DATA-BASED DECISION MAKING IN ONLINE SECONDARY COURSES: A MULTI-LEVEL EXAMINATION OF PRACTICES, DETERMINANTS, AND NEEDS.

AREEJ TAYEM

Thesis submitted to the University of Ottawa
in partial fulfillment of the requirements for the
degree of Doctor of Philosophy in Education

Faculty of Education
University of Ottawa

Acknowledgement

Completing this Ph.D. has been a journey filled with challenges, learning, and growth, and I would not have reached this milestone without the support of many incredible people.

First and foremost, I extend my deepest gratitude to my husband, whose unwavering encouragement and belief in me sustained me throughout this journey. To my three wonderful children, Jurie, Zineddin, and Mustafa, you have been my greatest source of joy and motivation. Your love, laughter, and understanding, even in the busiest of times, have made this achievement more meaningful. I am also profoundly grateful to my mother and siblings for sharing enthusiasm and being thousands of miles apart but a text away.

A special thanks to my supervisor, Dr. Isabelle Bourgeois, for her invaluable guidance, insight, and encouragement. Her expertise and support have been instrumental in shaping this research, and I am truly fortunate to have had her mentorship. I am equally grateful to my committee members for their thoughtful feedback, constructive criticism, and encouragement, which have greatly enriched this work.

Finally, I want to thank God Almighty who helped me attain an academic goal I had always wanted to pursue. This dissertation is a testament not only to my efforts but to the unwavering support and belief of those who stood by me. Thank you all!

Table of Contents

List of Tables and Figures

Chapter 1

Chapter 2

Chapter 3

Chapter 4

Abstract

Data-based decision-making (DBDM) has become a cornerstone of educational policy and practice, aiming to enhance student learning through conducting informed instructional and pedagogical decisions (Curry et al., 2016; Hebbecker et al., 2022; Peters et al., 2021; van der Scheer et al., 2016). By leveraging various forms of student data, such as assessment results, engagement metrics, and learning analytics, educators are expected to tailor instruction, identify struggling students, and improve overall academic outcomes (Faber et al., 2018; Voithofer & Golan, 2019). However, despite its potential, the effective implementation of DBDM remains inconsistent, particularly in secondary and online education, where research is limited. This thesis, structured as a series of three articles, explores global trends in teacher engagement with DBDM, the factors shaping its use among Ontario secondary school teachers in online courses, and the professional learning opportunities needed to strengthen their DBDM practices.

The first article presents a scoping review of international research on teacher DBDM, which reveals geographical and temporal patterns and highlights gaps in secondary and online education, underscoring the need for more sustainable DBDM support. The second article is a mixed methods study that investigates Ontario secondary teachers' engagement with DBDM in online courses and identifies key influencing factors such as collaboration, leadership, data quality, and teacher efficacy. The findings suggest that while collaboration and efficacy promote data use, concerns regarding data accessibility and DBDM-related anxiety pose barriers to effective DBDM use. The third article investigates Ontario secondary teachers' needs to be able to use data effectively by examining gaps in their data competencies and proposes targeted professional learning opportunities. Findings emphasize the necessity of training in AI-driven

analytics, subject-specific DBDM applications, and scenario-based learning to support teachers in effectively integrating data into their instructional practices.

Together, these studies contribute to a deeper understanding of teacher engagement with DBDM and offer empirical insights into the landscape that shape data use in education. By examining both enablers and barriers to data use within the online teaching environment, this research provides actionable recommendations for professional development, and future research to enhance data-informed teaching and improve student outcomes.

Résumé

La prise de décision basée sur les données (PDBD) est devenue une pierre angulaire de la politique et de la pratique éducatives, visant à améliorer l'apprentissage des étudiants en soutenant la prise de décisions pédagogiques éclairées (Curry et al., 2016; Hebbecker et al., 2022; Peters et al., 2021; van der Scheer et al., 2016). En exploitant diverses formes de données sur les élèves, telles que les résultats d'évaluation, les mesures d'engagement et les analyses d'apprentissage, les éducateurs sont censés adapter l'enseignement, identifier les élèves en difficulté et améliorer les résultats scolaires globaux (Faber et al., 2018 ; Voithofer & Golan, 2019). Cependant, malgré son potentiel, la mise en œuvre efficace de la PDBD reste incohérente, en particulier dans l'enseignement secondaire et en ligne, où la recherche est limitée. Cette thèse, structurée en une série de trois articles, explore les tendances globales de l'engagement des enseignants dans la PDBD, les facteurs qui façonnent son utilisation parmi les enseignants des écoles secondaires de l'Ontario dans les cours en ligne, et les opportunités d'apprentissage professionnel nécessaires pour renforcer leurs pratiques de PDBD.

Le premier article présente une revue de la recherche internationale sur la PDBD des enseignants, qui révèle des modèles géographiques et temporels et met en évidence des lacunes dans l'enseignement secondaire et en ligne, soulignant la nécessité d'un soutien plus durable à la PDBD.

Le deuxième article est une étude employant des méthodes mixtes qui examine l'engagement des enseignants du secondaire de l'Ontario dans la PDBD dans les cours en ligne et identifie les principaux facteurs d'influence tels que la collaboration, le leadership, la qualité des données et l'efficacité de l'enseignant. Les résultats suggèrent que si la collaboration et

l'efficacité favorisent l'utilisation des données, les préoccupations concernant l'accessibilité des données et l'anxiété liée à la PDBD constituent des obstacles à l'utilisation efficace de la PDBD.

Le troisième article procède à une évaluation des besoins des enseignants du secondaire en Ontario en examinant les lacunes dans leurs compétences en matière d’utilisation des données et propose des opportunités d'apprentissage professionnel ciblées. Les résultats soulignent la nécessité d'une formation à l'analyse pilotée par l'IA, aux applications PDBD spécifiques à une matière et à l'apprentissage basé sur des scénarios pour aider les enseignants à intégrer efficacement les données dans leurs pratiques d'enseignement.

Ensemble, ces études contribuent à une meilleure compréhension de l'engagement des enseignants dans la PDBD et offrent un aperçu empirique du paysage qui façonne l'utilisation des données dans l'éducation. En examinant les facilitateurs et les obstacles à l'utilisation des données dans l'environnement de l'enseignement en ligne, cette recherche fournit des recommandations pratiques pour le développement professionnel et la recherche future afin d'améliorer l'enseignement basé sur les données et les résultats des élèves.

Preface

This thesis follows an article-based format, consisting of three standalone research articles, an introductory chapter, and a concluding chapter. The overarching focus of the thesis is data-based decision-making (DBDM) in online secondary education in Ontario.

The introductory chapter provides a foundation for the thesis by offering a brief literature review that highlights existing research on DBDM and identifies a critical gap in understanding its application within online classrooms. It also contextualizes the study by describing Ontario's online education system. The chapter then identifies the research questions and describes how the three research articles are interconnected and build upon one another. Additionally, it presents the conceptual framework, which explains the theoretical models that guide the study, and discusses the overall methodology by describing the research design of each article and illustrating how the chosen methods support a comprehensive understanding of DBDM practices in online education.

The first article is a scoping review that synthesizes the literature and examines the international landscape of DBDM in K-12 classrooms, analyzing how teachers leverage data to enhance instructional practices. It highlights the impact of DBDM on teaching practices and student outcomes, the conditions that support successful implementation of data use, and the challenges that teachers face. Additionally, this review highlights a gap in the literature regarding DBDM in Ontario's online education system, setting the foundation for the subsequent articles in the thesis.

Building on these findings, the second article empirically investigates the use of DBDM in Ontario's online secondary schools through a mixed-methods approach. This study examines the extent to which teachers integrate data into their instructional decision-making and identifies key enablers and barriers to the adoption of DBDM. Using correlation and regression analyses, it assesses the factors influencing teachers' engagement with DBDM, drawing on conceptual frameworks related to best practices in data use. Given the increasing reliance on online education at the secondary level in Ontario, the study highlights the systemic and individual factors that influence data use by teachers and thus contributes to ongoing discussions on enhancing DBDM practices through targeted support and professional development.

The third article builds on data collected as part of the second study to examine the needs of Ontario secondary school teachers in online education pertaining to DBDM and explores how these needs can inform professional learning opportunities. The study identifies gaps in DBDM competencies among secondary school teachers in Ontario and proposes a model to support teachers in navigating the DBDM process. By aligning training opportunities with the specific needs highlighted by teachers, the article contributes to discussions on enhancing DBDM practices and strengthening instructional decision-making in online learning environments.

Finally, the concluding chapter synthesizes key findings from all three studies, discusses their implications for policy and practice, and suggests directions for future research. It reflects on the overarching themes that emerge from the research, highlighting common challenges and opportunities in data-based decision-making (DBDM) for secondary school teachers in online education.

Together, these chapters form a cohesive research trajectory, moving from a broad theoretical foundation to empirical analysis and practical recommendations. This thesis contributes to both academic scholarship and policy development by offering insights into the implementation of DBDM in online secondary education and informing strategies to enhance data-driven instructional decision-making.

Chapter 1: Introduction

In recent decades, the demand for accountability and measurable educational outcomes has prompted a global shift toward data-driven practices in education (Kempf, 2013). While the use of student performance data has enabled system-level comparisons and reforms, it has also introduced significant challenges. One of the most pressing challenges is the overreliance on narrow metrics (i.e., primarily standardized test scores), which may limit educators' ability to address diverse student needs, particularly in increasingly digital learning environments (Carrier & Whaland, 2018). This raises a central problem: **how can educators effectively use data to inform decision making without reducing education to a set of standardized outcomes?**

To address this problem, it is essential to first examine the historical evolution of data use in education, particularly how efforts to collect and analyze student performance data have influenced contemporary accountability practices. The increasing emphasis on educational data can be traced to broader shifts in educational policies around the world that prioritize student and school outcome monitoring. A significant milestone in this evolution was the introduction of the Programme for International Student Assessment (PISA) in 2000. Conducted by the Organisation for Economic Co-operation and Development (OECD), PISA assesses 15-year-old students' proficiency in reading, mathematics, and science every three years (Singer, 2018). Unlike other types of standardized tests that focus on curriculum-based knowledge, PISA emphasizes the application of skills to real-world problems, which positions it as a measure of how well education systems prepare students for life beyond school (von Davier et al., 2013). Therefore, PISA results are used to generate international rankings, comparing the performance of education systems across participating countries.

PISA’s comparative approach not only fueled global debates on the effectiveness of different education systems but also drove large-scale educational reform efforts as governments sought to improve their rankings (Breakspear, 2014; Tasaki, 2017). This growing emphasis on performance metrics has solidified the role of standardized assessments and reinforced accountability-driven reforms worldwide (Chalhoub-Deville, 2016; Taut & Palacios, 2016; Villani, 2018). Influenced by PISA and other large-scale evaluations, many education systems have adopted standardized testing as a key tool for measuring school effectiveness, tracking progress, and guiding decision-making (Dale, 2005; Spring, 2009; Kempf et al., 2015).

Previous research suggests that leveraging standardized test results to develop large-scale student data systems helps establish benchmarks for educational expectations and student outcomes, potentially enhancing pedagogical decision-making and instructional strategies (e.g., Cheng, 1999; Cheng & Curtis, 2004). Additionally, quantitative data can offer valuable insights into the broader contexts of education systems, helping policymakers and educators identify trends and address systemic needs across jurisdictions (Maier, 2010). However, more recent research highlights the unintended consequences of an overreliance on standardized tests for evaluating schools and student performance (Abdusyakur & Poortman, 2019; Kempf, 2015; Omoso et al., 2019). For instance, Kempf’s (2015) longitudinal study on standardized testing in the United States and Canada argues that an excessive focus on test scores fosters a test-oriented instructional approach, which narrows curricula by prioritizing assessed subjects while marginalizing others, such as the arts, physical education, and social sciences. Moreover, Kempf (2015) contends that this shift toward test-driven learning often contradicts educators' beliefs about best teaching practices. By sidelining student-centered approaches, such as differentiated instruction, standardized testing may fail to adequately support both high-achieving students and those who need additional academic support, ultimately limiting the effectiveness of the education system (Faber et al., 2018).

Standardization, which has long shaped traditional in-person education, plays an increasingly prominent role in online learning as well. In Ontario's K-12 education system, the standardization of online learning has been reinforced through provincial policies and centralized digital platforms, with the goal of ensuring that students across the province receive uniform instruction regardless of their geographic location (Ontario, 2020). While these measures promote equity and accessibility, they also limit teacher autonomy in course design and the ability to tailor instruction to diverse student needs. A study by Farhadi and Winton (2024), using critical discourse analysis to examine the evolution of Ontario Ministry of Education policies from 2006 to 2022, highlights how successive governments have used neoliberal discourses of personalization, access, and choice to justify increasing involvement of private actors in online education. Nevertheless, according to their analysis of governmental documents and media news, online learning in Ontario is neither personalized nor customizable but instead is centralized, standardized and, by design, operates independent of rather than interdependent with the community and students' needs. As a result, students are marginalized by systemic inequities and face exacerbated challenges. These findings align with broader critiques of online learning platforms that emphasize how centralized and market-driven education models can reinforce existing systemic inequities, particularly among students from marginalized backgrounds (Castañeda & Selwyn, 2018; Gilliard & Culik, 2016). Such designs risk further exacerbating digital divides and educational disparities, especially when equitable access to technology, support, and culturally relevant pedagogy is lacking.

This tension between systemic accountability requirements and the need to support high-quality, student-centered teaching practices is further compounded by the centralized nature of online learning. In Ontario's standards-based education system, educators are expected to ensure alignment with curriculum expectations and provincial assessments while also attending to diverse learner needs. Standards-based education differs from standardized education, which emphasizes uniform assessments and prescriptive teaching, by allowing greater flexibility in how learning goals are achieved. Within this standards-based framework, there remains room for more student-centered pedagogies, if learning outcomes are met consistently across schools. The challenge, then, lies in balancing system coherence and equity with teacher autonomy and responsiveness.

Teachers can play a more active role in navigating this challenge by leveraging multiple sources of student data while teaching online, rather than relying solely on standardized test results. In practice, they can gather and utilize diverse data sources to supplement standardized assessments, refine their teaching strategies, and address the specific needs of their students, while still meeting accountability requirements (Carlson et al., 2011; Faber et al., 2018; Heinrich & Good, 2018; Tsai et al., 2019). This approach not only enhances instructional effectiveness but also empowers teachers as key agents in shaping equitable and responsive learning environments. This practice is often referred to in the literature as *Data-Based Decision Making* (DBDM). A related and sometimes overlapping concept is *assessment literacy*, which refers to teachers' cognitive competencies in conducting high-quality assessment practices to improve student learning and their own instruction (DeLuca et al., 2016; Hull & Vigh, 2024). It includes teachers' knowledge of assessment purposes, what and how to assess, characteristics of high-quality assessment, skills in applying assessment tools, and the ability to communicate assessment results and provide effective feedback.

While assessment literacy focuses more specifically on the principles and practices of assessment, DBDM extends this scope by emphasizing the systematic integration of multiple types of data into both instructional and organizational decision-making. DBDM is defined as the systematic collection, review, and utilization of diverse data types—including summative and formative assessments, behavior data, attendance records, demographic information, class and homework assignments, and classroom observations—to improve student performance and address their educational needs (Marsh, 2006; 2012).

Numerous studies on the impact of DBDM in K-12 education across different settings provide substantial evidence that, when implemented under the right conditions, DBDM can enhance instructional efficacy and academic outcomes (e.g., Lai et al., 2014; Lai & McNaughton, 2016; Saleh, 2021; van Geel et al., 2016; van Geel et al., 2019; Ylimaki & Brunderman, 2019). However, since much of the existing literature is primarily focused on in-person education, further research on the application of DBDM in online teaching contexts is needed (Tayem & Bourgeois, 2025).

The Context of the Study

The landscape of online education in Ontario is shaped by a combination of government policies, digital platforms, and evolving instructional models. The Ontario Ministry of Education primarily supports online learning through the Virtual Learning Environment (VLE), a digital platform used by publicly funded school boards to deliver both blended and fully online courses. Ontario’s online education system consists of three distinct programs. The first is remote learning, which provides K-12 students with online instruction during extended disruptions to the traditional in-person learning caused by public health emergencies, natural disasters, or other unforeseen events (Government of Ontario, 2025). The second is the Independent Learning Centre (ILC), offered through TVO for English-language schools and TFO for French-language schools. This program provides asynchronous, self-paced courses for students outside the traditional school system, including adult learners and those seeking additional credits toward the Ontario Secondary School Diploma (OSSD). The third is the province's secondary school online learning policy, which mandates that secondary students complete a minimum of two online learning credits as part of the OSSD requirements, unless they opt out or receive an exemption (Ministry of Education, 2024). Table 1 outlines key differences between Ontario's main online education models:

Table 1

Comparison of Online Learning Models in Ontario

Feature	Remote Learning	TVO/TFO Independent Learning Centre (ILC)	Online Classes from School Boards
Target Audience	K-12 students in publicly funded schools (only offered in times of regular school closure)	Independent learners, adults, homeschooled students	Students enrolled in secondary schools of Ontario
Delivery Mode	Synchronous (fully online with teacher-led instruction)	Self-paced, asynchronous (i.e., there are no classes or teacher-led sessions)	Synchronous and asynchronous courses are offered
Interaction with Teachers	Regular interaction with school board teachers	Minimal; mostly self-directed learning with teacher involvement when required	Regular interaction with school board teachers
Assessment & Support	Teacher-led assessments and feedback	Self-paced assignments and mandatory standardized final exams	Teacher-led assessments and feedback

This study focuses on online classes offered by Ontario's publicly funded English and French school boards, which are required for secondary school students as part of their graduation requirements, as well as the TVO/TFO Independent Learning Centre (ILC), which provides asynchronous, self-paced courses for students outside the traditional school system. The analysis excludes remote learning, which is an emergency measure.

