Principals’ use of data analytics in Finnish schools

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ABSTRACT
Data analytics is widely accepted as a crucial aspect of effective school leadership, yet its utilization by principals has not been thoroughly examined in scholarly works. The potential of Educational Data Mining Tools (EDM) to provide a “big picture” for principals to address equity gaps among students is overlooked in the literature. This article explores the practical applications of these tools by principals in Finnish schools through semi-structured interviews. The research focuses on understanding the functional aspects, challenges, and implications of their engagement with data analytics tools. Findings indicate that principals primarily employ data analytics tools for administrative tasks such as timetable allocation or budget allocation, they rarely use them to monitor student performance. Challenges such as being the sole responsible person for data analysis and inadequate data training hinder their effective use of these tools. Future research aims to extend this research by engaging more principals from various countries to identify commonalities and differences in data analytics adoption, revealing context-specific challenges and potential best practices. Such insights can inform global discussions on data use for effective school leadership and better integration of technology for this purpose. Ultimately, the insights gained from our study can contribute to significant aspects to be considered in the development of EDM tools for school principals.

Keywords
educational leadership, educational data mining, data analytics tools, comparative study, principals’ practices

1. INTRODUCTION
Data analytics has been employed in the education field by different stakeholders for various purposes such as monitoring students’ absences, analyzing students’ learning outcomes, and evaluating teachers’ performance [7, 30, 23]. In the adoption of such technical tools, education stakeholders may encounter various problems such as limited digital literacy [24], however, it can be beneficial in different contexts [4]. While the potential of data analytics facilitates these stakeholders’ activities during the learning or teaching process, the adoption of these tools by principals is less widespread, for instance, compared to its adoption by teachers [35]. This poses a considerable gap between the recognized benefits of data-driven decision-making and the current utilization in educational leadership [15]. The data analytics utilization patterns among principals and their challenges are under-researched posing difficulty in understanding how potential changes toward more effective adoption of data analytics among principals can be supported [8, 41, 17].

This short paper addresses the gap in the literature by exploring the data analytics utilization patterns of principals in Finnish schools through semi-structured interviews. The article makes the following key contributions to the literature. Firstly, it adds to the empirical knowledge about the data analytics utilization patterns of principals. Moreover, it explores the purposes of the use of data analytics to see to what extent the potential of data analytics is realized for addressing equity gaps among students by principals. Secondly, it contributes to the understanding of how principals can better be supported in effectively utilizing these tools. It also informs the design of these tools and regarding policy.

Moreover, by indicating the current landscape of data analytics tools usage by principals, we also introduce important perspectives to consider in the development of data analytics tools for school principals. This can support and lead to the development of large-scale Academic Analytics (AA) and Educational Data Mining (EDM) tools.

2. LITERATURE REVIEW
EDM involves the development or application of data mining techniques specifically tailored to uncovering new insights within educational contexts [6], facilitating decision-making within educational institutions [9]. Presently, many EDM case studies focus on analyzing the growing volumes of log data generated by various computer-based learning environments, including multi-modal teacher-student interaction (e.g., [12]), students’ practice programming (e.g., [19]), learning management systems (e.g., [11]), digital learning re-

A. Karimov, M. Saarela, T. Kärkkäinen, and S. Aghayeva. Principals’ use of data analytics in finnish schools. In B. Paaßen and C. D. Epp, editors, *Proceedings of the 17th International Conference on Educational Data Mining*, pages 452–457, Atlanta, Georgia, USA, July 2024. International Educational Data Mining Society.

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https://doi.org/10.5281/zenodo.12729858

sources (e.g., [47]), intelligent tutors (e.g., [2]), study records (e.g., [37]), MOOCs (e.g., [14]), and educational games (e.g., [22]). The analysis of such data aids in understanding how students engage and learn within these systems.

In comparison, AA [16] encompasses the convergence of technology, information, organizational culture, and the utilization of data analytics for institutional management. Essentially, AA refers to the application of business intelligence within the realm of education, specifically aimed at uncovering meaningful patterns in educational data to identify academic issues like dropout rates and to aid in strategic decision-making [5, 10, 31]. This process primarily targets support for institutional administrators and educational policymakers. While students anticipate the use of data analytics to predict and enhance their learning outcomes, institutional administrators prioritize applying AA to monitor and enhance educational Key Performance Indicators, such as student retention.

Despite the exponential growth in EDM studies [36] and the aims of AA to streamline institutional decision-making [29], there remains a scarcity of empirically validated EDM and institutional AA systems or tools [20, 33]. Moreover, EDM and AA have been widely used in higher education institutions, but actual implementations in school contexts are less widespread. Thus, our research is concerned with the empirical requirements for building institutional analytics tools for school principals for organizational EDM, broader management, and AA for schools.

