on Software Engineering	1	125	0.44	United States
International Technology, Education and Development Conference	1			Spain

As the table shows, ACM Technical Symposium on Computer Science Education, together with Frontiers in Education Conference have each three articles published on the subject. Of the 13 conferences, nine are in the United States (**Erro! A origem da referência não foi encontrada.**). The next table (

Table 2. Journal papers.) shows the journals that have published work on this theme, including h-index (H), Scientific Journal Ranking (SJR), journal quartile (Q), and the country where the journal is based.

Table 2. Journal papers.

Journal	H	SJR	Q	Country
ACM SIGCSE Bulletin	12		Q4	United States
Communications in Computer and Information Science	40	0.17	Q3	Germany
Computers in Human Behavior	137	1.71	Q1	United Kingdom
Computer Science Education	18	0.42	Q2	United Kingdom
IEEE Trans. Educ.	61	0.68	Q1; Q2	United States
International Journal of Advanced Computer Science and Applications	3			United Kingdom
Interaction Design and Architecture(s	18	0.19	Q2; Q3; Q4	Italy
International Journal of Emerging Technologies in Learning	15	0.11	Q2; Q3	Germany
Sustainability	53	0.55	Q2	Switzerland
World Transactions on Engineering and Technology Education	10	0.26	Q2; Q3	Australia

As can be observed in the table, there are 10 journals that have published articles, one in each (

Table 2. Journal papers.).We found 136 different keywords, 168 in total. The most frequent keywords are CS1, programming Education & Educational Research, Educational Data Mining, Introductory programming, and programming aptitude as presented on the next table (Table 3. Most frequent keywords. And **Erro! A origem da referência não foi encontrada.**).

Table 3. Most frequent keywords.

Keyword	n
CS1	7
Programming	6
Education & Educational Research	3
Educational Data Mining	3
Introductory programming	3
programming aptitude	3
Academic performance	2
Achievement	2
Algorithmic thinking	2
Data processing	2
Data programming	2
Dehnadi's test	2
Introductory computing	2
Learning	2
Prediction	2

Fig. 3. Most common keywords

Programming learning difficulties	2
Scale	2
Self-efficacy	2
Validity	2

We found three keyword clusters presented on the following figure (Fig. 4. Keywords network visualization.):

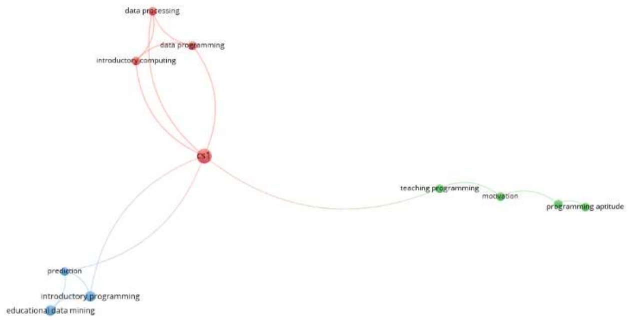


Fig. 4. Keywords network visualization.

As can be observed on the figure, the clusters found were:
C1: CS1, data processing, data programming, introductory computing.
C2: motivation, programming aptitude, self-efficacy and teaching programming.
C3: educational data mining, introductory programming and prediction.

Seven documents (23%) are written by two authors, six by three authors and another six by four authors (20%) (Fig. 5. Number of authors by document.).

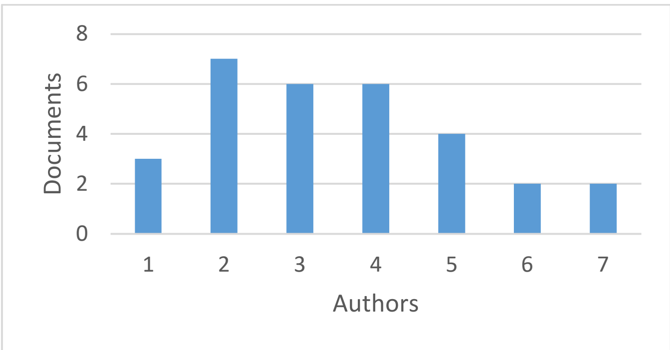


Fig. 5. Number of authors by document.

The 30 articles belong to a total of 93 authors. There are eleven that published two articles: A. Gomes, E. Deveci, E. Milkova, F. B. Correia, F. B. Tek, K. S. Benli, M. D. Ernst, P. H. Abreu, P. Pham and R. Ordóñez (as we can see in Table 4. Author's affiliation.).