Conceptual Framework

This thesis is grounded in two key types of conceptual frameworks: DBDM determinant models and DBDM process models (Nilsen, 2015). The first type, determinant frameworks, focus on the conditions necessary for effective DBDM implementation. Research suggests that for DBDM to be an effective approach, certain factors must be in place to ensure that the teaching environment supports rather than hinders its use. These frameworks identify and categorize the barriers and enablers influencing DBDM at various levels, from individual data users to broader organizational structures (e.g., Kelly & Downey, 2011; Schildkamp et al., 2017; Keuning et al., 2019). The second type, process frameworks, provide structured models that guide teachers through the different stages of DBDM. These models outline a systematic approach, beginning with identifying relevant and reliable data, followed by data analysis, interpretation, and ultimately applying the new information to enhance instruction (e.g., Marsh, 2012; Schildkamp et al., 2016). Both of these models are described in further detail in the sections that follow.

Determinant Framework

The first step in understanding DBDM effectiveness is to apply a determinant framework to investigate DBDM readiness and highlight key barriers or enablers to its implementation (Datnow & Hubbard, 2015; Hoogland et al., 2016; Schildkamp et al., 2017). Several determinant frameworks are proposed in the literature with varying degrees of complexity and comprehensiveness. For instance, the frameworks proposed by Datnow and Hubbard (2015) and Hoogland et al. (2016) identify several categories of factors that facilitate or inhibit teachers' data use and organize them along a continuum from *individual teacher beliefs* to *school-level practice* to *district accountability demands*. Even though the literature emphasizes the importance of using multiple sources of accurate and reliable data for successful DBDM implementation and use (e.g., Malin et al., 2009; Schildkamp et al., 2019; van Geel et al., 2016; van Geel et al., 2017), these frameworks are based solely on standardized assessment data.

Schildkamp et al. (2017), on the other hand, have developed a more comprehensive DBDM determinant framework that has been employed in several DBDM interventions (e.g., Carrier & Whaland, 2018; Faber et al., 2018; Lai & McNaughton, 2016; Pagan et al., 2019; Rangel et al., 2017; van Geel et al. 2017; Ylimaki & Brunderman, 2019). This multilevel framework helped lay the groundwork for later exploration and clarification of the factors that have a direct bearing on the success or failure of DBDM practice. The framework focuses on three influential factors: (1) organizational context, including leadership support, collaboration, and setting clear vision and norms; (2) user characteristics, such as opinions and attitudes, DBDM efficacy, and practical knowledge of DBDM inquiry process; and (3) data characteristics, such as employing high quality, timely, and usable data (See Table 2).

Table 2

Schildkamp et al. (2017) Determinant Model (p. 244)

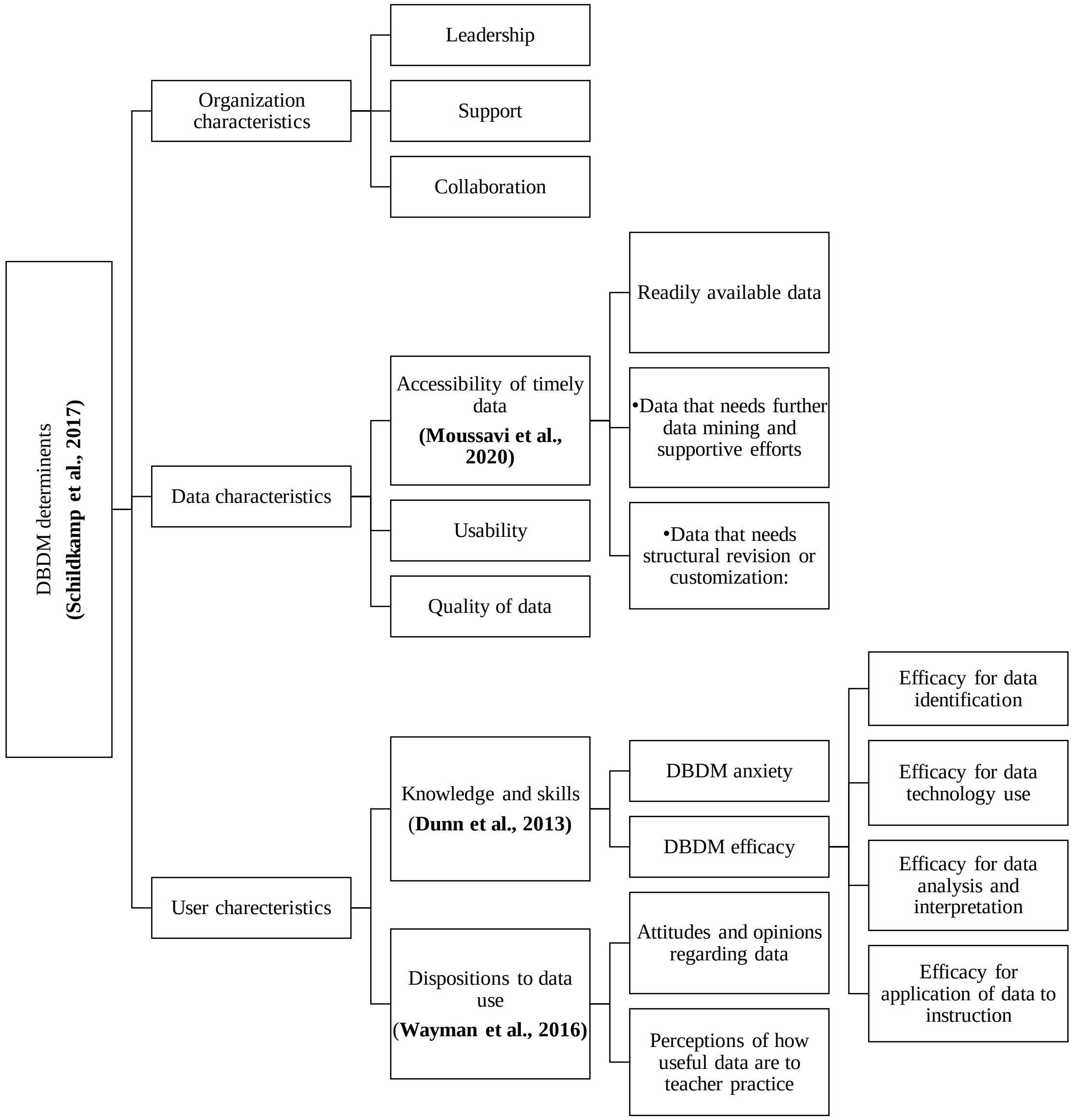
	Organization	**Data**	**User**
	• Vision and norms	• Accessibility of timely data	• Knowledge and skills

Enablers and barriers	• Leadership • Support • Collaboration	• Usability • Quality of the data	• Dispositions to use data

Although the framework developed by Schildkamp et al. (2017) provides a comprehensive overview of the high-level factors influencing DBDM effectiveness, its constructs are broad and require further specification for practical application. Other supplementary studies can be used to expand on and clarify the broad concepts in this framework. For instance, Moussavi et al. (2020) investigate the state of available data, the types of data, and their accessibility in online learning management systems in a higher education institution. Although the study was carried out in a different setting, the importance of data characteristics to DBDM success applies to K-12 schools as well. Thus, this study can be used to expand on the quality, usability, and accessibility of data in the Schildkamp framework. Moreover, Dunn et al. (2013) and Wayman et al. (2016) explore how teachers perceive and use data using Bandura's social-cognitive theory (1986) on teacher's self-efficacy for DBDM by describing the relationships between their attitudes towards DBDM and their actual behaviors in an online context. These frameworks – Dunn et al. (2013) and Wayman et al. (2016) – can be used to expand the user characteristics dimension in Schildkamp et al. (2017). The concept map shown in Figure 1 illustrates a comprehensive picture of the constructs derived from the original framework by Schildkamp et al. (2017) along with those identified in the supplementary studies. This map provides a more specific and clear description of the factors that influence teacher adoption of a DBDM approach in K-12 schools. (See Figure 1)

Figure 1

Concept map based on Schildkamp et al. (2017), Moussavi et al. (2020), Dunn et al. (2013), and Wayman et al. (2016)



This framework served as the foundation for developing the data collection instruments, including the survey and interview guide. It informed the design of survey items and interview questions to ensure they captured key determinants of DBDM effectiveness. Additionally, the framework guided both the quantitative and qualitative data analysis by providing a structured approach to interpreting findings. In the quantitative analysis, it helped categorize and assess variables related to DBDM readiness, barriers, and enablers. In the qualitative analysis, it served as a lens for coding and interpreting interview responses, allowing for a deeper understanding of teachers' experiences and perspectives on DBDM implementation.

Process Framework

A DBDM process framework helps articulate the steps that teachers need to follow in order to collect, understand, evaluate and analyze data, as well as create and implement instructional strategies based on data (Sun et al., 2016). Any gap in this chain of instructional actions would lead to ineffective teaching and learning in classrooms (Hawn, 2019). There are many DBDM process frameworks that have been validated and used in DBDM interventions such as the Data Teams model (Schildkamp et al.,2016), and the Data Inquiry model (Marsh, 2012). The Data Teams model is quite detailed but is not intended for daily use by teachers. It is more of a collaborative inquiry process focused on data use at the administrative level. A “Data Team” consists of a data expert, four to six teachers, and one to two (assistant) school administrators who work together to address an issue within the school by using data in a structured manner (Schildkamp et al., 2016). The Data Inquiry model, on the other hand, is a constructive data process model that does not restrict users and may be better suited for adoption by individual teachers. The model illustrates multiple leverage points at which data use interventions may occur. The Data Inquiry model contends that DBDM interventions should enable users to: 1) access and collect data, 2) organize, filter, and analyze data to elicit information, 3) integrate information with expertise to extract knowledge, 4) adjust action and practice, and 5) assess the effectiveness of the intervention and provide feedback.

Marsh’s (2012) process framework played a crucial role in the third article. It established a foundational benchmark for best practices in effective data use, serving as a reference point to evaluate teachers’ competencies in DBDM. By applying this framework, the study systematically identified gaps that may hinder effective implementation, highlighting areas where additional support or professional development is needed. In other words, Marsh's framework helped in guiding conversations with teachers around their previous DBDM training and their perceived learning needs for the future. Specifically, the study describes teacher self-reported competencies in data identification, interpretation, instructional application, as well as their proficiency with data tools to highlight areas where professional development is needed. This structured analysis did not only provided insight into teachers' self-perceived readiness for DBDM but also informed recommendations for targeted professional development initiatives aimed at enhancing their data literacy and instructional decision-making skills.

Article Structure and Methodology

The scarcity of existing research on DBDM to improve online teaching practices and student outcomes in secondary schools dictates that a broad perspective be taken to document the experiences and attitudes of teachers. Thus, this dissertation will consist of three studies based on different research designs. The first article is a scoping review, which follows the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al., 2018) to systematically map evidence, identify key concepts, and uncover knowledge gaps on DBDM. The second and third articles are based on an exploratory sequential mixed methods design to examine the link between DBDM determinants and use of data in online instruction by teachers working in Ontario secondary schools.

Epistemological Stance of the Thesis:

This thesis is guided by research questions rather than by a fixed hypothesis or theoretical framework. This reflects a pragmatic epistemological stance, which prioritizes inquiry and problem-solving over predefined assumptions. Pragmatism, articulated by scholars such as Biesta (2010), Capps (2019), Choo (2016), and Creswell (2012), emphasizes the practical application of knowledge in real-world contexts. It does not aim to uncover absolute truths but rather focuses on what works in a given situation, offering flexibility in both research design and methodology.

On a personal level, adopting pragmatism aligns with my own views on truth, knowledge, scientific inquiry, and ontology. First, pragmatic theories of truth, particularly Peirce's notion that truth emerges through inquiry (Capps, 2019), resonate with the exploratory nature of my study. Since my research seeks understanding rather than explanation, I begin with questions (not a hypothesis or a predetermined theory) believing that insights will emerge through the research process itself. Second, I share the pragmatic view that knowledge is cumulative and generated through ongoing inquiry (Choo, 2016). Accordingly, I make no assumptions about the current state of DBDM in Ontario. Instead, I aim to explore the existing landscape, identifying the enablers and barriers to DBDM, assessing teacher competencies, and determining future professional learning needs. Third, in line with the pragmatic approach to methodology, I use a mixed methods design. Pragmatists advocate for using any method (qualitative, quantitative, or both) that helps address the research problem effectively (Biesta, 2010). A mixed methods approach allows for a more comprehensive understanding of the research questions. Finally, regarding ontology, pragmatism does not assume a single, fixed reality. As Creswell (2012) explains, pragmatists view reality as dynamic and shaped by human experiences and actions. In my study, I do not seek to generalize findings universally; rather, I acknowledge that any conclusions drawn will reflect the particular context of the research and may evolve as conditions change.

For these reasons, pragmatism is especially well-suited to exploring the landscape of DBDM in Ontario. It supports an open-ended investigation into how teachers engage with data within their specific educational contexts. Rather than imposing a universal model of DBDM, this study aims to uncover the distinct needs, challenges, and enabling factors that influence data use in Ontario's secondary schools.

Article 1: Data-based decision-making by teachers in K-12 schools: A scoping review

The aim of this study is to expand the literature review and provide a comprehensive picture of how DBDM has been used in different countries around the world in the K-12 context as well as its effects on teacher practices and academic outcomes. The review follows PRISMA-ScR guidelines (Tricco et al., 2018) to systematically map evidence on DBDM in the K-12 context and identify key concepts and knowledge gaps. A comprehensive search across four databases (Education Source, ERIC, Web of Science, and Academic Search Complete) was conducted, using keywords related to data use and K-12 education. Inclusion criteria required studies to be conducted in K-12 settings, published in English (2013–2023), and focused on teacher use of data to improve classroom instruction. Studies on data use by school leaders, school boards, or for non-instructional purposes were excluded. A structured data extraction template was developed to capture information on article characteristics (e.g., country, level of students or their grade), engagement characteristics and contextual factors (e.g., type of DBDM intervention, duration, impact, frequency and intensity of educators' engagement, use of a framework to inform the intervention), barriers and facilitators to engagement, and results of any formal assessment of engagement (e.g., attitudes, beliefs, knowledge, benefits, students outcomes, and unintended consequences). A thematic analysis was undertaken using NVivo.

Article 2: Data-Based Decision Making in Online Classes: Exploring Current Practices and Prevailing Determinants

This study is based on an exploratory sequential mixed methods design to examine the extent to which teachers use data while teaching online courses in Ontario secondary schools, and the factors that influence their use of DBDM for instructional practices. A quantitative survey was first administered to 102 teachers (92 English-speaking and 10 French-speaking), followed by eight qualitative interviews to refine and expand the findings. Teachers were recruited directly through their school boards and through the Secondary Schools Teachers Federation. Alternative recruitment methods were also employed, such as social media posts, particularly for French-language teachers, due to ongoing labor action.

The survey instrument was developed using validated questions from prior research (Dunn et al., 2013; Moussavi et al., 2020; Schildkamp et al., 2017; Wayman et al., 2016) and covered nine themes, as demonstrated in the conceptual framework in Figure 1, including data use, leadership, support, collaboration, access, data quality, DBDM anxiety, efficacy, and perceptions. A semi-structured interview guide, informed by quantitative results, facilitated a deeper exploration of emerging themes. Quantitative data analysis was conducted in STATA, utilizing Spearman correlation and regression analysis to examine relationships between DBDM determinants and data usage. Factor analysis and binary variable comparisons ensured robustness. Qualitative data were analyzed through thematic analysis, combining deductive and inductive coding to identify patterns in participant experiences with data use. This mixed methods approach provided a comprehensive understanding of the contextual factors influencing

DBDM practices in online secondary education, while ensuring data triangulation for greater validity and depth of analysis.

Article 3: Exploring Secondary Teachers' Needs for Effective Data Use in Ontario's Online Classrooms

This study is also based on an explanatory sequential mixed methods design and sought to assess the professional development needs of Ontario online secondary school teachers in incorporating DBDM into their instructional practices. By identifying gaps between current practices and the best practices outlined in the literature, the study examines the barriers and enablers influencing participant engagement with data-informed instruction. The dataset used in the second article was collected using the same data collection instruments as the second study. This study specifically focused on four core DBDM competencies: data identification, data interpretation, instructional application, and data tools efficacy. Quantitative analysis involved descriptive statistics to categorize participant self-reported competencies, while qualitative data from open-ended survey responses and interviews were analyzed using thematic analysis with NVivo. The findings were synthesized providing targeted recommendations for professional development and institutional support to enhance DBDM capabilities among online secondary educators.

References

Abdusyakur, I., & Poortman, C. L. (2019). Study on data use in Indonesian primary schools. *Journal of Professional Capital and Community*, *4*(3), 198–215. https://doi.org/10.1108/JPCC-11-2018-0029

Biesta, G. (2010). Pragmatism and the philosophical foundations of mixed methods research. In A. Tashakkori & C. Teddlie (2nd ed.), *SAGE handbook of mixed methods in social & behavioral research* (p.p. 95–118). SAGE Publications, Inc. https://doi.org/10.4135/9781506335193.n4

Breakspear, S. (2014). How does PISA shape education policy making? Why how we measure learning determines what counts in education. In *Centre for Strategic Education Seminar Series Paper* (Vol. 40).

Capps, J. (2019). The pragmatic theory of truth. In E. N. Zalta (Eds.), *The Stanford Encyclopedia of Philosophy*. Retrieved from https://plato.stanford.edu/entries/truth-pragmatic/.

Carlson, D., Borman, G. D., & Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis*, *33*(3), 378–398. https://doi.org/10.3102/0162373711412765

Carrier, L. L., & Whaland, M. (2018). Left behind by policy: A case study of the influence of high stakes accountability policy on data-based decision making in one small, rural New Hampshire school. *The Rural Educator*, *38*(3), 12–26. https://doi.org/10.35608/ruraled.v38i3.217

Castañeda, L., & Selwyn, N. (2018). More than tools? Making sense of the ongoing digitizations of higher education. *International Journal of Educational Technology in Higher Education*, *15*(1), 22.

Chalhoub-Deville, M. (2016). Validity theory: Reform policies, accountability testing, and consequences. *Language Testing*, *33*(4), 453–472. https://doi.org/10.1177/0265532215593312

Cheng, L. (1999). Changing assessment: Washback on teacher perspectives and actions. *Teaching and Teacher Education, 15*(3), 253–271.