Research investigating the use of data analytics in educational settings often underscores its benefits for analyzing students' learning outcomes, defining at-risk students, and personalizing teaching according to the individual needs of students. For example, research by Zhang et al. (2018) indicates that learning analytics help to define factors that affect learning and also provide grounds for personalized instruction by providing learning diagnosis reports [46]. Ysseldyke & McLeod (2007) highlighted the importance of using data analytics tools to monitor the students' continuous feedback and to provide in-depth information to teachers, school administrators, and school psychologists that might inform improved instruction [45]. A longitudinal research carried out involving 53 primary schools by Van Geel et al. (2016) found that intervention based on data-driven decision-making increased students' achievement in math, particularly among students with disadvantaged socio-economic situations [43].

There is a significant gap in the literature on school administrators' usage of data analytics although the existing research indicates that the principals are the key players in the utilization of data analytics in their schools [44, 27]. Therefore, it is important to explore the challenges in adopting data analytics from the perspective of principals. Agasisti & Bowers (2017) group the barriers and impediments in using data analytics in education as follows [1]. Firstly, they highlight the ethical issue in data use considering the privacy dilemmas it may produce. Secondly, they identify the technical issues arising from the complexity of data and data integration. For the effective utilization of data, they highlight the importance of adequate data analytics tools. Thirdly, they underline how the design of adequate tools for classifying, analyzing, and providing support for decision-making is a costly investment. Therefore, often access to these tools is given to a very limited number of people, usually to leaders. The other systemic literature review conducted by Sousa et al. (2021) found the main challenges of utilizing data analytics in school contexts are ethical issues related to students' privacy and technical issues raised such as collecting data, internet connectivity, or the number of devices in classrooms [40].

Another significant concern surrounding EDM and AA pertains to the ethical and responsible utilization of educational data. This includes adherence to data protection regulations such as the EU-GDPR and respecting the privacy principles of all stakeholders involved [25, 38].

Previous research focused on the education leadership practices in Finland from various perspectives [26]. Heikka et al. (2020) investigated the pedagogical leadership plans in Finland [18]. They presented the leading pedagogical issues and processes within the early childhood education centers and these issues were creating structures for pedagogical development and reflection. Risku & Pulkkinen (2016) presented the role of school principals in the Finnish education system and their overall responsibilities [34]. They reflect that the school principal's role has changed radically during the last 30 years from being a head teacher implementing orders to the general manager of autonomous profit units. Previously they were selected among senior teachers who were promoted for good service to education, nowadays, the main requirements from them are understanding education development and having solid management skills to lead a school. Johnson (2007) also analyzed the role of school principals in the Finnish context [21]. This research demonstrated that school principals feel they take more responsibility compared to the past because of more administrative tasks nowadays. As a result, since they feel their work is very demanding, it causes work overload. While the previous research explored different education leadership practices in Finland, our research contributes to the current research by demonstrating how school principals in Finnish schools adopt data analytics tools.

We aim to present the current landscape of data analytics tools usage, and the main motivations and challenges in the adoption of such tools in Finnish schools. By presenting this, our goal is to provide valuable guidance for the development of large-scale EDM or AA tools based on the specific needs of school principals.

3. METHODOLOGY

To conduct this research, we utilized qualitative data collection methods, and the data was analyzed based on the thematic analysis.

3.1 Data collection

The school principals were recruited through the Finnish rectors association, and we collected data through semi-structured interviews, which lasted 40-45 minutes. The interviews were conducted online on Zoom in English and were recorded only after obtaining consent from the participants. All interviews started with school principals' introduction of the schools they work at. Later, they answered the following questions, and depending on their answers, we asked follow-up questions:

- As a school leader, which data analytics tools do you utilize?
- What is the primary purpose behind your use these tools?
- What challenges do you encounter in the application of these tools?
- If given the opportunity, what improvements would you contemplate making to these tools?

3.2 Data analysis

To analyze data, we employed the thematic data analysis method and the reason why we selected this method was its flexible and systematic exploration of participants' qualitative data [42]. We commenced the analysis with the identification of key themes based on participants' responses. Each question was treated as a category and the codes were also defined based on these questions previously. Following the transcription of interview recordings, two researchers independently reviewed the transcriptions to familiarize themselves with the data. Subsequently, they conducted a series of three meetings to discuss and establish the criteria for identifying themes and sub-themes within the data. In addition to the four codes defined based on the research questions before the study, we incorporated an additional code about the impact of regional or national authorities on the decision to adopt EDM tools. Furthermore, the coding process followed both inductive and deductive strategies. The inductive perspective allowed us to explore unanticipated themes in the responses. The deductive coding was implemented for predefined categories. The initial deductive codes included "Tool Utilization," examining the data analytics tools employed; "Reasons for Tool Adoption," investigating the main motivations behind tool selection; "Challenges in Tool Application," exploring difficulties faced during tool implementation; and "Potential Improvements to Tools," focusing on contemplated enhancements. This allowed for the emergence of additional themes and sub-themes within each category.