Table 4. Author's affiliation.

Author	Affiliation
A. Gomes	Coimbra Polytechnic - ISEC, Portugal
E. Deveci	Işik Üniversitesi, Istanbul, Turkey
E. Milkova	University of Hradec Králové, Czech
F. B. Correia	Coimbra Polytechnic - ISEC, Portugal
F. B. Tek	Işik Üniversitesi, Istanbul, Turkey
K. S. Benli	Işik Üniversitesi, Istanbul, Turkey
M. D. Ernst	University of Washington, United States
P. H. Abreu	Universidade de Coimbra, Portugal
P. Pham	Evergreen State College, United States

R. Anderson	University of Washington, United States
R. Ordóñez	Southern Adventist University, United States

The affiliation of these eleven authors is: one from the Czech Republic, three from Portugal, three from Turkey and four others from the United States. We found three clusters (Fig. 6. Author network visualization.):

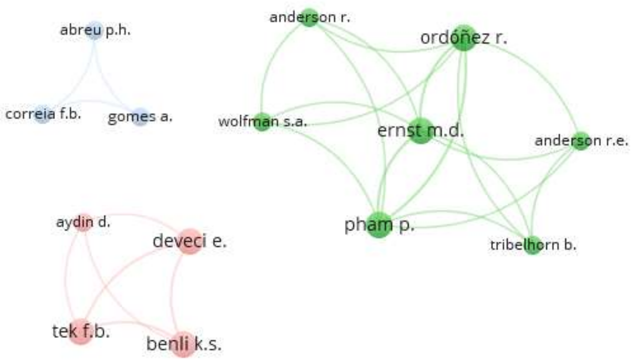


Fig. 6. Author network visualization.

From this figure, we can see that three clusters were found:
C1: A. Gomes, F. B. Correia and P. H. Abreu.
C2: R. Anderson, M. D. Ernst, R. Ordóñez, P. Pham, S. A. Wolfman and B. Tribelhorn.
C3: E. Deveci, D. Aydin, K. S. Benli and F. B. Tek.

Considering the first author, there are 18 different countries: United States has five documents, Australia, Brazil, New Zealand, Portugal, Spain and Turkey have two documents each (Fig. 7. Countries first author address.).

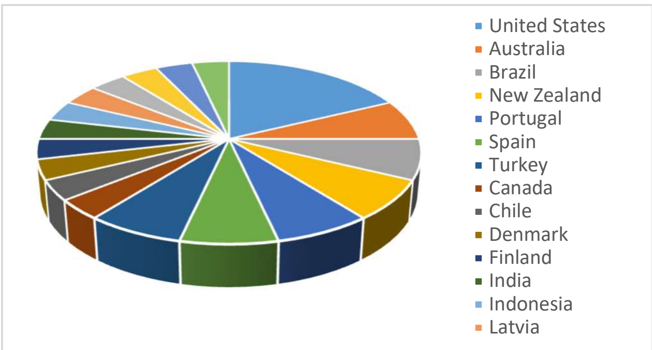


Fig. 7. Countries first author address.

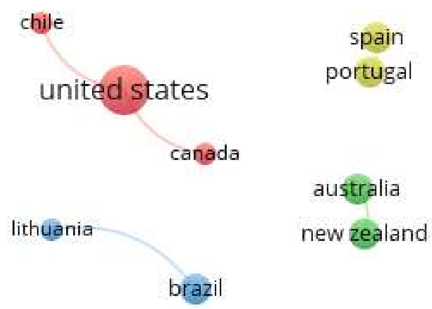


Fig. 8. Country network visualization.

Besides, we found four clusters (Fig. 8. Country network visualization.):

The clusters found on the countries were the following:
C1: Canada, Chile, and United States.
C2: Australia and New Zealand
C3: Brazil and Lithuania
C4: Portugal and Spain.

We can see that there is a great diversity of institutions that publish and work on the subject: Stanford University [30], Federal University of Alagoas [31], University of Durham [32], University of Auckland [33], Washburn University [34], University of Washington [35], University of Otago [36] and University of Helsink [37]. There are 17 organizations with more than two documents. (**Erro! Autorreferência de marcador inválida.**).

Table 5. Organization, more than two documents.