Cheng, L., & Curtis, A. (2004). Washback or backwash: A review of the impact of testing on teaching and learning. In L. Cheng, Y. Watanabe, & A. Curtis (Eds.), *Washback in language testing: Research contexts and methods* (pp. 3–17). Mahwah, NJ: Lawrence Erlbaum.

Choo, C. W. (2016). Pragmatist views of knowledge. In *The inquiring organization: How organizations acquire knowledge and seek information* (1–21). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199782031.003.0003

Creswell, J. W. (2012). Mixed methods designs. In *Educational research: Planning, conducting, and evaluating quantitative and qualitative research* (4th ed.). Saddle River, USA: Pearson Education.

Dale, R. (2005). Globalisation, knowledge economy and comparative education. *Comparative Education*, *41*(2), 117–149. https://doi.org/10.1080/03050060500150906

Datnow, A. & Hubbard, L. (2015). Teachers' use of assessment data to inform instruction: Lessons from the past and prospects for the future. *Teachers College Record (1970)*, *117*(4), 1–26. https://doi.org/10.1177/016146811511700408

DeLuca, C., LaPointe-McEwan, D., & Luhanga, U. (2016b). Teacher assessment literacy: A review of international standards and measures. Educational Assessment, Evaluation and Accountability, 28(3), 251–272. https://doi.org/10.1007/s11092-015-9233-6.

Dunn, K. E., Airola, D. T., Lo, J., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology*, *38*(1), 87–98.

Faber, J., Glas, C., & Visscher, A. J. (2018). Differentiated instruction in a data-based decision-making context. *School Effectiveness and School Improvement*, *29*(1), 43–63. https://doi.org/10.1080/09243453.2017.1366342

Farhadi, B., & Winton, S. (2024). E-Learning for the Public Good? The Policy Trajectory of Online Education in Ontario, Canada. *Educational Policy (Los Altos, Calif.)*, *38*(7), 1676–1712. https://doi.org/10.1177/08959048241267953

Gilliard, C., & Culik, H. (2016). Digital redlining, access, and privacy. *Common sense education*, *24*.

Hawn, M. A. (2019). *Data-wary, value driven: Teacher attitudes, efficacy, and online access for data-based decision making*. ProQuest Dissertations Publishing.

Heinrich, C., & Good, A. (2018). Research-informed practice improvements: Exploring linkages between school district use of research evidence and educational outcomes over time. *School Effectiveness and School Improvement*, *29*(3), 418–445. https://doi.org/10.1080/09243453.2018.1445116

Hoogland, I., Schildkamp, K., van der Kleij, F., Heitink, M., Kippers, W., Veldkamp, B., & Dijkstra, A. M. (2016). Prerequisites for data-based decision making in the classroom: Research evidence and practical illustrations.*Teaching and Teacher Education*, *60*, 377–386.

Hull, P., & Vígh, T. (2025). Teachers' assessment literacy: A descriptive literature review. *Hungarian Educational Research Journal*, *15*(2), 210-225.

Kelly, A., & Downey, C. (2011). Professional attitudes to the use of pupil performance data in English secondary schools. *School Effectiveness and School Improvement*, *22*(4), 415–437.[https://doi.org/10.1080/09243453.2011.600525](https://doi.org/10.

Kempf, A. (2015). *The pedagogy of standardized testing: The radical impacts of educational standardization in the US and Canada*. Springer.

Keuning, T., van Geel, M., Visscher, A., & Fox, J. P. (2019). Assessing and Validating Effects of a Data-Based Decision-Making Intervention on Student Growth for Mathematics and Spelling. *Journal of Educational Measurement*, *56*(4), 757–792. https://doi.org/10.1111/jedm.12236

Lai, M. K., & McNaughton, S. (2016). The impact of data use professional development on student achievement. *Teaching and Teacher Education*, *60*, 434–443. https://doi.org/10.1016/j.tate.2016.07.005

Lai, M. K., Wilson, A., McNaughton, S., & Hsiao, S. (2014). Improving achievement in secondary schools: Impact of a literacy project on reading comprehension and secondary school qualifications. *Reading Research Quarterly*, *49*(3), 305–334. https://doi.org/10.1002/rrq.73

Maier, U. (2010). Accountability policies and teachers' acceptance and usage of school performance feedback - A comparative study. *School Effectiveness and School Improvement*, *21*(2), 145–165. https://doi.org/10.1080/09243450903354913

Malin, J., & Brown, C. (2019). What we want, why we want it: K-12 educators' evidence use to support their grant proposals. *International Journal of Education Policy and Leadership*, *15*(3), (1-19). https://doi.org/10.22230/ijepl.2019v15n3a837

Marsh, J. A. (2012). Interventions promoting educators' use of data: Research insights and gaps. *Teachers College Record*, *114*(11), 1–48.

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). Making sense of data-driven decision making in education (1-18). In *Policy File*. RAND Corporation.

Ministry of Education. (2024). Online and remote learning. Retrieved from: https://www.ontario.ca/document/ontario-schools-kindergarten-grade-12-policy-and-program-requirements-2024/online-and-remote-learning

Moussavi, M., Amannejad, Y., Moshirpour, M., Marasco, E., & Behjat, L. (2019). Importance of data analytics for improving teaching and learning methods. In *Data Management and Analysis* (pp. 91–101). Springer International Publishing. https://doi.org/10.1007/978-3-030-32587-9_6

Niemann, D., Martens, K., & Teltemann, J. (2017). PISA and its consequences: Shaping education policies through international comparisons. *European Journal of Education*, *52*(2), 175–183. https://doi.org/10.1111/ejed.12220

Nilsen, P. (2015). Making sense of implementation theories, models and frameworks. *Implementation Science*, *10*(1), 1–13. https://doi.org/10.1186/s13012-015-0242-0

Omoso, E., Schildkamp, K., & Pieters, J. (2019). Data use in Kenyan secondary schools. *Journal of Professional Capital and Community*, *4*(3), 216–231. https://doi.org/10.1108/JPCC-11-2018-0027

Ontario. (2020). Ontario moving to standardized online testing for students. Retrieved from: https://news.ontario.ca/en/release/58493/ontario-moving-to-standardized-online-testing-for-students.

Ontario Ploicy (2025). Education Ontario Policy and program memorandum. Retrieved from https://www.ontario.ca/document/education-ontario-policy-and-program-direction/policyprogram-memorandum-164

Pagan, S., Magner, K., & Thibedeau, C. (2019). Supporting data-driven decision making in a Canadian school district. *Int. J. Digit. Soc, 10*, 1510-1515.

Rangel, V. S., Bell, E. R., & Monroy, C. (2017). A descriptive analysis of instructional coaches' data use in science. *School Effectiveness and School Improvement*, *28*(2), 217–241. https://doi.org/10.1080/09243453.2016.1255232

Sahlberg, P. (2011). PISA in Finland: An education miracle or an obstacle to change?. *Center for Educational Policy Studies Journal*, *1*(3), 119–140. Retrieved from https://doaj.org/article/ec67f2da9a3c4f78abd4077a3dd8de13

Saleh, A. (2021). The effectiveness of differentiated instruction in improving Bahraini EFL secondary school students in reading comprehension skills. *REiLA*, *3*(2), 135–145. https://doi.org/10.31849/reila.v3i2.6816

Schildkamp, K., Poortman, C., & Handelzalts, A. (2016). Data teams for school improvement. *School Effectiveness and School Improvement*, *27*(2), 228–254. [https://doi.org/10.1080/09243453.2015.1056192](https://doi.org

Schildkamp, K., Poortman, C., Luyten, H., & Ebbeler, J. (2017). Factors promoting and hindering data-based decision making in schools. *School Effectiveness and School Improvement*, *28*(2), 242–258. https://doi.org/10.1080/09243453.2016.1256901

Singer, J., Braun, H., & Chudowsky, N. (2018). *International education assessment*. Washington, DC: National Academy of Education.

Spring, J. (2009). *Globalization of education: An introduction*. New York: Routledge.

Sun, J., Przybylski, R., & Johnson, B. J. (2016). A review of research on teachers' use of student data: from the perspective of school leadership. *Educational Assessment, Evaluation and Accountability*, *28*(1), 5–33.https://doi.org/10.1007/s11092-016-9238-9

Tasaki, N. (2017). The impact of OECD-PISA results on Japanese educational policy. *European Journal of Education*, *52*(2), 145–153. https://doi.org/10.1111/ejed.12217

Taut, S. & Palacios, D. (2016). Intended and unintended interpretations and uses of PISA results: A consequential validity perspective. RELIEVE, 22 (1), art. M8.

Tayem, A., & Bourgeois, I. (2025). Data-based decision-making by teachers in K-12 schools: A scoping review. *Canadian Journal of Learning and Technology 50*(3), 1–23.

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Annals of Internal Medicine*, *169*(7), 467- 485. https://doi.org/10.7326/M18-0850

Tsai, Y., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *50*(6), 2839–2854. https://doi.org/10.1111/bjet.12846

van Geel, M., Keuning, T., Visscher, A., & Fox, J. (2019). Changes in educational leadership during a data-based decision making intervention. *Leadership and Policy in Schools*, *18*(4), 628–647. https://doi.org/10.1080/15700763.2018.1475574

van Geel, M. J. M., Keuning, T., Visscher, A. J., & Fox, G. J. (2016). Assessing the effects of a school-wide data-based decision-making intervention on student achievement growth in primary schools. *American Educational Research Journal*, *53*(2), 360–394. https://doi.org/10.3102/0002831216637346

van Geel, M., Visscher, A. J., & Teunis, B. (2017). School characteristics influencing the implementation of a data-based decision making intervention. *School Effectiveness and School Improvement*, *28*(3), 443–462. https://doi.org/10.1080/09243453.2017.1314972

Villani, M. (2018). The production cycle of PISA data in Brazil. *Sisyphus*, *6*(3). https://doi.org/10.25749/sis.15100

von Davier, M., Gonzalez, E., Kirsch, I., & Yamamoto, K. (2013). *The role of international large-scale assessments: Perspectives from technology, economy, and educational research* (1st ed. 2013.). https://doi.org/10.1007/978-94-007-4629-9

Wayman, J. C., Wilkerson, S. B., Cho, V., Mandinach, E. B., & Supovitz, J. A. (2016). Guide to using the Teacher Data Use Survey. REL 2017-166. Regional Educational Laboratory Appalachia.

Ylimaki, B., & Brunderman, L., (2019). School development in culturally diverse U.S. schools: Balancing evidence-based policies and education values. *Education Sciences*, *9*(84), 1–15. https://doi.org/10.3390/educsci9020084

Chapter Two: Data-Based Decision Making by Teachers in K-12 Schools: A Scoping Review

Abstract

Despite the widespread adoption of data-based decision making (DBDM) policies in schools around the world, there is limited understanding of how teachers use DBDM in K-12 classrooms and the impact of DBDM training on teacher practices and student outcomes. This scoping review aims to provide an overview of the existing literature on the uses of DBDM by teachers globally and identify gaps in the field. The findings (a) highlight a geographical and temporal clustering, with a notable emphasis on studies conducted in the United States and the Netherlands and published in 2016–2017 and 2020–2022; (b) identify a gap in the literature, particularly in the context of online and secondary schools, where the predominant focus has been on elementary and in-person settings; and (c) suggest that although DBDM interventions have been found helpful in altering teacher practices and student outcomes, there is still a need for more sustainable support to enhance DBDM implementation. The study concludes with recommendations for future DBDM research, building on implications from previous interventions.

***Keywords*:** data-based decision making, K-12 education, teacher practices, student outcomes

La prise de décision fondée sur les données par les enseignants dans les écoles primaires et secondaires : Examen de la portée

Résumé

Malgré l'adoption généralisée des politiques de prise de décision fondée sur les données probantes (PDDP) dans les écoles à travers le monde, peu d'information est disponible au sujet de l'utilisation de la PDDP par les enseignants œuvrant aux paliers primaire et secondaire, ainsi que sur l'impact de la formation en PDDP sur le comportement des enseignants et les résultats scolaires. Cette recension exploratoire vise à fournir un aperçu des écrits actuels sur les usages de la PDDP par les enseignants à l'échelle mondiale et à identifier les lacunes dans le domaine. Les résultats mettent en évidence les points suivants : (a) les études réalisées jusqu'à présent peuvent être groupées de manière géographique et temporelle, et ont surtout été réalisées aux États-Unis et aux Pays-Bas; de plus la majorité des études ont été publiées en 2016-2017 et 2020-2022 ; (b) il existe des lacunes importantes dans les écrits actuels, notamment par rapport au contexte des écoles en ligne et secondaires - les études actuelles reflètent davantage un intérêt pour les écoles élémentaires et les contextes d'études en présentiel ; et (c) les études recensées suggèrent que, bien que les interventions relatives à la PDDP se soient révélées utiles pour modifier les pratiques des enseignants et les résultats scolaires, les enseignants ont besoin d'un soutien plus durable pour améliorer la mise en œuvre de la PDDP. Enfin, l'article fournit des recommandations pour la recherche sur la PDDP, en s'appuyant sur les conclusions des interventions précédentes.

Mots-clés : prise de décision fondée sur les données probantes, éducation primaire et secondaire , pratiques enseignantes , résultats des élèves

Introduction

Educational technology developments over the past two decades have resulted in increased amounts of data available to decision-makers and innovative ways of utilizing them, particularly in the kindergarten through Grade 12 (K-12) context (Behrens et al., 2018; Datnow & Hubbard, 2015). Edtech tools, such as learning management systems, adaptive learning platforms, and digital assessments, generate vast amounts of data about student learning behaviours, engagement, and performance. These technologies afford educators real-time access to detailed information about student progress, which allows for more personalized instruction and timely interventions (Weller, 2020). In addition, they facilitate the collection of data that can be used not only for student assessment but also for pedagogical decision-making, helping teachers make data-driven improvements to their teaching practices.

In education, data-based decision making (DBDM) refers to the use of empirical evidence to inform educational policies, practices, and decisions (Schildkamp & Ehren, 2013). At its core, DBDM involves the systematic collection, examination, and utilization of various types of educational data (e.g., summative and formative assessments, behavioural data, attendance records, demographic information, to-class and homework assignments, classroom observations, etc.), with a primary objective of enhancing student performance and tailoring educational strategies to meet their individual needs (Marsh et al., 2006; Marsh, 2012). Through the analysis of such data, educators can pinpoint areas where students require additional support, adapt instructional strategies, and implement targeted interventions (Carlson et al., 2011; Faber et al., 2018; Heinrich & Good, 2018; Tsai et al., 2019).

The adoption of DBDM has gained global attention, recognizing its significance in ensuring accountability and driving effective decision-making (Cheng, 1999; Cheng & Curtis, 2004; Maier, 2010). On an international scale, numerous interventions and policies have been implemented to encourage teachers and school leaders to embrace DBDM in conducting well-informed, high-quality decisions. Some of these interventions have focused on specific schools or districts such as the AZiLDR model in Arizona (Ylimaki & Brunderman, 2019), Instructional Coaches in Texas (Rangel et al., 2017), and The Learning Schools Model in New Zealand (Lai et al., 2014). Others have been larger in scope and involved nationwide efforts, such as the Focus Intervention, a 2-year training project in the Netherlands through which all primary school teachers in Dutch public schools were trained on using DBDM to improve their teaching methods (van Geel et al., 2016a). The goal of these interventions, regardless of their scope, is to equip teachers with the knowledge and abilities necessary to implement and sustain DBDM. However, due to policies that caused high accountability pressure in some education systems around the world, such as the *No Child Left Behind Act* in the United States (Kempf, 2015), mandatory test-based school accountability policies in Germany (Maier, 2010), Ofsted Inspections and League Tables in the United Kingdom (Schildkamp et al., 2017), and the Education Quality and Accountability Office assessments in Ontario, Canada (Kempf, 2015), the focus of DBDM interventions has mainly been on the use of data from standardized assessments to demonstrate school accountability rather than to enhance the teaching and learning experience (Kempf, 2015).

This scoping review aims to examine comprehensively the landscape of DBDM in the K-12 context for instructional purposes by including studies that assess established interventions targeting the use of data by teachers at the classroom level, as well as how, and the extent to which, teachers use data in their daily practice to inform their instruction. A scoping review was chosen because it is well-suited to mapping a broad and diverse body of literature, offering a comprehensive overview of the topic across various methodologies and contexts. This approach helps identify research gaps and provides a global perspective on the impact of DBDM. However, given that some of the studies included can lack quality and/or methodological rigour, scoping reviews can be challenging. Additionally, although scoping reviews are effective for identifying trends and gaps in the literature, they do not offer in-depth analyses of individual studies, which can limit the researcher's ability to draw detailed conclusions about specific interventions or outcomes. Despite these challenges, a scoping review is ideal for answering the following research questions: 1. How do teachers around the world engage in DBDM for instructional purposes? 2. To what extent do DBDM interventions influence teachers' instructional practices and student outcomes?

Methods

The review follows PRISMA-ScR guidelines (Tricco et al., 2018) to systematically map evidence, identify key concepts, and uncover knowledge gaps. This framework ensured a rigorous approach to searching, screening, and selecting articles on data use for decision-making in K-12 education.

Article Search and Screening Process

With the assistance of a university librarian, a comprehensive search across four electronic databases was conducted (i.e., *Education Source*, *ERIC*, *Web of Science*, and *Academic Search Complete*). Keywords and controlled vocabulary related to the research question were used as illustrated in Table 1.

