Enhancing student digital skills: Adopting an ecosystemic School Analytics approach

***Abstract*—Orchestrating holistic school improvement requires school leaders to effectively engage in the tasks of collecting and processing diverse educational data from the school ecosystem, and more importantly, to be able to 'translate' these analyses to specific remedying actions for targeted improvement. However, these processes can be cumbersome, especially given that existing 'School Analytics' methods aiming to support them have mainly focused on the former task, but have yet to explicitly address the latter. In this context, the paper presents and initially validates a novel School Analytics approach, which employs fuzzy-set Qualitative Comparative Analysis as the means to provide leaders with actionable insights on how to create the school conditions for fostering students' learning outcomes, focusing on 'digital skills' as a case study.**

Keywords- School Analytics; Data-driven Decision Making; School Leadership; Educational Data; Digital Skills

I. Introduction

School accountability and internal holistic improvement present a major need in many educational systems around the world and require schools to meet both externally-defined performance mandates as well as, at the same time, improve the teaching and learning provisions for all students. To effectively engage in these tasks, it is increasingly acknowledged that school leaders can employ data-driven '*School Analytics'* methods, namely methods that allow them to collect, analyze and act upon educational data which are generated from many factors of the school ecosystem, at three conceptual layers [1]:

- **Micro layer**, which refers to the learning and assessment practices occurring either within or beyond the physical premises of the school. For example, indicative factors at this layer include the teachers and students of the school, as they engage in the teaching and learning process.
- **Meso layer**, which refers to the monitoring and evaluation of the teaching staff skills and practices as well as the curriculum planning procedures of the school. For example, indicative factors at this layer include the teachers of the school, as they engage in the design of their daily practice.
- **Macro Layer**, which refers to the organizational development processes of the school. For example, indicative factors at this layer include the principals of the school, as they orchestrate the management of school equipment and arrange for systematic professional development for teachers, as well as the teachers of the school as they contribute in formulating a school culture and a strategic vision with the principals.

In this complex ecosystem, it becomes evident that school leaders require holistic methods for data collection and analysis across these school layers, in order to have a better overview of how the school operates and what are the specific needs for improvement [2]. Furthermore, an additional level of support that school leaders commonly require is for translating these needs to actionable insights for school improvement, namely what actions to take to improve the school's performance and outcomes [3]. However, such levels of decision support are not yet adequately provided by existing decision support systems [2].

This work takes a step to address this issue, building on the concept of School Analytics within a particular case study, namely to identify the school conditions that foster students' *digital skills*. The reason for focusing on these skills is that they are considered a core strand of the 21st century skillset (e.g., [4]) and industry work-force requirements are shifted towards attaining and exploiting such competences [5]. Therefore, it is reasonable to argue that identifying new ways to improve the schools' capacity to foster students' digital skills is a worthy challenge to address.

In this particular case study context, the limited existing studies have primarily focused on investigating how the school ecosystem affects the use/uptake of ICT for particular actors (mainly teachers) (e.g., [6], [7]). Furthermore, more recent works have begun to study how school ecosystemic factors influence students' learning, however these pioneering studies are still scarce and mainly focus on instrument development for measuring this level of influence with limited capacity to inform leaders' decision making (e.g., [8]).

Therefore, the contribution of this work (as part of an on-going agenda) is to capitalize and extend on prior studies to not only outline school ecosystemic factors (related to ICT) which impact students' digital skills, but more importantly to identify specific configurations of these factors (i.e., combinations being present or absent from a school) that can lead to high students' digital skills. To offer this novel perspective, the paper introduces the use of **fuzzy-set Qualitative Comparative Analysis** (fs-QCA) method [9], which is discussed in the next section. To the best of our knowledge, this is the first attempt to derive such actionable insights for supporting data-driven school leadership.

The remainder of the paper is structured as follows. Section II presents the concept of School Analytics and the fsQCA analysis method. Section III presents the research methodology, and section IV describes the results of the study. Finally, section V discusses conclusions and future work.