Organizations
Aalborg University, Denmark
Fed Univ Alagoas UFAL, Maceio, Brazil
Isik Univ, Dept Comp Engn, TR-34980 Istanbul, Turkey
Isik Univ, Psikol Bolumu, Istanbul, Turkey
Lublin Univ Technol, Lublin, Poland
Southern Adventist University, United States
SRM Univ, Comp Sci & Applicat, Tamil Nadu, India
Univ Alicante, Lucentia Res Grp, Spain
Univ Botswana, Dept Comp Sci, Gaborone, Botswana
Univ Coimbra, Portugal
Univ Fed Campina Grande, Brazil
Univ Hradec Kralove, Hradec Kralove, Czech Republic
Univ Otago, Dept Comp Sci, New Zealand
Univ Phayao, Thailand
Univ Teknol PETRONAS, Malaysia
University of Washington, United States
Washburn University, United States

There are 8 documents that have been cited over ten times (**Erro! A origem da referência não foi encontrada.**.). Piech, C., Sahami, M., Koller, D., Cooper, S., Blikstein, P.; 2012; Modeling how students learn to program; SIGCSE'12 - Proceedings of the 43rd ACM Technical Symposium on Computer Science Education, pp. 153-158 was cited 96 times. Costa, E.B., Fonseca, B., Santana, M.A., de Araújo, F.F., Rego, J.; 2017; Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses; Computers in Human Behavior, (73), pp. 247-256. was cited 71 times. Watson, C., Li, F.W.B., Godwin, J.L.; 2013; Predicting performance in an introductory programming course by logging and analyzing student programming behaviour; Proceedings - 2013 IEEE 13th International Conference on Advanced Learning Technologies, ICALT 2013, pp. 319-323 was cited 65 times. Next we present the clusters of the most cited authors' networks (Fig. 9. Most cited author's network visualization..)

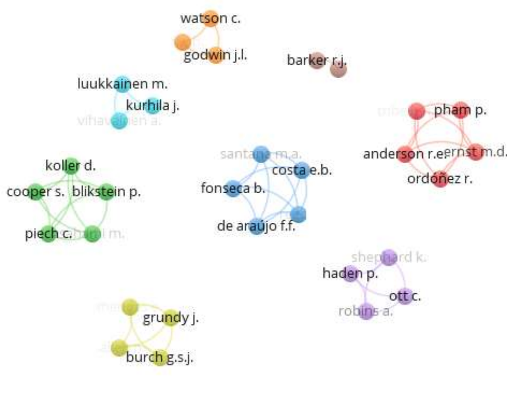


Fig. 9. Most cited author's network visualization.

We found one cluster of the countries of origin of the most cited authors (Australia and New Zealand).

V. CONTENT RESULTS

From the full set of 30 analysed papers, to answer the content related research question (*CQ1: Which papers use machine learning as a technique?),* we noticed that 11 use machine learning related techniques [30] [31] [32] [38] [39] [40] [41] [42] [43] [44] [45] published in 2006 [45], 2012 [30], 2013 [32], 2017 [31] [39] [41] [42], 2018 [40] [43] and 2019 [38] [44], and regard studies performed in different Universities from different countries.The second content related research question (*CQ2: What kind of data was used?)* aims at knowing the data used for the study. For this, we need to analyse the sample size, but also the type of information present on the data. As for the sample size, the studies analysed were performed considering samples that go from 41 students in [39] to 505 in [40]. One of these studies [31] even considers two different samples of students: a sample of [41] 1 students enrolled in regular classes and another one of 262 students enrolled in online classes. As for the information present on the data, it included sociodemographic data [39], [42] [45], psychometric data [38] [41] [44], statistical data [41] [44], data related to course activity and course statistics [31] [39] [43] [45], previous grades [42], and data concerning automatically evaluated programming exercises [30] [32] [40]. For the third content related research question (*CQ3: What is the aim of the publication?)*, we could see that the aims stated for each study include improving the skills of each student in programming [44], predicting students' performance [42] [38] [32] [39] [41] or program correctness [40], identify at-risk students [43], explore the effects of an instructional intervention for increasing student motivation [45] , graphically model students' progress [30], and also compare the effectiveness of different educational data mining techniques [31].All these 11 studies tried to use machine learning to try to predict students' grades, and to try to answer the fourth content related research question (*CQ3: What is the aim of the publication?*) we analysed the publications' content and were able to realise that the machine learning tasks considered were unsupervised machine learning techniques [30], but also supervised ones as regression [32] [38] [43] [45] and classification [31] [39] [40] [41] [42] [44].