3.3 Participants

We conducted this research with four school principals who work in Finland. Table 1 shows the profiles of schools where these school principals work. Principal A leads a comprehensive Grades 1-12 institution with a substantial student body of approximately 1200. Principal B manages a school specializing in Grades 10-12 with around 1050 students, while Principal C heads a more focused Grade 10-12 school with a smaller enrollment of approximately 175 students. Principal D presides over a Grades 6-7 school with around 400 students.

4. RESULTS

In our study, we interviewed four principals in Finland to explore their utilization of data tools, their purposes for using them, encountered challenges, and envisioned improvements (Table 2).

Table 1: The school profile of interviewed principals

Principal	School Type	School Size
Principal A	Grades 1-12	$\approx$ 1200 students
Principal B	Grades 10-12	$\approx$ 1050 students
Principal C	Grade 10-12	$\approx$ 175 students
Principal D	Grades 6-7	$\approx$ 400 students

Our findings indicate that while principals mainly utilize learning analytics for conducting administrative tasks, they also use these tools to oversee students' academic performance over time. These administrative tasks include allocating budget, preparing timetables, organizing study groups, and managing new student admissions. They utilize various tools such as SAP, Google Forms, Google Sheets, Excel, Primus, and Vilma. Principals tend to check data related to academic performance less frequently compared to their administrative tasks, typically on a weekly or monthly basis. They rely on teachers' reports for analyzing students' performance data and occasionally refer to national exam results or PISA reports. One of the most important educational data analytics that they focus on is the well-being of students. For this, in addition to the well-being survey by the Ministry of Education, principals also develop their own surveys to collect data on students' well-being. This is not required from the educational authorities and is initiated by the school principals themselves. Another significant data for principals is students' attendance and behavior and teachers are the responsible person for this data input. This type of data is generally categorical such as the yellow color representing that the teacher is satisfied with the student's behavior. In addition to that, teachers can also add qualitative data to describe student's behavior in detail. Students' behavior data is widely utilized as a tool to communicate with parents.

Principals also collect data related to teachers. The most common data are the number of hours they teach and this data is used in the preparation of the timetables on a system called, Primus. Furthermore, principals utilize Excel to track the number of hours that the teachers participate in the training. This data is used while reporting to the Ministry of Education as it is one of the required data from schools.

In our research, we also focused on understanding whether formal authorities also impact their decision on the adoption of the data analytics tools. Based on principals' responses, they do not receive any formal notification about the usage of any certain tools, however, at the same time, the number of educational data analytics tools is limited and the most famous one is Vilma. Some used this system since 1997 and though some similar systems were developed, they failed either in the launch or adoption phase over this time.

School principals provided feedback on the challenges that they encounter while using the data analytics tools and what can be done to solve such issues. Firstly, they mentioned the need for integrated data analytics tools. They collect educational data from different sources, and to analyze them, they need to utilize various systems. Thus, it would facil-

Table 2: Participants' data tools usage, purposes, and challenges

Principal	Data Tools Used & Purposes	Challenges
Principal A	Vilma, Google Forms, Primus, Excel (Budgeting, Well-being surveys, Timetables, Student behavior)	Integration of data tools, Manual timetable creation, Lack of automated notifications for student performance
Principal B	Vilma, Primus (Timetables, Student performance, Subject selection, Predictions)	Improved prediction tools needed for new student admissions, Manual timetable and study group creation, Limited supporter for data systems
Principal C	Vilma, Primus (Absence monitoring, Student's academic performance data, Teaching hours)	Lack of automation in data systems, Limited detailed data, Privacy regulations on special needs data
Principal D	Vilma, Primus, Google-based tools, Excel (Teacher workshops, Absence monitoring, Collecting student feedback)	Need for a system to support teacher usage of detailed data, Costly access for teachers, Limited supporter for data systems, Isolation of detailed data access to the principal

itate their activities if all these were combined in a single platform. Secondly, the current data analytics tools require additional time to learn to be able to utilize them effectively. Principals think that their responsibilities are diverse and many, thus focusing on only using these data analytics tools takes more time from them. This restricts them from using data analytics tools effectively and according to principals, user-friendly systems with guided features can facilitate this process. Another perspective was building collaborative systems to involve more staff in data analysis. This can help school principals not to take all burden and other administration staff can share duties in the usage of these tools. Thirdly, school principals also mentioned that they would like to have automation in the data analytics tools. Preparing timetables is a time-consuming task and it does not bring any additional value to the school leadership. They proposed having an automated timetable can solve this issue. In addition to organizing timetables, another automation proposal was data entry of students' absences since this activity is done manually and takes much time.