II. Background

A. School Analytics for ecosystemic school Leadership

The concept of School Analytics has been recently proposed to describe a conceptual framework of data Analytics aiming to support decision making for *K-12 school leadership* [1]. In particular, School Analytics builds on the layered depiction of schools outlined previously, and posits the standpoint that school leaders need to be able to identify, collect, measure, process and act upon educational data from across these school layers and build their decision making upon insights derived from the joint analysis of such data. The goal of exploiting School Analytics is to facilitate school leaders to effectively and holistically orchestrate their schools' strategic planning and optimize the learning conditions for all students.

In this work, we focus on a case study of using School Analytics, namely to investigate how educational data regarding the use anduptake of ICT across school factors can be jointly processed to support leaders understand and, also, plan for the conditions to improve students' digital skills.

In this context, there have been some initial works which have outlined and studied school factors which are significantly related to the uptake and use of ICT in the school from a holistic perspective, and could contribute to fostering students' digital skills. In particular, [10] proposed a School ICT Competence profiling framework, which primarily comprised the factors of school ICT infrastructure, the school culture, principals' attitudes towards digital technologies, the level of ICT use in the curriculum, as well as teachers' digital skills, professional development, attitudes towards digital technologies and level of use in their practice.

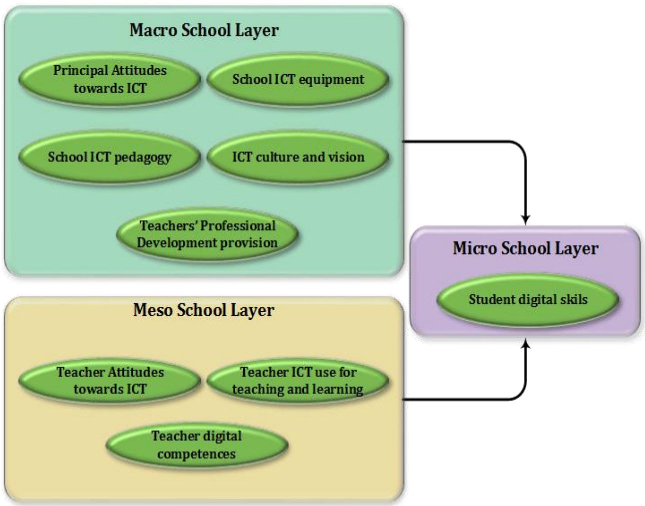

Figure 1: Conceptual School Analytics model comprising factors influencing students' digital skills

Similarly, [8] proposed the Extensive Digital Competence (EDC) model, which also outlined school factors affecting students' digital skills; namely school vision, ICT infrastructure, teacher ICT professional development, teacher digital skills, teacher ICT use in their practice as well as ICT-related attitudes. Furthermore, [11] proposed as important factors the teachers' digital skills and the teachers' level of use of digital technologies in their school practice.

Based on the synthesis of these works, a School Analytics ecosystemic factor model can be defined for this study (Fig.1). As the Figure 1 depicts, the model is structured against the three school organizational layers and comprises the overarching set of the school factors that existing works have outlined. To ensure robustness of the School Analytics model, it will be validated in terms of goodness-of-fit using a diverse range of metrics (Section IVA).

Furthermore, as previously mentioned, the contribution of this work aims to effectively support leaders' decision making, by outlining which configurations of the factors of the School Analytics model (i.e., combinations of these factors being present or absent from a school) can explain high levels of students' digital skills, and therefore inform leaders on the specific school areas to improve to meet their goal. To offer these insights, this work proposes the use of fuzzy-set QCA (fs-QCA).

B. fsQCA method

fsQCA is a configurational data analysis method [9], which takes a step beyond existing regression-based methods. More specifically, the added value of fsQCA is that, unlike regression-based methods, it aims to identify logical connections among (a) different configurations of causal conditions (independent and/or independent constructs) that can explain a desired outcome and (b) the desired outcome itself [12]. In essence, it creates a set of rules that highlight which causal configurations of potential factors can explain a desired outcome and under which circumstances. Therefore, whereas regression-based models would highlight which individual conditions are potentially significant for a desired outcome, fsQCA can provide deeper insights on which causal configurations among conditions can explain the desired outcome.