The algorithms considered for the tasks, as to answer the fifth content related research question (*CQ5: Which algorithms were considered?)* were artificial neural networks / multilayer perceptron [31] [40] [42] [44], decision trees [31] [40] [42], support vector machines [31] [40], naive bayes [31] [41] [42], logistic [40] and linear [32] [38] [45] regression, J48 [39] [42], Sequential minimal optimization [42], markov models [30], decision rules, standard Voting, and object tracking procedures [[41] and, finally, best-subset-regression and LASSO regression [43]. Finally, to answer the last content related research question (*CQ6: What were their findings?*), the available information led us to realise that the studies' findings included cases when the techniques used were suited for the task at hand [31] [40], where the approach was considered to be a good early predictor of performance [32], some even stating that the most predictive variables turned out to be students' attitude towards programming [38] or the national test score for mathematics [39], and reaching the ultimate goal to help institutions identify students in need for extra help [30] [42] [43].

REFERENCES

[1] S. Bergin and R. Reilly, "Programming: Factors that Influence Success," in Proceedings of the 36th SIGCSE Technical Symposium on Computer Science Education, 2005.

[2] B. A. Becker, G. Glanville, R. Iwashima, C. McDonnell, K. Goslin and C. Mooney, "Effective Compiler Error Message Enhancement for Novice Programming Students," Computer Science Education, pp. 148-175, 2016.

[3] J. Bennedsen and M. E. Caspersen, "Failure rates in introductory programming," in ACM SIGCSE Bulletin, 2007.

[4] A. Robins, J. Rountree and N. Rountree, "Learning and Teaching Programming: A Review," Computer Science Education, pp. 137-172, 2003.

[5] D. Horton and M. Craig, "Drop, Fail, Pass, Continue: Persistence in CS1 and Beyond in Traditional and Inverted Delivery," in ACM Technical Symposium on Computer Science Education, 2015.

[6] E. Lahtinen, K. Ala-Mutka and H. M. Järvinen, "A study of the difficulties of novice programmers," in ACM SIGCSE Bulletin, 2005.

[7] Y. Qian and J. Lehman, "Students' Misconceptions and Other Difficulties in Introductory Programming: A Literature Review," ACM Transactions on Computing Education, 2017.

[8] K. B. Bruce, "Five Big Open Questions in Computing Education," in ACM Inroads, 2018.

[9] M. Barak, J. Harward and G. L. S. Kocur, "Reducing the dropout rate in an introductory programming course," Journal of Science Education and Technology, pp. 71-76, 2007.

[10] E. Frank, C. Pal, H. M and I. Witten, Data Mining: Practical Machine Learning Tools And Techniques, ELSEVIER SCIENCE & TECHNOLOGY, 2013.

[11] E. Fernandes, M. . Holanda, M. Victorino, Borges, R. Carvalho and G. VanErven, "Educational data mining: Predictive analysis of academic performance of public school students in the capital of brazil," Journal of Business Research, vol. 94, p. 335–343, 2019.

[12] H. Aldowah, H. . Al-Samarraie and W. M. Fauzy, "Educational data mining and learning analytics for 21st century higher education: A review and synthesis," Telematics and Informatics, vol. 37, pp. 13-49, 2019.

[13] C. Romeno and S. Ventura, "Educational data mining: A survey from 1995 to 2005," Expert systems with applications, vol. 33, no. 1, p. 135–146, 2007.

[14] B. Bakhshinategh, O. Zaiane, S. ElAtia and D. Ipperciel, "Educational data mining applications and tasks: A survey of the last 10 years," Education and Information Technologies, vol. 23, no. 1, p. 537–553, 2018.

[15] R. Baker and K. Yacef, "The state of educational data mining in 2009: A review and future visions," JEDM— Journal of Educational Data Mining, vol. 1, no. 1, pp. 3-17, 2009.

[16] C. Romero and S. Ventura, "Educational data mining: a review of the state of the art," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 6, no. 601-618, p. 40, 2010.

[17] S. Mohamad and Z. Tasir, "Educational data mining: A review," Procedia-Social and Behavioral Sciences, vol. 97, no. 2013, pp. 320-324, 2013.

[18] Z. Papamitsiou and A. Economides, "Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence," Journal of Educational Technology & Society, vol. 17, no. 4, pp. 49-64, 2014.