Table 1

Keywords and Controlled Vocabulary Used in the Search

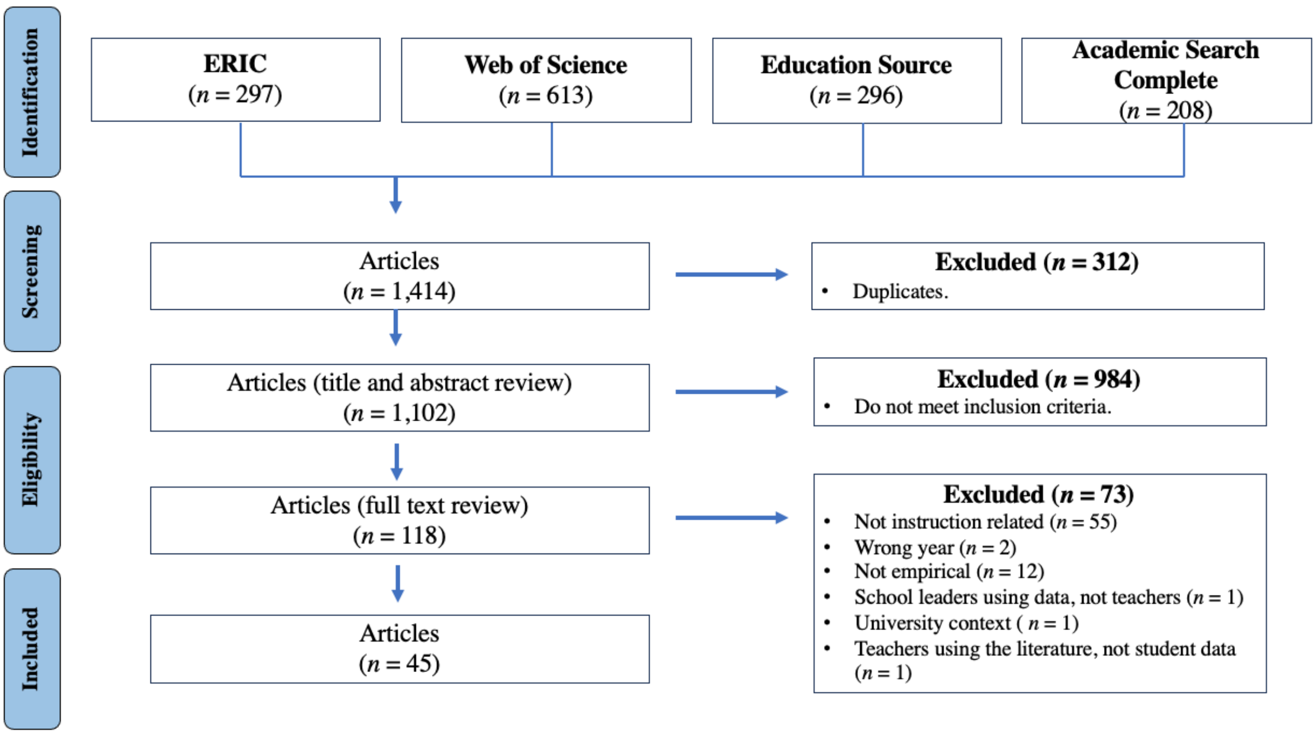
Criteria	**Search Words**
Context 1	Data use/ or data-based decision making/ or data-driven decision making/ or learning analytics
Context 2	K-12/ or schools/ or elementary schools/ or middle schools/ or private schools/ or public schools/ or secondary schools/ elementary school students/ or middle school students/ or secondary school students/ secondary school teachers/ or public school teachers/ or elementary school teachers/ or high school teachers/ or junior high school teachers/ or middle school teachers/ (school* or kindergarten*).ti,ab

Note. Key terms were searched in article titles and abstracts using the ti,ab field code to ensure relevance and precision in the result

To be included in the review, studies had to be conducted in K-12 settings and published in English between 2013 and 2023. Studies also needed to explore how teachers use data to improve teaching practices and make pedagogical decisions at the classroom level. Studies examining data use by school leaders, districts, or for purposes other than teaching improvement, such as accountability, were excluded. The initial search identified 1,414 articles, with 312 duplicates removed. Interrater reliability was ensured through independent screening of 5% of the articles, showing a 92% agreement. Discrepancies were resolved through follow-up discussions. Following the Search Process Flow diagram (Tricco et al., 2018), 984 articles were excluded as they did not meet the inclusion criteria. Additionally, 73 articles were excluded during the screening process for the following reasons: 55 were not instruction-related, two were published in the wrong year, 12 were not empirical, one focused on school leaders' use of data rather than by teachers, one was set in a university context, and two involved teachers using literature rather than student data. Ultimately, 45 articles were selected for data extraction (Figure 1).

Figure 1

PRISMA-ScR Diagram



Note. Adapted from Tricco et al. (2018).

Data Extraction Process

For a systematic and flexible data extraction process, a template was developed to capture comprehensive information that included article identifiers and overview, context of the study, DBDM intervention details, and outcomes of the intervention (Table 2).

Table 2

Elements in the Data Extraction Template

Variables	Detailed Elements
Article identifiers	author, title, journal, year

Context of the study	country, subject matter, teaching environment (i.e., online/in-person), grade level
Aim and research design	aim of the study, number of teachers, number of students, research design
DBDM intervention details	intervention type, sources of data used by teachers, previous DBDM professional development, duration of the intervention, reported outcome on teacher practices, reported outcome on student's academic performance, implications regarding training or challenges

This review has several limitations. It includes English-language studies only, potentially missing relevant research published in other languages. Additionally, the review's data, gathered in June 2023, may not cover the most recent studies, particularly those on online learning published after that date. Finally, the focus was primarily on the effects of DBDM interventions on teacher practices and student outcomes, possibly overlooking other variables like school culture and leadership support that might impact intervention effectiveness.

Findings

To provide succinct responses to the two research questions, the findings are organized into two main sections. First, an overview of the research on DBDM will provide key contextual elements that describe the body of studies included as part of the review, and second, a more in-depth analysis of the findings of the included studies will focus on the effects of DBDM interventions on teaching practices.

Geographical and Temporal Concentration of Studies Review

To understand the evolving landscape of DBDM, a critical examination of the included studies reveals a notable concentration of research in the United States (62%) and the Netherlands (25%), clustered around two key periods: 2016–2017 and 2020–2022. Although countries such as Canada, Denmark, Germany, Indonesia, and Spain also contributed to the advancement of research in this field, with almost 13% combined, their collective efforts did not exhibit the same level of magnitude, reflecting a more limited engagement with DBDM in schools. Figure 2 shows the distribution of studies by country and Figure 3 displays their temporal distribution.

Figure 2

Geographical Distribution of Studies Reviewed

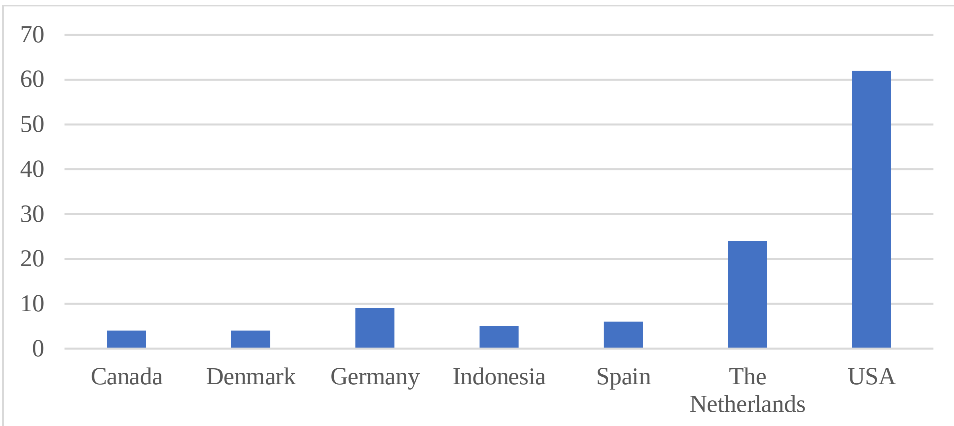
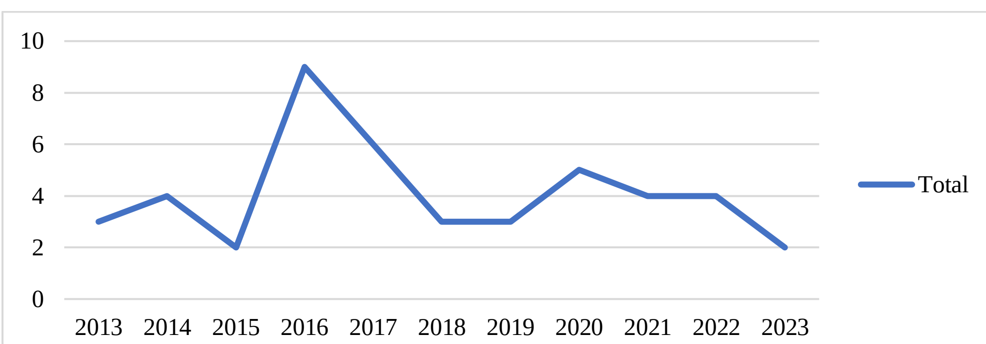


Figure 3

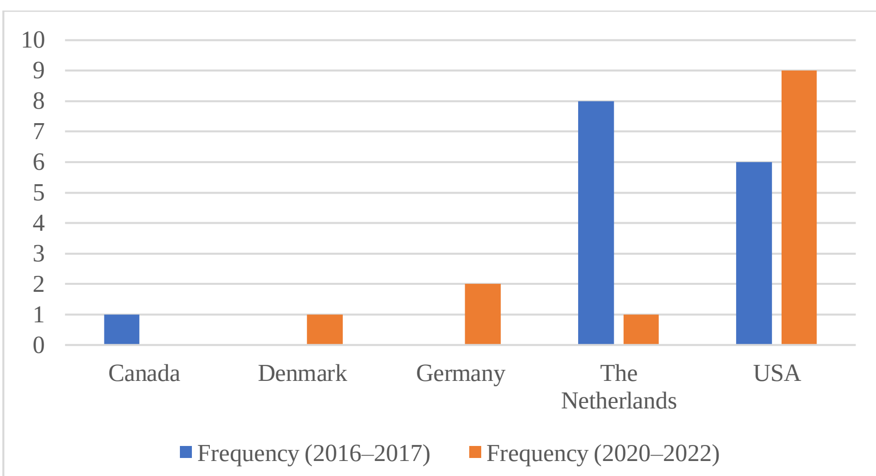
Temporal Concentration of Studies on Teachers' Use of DBDM for Instructional Purposes Published Worldwide (2013 –2023)



As can be seen in Figure 4, the findings demonstrate that during the first period (2016–2017), both the USA and the Netherlands are the leading countries by the number of research studies conducted within this timeframe. However, a notable shift is observed in subsequent years with a decline in research efforts in the Netherlands and a small increase in the USA, which retained its lead in this field. The number of research articles in each country could be an indicator of DBDM institutional support, educational priorities, and the integration of DBDM into teaching practices. For example, the higher research output in the USA may suggest a stronger emphasis on studying and implementing DBDM for instructional practices, supported by policies, funding, and professional development. In contrast, the decline in research in the Netherlands could indicate a reduced focus or prioritization of DBDM, possibly pointing to less frequent use or investigation of these practices among teachers.

Figure 4

Number of Studies Addressing Teacher Utilization of Data to Improve Teaching Practices in 2016–2017 and 2020–2022



Educational Setting

A number of factors related to the educational setting within which DBDM interventions took place were examined as part of the review; these include the specific grade levels targeted by DBDM initiatives, and the online or in-person contexts that influenced the design and implementation of these initiatives.

Grade Level. Most of the studies reviewed (71%; n = 32) were conducted in elementary schools that include Grades 1 to 8. In addition to these, approximately 18% of the studies reviewed (n = 8) were conducted in K-12 schools. Although categorized separately, K-12 schools overlap significantly with elementary schools. The focus on the elementary context in the reviewed studies emphasizes the potential role played by DBDM in primary schooling; however, this emphasis also raises questions about the lack of attention given to DBDM interventions conducted in Grades 9 through 12. As seen in Table 3, these studies account for only 11% of the studies reviewed (n = 5).

Table 3

Studies Investigating Teacher Data Utilization to Improve Teaching Practices in Each Grade Level

Grade/School Level	Frequency	Percentage	Cumulative
Elementary	32	71.11	71.11
K-12	8	17.78	88.89
Secondary/High school	5	11.11	100.00
Total	45	100.00	

In-Person vs. Online Context. This scoping review included studies conducted within traditional, in-person educational settings. While a handful of these studies (i.e., Admiraal et al., 2020; Campos et al., 2021; Peters et al., 2021; Regan et al., 2023; Truckenmiller et al., 2022) included learning analytics and computer-based assessment methods, it should be noted that these advancements were implemented within a conventional classroom environment. Furthermore, these studies are relatively recent, potentially indicating a recent surge in technology-assisted educational data use within traditional in-person classrooms. This focus on in-person contexts underscores an important gap in understanding how teachers use DBDM in other modalities such as online or hybrid learning environments.

Teacher Engagement with DBDM for Instructional Purposes

More than half of the studies reviewed (*n* = 25) focused on teacher engagement with DBDM for instructional purposes, highlighting four main themes. Most studies (*n* = 14) examined teachers' data literacy skills, which showcase varying proficiency levels in using data to inform instruction, directly addressing how teachers engage with DBDM (e.g., Gelderblom et al., 2016, Ho, 2022; Hoover & Abrams, 2013; van den Bosch et al., 2017). Five studies focused on data accessibility and types of data available, which demonstrate that easy access to relevant data enhances instructional decision-making (e.g., Abdusyakur & Poortman, 2019; Admiraal et al., 2020; Farley-Ripple et al., 2019). Three studies explored teachers' perceptions and self-efficacy regarding DBDM, showing that confidence and attitudes influence data use (e.g., De Simone, 2020; Reed, 2015). Lastly, five studies identified factors that facilitate or hinder DBDM, offering insights into the contextual barriers and supports that affect its implementation (e.g., Abdusyakur & Poortman, 2019; Copp, 2017; Schildkamp et al., 2017).

Impact of DBDM on Instructional Practices and Student Outcomes

The main purposes of DBDM are to support the improvement of instructional practices as well as student outcomes. As shown in Table 4, 20 studies focused on evaluating these potential impacts in a variety of different interventions. The studies can be classified according to the length or duration of the DBDM intervention evaluated, the extent to which participants had received professional development (PD) related to data use prior to the evaluated interventions, and the sources of data used by teachers.

Table 4

DBDM Interventions Overview

Year	Study	Intervention	Duration	PD	Data Source	Change in Teacher practices	Change in Student Outcome
2013	Dunn et al.	Statewide Professional Development Program: Aims to increase teacher use of DBDM in a Pacific Northwestern state. The intervention was evaluated using the Data-Driven Decision-Making Efficacy and Anxiety **(**3D-MEA) inventory.	< 1 y	Yes	Different sources	N	NT
2014	Schifter et al.	The Using Data Workshop: Offers a workshop to help teachers interpret and use data from project dashboards, with a focus on professional development during summer institutes.	< 1 y	Yes	Learning analytics	P	NT
	Staman et al.	The Focus Intervention: A 2-year training course for primary school teams aimed at acquiring knowledge and skills related to DBDM for instructional purposes.	2 y	Yes	Student Assessment	P	NT
2015	Marsh et al.	Coaching and PLC Intervention: Combines coaching and professional learning communities to support teachers in data utilization.	1 y	Yes	Student Assessment	P	NT
2016	Christman et al.	The Linking Intervention: focuses on teacher learning about mathematics instruction, and aims to	1 y	Yes	Student Assessment	P	NT

		elevate data utilization practices.					
	Curry et al.	Data-Informed Instructional Model: provides K-12 teachers with a model for data-informed instruction, which enhances teaching and learning at the classroom level.	1 y	NM	Different sources	P	H
	Ebbeler et al.	Teams Intervention: Forms teams of teachers and teacher leaders to create a community of practice focused on using data to enhance instruction.	2 y	Yes	Different sources	P	NT
	van der Scheer et al.	DBDM Intervention for Grade 4 Math Teachers: focused on data-based decision making for Grade 4 math teachers.	1 y	Yes	Student Assessment	P	H
	van Geel et al.	The Focus Intervention: A two-year training course for primary school teams aimed at acquiring knowledge and skills related to DBDM for instructional purposes.	2 y	Yes	Student Assessment	NT	H
2017	Staman et al.	DBDM Training for Differentiated Instruction: Trains teachers in DBDM to provide differentiated instruction.	2 y	Yes	Student Assessment	P	NT
	van der Scheer & Visscher	DBDM Intervention for Grade 4 Math Teachers: focused on data-based decision making for Grade 4 math teachers.	1 y	Yes	Student Assessment	P	NT
2018	Faber et al.	Differentiated Instruction Training: Provides teachers with training to give differentiated instruction to students.	2 y	Yes	Student Assessment	NT	L
2019	Filderman et al. (2019)	Guidelines for DBDM Implementation: Offers guidelines to support effective DBDM implementation for students with or at risk for reading disabilities in secondary grades.	< 1 y	No	Computer adaptive testing	P	NT
2020	Andersen	Data-Informed Evaluation Culture: aims to create a	< 1 y	Yes	Student Assessment	N	NT

		data-informed evaluation culture within participating schools in Denmark through comprehensive data training.					
2021	Campos et al.	Learning Analytics Dashboard Support Intervention: focuses on assisting teachers in utilizing data from a learning analytics dashboard designed to facilitate student collaboration and discussion in mathematics. Its goal is to deepen conceptual understanding in mathematics.	2 y	Yes	Learning analytics	P	NT
	Datnow et al.	Teacher Collaborative Efforts Intervention: seeks to promote students' math achievement by fostering collaborative efforts among teachers to improve instruction, including utilizing relevant data.	4 y	NM	Student Assessment	P	NT
	Peters et al.	Teacher Training in Differentiated Instruction: Provides teacher training on differentiating instruction using Learning Progress Assessment (LPA) and Reading Sportsman (RS) materials.	1 y	Yes	Computer adaptive testing	NTR	M
2022	Hebbecker et al. (2022)	DBDM Framework-based Intervention: Based on van Geel et al.'s (2016a) DBDM framework, this intervention assists teachers in decision-making based on data.	4 y	Yes	Student Assessment	P	H
2023	Regan et al.	Technology-based Graphic Organizer Intervention: Utilizes technology-based graphic organizers, online modules, long-range planning, and virtual professional learning community activities to support data utilization.	1 y	Yes	Computer adaptive testing	P	NT
	Rodríguez-Martínez et al.	Personalized Homework Intervention: Assists teachers in using Learning Analytics (LA) to personalize students'	< 1 y	No	Computer adaptive testing	NT	H

	homework based on formative assessment results.	