Capitalizing on these benefits, fsQCA has been exploited in different contexts, e.g., to elicit new insights on which behavioral patterns of users can explain customers' purchase history in the context of e-commerce [13] as well as a means to understand the causal patterns of factors stimulating employees' behaviors in the context of service management ([14]). Furthermore, fsQCA was also very recently introduced in the education field to provide a new understanding of the causal factors affecting students' intention to follow Computer Science studies [15]. Overall, based on the existing promising findings across different fields of application, it is reasonable to argue that fsQCA could provide a way to unravel which configurations of school ecosystemic factors can explain a high level of students' digital skills, and contribute to the decision making process of school leaders.

III. RESEARCH METHODOLOGY

A. Research Proposition and Methodology

To conceptualize the challenge and contribution at hand, an underlying research proposition has been defined:

- **Research Proposition**: No single configuration of school ecosystemic factors leads to high student digital skills; rather, there exist multiple, equally effective configurations of causal factors.

To address this research proposition, the following methodology was defined: First, a School Analytics ecosystemic factor model was defined (presented in section IIA), which capitalized on existing works and comprised school factors which can affect students' digital skills. The resulting model was evaluated for goodness-of-fit using a diverse range of indicators (described in section IVA). Second, building on this model, fsQCA was utilized to unravel distinct configurations of these school factors leading to high student digital skills. Initial evaluation results are based on the evaluation metrics of the fsQCA method, namely solution consistency and coverage, which are discussed in section IV.

B. Dataset

The dataset utilized was generated in the context of a major cross-European study [16]. The study was conducted by the European Commission and aimed to collect questionnaire-based data regarding how ICT is being utilized and incorporated within school processes. The dataset used in this work (after omitting missing values) contained data from 2995 schools (principals), 7897 teachers and 42135 students. Furthermore, the dataset provided data to populate all aspects of the defined School Analytics ecosystemic factor model, as outlined in Table I. All data used in this work were measured through 4-point Likert-scale questionnaire items. A full description of each data type and questionnaire items for each one is discussed in [16].

TABLE I. OVERVIEW OF DATASET

School Layer	Data Type utilized
Macro	• **Principals' self-reported attitudes** towards using ICT to enhance students' learning; • Availability of **ICT equipment** in the school; • **ICT culture and vision** in the school (e.g., staff/parents views on using ICT, ICT being a core aspect of school strategy); • **ICT pedagogy** in the school (e.g., exploitation of appropriate content/ models for ICT teaching, level of ICT fusion in curriculum); • Availability and systematic delivery of **teachers' ICT professional development**
Meso	• **Teachers self-reported attitudes** towards using ICT to support teaching and learning; • **Teachers' self-reported digital skills** in using ICT to support their practice; • **Teachers' level of ICT use** in their teaching practice
Micro	• Students' **level of ICT skills**

C. FsQCA methodology

This study used fsQCA using the fs/QCA 2.5 software. As aforementioned, fsQCA identifies patterns between independent and dependent model constructs, which explain a specific outcome. Therefore, it can be used to unravel whether some constructs affect the outcome only under specific cases (insights which are not provided by regression analyses).

The first step in fsQCA is to define what the outcome is (in this work: high students' digital skills) and which are the constructs that will used to explain this outcome (i.e., school ecosystemic factors). The next step is to calibrate all constructs into fuzzy sets, whose values range between [0,1] depicting the level of membership; a value of 1 represents full membership and a value of 0 representing non-membership. This work adopted a direct method of calibration for the fuzzy sets [17]. More specifically, this method includes direct assignment of three threshold values, that were used to transform the data to their fuzzy equivalent. Since the data were coded as 4-point Likert scales, following the guidelines of [18], the threshold value for full membership was defined at 4, for non-membership at 1 and the crossover threshold was defined at 2,5. Following this step, fsQCA generated a *truth table* of 2^k rows, with k being the number of constructs and each row representing each possible configuration of these constructs leading to an outcome (e.g., two constructs would generate four potential configurations). For these configurations, a minimum threshold was defined to assess the degree to which each configuration was supported by the constructs (in this case, the threshold was set at 0.8). Configurations under this threshold were eliminated.

The final step was to assess the truth table in terms of frequency and consistency [17]. Frequency refers to the number of constructs in each configuration. Consistency refers to the degree to which the defined configurations are consistent with the outcome (i.e., they provide a configuration which connects constructs with the outcome) [18]. A frequency cut-off point was defined so as to ensure that a minimum number of observations was obtained. The frequency cut-off point was set at 3 [18], and the consistency threshold was set at 0,85. The resulting data were used to address the research proposition.