[19] M. :. V. Martins and D. Fonseca, "Educational data mining: A literature review," in 13th Iberian Conference on Information Systems and Technologies (CISTI), 2018.

[20] C. Jalota and R. Agrawal, "Analysis of educational data mining using classification," in International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), 2019.

[21] J. Merigo and J. Yang, "A bibliometric analysis of operations research and management science," Omega, vol. 73, pp. 37-48, 2017.

[22] I. Zupic and T. Čater, "Bibliometric Methods in Management and Organization," Organizational Research Methods, vol. 8, no. 3, 2015.

[23] M. Cobo, A. López-Herrera, E. Herrera-Viedma and H. F., "SciMAT: A new science mapping analysis software tool," Journal of the American Society for Information Science, vol. 3, no. 8, pp. 1609-1630, 2012.

[24] G. Aparicio, T. Iturralde and A. Maseda, "Conceptual structure and perspectives on entrepreneurship education research: A bibliometric review," European Research on Management and Business Economics, vol. 5, no. 3, pp. 105-113, 2019.

[25] A. Booth, A. Sutton and D. Papaioannou, Systematic Approaches to a Successful Literature Review, 2md ed, SAGE Publications Ltd, 2016.

[26] A. Pritchard, "Statistical Bibliography or Bibliometrics," Journal of Documentation, vol. 25, pp. 348-349, 1969.

[27] H. F. Moed, Citation Analysis in Research Evaluation, vol. 9, Springer, 2005, p. 348.

[28] S. M. R. P. Z. e. a. Bojović, "An overview of forestry journals in the period 2006–2010 as basis for ascertaining research trends," Scientometrics, vol. 8, p. 1331–1346, 2014.

[29] W. G. M. H. G. e. a. Liu, "Profile of developments in biomass-based bioenergy research: a 20-year perspective," Scientometrics, vol. 99, p. :507–521, 2014.

[30] C. Piech, M. Sahami, D. Koller, S. Cooper and P. Blikstein, "Modeling how students learn to program," in SIGCSE'12 - Proceedings of the 43rd ACM Technical Symposium on Computer Science Education, 2012.

[31] E. Costa, B. Fonseca, M. Santana, F. de Araújo and J. Rego, "Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses," Computers in Human Behavior, vol. 73, pp. 247-256, 2017.

[32] C. Watson, F. Li and J. Godwin, "Predicting performance in an introductory programming course by logging and analyzing student programming behavior," in Proceedings - 2013 IEEE 13th International Conference on Advanced Learning Technologies, ICALT 2013, 2013.

[33] N. Salleh, E. Mendes, J. Grundy and G. Burch, "An empirical study of the effects of conscientiousness in pair programming using the five-factor personality model," in International Conference on Software Engineering, 2010.

[34] R. Barker and E. Unger, "A predictor for success in an introductory programming class based upon abstract reasoning development," in ACM SIGCSE Bulletin, 1983.

[35] A. Vihavainen, M. Luukkainen and J. Kurhila, "Using students' programming behavior to predict success in an introductory mathematics course," in 6th International Conference on Educational Data Mining, 2013.

[36] R. Anderson, M. Ernst, R. Ordóñez, P. Pham and B. Tribelhorn, "A data programming CS1 course," in 46th ACM Technical Symposium on Computer Science Education, 2015.

[37] C. Ott, A. Robins, P. Haden and K. Shephard, "Illustrating performance indicators and course characteristics to support students' self-regulated learning in CS1," in Computer Science Education, 2015.

[38] C. Alvarez, A. Wise, S. Altermatt and I. Aranguiz, "Predicting academic results in a modular computer programming course," in LALA 2019 - Proceedings of the 2nd Latin American Conference on Learning Analytics, Valdivia, Chile, 2019.

[39] M. Ayub and O. Karnalim, "Predicting Outcomes in Introductory Programming using J48 Classification," World Transactions on Engineering and Technology Education, vol. 15, no. 2, pp. 132-136, 2017.

[40] D. Gil, J. Fernández-Alemán, J. Trujillo, G. García-Mateos, S. Luján-Mora and A. Toval, "The Effect of Green Software: A Study of Impact Factors on the Correctness of Software," Sustainability, vol. 10, no. 10, 2018.

[41] A. Gilal, J. Jaafar, M. Omar, S. Basri, I. Aziz, Q. Khand and M. Hasan, "Suitable Personality Traits for Learning Programming Subjects: A Rough-Fuzzy Model," International Journal of Advanced Computer Science and Applications(IJACSA), vol. 8, no. 8, 2017.