Note. PD=Professional Development; NM=Not Mentioned, Teacher behaviour (P = Positive, N = Negative, NTR = Neutral, NT = Not tested); Student outcome (H = High, M = Moderate, L = Low, NT = Not tested

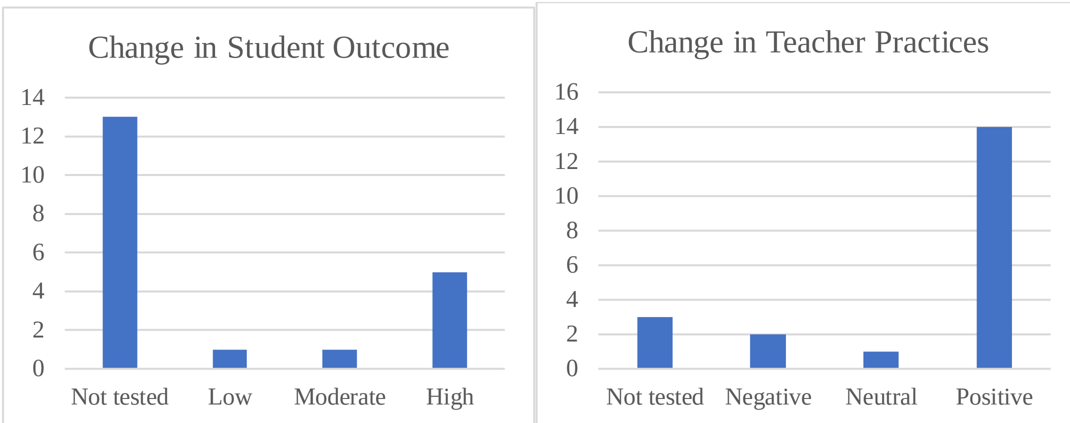
Duration and Previous Professional Development. The interventions included in the studies reviewed range from a condensed one-session professional development workshop (e.g., Schifter et al., 2014) to a 4-year program (e.g., Hebbecker et al., 2022). To gain a clearer understanding of this dimension, interventions were categorized based on their duration (Table 4). Most interventions were conducted within one to two academic years (*n* = 13). A notable subset of interventions lasted less than 1 year (*n* = 5), while only two interventions, one in the Netherlands (Hebbecker et al., 2022) and one in the US (Datnow et al., 2021), took place over a comprehensive 4-year period. The findings also demonstrate that in 16 out of the 20 interventions, teachers had some level of data literacy training prior to the DBDM professional development. For two of the remaining four interventions, it was undetermined whether teachers had prior data literacy training rather than a definitive absence of such training.

Sources of Data Used by Teachers. More than half of the studies reviewed (*n* = 11) indicated that the main source of data used by teachers as part of the DBDM intervention was generated through student assessment, and four additional studies used assessment data from computer adaptive testing. Other studies also featured learning management systems as a source of data (*n* = 2) or different sources (*n* = 3).

Impact of DBDM Interventions. The impacts of DBDM interventions on instructional practices employed by teachers as well as on student outcomes were assessed in the 20 evaluative studies reviewed. DBDM interventions were assessed as having a “positive” impact on instructional practices if the study findings included one of the following elements: (a) increased emotional, analytical, and/or intentional data sensemaking and data literacy skills; (b) increased or enhanced discussions amongst colleagues on data use and the creation of professional learning communities; (c) instructional adjustments using data; (d) capacity-building for DBDM; (e) increased teacher awareness of data use for school development and instruction; or (f) changes in teacher efficacy related to implementing instructional strategies. The impact of the DBDM interventions on instructional practices was assessed as "neutral" if teachers maintained the same level of data use, and was assessed as "negative" if the intervention did not contribute to the development of new skills or positive attitudes related to DBDM. In some studies, no change in teacher practices was measured, as the focus was solely on student outcomes. The impact of the DBDM interventions on student outcomes was also examined within the 20 evaluative studies. These impacts were considered "high" if the DBDM intervention resulted in: (a) increased student understanding of the learning materials; (b) increased student motivation and engagement; or (c) improved scores on standardized tests. DBDM impacts were considered "moderate" if after the intervention: (a) students recognized the importance of setting challenging learning goals; or (b) there was a small positive effect on student achievement in standardized tests. Lastly, the impact was considered "low" if no evident positive effects were found on student outcomes. In some studies, however, no measurement of student outcomes was included, as the focus was solely on changes in teacher practices.

Figure 5

The Impact of DBDM Interventions on Instructional Practices and Student Outcomes



As illustrated in Figure 5, the number of studies that evaluated the impact of DBDM interventions on instructional practices (*n* = 17) is higher than those focusing on student outcomes (*n* = 7). However, in both dimensions, the positive impacts of DBDM on instructional practices and the high impact of the interventions on student outcomes were more commonly found than neutral/moderate or negative/low impacts. Moreover, most of the reviewed studies evaluated the impact of a DBDM intervention on one of the two dimensions; studies that explored the effect of DBDM interventions on both teachers and students were less common (i.e., Curry et al., 2016; Hebbecker et al., 2022; Peters et al., 2021; van der Scheer et al., 2016).

Discussion and Implications

This scoping review offers a comprehensive examination of the landscape of DBDM use by teachers in the K-12 context, which addresses geographical and temporal concentrations, educational settings, and the impact of DBDM interventions. This discussion is based on the review of all 45 articles, providing an in-depth analysis of the current state of the field.

Temporal and Geographical Patterns in Research Distribution

Temporal and geographical patterns in research distribution on DBDM shed light on global variations in how teachers engage with data for instructional purposes. Temporal trends reveal how research on teacher engagement aligns with shifts in policies, technologies, and educational reforms, while geographical patterns highlight disparities driven by contextual factors such as access to resources or institutional support (Christman et al., 2016; Curry et al., 2016; Farrell & Marsh, 2016a, 2016b; Michaud, 2016; Park & Datnow, 2017). By comparing regions and time periods, we can identify factors that contributed to DBDM adoption for instructional purposes by teachers at the classroom level. Additionally, gaps in research across certain areas or periods can guide future studies to explore underrepresented contexts, offering a more comprehensive understanding of DBDM's global impact.

The observed concentration of studies in the United States and the Netherlands found in this review aligns with the existing literature, which highlights these countries' efforts in implementing and studying DBDM. The initial surge in articles during 2016–2017 coincides with pivotal policy reforms in the United States (Park & Datnow, 2017) and the Netherlands (Schildkamp et al., 2017), which aimed to reshape the educational landscape, particularly concerning data use and DBDM. Subsequently, a resurgence of research interest appears in the literature during 2020–2022. This period saw an increased focus on technology and computer-based assessment incorporation, which placed DBDM at the forefront of educational change.

First Period (2016–2017). Signed in 2015, the Every Student Succeeds Act marked a shift in US education policy, moving away from high-stakes testing under No Child Left Behind. This Act introduced flexible accountability measures, reduced the emphasis on standardized tests, and encouraged data use for instructional improvement (Shirely, 2017). Research from this period focused on how educators utilized diverse data forms to enhance teaching (e.g., Curry et al., 2016; Park & Datnow, 2017). Similarly, declining student performance in international assessments prompted the adoption of DBDM policies in the Netherlands. Initiatives such as the 'Focus' intervention equipped educators with skills to monitor progress and tailor their instruction according to students' needs, which resulted in improvement in teaching practices and student outcomes (Faber et al., 2018; Schildkamp et al., 2017).

Second Period (2020–2022). Studies published during this period show that teachers started to incorporate technology such as learning analytics and computer-based assessments to collect and analyze data, which reshaped and eased the use of DBDM to support learning (Admiraal et al., 2020; Campos et al., 2021; Truckenmiller et al., 2022). Although the Netherlands saw a decline in research during this period, the DBDM frameworks developed for Dutch schools, such as the Data Teams framework (Schildkamp et al., 2016) and the DBDM process model (van Geel et al., 2016a), created the foundation for subsequent studies. These frameworks have been successfully adopted in various international contexts, including Denmark (e.g., Andersen, 2020), the United States (e.g., Datnow et al., 2018; Michaud, 2016; Ylimaki & Brunderman, 2019), New Zealand (e.g., Lai et al., 2014; Lai & McNaughton, 2016), and Germany (e.g., Hebbecker et al., 2022). However, there is notable limited research on teacher use of DBDM at the classroom level in Canada, with only one relevant study (Copp, 2017) addressing policy incentives and data use across Canadian schools.

Educational Settings

The exploration of educational settings in which DBDM is implemented demonstrates that there is a predominant focus on in-person teaching at the primary/elementary level in the reviewed studies (e.g., Staman et al., 2017; van der Scheer & Visscher, 2017); this raises questions about the extent to which DBDM practices can be adapted to secondary education settings and different learning modalities. Addressing these complexities requires further study to understand the transferability and effectiveness of DBDM strategies at higher grade levels. Moreover, existing literature on online education emphasizes the potential of learning analytics and real-time data to inform personalized instruction (e.g., Behrens et al., 2018; Campos et al., 2021). However, no studies explore how educators can leverage data effectively in an online-learning environment. Thus, there is a need for research that examines the practical integration of DBDM in these educational settings.

Examining the Impact of DBDM Interventions

The findings underscore the importance of tailored interventions and ongoing professional development for effective DBDM implementation. This aligns with Schildkamp et al.'s (2017) DBDM Determinant Model, which highlights three key factors for successful DBDM interventions: organizational context, data characteristics, and user characteristics (Table 5).

Table 5

Determinant Model

	Organization	**Data**	**User**
Enablers and barriers	• Vision and norms • Leadership • Support • Collaboration	• Accessibility of timely data • Usability • Quality of the data	• Knowledge and skills • Dispositions to use data

Note. Schildkamp et al. (2017, p. 244).

Organizational Context: Effective DBDM requires strong leadership support, collaboration, and a clear vision, as Schildkamp et al. (2017) emphasize. Studies in this review address some aspects, such as coaching support (Andersen, 2020), collaboration through communities of practice (Marsh et al., 2015; van Geel et al., 2016b), and leadership (Copp, 2017; Ylimaki & Brunderman, 2019). However, they often overlook the 'vision and norms' of institutions.

Data Characteristics: High-quality, timely, and usable data are crucial for DBDM. While many studies focus on assessment and standardized test data, there is a growing recognition of the need for diverse data sources. Researchers such as Curry et al. (2016), Dunn et al. (2013), and Ebbeler et al. (2016) advocate for a multifaceted data approach, emphasizing that diverse data sources enhance the impact on student outcomes. Even studies focusing on assessment data, such as Datnow et al. (2021) and Faber et al. (2018), highlight the importance of incorporating diverse sources of data.

User Characteristics: The predominant focus in the literature is on enhancing teachers' data literacy and positive attitudes toward data use (e.g., Ebbeler et al., 2016; Staman et al., 2014; van der Scheer & Visscher, 2017). Effective training can improve these characteristics, with longitudinal, well-designed professional development showing positive effects on both teacher practices and student achievement (e.g., Andersen, 2020; Campos et al., 2021; Christman et al., 2016). However, Hebbecker et al. (2022) suggest that even short professional development sessions, combined with practical support and resources, can be sufficient for implementing DBDM effectively.

Although DBDM interventions have been found helpful in altering teacher practices and improving student outcomes, there remains a need for more sustainable and ongoing support to enhance DBDM implementation (Abdusyakur & Poortman, 2019; Admiraal et al., 2020; Staman et al., 2017). Short-term interventions or training programs, although effective in the short run, may not fully address the complexities of integrating DBDM into daily teaching practices (Andersen, 2020; van den Bosch et al., 2017). To ensure lasting change, interventions must prioritize building systemic capacity through continued professional learning opportunities, access to high-quality resources, and institutional support structures (Farley-Ripple et al., 2019; Rodríguez-Martínez et al., 2023). These efforts would enable teachers to embed data use more deeply into their instructional practices, thereby fostering sustained improvements in both teaching and learning outcomes.

Conclusion

This scoping review enhances understanding of DBDM in K-12 schools by examining how teachers use student data to guide their pedagogical and instructional practices. It highlights shifts from using DBDM for accountability to improving instruction (Kempf, 2015; Schildkamp & Ehren, 2013), and identifies gaps such as the need for research at the secondary/high school level and in online-learning contexts. The review also explores the impact of DBDM interventions on teacher practices and student outcomes (Hebbecker et al., 2022; Peters et al., 2021; Rodríguez-Martínez et al., 2023). As educational practices evolve, further research is needed to address gaps in secondary education, online learning, and under-represented geographical areas, aiming for a broader, more global understanding of DBDM trends. By addressing existing research gaps and fostering discussions on its implications, future studies can contribute to a more global and nuanced understanding of DBDM. Such efforts are essential for ensuring that data use in education translates into improved instructional practices and better outcomes for students across diverse contexts.

References

Abdusyakur, I., & Poortman, C. L. (2019). Study on data use in Indonesian primary schools. *Journal of Professional Capital and Community*, *4*(3), 198–215. https://doi.org/10.1108/JPCC-11-2018-0029

Admiraal, W., Vermeulen, J., & Bulterman-Bos, J. (2020). Teaching with learning analytics: How to connect computer-based assessment data with classroom instruction? *Technology, Pedagogy and Education*, *29*(5), 577–591. https://doi.org/10.1080/1475939X.2020.1825992

Andersen, I. G. (2020). What went wrong? Examining teachers' data use and instructional decision making through a bottom-up data intervention in Denmark. *International Journal of Educational Research*, *102*, 101585. https://doi.org/10.1016/j.ijer.2020.101585

Behrens, J., Piety, P., DiCerbo, K., & Mislevy, R. (2018). Inferential foundations for learning analytics in the digital ocean. In D. Niemi, R. D. Pea, B. Saxberg, & R. E. Clark (Eds.), *Learning analytics in education* (pp. 1–48). Information Age Publishing Inc.

Campos, F. C., Ahn, J., DiGiacomo, D. K., Nguyen, H., & Hays, M. (2021). Making sense of sensemaking: Understanding how K-12 teachers and coaches react to visual analytics. *Journal of Learning Analytics*, *8*(3), 60–80.

Carlson, D., Borman, G. D., & Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis*, *33*(3), 378–398. https://doi.org/10.3102/0162373711412765

Cheng, L. (1999). Changing assessment: Washback on teacher perspectives and actions. *Teaching and Teacher Education*, *15*(3), 253–271.

Cheng, L., & Curtis, A. (2004). Washback or backwash: A review of the impact of testing on teaching and learning. In L. Cheng, Y. Watanabe, & A. Curtis (Eds.), *Washback in language testing: Research contexts and methods* (pp. 3–17). Lawrence Erlbaum.

Christman, J. B., Ebby, C. B., & Edmunds, K. A. (2016). Data use practices for improved mathematics teaching and learning: The importance of productive dissonance and recurring feedback cycles. *Teachers College Record*, *118*(11), 1–32.

Copp, D. T. (2017). Policy incentives in Canadian large-scale assessment: How policy levers influence teacher decisions about instructional change. *Education Policy Analysis Archives*, *25*, 115.

Curry, K. A., Mwavita, M., Holter, A., & Harris, E. (2016). Getting assessment right at the classroom level: Using formative assessment for decision making. *Educational Assessment, Evaluation and Accountability*, *28*, 89–104.

Datnow, A., & Hubbard, L. (2015). Teachers' use of assessment data to inform instruction: Lessons from the past and prospects for the future. *Teachers College Record*, *117*(4), 1–26. https://doi.org/10.1177/016146811511700408

Datnow, A., Choi, B., Park, V., & John, E. S. (2018). Teacher talk about student ability and achievement in the era of data-driven decision making. *Teachers College Record*, *120*(4), 1–34.

Datnow, A., Lockton, M., & Weddle, H. (2021). Capacity building to bridge data use and instructional improvement through evidence on student thinking. *Studies in Educational Evaluation*, *69*, 100869.

De Simone, J. J. (2020). The roles of collaborative professional development, self-efficacy, and positive affect in encouraging educator data use to aid student learning. *Teacher Development*, *24*(4), 443–465.

Dunn, K. E., Airola, D. T., Lo, W. J., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology*, *38*(1), 87–98.

Ebbeler, J., Poortman, C. L., Schildkamp, K., & Pieters, J. M. (2016). Effects of a data use intervention on educators' use of knowledge and skills. *Studies in Educational Evaluation*, *48*, 19–31.

Faber, J., Glas, C., & Visscher, A. J. (2018). Differentiated instruction in a data-based decision-making context. *School Effectiveness and School Improvement*, *29*(1), 43–63. https://doi.org/10.1080/09243453.2017.1366342

Farley-Ripple, E. N., Jennings, A. S., & Buttram, J. (2019). Toward a framework for classifying teachers' use of assessment data. *AERA Open*, *5*(4), 2332858419883571.

Farrell, C. C., & Marsh, J. A. (2016a). Metrics matter: How properties and perceptions of data shape teachers' instructional responses. *Educational Administration Quarterly*, *52*(3), 423–462.

Farrell, C. C., & Marsh, J. A. (2016b). Contributing conditions: A qualitative comparative analysis of teachers' instructional responses to data. *Teaching and Teacher Education*, *60*, 398–412.

Filderman, M. J., Austin, C. R., & Toste, J. R. (2019). Data-based decision making for struggling readers in the secondary grades. *Intervention in School and Clinic*, *55*(1), 3–12.

Gelderblom, G., Schildkamp, K., Pieters, J., & Ehren, M. (2016). Data-based decision making for instructional improvement in primary education. *International Journal of Educational Research*, *80*, 1–14.

Hebbecker, K., Förster, N., Forthmann, B., & Souvignier, E. (2022). Data-based decision-making in schools: Examining the process and effects of teacher support. *Journal of Educational Psychology*, *114*(7), 1695.