IV. FINDINGS

A. Validation of School Analytics ecosystemic factor model

The first step of the research methodology was to validate the School Analytics ecosystemic factor model in terms of Reliability and Validity, as well as goodness-of-fit through exploratory and confirmatory factor analyses. More specifically, regarding **Reliability**, based on the Cronbach's alpha coefficient, all model constructs were above the recommended threshold of 0,7 (see Table III in Appendix). Additionally, regarding reliability for item-level loadings, the analysis showed that all loadings were satisfactory, with values greater than 0,65. Regarding **Validity**, as Table III (Appendix) depicts, convergent validity was ensured based on the Average Variance Extracted (AVE) scores, which were all above a satisfactory threshold of 0,45, all correlations between constructs were lower than 0,80 (indicating low inter-relatedness between them), and the square root AVEs for all constructs (i.e., diagonal elements in bold) were higher than the corresponding correlations, ensuring discriminant validity.

Additionally, the model was also successfully inspected for **multicollinearity** (namely whether two or more predictor constructs were highly linearly correlated) and was lower than the maximum threshold of variance inflation factor for each construct (i.e., below 3). In terms of **goodness-of-fit**, the School Analytics model was assessed using the widely-used indices of chi-square statistic, the comparative fit index (CFI) and the root mean square error of approximation (RMSEA). The results of all indices were within the commonly accepted ranges, i.e., x^2/df: 98,1, CFI: 0,896 and RMSEA: 0,04.

Finally, **contrarian analysis** [19] was performed in order to elicit if the data contained cases in which a specific construct could have multiple effects (i.e., positive, negative and no effect) when compared to different other constructs.

The results from the contrarian analysis in this study indeed showed that such cases existed for all model constructs (not presented due to lack of space). Therefore, the need to further study and unravel such complex relationships among constructs calls for additional and deeper analyses, which were performed using fsQCA.

TABLE II. CONFIGURATIONS FOR HIGH STUDENT DIGITAL SKILLS

Model Constructs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Principal Attitudes	●	●	●		●	⊗		
Teacher Professional Development			●	⊗	⊗		⊗	⊗
School Equipment				⊗			⊗	●
School Culture / Vision		●	●	●	●	●	⊗	⊗
School Pedagogy			⊗			●	●	⊗
Teacher ICT use in classroom	●			●	●			
Teacher Attitudes	●	⊗		●		●	●	●
Teacher digital skills		●				●	●	●
Solution Raw Coverage	***0,31***	***0,25***	***0,37***	***0,21***	***0,23***	***0,25***	***0,23***	***0,21***
Solution Unique Coverage	***0,025***	***0,010***	***0,038***	***0,017***	***0,042***	***0,012***	***0,038***	***0,037***
Solution Consistency	***0,86***	***0,91***	***0,87***	***0,94***	***0,92***	***0,93***	***0,92***	***0,93***

B. *Results from fsQCA analysis*

The fsQCA analysis revealed 8 distinct configurations of school ecosystemic factors which can lead to high students' digital skills (Table II). This solution is deemed satisfactory due to the very high level of **overall coverage** (*cov*=0,569) and **overall consistency** (*con*=0,83). This means that (a) students' digital skills can be robustly inferred based on the defined constructs and their configurations (*coverage* – equivalent of R^2 in regression analyses) and (b) the defined configurations provide sufficient antecedents for the desired outcome (consistency) [20]. Furthermore, the solution table (Table II) includes consistency values for each configuration, with all values being above the threshold (>0.85).

In Table II, for each configuration, black circles indicate that the corresponding school factor is present in the configuration, crossed-out white circles indicate absence of a factor, whereas blank cells indicate that the corresponding factor can be equally present or absent ("don't-care-condition"). As the Table II depicts, in the first three configurations, principals' positive attitudes are the main element leading to high students' digital skills. More specifically, principals' positive attitudes lead to high student digital skills when they are complemented by (a) teachers' positive attitudes towards ICT and also high levels of actual ICT use in the classroom (Configuration #1). Another path to high students' digital skills combines principals' positive attitudes with either high levels of teacher digital skills and a supportive culture / vision for ICT in the school (even in the absence of positive attitudes of teachers - Configuration #2) or a supportive school culture/vision coupled with a systematic focus on enhancing teachers' digital skills (even in the absence of supportive pedagogy in the school - Configuration #3).