[42] M. Sivasakthi, "Classification and prediction based data mining algorithms to predict students' introductory programming performance," in 2017 International Conference on Inventive Computing and Informatics (ICICI), 2017.

[43] B. C. Christensen, B. Bemman, H. Knoche and R. Gade, "Pass or Fail? Prediction of students' Exam Outcomes from Self-reported Measures and Study Activities," Interaction Design and Architecture(s), vol. 39, pp. 44-60, 2019.

[44] J. Figueiredo and F. García-Peñalvo, "Teaching and learning strategies of programming for university courses," in TEEM'19: Proceedings of the Seventh International Conference on Technological Ecosystems for Enhancing Multiculturality, 2019.

[45] H. &. H. J. Burn, "Why Should I Care? Student Motivation In An Introductory Programming Course," in 2006 Annual Conference & Exposition, Chicago, 2006.

[46] Y. S. K. T. C. &. S. J. P. Chen, "A mobile learning system for scaffolding bird watching learning," Journal of Computer Assisted Learning, vol. 19, no. 3, p. 347–359, 2003.

[47] R. L. Wang, R. Wiesemes and C. Gibbons, "Developing digital fluency through ubiquitous mobile devices: Findings from a small-scale study," Computers & Education, vol. 58, no. 1, 2012.

[48] D. McConatha, M. Praul and M. J. Lynch, "Mobile Learning in Higher Education: An Empirical Assessment of a New Educational Tool," Turkish Online Journal of Educational Technology, vol. 7, no. 3, pp. 15-21, 2008.

[49] N. S. Alzaza and A. R. Yaakub, "Students' Awareness and Requirements of Mobile Learning," American Journal of Economics and Business Administration , vol. 3, no. 1, pp. 1945-5488, 2011.

[50] B. Bannan, J. Cook and N. Pachler, "Reconceptualizing design research in the age of mobile learning," Interactive Learning Environments, vol. 24, no. 5, pp. 938-953, 216.

[51] E. Baran, "A Review of Research on Mobile Learning in Teacher Education," Educational Technology & Society, vol. 17, no. 4, p. 17–32, 2014.

[52] A. Al-Hunaiyyan, S. Al-Sharhan and R. Alhajri, "A New Mobile Learning Model in the Context of Smart Classroom Environment:: A Holistic Approach," International Journal of Interactive Mobile Technologies, vol. 11, no. 3, pp. 39-56, 2017.

[53] O. Viberg, A. Andersson and M. Wiklund, "Designing for sustainable mobile learning – re-evaluating the concepts “formal” and “informal”," Interactive Learning Environments, 2018.

[54] B. O'Bannon and K. Thomas, "Mobile phones in the classroom: Preservice teachers answer the call," Computers & Education, vol. 10, no. 22, pp. 110-122, 2015.

[55] J.-L. Hung and K. Zhang, "Examining mobile learning trends 2003–2008: a categorical meta-trend analysis using text mining techniques," Journal of Computing in Higher Education, vol. 24, no. 1, pp. 1-17, 2012.

[56] W. W. Y. C. C. K. H. L. C. &. H. S. Wu, "Review of trends from mobile learning studies: A meta-analysis," Computers & Education, vol. 59, pp. 817-827, 2012.

[57] G. Krull and J. M. Duart, "Research Trends in Mobile Learning in Higher Education: A Systematic Review of Articles (2011 –2015)," International Review of Research in Open and Distributed Learning, vol. 18, no. 7, 2017.

[58] C. Pimmera, M. Mateescub and U. Gröhbiela, "Mobile and ubiquitous learning in higher education settings. A systematic review of empirical studies," Computers in Human Behavior, vol. 63, pp. 490-501, 2016.

[59] Q.-K. Fu and G.-J. Hwang, "Trends in mobile technology-supported collaborative learning: A systematic review of journal publications from 2007 to 2016," Computers & Education, vol. 119, pp. 129-143, 2018.

[60] A. Sönmez, L. Göçmez and D. &. A. M. Uygun, "A review of Current Studies of Mobile Learning," Journal of Educational Technology & Online Learning, vol. 1, no. 1, pp. 13-27, 2018.

[61] C. Lai, "Trends of mobile learning: A review of the top 100 highly cited papers," British Journal of Educational Technology, p. 1–22, 2019.