Heinrich, C., & Good, A. (2018). Research-informed practice improvements: Exploring linkages between school district use of research evidence and educational outcomes over time. *School Effectiveness and School Improvement*, *29*(3), 418–445. https://doi.org/10.1080/09243453.2018.1445116

Ho, J. E. (2022). What counts? The critical role of qualitative data in teachers' decision making. *Evaluation and Program Planning*, *91*, 102046.

Hoover, N. R., & Abrams, L. M. (2013). Teachers' instructional use of summative student assessment data. *Applied Measurement in Education*, *26*(3), 219–231.

Kempf, A. (2015). The school as factory farm: All testing all the time. In *The pedagogy of standardized testing* (pp. 13–28). Palgrave Macmillan US. https://doi.org/10.1057/9781137486653_2

Lai, M. K., & McNaughton, S. (2016). The impact of data use professional development on student achievement. *Teaching and Teacher Education*, *60*, 434–443. https://doi.org/10.1016/j.tate.2016.07.005

Lai, M. K., Wilson, A., McNaughton, S., & Hsiao, S. (2014). Improving achievement in secondary schools: Impact of a literacy project on reading comprehension and secondary school qualifications. *Reading Research Quarterly*, *49*(3), 305–334. https://doi.org/10.1002/rrq.73

Maier, U. (2010). Accountability policies and teachers' acceptance and usage of school performance feedback – A comparative study. *School Effectiveness and School Improvement*, *21*(2), 145–165. https://doi.org/10.1080/09243450903354913

Marsh, J. A. (2012). Interventions promoting educators' use of data: Research insights and gaps. *Teachers College Record*, *114*(11), 1–48.

Marsh, J. A., Bertrand, M., & Huguet, A. (2015). Using data to alter instructional practice: The mediating role of coaches and professional learning communities. *Teachers College Record*, *117*(4), 1–40.

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006, Nov 7). Making sense of data-driven decision making in education [Occasional Paper]. RAND Corporation.

Michaud, R. (2016). The Nature of Teacher Learning in Collaborative Data Teams. Qualitative Report, 21(3), 529-545. https://doi.org/10.46743/2160-3715/2016.231.

Park, V., & Datnow, A. (2017). Ability grouping and differentiated instruction in an era of data-driven decision making. *American Journal of Education*, *123*(2), 281–306.

Peters, M. T., Förster, N., Hebbecker, K., Forthmann, B., & Souvignier, E. (2021). Effects of data-based decision-making on low-performing readers in general education classrooms: Cumulative evidence from six intervention studies. *Journal of Learning Disabilities, 54*(5), 334–348.

Rangel, V. S., Bell, E. R., & Monroy, C. (2017). A descriptive analysis of instructional coaches' data use in science. *School Effectiveness and School Improvement*, *28*(2), 217–241. https://doi.org/10.1080/09243453.2016.1255232

Reed, D. K. (2015). Middle level teachers' perceptions of interim reading assessments: An exploratory study of data-based decision making. *RMLE Online: Research in Middle Level Education*, *38*(6).

Regan, K., Evmenova, A. S., Mergen, R. L., Verbiest, C., Hutchison, A., Murnan, R., Field, S., & Gafurov, B. (2023). The feasibility of using virtual professional development to support teachers in making data-based decisions to improve students' writing. *Learning Disabilities Research & Practice, 38*(1), 40–56.

Rodríguez-Martínez, J. A., González-Calero, J. A., del Olmo-Muñoz, J., Arnau, D., & Tirado-Olivares, S. (2023). Building personalised homework from a learning analytics based formative assessment: Effect on fifth-grade students' understanding of fractions. *British Journal of Educational Technology*, *54*(1), 76–97.

Schifter, C., Natarajan, U., Ketelhut, D. J., & Kirchgessner, A. (2014). Data-driven decision-making: Facilitating teacher use of student data to inform classroom instruction. *Contemporary Issues in Technology and Teacher Education*, *14*(4), 419–432.

Schildkamp, K., & Ehren, M. (2013). From "intuition" to "data"-based decision making in Dutch secondary schools? In K. Schildkamp, M. K. Lai, & L. Earl (Eds.), *Data-based decision making in Education* (pp. 49–67). Springer Netherlands.

Schildkamp, K., Poortman, C., & Handelzalts, A. (2016). Data teams for school improvement. *School Effectiveness and School Improvement*, *27*(2), 228–254. https://doi.org/10.1080/09243453.2015.1056192

Schildkamp, K., Poortman, C., Luyten, H., & Ebbeler, J. (2017). Factors promoting and hindering data-based decision making in schools. *School Effectiveness and School Improvement*, *28*(2), 242–258. https://doi.org/10.1080/09243453.2016.1256901

Shirley, D. (2017). *The new imperatives of educational change: Achievement with integrity*. Routledge. https://doi.org/10.4324/9781315682907

Staman, L. L., Timmermans, A. A., & Visscher, A. A. (2017). Effects of a data-based decision making intervention on student achievement. *Studies in Educational Evaluation*, *55*, 58–67.

Staman, L., Visscher, A. J., & Luyten, H. (2014). The effects of professional development on the attitudes, knowledge and skills for data-driven decision making. *Studies in Educational Evaluation*, *42*, 79–90.

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine*, *169*(7), 467–485. https://doi.org/10.7326/M18-0850

Tsai, Y., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *50*(6), 2839–2854. https://doi.org/10.1111/bjet.12846

Truckenmiller, A. J., Cho, E., & Troia, G. A. (2022). Expanding assessment to instructionally relevant writing components in middle school. *Journal of School Psychology*, *94*, 28–48. https://doi.org/10.1016/j.jsp.2022.07.002

van den Bosch, R. M., Espin, C. A., Chung, S., & Saab, N. (2017). Data-based decision-making: Teachers' comprehension of curriculum-based measurement progress-monitoring graphs. *Learning Disabilities Research & Practice*, *32*(1), 46–60.

van Geel, M., Keuning, T., Visscher, A. J., & Fox, J.-P. (2016). Assessing the Effects of a School-Wide Data-Based Decision-Making Intervention on Student Achievement Growth in Primary Schools. *American Educational Research Journal*, *53*(2), 360–394. https://doi.org/10.3102/0002831216637346

van Geel, M., Keuning, T., Visscher, A., Fox, J. P., & Moolenaar, N. M. (2016b). The transformation of schools' social networks during a data-based decision making reform. *Teachers College Record*, *118*(9), 1–33.

van der Scheer, E. A., & Visscher, A. J. (2016). Effects of an intensive data-based decision making intervention on teacher efficacy. *Teaching and Teacher Education*, *60*, 34–43.

van der Scheer, E. A., Glas, C. A., & Visscher, A. J. (2017). Changes in teachers' instructional skills during an intensive data-based decision making intervention. *Teaching and Teacher Education*, *65*, 171–182.

Ylimaki, B., & Brunderman, L., (2019). School development in culturally diverse U.S. schools: Balancing evidence-based policies and education values. *Education Sciences*, *9*(84), 1–15. https://doi.org/10.3390/educsci9020084

Chapter 3: Data-Based Decision Making in Online Classes: Exploring Current Practices and Prevailing Determinants

Abstract

This study examines the extent to which Ontario secondary teachers use data to enhance their instructional practices in online courses and identifies the factors influencing their engagement with data-based decision-making (DBDM). Amid the growing reliance on online education, understanding how teachers integrate student data into pedagogical decisions remains underexplored, particularly in Ontario. Addressing this gap, this study investigates teachers' use of DBDM and explores how systemic and individual factors shape these practices. Using a sequential explanatory mixed methods design, the study analyzes survey responses from 102 teachers and 8 follow-up interviews. Findings indicate that collaboration, DBDM efficacy, anxiety, data quality, and leadership influence data use. Collaboration and efficacy emerged as key drivers, while anxiety and concerns about data quality posed challenges. These insights highlight the need for targeted interventions, such as professional development, leadership support, and improved data accessibility, to optimize DBDM in online teaching.

Key word: data-based decision making, online education, secondary education, Ontario

Résumé

Cette étude examine dans quelle mesure les enseignants du secondaire en Ontario utilisent les données pour améliorer leurs pratiques pédagogiques dans les cours en ligne et identifie les facteurs qui influencent leur engagement dans la prise de décision basée sur les données (PDBD). Alors que l'enseignement en ligne est de plus en plus utilisé, la façon dont les enseignants intègrent les données des élèves dans leurs décisions pédagogiques reste peu étudiée, en particulier en Ontario. Pour combler cette lacune, cette étude examine l'utilisation que font les enseignants de la prise de décision basée sur les données et explore la manière dont les facteurs systémiques et individuels façonnent ces pratiques. À l'aide de méthodes mixtes explicatives séquentielles, l'étude analyse les réponses à un sondage de 102 enseignants et huit entretiens individuels. Les résultats indiquent que la collaboration, l'efficacité de la PDBD, l'anxiété, la qualité des données et le leadership influencent de manière significative l'utilisation des données. La collaboration et l'efficacité sont apparues comme des facteurs clés, tandis que l'anxiété et les préoccupations relatives à la qualité des données semblent nuire à leur utilisation. Ces résultats soulignent la nécessité d'interventions ciblées, telles que le développement professionnel, le soutien au leadership et l'amélioration de l'accessibilité des données, afin d'optimiser la PDBD dans l'enseignement en ligne.

Key word: data-based decision making, online education, secondary education, Ontario

Introduction

Over the last three decades, increasing accountability requirements in education systems worldwide have resulted in the increased use of standardized testing as a means of tracking the performance of schools over time (Halverson, 2014). Some research suggests that using the results of standardized tests to build big data systems aids in setting expectations for education and student outcomes, which in turn can have positive influence on pedagogical decision-making and teaching strategies (e.g., Maier, 2010; Cheng, 1999; Cheng & Curtis, 2004). However, numerous studies provide substantial evidence that the excessive use of quantitative data from standardized testing to assess school and student performance can have negative effects on the overall quality of education by putting an emphasis on tested content to the exclusion of untested content (Abdusyakur & Poortman, 2019; Kempf, 2015; Omoso et al., 2019).

This tension between systemic accountability requirements and a need to support high-quality student-centred teaching practices can be eased by considering multiple sources of student data instead of focusing solely on standardized test results (Curry et al., 2016; Ebbeler et al., 2016). In practice, teachers can gather and use a variety of student data that supplement the results of standardized tests, fulfill the specific needs of students, and still meet accountability requirements (Carlson et al., 2011; Faber et al., 2018; Heinrich & Good, 2018; Tsai et al., 2019). One approach that can enable teachers to reach these goals is *Data-Based Decision Making* (DBDM), which is the systematic collection, review, and utilization of different types of data (e.g., summative and formative assessments, behavior data, attendance records, demographic information, class and homework assignments, classroom observations, etc.) to improve student performance (Marsh, 2006). Numerous studies on the impact of using DBDM in K-12 educational settings have found that DBDM can enhance education by improving instructional efficacy and pedagogical decision making (e.g., Lai et al., 2014; Lai & McNaughton, 2016; Saleh, 2021; van Geel et al., 2016; van Geel et al., 2019; Ylimaki & Brunderman, 2019). However, much of this literature is primarily restricted to in-person education; given the recent inclusion of online teaching in various educational contexts, more research on DBDM related to online education is necessary (Tayem & Bourgeois, 2025).

In Ontario, graduation requirements demand that students, beginning with the cohort that entered Grade 9 in the 2020-21 school year, earn a minimum of two online learning credits to obtain their Ontario Secondary School Diploma (OSSD) unless they have opted out or been exempted (Ministry of Education, 2024). This study therefore aims to contribute to the literature by investigating how Ontario secondary teachers use DBDM as part of their online teaching practices, as well as the factors that hinder or support the use of this approach. By addressing this gap, this study seeks to enhance our understanding of how DBDM can be effectively adapted to online education, ultimately supporting teachers in making data-informed decisions that improve student engagement and achievement in virtual learning contexts.

Literature Review

DBDM can be understood through frameworks developed by progressive and mainstream educators, whose works and theories over the last century have shaped the field of education. For instance, John Dewey's experiential learning, which emphasizes problem-solving and active engagement, mirrors the iterative nature of DBDM, where educators analyze data to refine their teaching practices according to students' needs (Connelly & Candinin, 1989; Dewey, 1916). Paulo Freire's critical pedagogy, advocating for dialogue and student-centered approaches, underscores the importance of using data to empower learners and address inequities among marginalized students (Freire, 1970). Jean Piaget's cognitive development theory highlights the need to differentiate instruction based on students' developmental stages, which resonates with the principle of DBDM in tailoring teachers' decisions to meet diverse learner needs (Piaget,1977). These foundational theories support the idea that teachers should continuously reflect on their teaching strategies and leverage data to explore innovative possibilities for enhancing education.

On the ground, however, these fundamental reflective teaching methods and schooling concepts are sometimes challenged by political demands for standardization and data-driven accountability; these are increasingly used to guide both teacher training and in-service professional development, as well as school evaluation (Schildkamp et al, 2016). As a result, teachers are pressured to gear their teaching toward better test results rather than toward learning and alternate methods of assessment (Carrier & Whaland, 2018; Dunn et al., 2013). The literature emphasizes the positive impact of taking an evidence-informed approach to teaching and learning (Barry, 2006; Carlson et al., 2011; Galway & Sheppard, 2015; Haecker et al., 2017). However, to avoid the adverse impact of using data collected solely from standardized tests for accountability purposes, researchers underscore the necessity of gathering empirical data through various approaches to improve teaching practices and pedagogical decisions (Galway & Sheppard, 2015; Levacic & Glatter, 2001; McIntosh et al., 2018; Schildkamp et al., 2013; van Geel et al., 2016; Wilcox et al., 2021).

Balancing DBDM for Accountability and Instructional Improvement

Evidence-informed approaches to teaching, such as DBDM, rely on factual data to supplement teachers' intuition and experience (Keuning et al., 2019; Schildkamp et al., 2019; van Geel et al., 2017). Interest in DBDM stems from school accountability requirements in various jurisdictions, as stipulated in policies such as the No Child Left Behind (NCLB) Act in the United States (Kempf, 2015), mandatory test-based school accountability policies in Germany (Maier, 2010), Ofsted inspections and League Tables in the United Kingdom (Schildkamp et al., 2017), and the Education Quality and Accountability Office (EQAO) assessments in Ontario (Kempf, 2015). However, a large-scale study in the Netherlands showed that even in situations where there are no mandatory national accountability requirements that could affect the ultimate goal of data use, or where no national standardized assessments are required, schools still appear to be using data for accountability more than for instructional purposes (Schildkamp et al., 2017). While the use of data for accountability purposes is important in conveying expectations about overall school performance, the potential of DBDM extends to other aspects of the school system. One of DBDM's most promising uses is tailored or differentiated instruction to improve students' academic performance. DBDM provides the means through which teachers can refine their teaching strategies by combining data-driven insights with their intuition and expertise (Faber et al., 2018; Pott, 2022; Schildkamp et al., 2019; Tomlinson, 2017; van Geel et al., 2019).

Using DBDM for Instructional Purposes in Online Classes

Online learning has become an integral part of some education systems worldwide, given that it offers the flexibility and accessibility that traditional in-person learning environments often lack (Weller, 2020). In Ontario, online education gained prominence following the Ministry of Education’s decision to introduce online learning requirements in secondary schools. Beginning with the graduating class of 2023-2024, students in Ontario are required to complete at least two online courses to earn their Ontario High School Diploma, unless they opt out (Ministry of Education, 2024). This shift was intended to ensure that students develop digital literacy and adaptability in increasingly digital work and learning environments (Kapoor, 2019).

However, the implementation of this new requirement has raised concerns about teachers' readiness to deliver effective online instruction and their capacity to make pedagogical decisions that support student success in virtual classrooms (Nuland et al., 2020). Critiques of Ontario's online learning policies further highlight structural issues that exacerbate inequalities. A study by Farhadi and Winton (2024) analyzed the evolution of these policies from 2006 to 2022 and revealed that online learning in Ontario is highly centralized, standardized, and detached from community contexts. Such characteristics undermine personalization and differentiation in learning, resulting in an approach that inadvertently perpetuates systemic inequities, including those related to gendered and racialized poverty. These findings underscore the urgent need for strategies that can bridge the gap between policy intentions and classroom realities.

A suggestion to addressing these challenges is the use of DBDM, which includes *learning analytics* as a key component. While DBDM provides a broad framework for using data to guide decisions, *learning analytics* focuses specifically on the collection, analysis, and interpretation of data generated automatically in online learning management systems and its usage in improving teaching and learning outcomes (Prinsloo & Slade, 2019). In online settings, learning analytics enables educators to track students' progress through detailed logs, including assignment submissions, discussion participation, time spent on tasks, and quiz performance. These analytics can provide actionable insights for identifying at-risk students, personalizing instruction, and refining course design (Gudivada, et al., 2019; Kovanovic et al., 2021).

Despite its potential benefits, the adoption of learning analytics varies widely among educators, with its effectiveness depending on access to training, availability of relevant data, and alignment with pedagogical goals (Schilkamp et al., 2017). In Ontario, the integration of learning analytics into online courses is still an emerging practice, particularly at the secondary level (Tayem & Bourgeois, 2025). Understanding how teachers use data to make informed instructional decisions remains a key area of investigation, particularly in the context of growing reliance on digital learning environments (Tayem & Bourgeois, 2025). Thus, this study aims to build on this foundation by examining how Ontario secondary school teachers leverage learning analytics and other data-based decision-making approaches to enhance their online teaching practices, as well as the barriers and enablers they encounter in doing so. In order to address this gap, this study sought to investigate the following research questions: (1) To what extent do teachers use data in their online teaching to enhance their teaching practices in Ontario secondary schools? (2) What factors influence teachers' use of DBDM in their teaching practices?