The following two configurations outline teachers' use of ICT in the classroom within a nurturing school culture / vision as the recurring factors. In particular, when these factors are combined with positive teachers' attitudes, they can lead to high student digital skills, even in the absence of systematic professional development provision and inadequacies in the availability of ICT equipment in the school (Configuration #4). Additionally, these two prime factors lead to high student outcomes when coupled with principals' positive attitudes towards ICT even when systematic professional development provision was not provided (Configuration #5).

In the final three configurations, the recurring influencing factors are teachers' positive attitudes and high digital skills. When these factors are present in a school, they can lead to high students' digital skills either (a) supported by a nurturing school (and community) culture/vision and pedagogy (even in the absence of principals' positive personal attitudes - Configuration #6), (b) supported by supported by a robust plan for ICT pedagogy in the school (in the absence of systematic professional development provision, inadequacies in the availability of ICT equipment and within a less nurturing school culture/vision - Configuration #7), or (c) in the absence of systematic professional development provision or a nurturing school culture/vision and supportive pedagogy, but fully supported by adequate and available ICT equipment (Configuration #8).

V. CONLUSIONS AND FUTURE WORK

This paper presented initial results from an on-going agenda to investigate how School Analytics methods can be utilized to inform school leaders' decision making. Building on a case study, the contribution of this work was to introduce a data analysis method (i.e., fsQCA) with the potential to effectively support School Analytics approaches and evaluate its potential in a preliminary manner. The generated results were promising in terms of the inherent evaluation metrics of the fsQCA method (namely consistency and coverage), and it is argued that additional research should be focused on further scrutinizing and refining how this method can effectively inform school leaders' decision making.

Therefore, future work in this agenda should focus on gaining additional insights on the capacity of the fsQCA method to act as a means to inform School Analytics methods and support systemic school leadership. As a first step, it is important to obtain additional evaluation results to corroborate the initial findings, for example using propensity score matching on the same dataset [21]. This protocol will allow to investigate whether students who were exposed to the eight configurations outlined by the fsQCA method had significantly higher levels of digital skills compared to students not exposed to such configurations.

Additionally, future evaluation methods should aim to investigate the application of this method in more generic contexts i.e., beyond the specific case study and dataset used in this work. Furthermore, longitudinal studies should be designed, so as to collect rich pools of both quantitative and qualitative data in real-life investigations in schools. Capitalizing on these data, thorough insights could be derived on the added value and actual impact of using fsQCA to support school leaders to meet both externally-defined performance mandates as well as improve the teaching and learning provisions for all students.

ACKNOWLEDGMENT

REFERENCES

[1] S. Sergis, and D.G. Sampson, "School Analytics: A Framework for Supporting School Complexity Leadership," In Competencies in Teaching, Learning and Educational Leadership in the Digital Age, J.M. Spector, D. Ifenthaler, D.G. Sampson, and P. Isaias Eds, Springer International Publishing, pp. 79-122, 2016.

[2] S. Sergis, and D.G. Sampson, "Data-driven decision making for school leadership: A critical analysis of supporting systems," In ICT in Education in Global Context, R. Huang, Kinshuk, and J. Price, Eds, Springer Berlin Heidelberg, pp. 145-171, 2016

[3] J.A. Marsh, and C.C. Farrell, "How leaders can support teachers with data-driven decision making A framework for understanding capacity building," Educational Management Administration & Leadership, pp. 1-21, 2014

[4] US Department of Education. "Partnership for 21st century skills," Retrieved from http://www.p21.org/, 2016.

[5] OECD, "Measuring the digital economy: A New perspective,", 2014

[6] R. Vanderlinde, K. Aesaert, and J. Van Braak, "Institutionalised ICT use in primary education: A multilevel analysis," Computers & Education, vol. 72, pp. 1-10, 2014.

[7] Gil-Flores, J., Rodríguez-Santero, J., & Torres-Gordillo, J. J. (2017). Factors that explain the use of ICT in secondary-education classrooms: The role of teacher characteristics and school infrastructure. *Computers in Human Behavior, 68*, 441-449.