Challenges mentioned by the school principals while using data analytics tools differ depending on the sizes of schools. While larger school (more than 1000 students) principals encounter more challenges, these issues are less for the smaller schools. According to them, while the teachers who work at their schools have enough digital literacy to utilize these platforms, due to privacy and regulation restrictions, all the management and monitoring of the tools are carried out by the principals. With one person's responsibility, effective usage of data analytics tools can become challenging as it places a significant burden on the principal to handle both administrative duties. Another challenge for larger schools is the cost and setup of these tools since they are required to spend more time and budget on them. From the perspective of smaller schools, the main challenge is limited prior experience in using such tools. In some cases, the newly appointed school principals are the first people who utilize these platforms and educate their teachers about the tools' functionalities.

5. DISCUSSION

This research provides the results from interviews with principals in Finland about their motivations, challenges, and potential solutions to these issues in using data analytics tools.

We found that one of the main reasons why school principals use data analytics tools is to conduct their administrative tasks. Lunenburg (2010), Fisher (2020), and Aravena & González (2021) also mention in their studies that school principals' primary tasks are related to the administration and organization particularly due to the changes in school leadership duties during the last three decades [3, 28, 13]. Thus, our findings align with the descriptions of school principal duties and naturally, they adopt tools to conduct their most critical administrative tasks more efficiently.

In our research, we also reported that school principals in Finland mainly rely on teachers to monitor the academic performance of students, however, biweekly or monthly, they also review the overall classroom performance and intervene if needed. This is similar to the practices in some countries such as the USA and we also observe totally different aspects in other countries such as Chile. Reid (2021) supports our findings that school principals in the USA also think that they currently focus on administrative tasks and they expect that in the future the role of principal will evolve in a way that they will concentrate on supporting student emotion and learning [32]. Aravena & González (2021) report that school principals in Chile take as equal responsibilities as possible alongside with their administrative tasks to monitor student learning [3].

Our findings show that one of the challenges they encounter in the adoption of data analytics tools is their limited time to learn and utilize new tools. Johnson (2007) also mentions in their research that according to the survey results conducted by the Finnish Headmasters' Association (SUREFIRE) and The Advisory Committee of Headmasters, 97 % of the headmasters felt, that their workload has been increasing in recent years. This indicates that the adoption of any new tools would even increase their daily tasks. Principal C also highlighted the importance of possessing a collaborative data analytics system which would decrease their workload and instead of being the only responsible person, they can share these tasks among teachers and other administration employees. Soncin & Cannistrà (2022) also propose in their research that having an educational data scientist at school may represent a concrete solution to foster more efficient and effective use of educational data analytics since effective usage of educational data analytics tools is a time-consuming task and it would be challenging for the school principal to conduct it by themselves [39].

Another result from our research was alterations in the challenge types according to school sizes. More specifically, while principals of larger schools (i.e., schools with more than 1000 students) encountered more challenges, principals of smaller schools encountered far less for these issues.

The limitation of this study is the number of interviewed school principals is four and this number could be more to collect more responses from different principals. To mitigate this issue, we particularly interviewed school principals with different backgrounds. This helped us to own diverse perspectives in the usage of data analytics tools.

6. CONCLUSIONS

This research investigates the use of data analytics by school principals in Finland. We employed semi-structured interviews with four school principals and analyzed their engagement with data analytics tools. Through that, our research extends the existing literature by providing insights into the practical applications, challenges, and implications of data analytics tools for school principals in Finland.

The findings demonstrate that principals in Finland predominantly use data analytics tools for administrative tasks such as timetable allocation and budget preparation. While these tools are not extensively used for monitoring student performance, they are occasionally employed for overseeing academic outcomes. The study also identifies challenges faced by principals, including the lack of dedicated time for learning new tools and the need for integrated, user-friendly, and collaborative systems. Additionally, principals think that automation in certain tasks, such as timetable creation and data entry for student absences, can solve some of these issues.

As future research, we aim to expand the scope by involving principals from various countries to identify commonalities and differences in data analytics adoption. This comparative approach aims to uncover context-specific challenges and potential best practices, informing discussions on global standards for integrating technology in educational leadership.

7. ACKNOWLEDGMENTS

The work was supported by the Innovative School Principals and the Academy of Finland (project no. 356314).

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