Conceptual Framework

Although several studies have shown that the use of DBDM for adaptive, tailored education can enhance students' academic performance (e.g., Faber et al., 2018; Lee et al., 2012; Schildkamp et al., 2017; van Geel et al., 2016; van Geel et al., 2017), it is important to recognize that this is not always the case. The effects of a DBDM intervention on student outcomes can vary, ranging from high intervention effects to small or even negative intervention effects (Carr-Hill et al., 2016). Recognizing that data alone will not guarantee effective use, previous studies show that ideal DBDM practices must be supported by determinant frameworks (Nilsen, 2015). Determinant frameworks aim to identify and organize the various barriers and enablers to DBDM implementation at different levels, from the individual data user to the organizational level and beyond (e.g., Kelly & Downey, 2011; Schildkamp et al., 2017; van Keuning et al., 2019). Among these, Schildkamp et al. (2017) developed the most comprehensive DBDM determinant framework that has been employed in numerous DBDM interventions (e.g., Carrier & Whaland, 2018; Faber et al., 2018; Lai & McNaughton, 2016; Pagan et al., 2019; Rangel et al., 2017; van Geel et al. 2017; Ylimaki & Brunderman, 2019). This multilevel framework helped lay the groundwork for later exploration of determinants that have a direct bearing on the success or failure of DBDM practices. The framework focuses on three influential factors: (1) organizational context, including leadership support, collaboration, and setting clear vision and norms; (2) user characteristics, such as opinions and attitudes, DBDM efficacy, and practical knowledge of the DBDM inquiry process; and (3) data characteristics, such as employing high quality, timely, and usable data (See Table 1).

Table 1

Schildkamp et al. (2017) Determinant Model (p. 244)

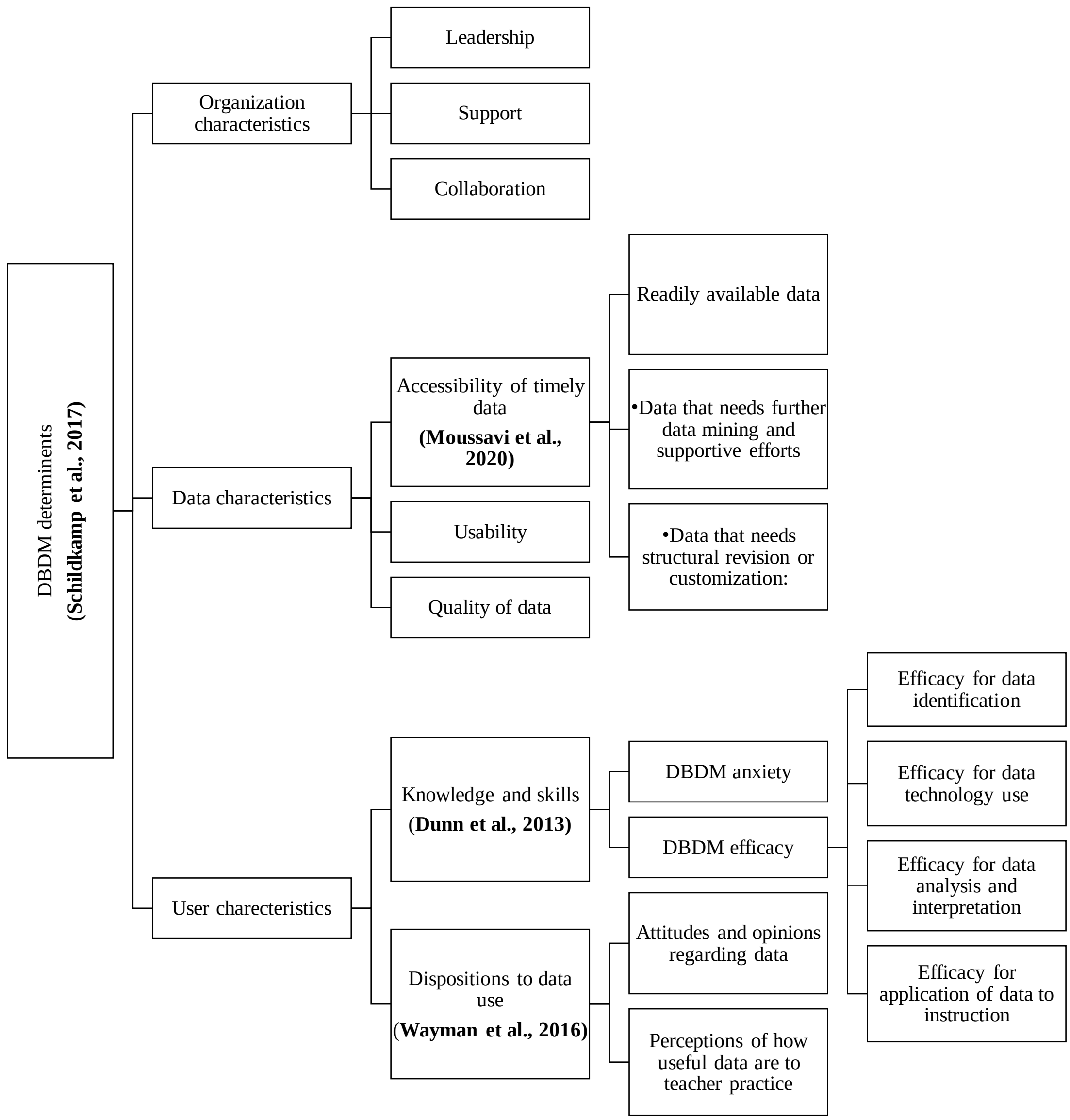
	Organization	**Data**	**User**
Enablers and barriers	• Vision and norms • Leadership • Support • Collaboration	• Accessibility of timely data • Usability • Quality of the data	• Knowledge and skills • Dispositions to use data

Although the framework developed by Schildkamp et al. (2017) is quite comprehensive, its constructs are broad and require more specification. Other supplementary studies can be used to expand on and clarify the broad concepts in this framework (See Figure 1). For instance, Moussavi et al. (2020) investigate the state of available data, the types of data, and their accessibility in online learning management systems in a higher education institution. Although the study was carried out in a health institution setting, the importance of data characteristics to DBDM success is applicable in educational institutions. Thus, this study can be used to expand on the quality, usability, and accessibility of data in the Schildkamp framework. Moreover, Dunn et al. (2013) and Wayman et al. (2016) explore how teachers perceive and use data using

Bandura's social-cognitive theory (1986) on teacher self-efficacy for DBDM by describing the relationships between their attitudes towards DBDM and their actual behaviors in an online context. These frameworks – Dunn et al. (2013) and Wayman et al. (2016) – can be used to expand the user characteristics dimension in Schildkamp et al. (2017). The concept map in Figure 2 illustrates a comprehensive picture of the constructs derived from the original framework by Schildkamp et al. (2017) along with those identified in the supplementary studies. This map will allow for a more specific and clear understanding of the factors that influence teacher adoption of a DBDM approach in schools.

Figure 1

A concept map of DBDM determinants (Dunn et al., 2013; Moussavi et al., 2020; Schildkamp et al., 2017; Wayman et al., 2016)



Methodology

Research Design

This study employed an explanatory sequential mixed methods design to examine the correlation between DBDM determinants and teachers' use of data in online instruction in Ontario secondary schools. Given the limited research on DBDM in online teaching, a broad perspective was necessary (Tayem & Bourgeois, 2025). Thus, a quantitative survey was followed by qualitative interviews to refine findings and explore teachers' perceptions and practices (Braun & Clarke, 2022; Nardi, 2003).

Participants

Ontario teachers who taught one or more online courses at the secondary level (grades 9 to 12) between the academic years 2021-2022 and 2023-2024 were recruited from English and French school boards across Ontario. A total of 102 teachers completed the survey (92 English-speaking teachers and 10 French-speaking teachers). Additionally, eight follow-up interviews were conducted with seven English-speaking teachers and one French-speaking teacher.

Procedures

An external research application was submitted to all English school boards in Ontario, and approvals were obtained from nine. To broaden the research scope and reach as many participants as possible, the Ontario Secondary School Teachers' Federation (OSSF) was also contacted, and through them an invitation was sent to all secondary school teachers delivering online courses. French-speaking teachers for this study were recruited through an alternative method due to potential labour action in some school boards in Ontario at the time of data collection. The recruitment process involved searching for publicly available contact information of teachers working in French-language schools through various online platforms. This method allowed for reaching out to educators directly, bypassing the usual channels through school boards. Given the labour disruption, this strategy was crucial in ensuring that French-speaking teachers were still able to participate in the study, despite the lack of institutional support for recruitment during that period.

All participants from the who agreed to be contacted for interviews were contacted. A semi-structured interview guide was used to highlight various survey findings in an effort to triangulate and expand upon the quantitative data (Jick, 1979). Both the survey and the interviews were conducted in the 2023-2024 school year.

Instruments

A review of the literature revealed useful field-tested questions from relevant research studies, including Dunn et al. (2013), Moussavi et al. (2020), Schildkamp et al. (2017), and Wayman et al. (2016). Questions from these studies were adapted to develop the survey instrument, in addition to the conceptual framework presented in Figure 1. The survey was reviewed by experts in the field, who provided feedback on the clarity, coherence, and relevance of the items in relation to the research objectives. The survey instrument included nine main themes, as described in Table 2 below:

Table 2

Key Themes in the Data Collection Instrument

Survey themes	Description
Data use	Extent to which respondents use data in their daily practices and why (e.g., pedagogical decision-making, problem solving, etc.)
Leadership	Views of respondents on the extent to which leaders encourage them to use data effectively (e.g., act as role models), openly discuss data with their teachers, and focus on developing teachers' data use skills
Support	Support received by respondents to engage in DBDM, such as time, training, guidance, and resource allocation
Collaboration	Extent to which respondents collaborate with peers or participate in communities of practice related to DBDM
Access	Accessing the data teachers need when they need it. This includes availability, ease of retrieval, and whether the data are up-to-date and applicable to their decision-making processes.
Data quality	Availability of data that are accurate, reliable, complete, and useful for decision-making.

DBDM anxiety	Teacher's self-judgment of their sense of trepidation, tension, and apprehension related to their ability to successfully engage in DBDM
DBDM efficacy	Teachers' beliefs in their ability to success- fully complete the tasks associated with DDDM in order to improve student outcomes
DBDM perceptions	Respondent perceptions of the usefulness of data and DBDM

Note. In this study, the term *anxiety* refers specifically to the feelings of unease, hesitation, or stress that teachers experience in relation to using data for instructional decision-making. It is important to clarify that this usage does not align with the clinical definition of anxiety as outlined in the DSM-5. Rather, it denotes a situational and task-related form of anxiety commonly found in professional contexts when individuals are required to engage with unfamiliar tools or processes. Teachers' continued participation in DBDM activities despite these feelings indicates that the anxiety is manageable and functional, not debilitating, and should be understood as a normal response to perceived challenges in practice.

Given the sequential design of the study, the interview guide was informed by the quantitative findings. For instance, specific themes or trends observed in the survey responses were used to refine and tailor the interview questions, ensuring a deeper exploration of key areas such as data usage practices, challenges, and contextual factors influencing decision-making. Each interview lasted approximately 30 minutes. All interviews were conducted online, and audio recorded with participants' consent to ensure accuracy and were subsequently transcribed verbatim.

Analytical Approach

First, to assess the validity of the categorized variables created for analyzing the survey results, I conducted a Shapiro-Wilk W test for normality. Each categorized variable consisted of multiple items, and the test was used to determine whether the data followed a normal distribution. The results of the Shapiro-Wilk test informed subsequent statistical analyses by ensuring appropriate methodological choices based on the distribution of the data. (See Appendix A)

The categorized variables identified above were processed using two distinct methods: simple averages and factor analysis. The simple averages approach provides unweighted composite scores for items in each category by calculating the mean of grouped items, which provided equal contribution from each item. In contrast, factor analysis was employed to generate weighted composite scores based on the underlying relationships among the grouped items, which allows for a more nuanced representation of the constructs. These two methods were utilized to ensure the reliability and robustness of the analysis by examining the consistency of relationships among variables across different scoring techniques (Kim & Mueller, 1978). Please refer to Moreover, data was converted into binary variables and compared to non-binary data to further ensure robustness by testing the stability and consistency of the relationships between variables under different data conditions. (See Appendix B for the analysis of binary data)

Data were analyzed in Stata using descriptive, Spearman correlation, and regression analysis to explore and validate the relationships between the variables (De Vaus & de Vaus, 2013). The regression equation for the analysis is as follows:

$$Y = B_0 + \sum_{i=1}^{8} B_i X_i + \epsilon$$

- Y = **Usage** (dependent variable)
- B_0= Intercept (constant term)
- X_i = Independent variables, where:
  - X_1 = **Leadership**
  - X_2 **Support**
  - X_3 = **Collaboration**
  - X_4 = **Access**
  - X_5 = **Data Quality**
  - X_6 = **Anxiety**
  - X_7 = **Efficacy**
  - X_8 = **Perceptions**
- B = Coefficients representing the effect of each independent variable on **Usage**
- ϵ is the standard error, with robust standard errors reported (Huntington-Klein, 2022).

The analytical approach to analyzing the qualitative data was structured around identifying key themes related to DBDM among educators. Thematic analysis was employed by coding responses based on the predefined categories demonstrated in Table 1. The analysis was guided by both deductive and inductive approaches, using existing theoretical constructs while remaining open to emerging themes that provided deeper insights into educators' engagement with data (Flick, 2006). Triangulation across quantitative and qualitative data, as well as alignment with relevant literature and policy, enhanced the overall credibility and trustworthiness of the findings.

Limitations

The study's findings should be interpreted with several limitations in mind. Despite random selection, recruitment was hindered by many district school boards opting out, resulting in a voluntary sample and potential self-selection bias. The lower number of French-speaking participants may have further impacted results. While the sample size allowed for statistical analysis, it may not fully represent Ontario's online secondary school teachers, affecting generalizability. Missing data due to non-responses was mitigated through imputation. Although qualitative analysis enriched the findings, the study's focus on Ontario's secondary schools limits its applicability to other contexts. Therefore, future research across provinces or countries could provide comparative insights into DBDM practices. Finally, the quantitative findings illustrate simple correlations and do not make claims about impact or any causal relationship between the variables.

Findings

1- To what extent do teachers use data in their online teaching to enhance their teaching practices in Ontario secondary schools?

The survey and interview data reveal that Ontario secondary school teachers frequently utilize data while teaching online, predominantly for problem-solving, decision-making, and anticipating potential challenges. Survey results indicate that nearly 77% of teachers (n = 78) reported that they *always* or *usually* use data to find solutions to problems they face during the course, 62% (n = 63) reported that they *always* or *usually* use it to make decisions about teaching materials, methods, or assignments, and 57% (n = 58) reported that they *always* or *usually* use data proactively to navigate and address future issues. This demonstrates a nuanced reliance on data for informed decision-making in online classrooms.

The qualitative data enrich this perspective by illustrating how teachers use data in context-specific ways. For instance, **tracking student progress** emerges as a central theme in the qualitative data analysis. Teachers frequently refer to online learning management systems like Brightspace to monitor grades, assignment completion, and time spent on activities. This data allows educators to identify struggling students, adapt their teaching, and, when necessary, intervene through targeted support or tailored instructional strategies.

Moreover, data is leveraged to **evaluate the effectiveness of teaching materials** and lessons. Teachers often revise or replace ineffective assessments based on student performance data, ensuring that their instructional practices align with learning goals and curricular expectations. For instance, ***Participant B*** explained how they design lessons around curriculum outcomes and then modify them if data reveals that students are struggling. Similarly,

Participant G highlighted the importance of reflecting on formative and summative assessment results to improve future iterations of courses.

Data is also instrumental in **personalizing the learning experience** for students. Teachers analyze data to adapt lessons to students' needs, abilities, and learning styles, especially in blended environments where face-to-face interactions complement data-driven insights. For example, ***Participant D*** noted using data to incorporate student interests and abilities into course design, particularly for younger students or those in blended learning models. In addition, teachers employ data to address broader student engagement and equity issues. Several participants highlighted using data to track student activity levels, such as log-in times and participation rates, to identify disengaged students. This not only helps address individual learning challenges but also aids in ensuring the safety and well-being of students in precarious circumstances, as noted by ***Participant F***.

2- What factors influence teachers' use of DBDM in their teaching practices?

This section examines factors influencing teachers' use of DBDM by integrating quantitative and qualitative findings. Spearman correlation and regression analysis assess the relationship between usage (dependent variable) and factors such as leadership, support, collaboration, data access and quality, DBDM anxiety, efficacy, and perceptions. Thematic analysis is used to triangulate qualitative data.

Descriptive Statistics

The descriptive statistics, as demonstrated in Table 3, highlight variability in teachers' individual practices and institutional conditions regarding DBDM. On a Likert scale of 1 to 5, the average score for teachers using DBDM was **3.07 (SD = 0.99),** indicating moderate engagement in data use practices. Other variables such as efficacy (**M = 2.90, SD = 0.56),** collaboration **(M = 2.85, SD = 0.67),** and data quality **(M = 2.87, SD = 0.64)** suggest there is room for improvement in the conditions that support effective DBDM. Anxiety related to DBDM had a lower mean of **2.02 (SD = 0.82),** indicating relatively moderate levels of apprehension among teachers.