[8] Aesaert, K., van Braak, J., Van Nijlen, D., & Vanderlinde, R. (2015). Primary school pupils' ICT competences: Extensive model and scale development. *Computers & Education, 81*, 326-344.

[9] C.C. Ragin, "Fuzzy-set social science," University of Chicago Press, 2000

[10] S. Sergis, and D.G. Sampson, "From teachers' to schools' ICT competence profiles," In Digital systems for open access to formal and informal learning, D.G. Sampson, D. Ifenthaler, J.M. Spector, P. Isaias, Eds. Springer International Publishing, pp. 307-327, 2014.

[11] M. Skryabin, J. Zhang, L. Liu, and D. Zhang, "How the ICT development level and usage influence student achievement in reading, mathematics, and science," Computers & Education, vol 85, pp. 49-58, 2015.

[12] P.C. Fiss, "Building better causal theories: A fuzzy set approach to typologies in organization research," Academy of Management Journal, vol. 54, no. 2, pp. 393-420, 2011.

[13] I.O. Pappas, P.E. Kourouthanassis, M.N. Giannakos, and V. Chrissikopoulos, "Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions," Journal of Business Research, vol. 69, no. 2, pp.794-803, 2016.

[14] A. Leischnig, and K. Kasper-Brauer, "Employee adaptive behavior in service enactments," Journal of Business Research, vol. 68, no. 2, pp. 273-280, 2015.

[15] I. Pappas, M.N. Giannakos, M.L. Jaccheri, and D.G. Sampson, "Assessing student behavior in computer science education with an fsQCA approach: The role of gains and barriers," ACM Transactions on Computing Education [accepted for publication].

[16] P. Wastiau, R. Blamire, C. Kearney, V Quittre, E. Van de Gaer, and C. Monseur, "The use of ICT in education: a survey of schools in Europe," European Journal of Education, vol. 48, no. 1, pp. 11-27, 2013.

[17] Ragin, C. C. 2008. Redesigning social inquiry: Fuzzy sets and beyond. Chicago, IL: University of Chicago Press

[18] I.O. Pappas, M.N. Giannakos, and D. Sampson, Making Sense of Learning Analytics with a Configurational Approach. In *Proceedings of the workshop on Smart Environments and Analytics in Video-Based Learning*, 2016.

[19] A.G. Woodside, "Embrace• perform• model: Complexity theory, contrarian case analysis, and multiple realities," Journal of Business Research, vol. 67, no. 12, pp. 2495–2503, 2014.

[20] JM Mendel, and MM Korjani, "Charles Ragin's fuzzy set qualitative comparative analysis (fsQCA) used for linguistic summarizations," Information Sciences, vol 202, pp. 1-23, 2012.

[21] M. Caliendo, and S. Kopeinig, "Some practical guidance for the implementation of propensity score matching," Journal of economic surveys, vol. 22, no. 1, pp. 31-72, 2008

Appendix

TABLE III. DESCRIPTIVE STATISTICS, INTER-CONSTRUCT CORRELATIONS AND RESULTS FROM VALIDITY MEASURES

Model Constructs	Mean (SD)	Cronbachs' *a*	AVE	1	2	3	4	5	6	7	8	9
1. Principal Attitudes	3,38(0,44)	0,861	0,9	**,95**								
2. Teacher Professional Development	2,06(0,58)	0,794	0,5	,155**	**,70**							
3. School Equipment	2,39(0,75)	0,823	0,5	,048**	,165**	**,70**						
4. School Pedagogy	2,64(0,65)	0,841	0,45	,098**	,123**	,314**	**,67**					
5. School Culture / Vision	3,33(0,57)	0,815	0,9	,183**	,116**	,227**	,420**	**,95**				
6. Teacher Attitudes	3,36(0,47)	0,802	0,45	,093**	,065**	,034**	,011*	,048**	**,67**			
7. Teacher digital skills	2,66(0,77)	0,901	0,7	,049**	,047**	,037**	,043**	,048**	,231**	**,84**		
8. Teacher ICT use in classroom	1,46(0,63)	0,807	0,9	,041**	,030**	,017**	-,017**	,022**	,038**	,023**	**,95**	
9. Student Digital Skills	2,56(0,77)	0,939	0,9	,029**	,047**	,044**	,046**	,009*	,013**	,029**	,138**	**,95**