Table 3

Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
usage	102	3.068627	0.9954111	1	5
leadership	87	2.731801	0.8816813	1	4
support	97	2.017182	0.7748523	1	4
collaboration	96	2.848958	0.6693272	1	4
access	94	2.952128	0.6395107	1	4
Data quality	95	2.870175	0.6419068	1.333333	4
anxiety	95	2.021053	0.8183916	1	4
efficacy	93	2.901075	0.5576532	1.4	4
perceptions	91	3.050235	0.5910802	1.285714	4

Correlation Analysis

Table 4 presents the Spearman's rank correlation coefficients calculated using factor analysis. To ensure robustness, correlation was also calculated using simple averages weights. The results were highly consistent with those obtained via Spearman's rank correlation, with patterns remaining stable across all variables. (See table 5)

Table 4

Spearman's Rank Correlation Coefficients Using Factor Analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) usage factor	1.000								
(2) leadership factor	0.452	1.000							
(3) support factor	0.227	0.350	1.000						
(4) collaboration factor	0.414	0.338	0.256	1.000					
(5) data access factor	0.339	0.468	0.433	0.434	1.000				
(6) data quality factor	0.458	0.437	0.369	0.433	0.612	1.000			
(7) anxiety factor	-0.166	-0.214	-0.124	-0.118	-0.064	-0.131	1.000		
(8) efficacy factor	0.460	0.553	0.404	0.260	0.412	0.565	-0.397	1.000	
(9) perceptions factor	0.290	0.366	0.243	0.345	0.315	0.253	-0.448	0.453	1.000

Spearman rho = 0.453

Table 5

Spearman's Rank Correlation Coefficients Using Simple Average Weight.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) usage	1.000								
(2) leadership	0.435	1.000							
(3) support	0.244	0.377	1.000						
(4) collaboration	0.437	0.353	0.275	1.000					
(5) access	0.397	0.487	0.486	0.420	1.000				
(6) data quality	0.491	0.437	0.403	0.420	0.631	1.000			
(7) anxiety	-0.166	-0.185	-0.115	-0.083	-0.050	-0.124	1.000		
(8) efficacy	0.480	0.539	0.414	0.281	0.437	0.600	-0.427	1.000	
(9) perceptions	0.281	0.376	0.244	0.335	0.317	0.270	-0.440	0.423	1.000

Spearman rho = 0.423

The results reveal strong similarities between both approaches – simple average weight and factor analysis – with consistent patterns in the relationships among variables. Notably, ***usage*** shows notable positive correlations with several variables in both tables. For instance, ***data quality*** exhibits the strongest correlation with ***usage***, at 0.491 using simple averages and 0.458 using factor analysis, indicating its crucial role in fostering usage regardless of the weighting method. Similarly, ***efficacy*** is strongly correlated with ***usage***, with coefficients of 0.480 and 0.460, respectively. Positive correlations between ***usage*** and ***collaboration*** (0.437 and 0.414) and between ***usage*** and ***leadership*** (0.435 and 0.452) further highlight the significance of collaborative practices and leadership support in promoting data usage. Additionally, a consistent negative relationship is observed between ***usage*** and DBDM ***anxiety*** (-0.166 in both tables), suggesting that higher anxiety levels are associated with lower usage.

Beyond **usage**, other notable correlations emerge. **Leadership** and **efficacy** are strongly correlated (0.539 and 0.553), indicating that supportive leadership enhances confidence in data-related skills. Similarly, **access to data** and **data quality** exhibit high correlations (0.631 and 0.612), emphasizing the interplay between data accessibility and quality. A negative correlation between **anxiety** and **perceptions** (-0.440 and -0.448) suggests that increased anxiety contributes to more negative perceptions of data-driven practices. While both weighting methods yielded similar results, factor analysis slightly increased the strength of some correlations, such as those involving **leadership** and **efficacy**, potentially capturing more nuanced relationships. The overall Spearman rho values (0.423 for simple averages and 0.453 for factor analysis) confirm the robustness of the relationships across methods (Schober et al., 2018). These findings highlight the importance of leadership, data quality, efficacy, and collaboration in supporting data usage, while identifying anxiety as a potential barrier.

Regression Analysis

The results from Table 6 highlight the key predictors of usage based on a linear regression model using factor analysis. In this model, **collaboration** emerges as a notable positive predictor of usage (at the 5% level), underscoring the importance of fostering collaborative practices and communities of practice in increasing DBDM usage. Similarly,

efficacy shows a positive association with usage in both models, with a significant effect in the simple average model (5% level) and a near-significant effect in the factor analysis model (10% level). Other variables, such as **leadership, support**, **data access**, **data quality**, and **anxiety**, do not achieve statistical significance, though the coefficients provide insight into their directional relationships. Again, correlation was calculated using simple averages weights and reveal consistent patterns. (See table 7).

Table 6

Linear Regression Using Factor Analysis Weighted Variables

Usage	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Leadership factor	.168	.111	1.51	.135	-.054	.391	
Support factor	-.094	.102	-0.92	.36	-.298	.11	
Collaboration factor	.249	.111	2.23	.029	.027	.471	**
Data access factor	-.074	.139	-0.53	.595	-.35	.202	
Data quality factor	.193	.135	1.43	.158	-.077	.463	
Anxiety factor	.04	.107	0.37	.711	-.173	.253	
Efficacy factor	.273	.149	1.83	.072	-.025	.57	*
Perceptions factor	.097	.118	0.82	.413	-.138	.333	
Constant	-.053	.09	-0.60	.553	-.232	.125	
Mean dependent var		-0.034	SD dependent var			0.964	
R-squared		0.409	Number of obs			79	
F-test		6.066	Prob > F			0.000	
Akaike crit. (AIC)		193.728	Bayesian crit. (BIC)			215.053	

**** p<.01, ** p<.05, * p<.1*

Table 7

Linear Regression Using Simple Average Weighted Variables

Usage	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Leadership	.173	.124	1.40	.166	-.074	.42	
Support	-.131	.13	-1.01	.316	-.389	.128	
Collaboration	.403	.162	2.49	.015	.08	.726	**
Data access	-.069	.212	-0.33	.745	-.492	.354	

Data quality	.259	.209	1.24	.22	-.158	.675	
Anxiety	.062	.131	0.47	.639	-.199	.323	
Efficacy	.529	.26	2.03	.046	.01	1.048	**
Perceptions	.151	.194	0.78	.438	-.235	.537	
Constant	-1.002	.846	-1.18	.241	-2.69	.686	

Mean dependent var	3.034	SD dependent var	0.959
R-squared	0.427	Number of obs	79
F-test	6.519	Prob > F	0.000
Akaike crit. (AIC)	190.537	Bayesian crit. (BIC)	211.862

**** p<.01, ** p<.05, * p<.1*

Thematic Analysis

The thematic analysis of the interview data reveals that the themes of 1- collaboration, 2- efficacy, and 3- anxiety were more apparent, which corroborates the results of the quantitative analysis.

Collaboration. The **collaboration** theme highlights the value that educators place on working together to interpret and apply data effectively to their teaching practices (Schildkamp et al., 2017). Many participants highlighted how collaborative efforts foster a sense of shared expertise and improve the practical application of data. Participant A, for example, emphasized the importance of peer support, noting, *"I have a lot of colleagues who are very willing to share ideas about how to use data, and we bounce ideas off each other. You know, 'What did you do?' or, 'What worked for you?"* This illustrates how collaboration provides educators with diverse perspectives and practical strategies, helping them feel more confident and supported in their decision-making.

Collaboration also seems to allow educators to better address gaps in their own knowledge or skills. Participant D shared, *"I think that working with colleagues is probably one of the most helpful ways of using the data, because somebody else might have a different* *perspective or a different way of interpreting it."* This highlights how collaborative discussions can reveal new interpretations of data, enabling teachers to apply insights in ways they might not have considered independently. Similarly, Participant A reflected on the benefits of exchanging teaching strategies, stating, *"We'll talk about the different types of activities we can do, and that's very helpful because then you're not just sitting in isolation trying to figure it all out."* This sense of collective problem-solving approach not only enhances data use but also mitigates feelings of professional isolation.

Nevertheless, some participants identified challenges in fostering meaningful collaboration. Participant B, for example, noted that collaboration often requires deliberate effort and openness, saying, *"It's helpful when we have time to actually sit down together and go through things, but sometimes people are hesitant to share because they're unsure or don't want to feel judged."* This highlights how trust and psychological safety are essential to creating effective collaborative environments. Participant D further explained how time constraints can hinder collaboration, remarking, *"We don't always have the opportunity to sit down and really dive into the data together, especially when things are busy."* These challenges suggest that while collaboration is highly valued, structural barriers such as time limitations and organizational cultural dynamics can impede its full potential.

Efficacy. The **efficacy** theme explores teachers' skills and competencies in using data to make informed decisions and improve learning outcomes. These skills include data identification, interpretation, application, and technology use (Dunn et al., 2013). Most participants described using data to evaluate their teaching practices and adjust approaches accordingly. For instance, Participant A explained, *"I review data on student progress, attendance, and performance on assessments to identify gaps in my teaching and determine* *where I need to adjust my approach."* Similarly, Participant C noted, *"I analyze student login records and their performance in other courses to pinpoint students who might need additional support,"* underscoring the importance of digging deeper into data to address individual needs. Participant E described evaluating the relevance of assignments based on feedback, saying, *"When students overwhelmingly found one assignment irrelevant, I discarded it and redesigned the activity to better align with their learning needs."*

Several participants stressed the importance of interpreting data with caution. Participant E argued, *"Data is never neutral; it's created and interpreted through subjective lenses. It's a tool for guidance, not a definitive answer."* This perspective was echoed by Participant B, who emphasized, *"We need to focus on students' potential for growth rather than limiting our expectations based on their past performance." Similarly, Participant F shared, "I analyze engagement data, like video view times and student activity levels, to adjust my course content and improve its relevance to students".* These examples highlight a shared belief that data should inform teaching strategies while being contextualized within broader pedagogical insights.

However, participants also noted challenges in working with data. Participant A remarked, *"Dealing with large datasets can be overwhelming without advanced tools or training, like AI, to assist in identifying patterns."* Another pressing issue, as Participant E explained, is the ability of analyzing student data in depth: *"It's not easy. Not everybody has the skill to analyze data in depth. Well, not everybody has the skill to understand where the issues are when they're identified either"*. They also added, *"Often, using data ends up being kind of when a student's struggling or something like that, that's when you would dig into a specific student"*. This reactive approach means that teachers tend to analyze student data in-depth when a problem arises, rather than using it proactively to guide instruction.

Anxiety. The anxiety theme underscores the challenges and uncertainties educators face when working with data, including feelings of trepidation, tension, and apprehension about their ability to successfully engage in DBDM (Dunn et al., 2013). Many participants expressed feeling unsure about how to fully utilize the data and learning analytics features in the learning management systems they use to enhance their teaching practices, which is also consistent with survey findings, indicating that approximately 27 % of respondents feel intimidated by the process of connecting data analysis to their instructional practice and/or fear appearing incompetent. In discussions with teachers, several signs of apprehension about using data to enhance teaching practices were observed. These signs often manifest as feeling overwhelmed, a lack of trust in data, and inadequate data literacy skills.

Participant E expressed a deep sense of **overwhelm**, stating, “I don't even know where to start with this data. Sometimes there's just so much of it, and it all seems complicated.” Participant E had a similar feeling and said “So, I think data is such a broad word to use, because there's so much data types, different kinds of data that you could be using. Predominantly, when we discuss amongst teachers, especially others who are teaching the same course, or even if they're not teaching the same course, they're just trying to figure out what to do with data and where to go with the student next.” This feeling of being swamped by data is common when teachers are unsure of how to approach or interpret the information they are expected to use.

Moreover, teachers expressed their **lack of trust** in the data itself, and questioned whether the data accurately reflects what happens in the classroom. For instance, Participant E explained, *“One of the pieces I struggle with while teaching virtually is like, we don’t see the kids! A lot of the learning is invisible to us.”* Without face-to-face interaction, they worry about missing critical signs of student engagement that data cannot compensate for. Similarly, Participant F highlighted the limitations of online data in capturing students' well-being: “A student may log in almost every day and hand in work, but their life is going terribly and they’re falling to pieces, and we don’t know.” These concerns underscore teachers’ anxiety about relying on data that may be incomplete or misleading, ultimately affecting their ability to support students effectively.

Anxiety about teachers’ data literacy skills and the effective use of data was also noted. Participant B admitted, “I don’t probably use data as much or as effectively as I could,” highlighting a lack of confidence in their data usage. They added, “A lot of my data is more like the overall expectations rather than the specific expectations,” suggesting uncertainty about its precision. Technical unfamiliarity further compounds this anxiety, particularly with Artificial Intelligence. Participant D remarked, “I’m very unfamiliar with AI. I can recognize that it’s probably integrated in some of the things that I do, but I’m not aware that it’s integrated,” illustrating a lack of awareness in leveraging AI for data insights.

Discussion

The findings from both the quantitative and qualitative data reveal nuanced insights into the determinants of DBDM usage among educators in Ontario. The quantitative analysis identified collaboration, and DBDM efficacy as the most significant predictors of DBDM usage, with anxiety, leadership, access to data, quality of data, and perceptions playing smaller but still noteworthy roles. These results are supported and enriched by qualitative findings as well as the literature, which further highlights the roles of both systemic and individual factors in shaping teacher engagement with data.

Systemic Factors

Leadership was identified as an enabler of effective DBDM usage in the quantitative data, echoing the participants' emphasis on the importance of guidance and resource allocation. This finding aligns with prior research (e.g., Copp, 2017; Schildcamp et al., 2017; Ylimaki & Brunderman, 2019), which emphasizes the pivotal role of school leadership in fostering a culture that prioritizes data-driven practices. However, inconsistent leadership practices can limit data use, which requires the need for structured and equitable support systems (Hebbecker et al., 2022).

Collaboration stood out as a vital component of successful DBDM practices. Both the statistical significance of this variable and the qualitative data suggest that working with colleagues provides a platform for sharing ideas and strategies. Yet, structural and personal barriers such as time constraints and a lack of trust among colleagues highlight the challenges of fostering meaningful collaboration. These findings suggest that schools and institutions must actively cultivate collaborative cultures, perhaps through dedicated time for team discussions or professional learning communities, which is also consistent with the work of Marsh et al. (2015) and van Geel et al. (2017). A structured approach to collaboration, such as creating communities of practice (DuFour et al., 2005), can further enhance teachers' engagement with data by establishing shared norms, fostering trust, and encouraging collective problem-solving.

Access to Timely and High-Quality Data was another strong predictor of DBDM usage. Participants underscored that while data is often available, its usability remains a challenge. This disconnect between access and usability reflects a need for improved training and user-friendly data tools to bridge the gap between availability and practical application. This mirrors findings in Schildkamp et al. (2017) and Moussavi et al. (2020), who emphasize the importance of having high-quality, timely, and usable data for successful DBDM practices.

Individual Factors

DBDM Anxiety was identified as both a barrier to data use and a reflection of the broader challenges faced by educators. Quantitative results indicated a negative relationship between anxiety and DBDM usage. However, the qualitative findings revealed specific issues that contribute to teachers' anxiety regarding data use. These issues manifest as feelings of overwhelm, distrust in data, and inadequate data literacy skills, which further complicate educators' ability to confidently engage with data. This nuanced understanding of the factors contributing to feeling trepidation adds to our understanding of DBDM anxiety as described in Dunn et al. (2013), as it emphasizes that the challenge is not simply an emotional barrier but a reflection of systemic and practical obstacles that hinder teachers' use of data.

Efficacy was identified as an important themein both the quantitative and qualitative analyses, underscoring its critical role in DBDM practices. Educators with higher levels of self-efficacy were not only more willing to engage with data but also demonstrated greater resilience in overcoming barriers to its use, which is again consistent with Schildkamp et al. (2017) and Dunn et al. (2013). Qualitative insights revealed that confidence in one’s ability to interpret and apply data was a driving force behind more effective integration of DBDM into teaching practices. This aligns with quantitative findings, where efficacy was a strong predictor of DBDM usage. Positive perceptions of DBDM also surfaced in the qualitative data, with educators highlighting its potential to improve teaching and learning outcomes. However, these perceptions were often moderated by the practical challenges of implementation, emphasizing the need for targeted support and training to bridge the gap between intention and practice.

While our data showcases the potential for improving teaching practices, its use exists within a broader sociopolitical framework shaped by Ontario's e-learning policies, as critiqued by Farhadi and Winton (2024). Their critical historiography of e-learning policy in Ontario illustrates how the neoliberal focus on personalization, access, and choice often masks the centralization and standardization of online learning systems. This broader policy context, characterized by privatization, commodification of public institutions, and economic rationality, creates structural inequalities. These inequalities challenge the promise of personalized and inclusive learning environments, as online systems are designed to operate independently of community dynamics rather than interdependently with them.

Interplay Between Systemic and Individual Factors

The relationship between systemic and individual factors is not linear or separate but interactive and mutually reinforcing. For instance, as our data suggest, strong leadership and collaborative structures not only provide external supports but also enhance teachers' sense of efficacy and reduce anxiety. Conversely, systemic shortcomings, such as lack of accessible, high-quality data or insufficient time for collaboration, can exacerbate individual-level challenges like low confidence or hesitation in using data. This interplay indicates that efforts to build individual competencies (e.g., through professional development) are unlikely to succeed in isolation unless accompanied by systemic supports (Schilkamp et al., 2016). In this way, the organizational context actively shapes (and is shaped by) teachers' beliefs, emotions, and practices related to DBDM (Wayman et al., 2016).

While our data showcases the potential for improving teaching practices through DBDM, its use exists within a broader sociopolitical framework shaped by Ontario's e-learning policies, as critiqued by Farhadi and Winton (2024). Their critical historiography of e-learning policy in

Ontario illustrates how a focus on personalization, access, and choice often masks the centralization and standardization of online learning systems. This broader policy context, characterized by privatization, commodification of public institutions, and economic rationality, creates structural inequalities, which challenge the promise of personalized and inclusive learning environments, as online systems are designed to operate independently of community dynamics. These concerns echo wider critiques of online education models, which warn that centralized, market-driven approaches can reproduce and intensify existing inequities, particularly for students from marginalized backgrounds (Castañeda & Selwyn, 2018; Gilliard & Culik, 2016).

Conclusion

This study underscores the tension between teachers' efforts to use data for adaptive, student-centered practices and the systemic constraints of Ontario's online learning environment. While teachers strive to address students' individual learning needs and engage in reflective practices, they face policies that often prioritizes efficiency and standardization over meaningful personalization and equity. This challenge is compounded by systemic factors such as the lack of guidance, limited collaboration opportunities, and difficulties in accessing timely, high-quality data. On the individual level, teachers' data use is influenced by their sense of efficacy and anxiety, which underscores the need for targeted professional development that builds confidence and reduces apprehension. Addressing these barriers requires interventions that not only improve system-wide support structures but also empower Ontario secondary school teachers with the skills and resources needed to integrate data effectively into their practice.

The findings of this study suggest several avenues for future research aimed at enhancing the use of DBDM among secondary school teachers in Ontario's online learning context. To address the factors that impact DBDM usage identified in the quantitative and qualitative analysis, future studies should consider designing targeted interventions. These interventions could begin with a comprehensive needs assessment to identify successful models and understand teachers' perceptions of their training needs.

References

Abdusyakur, I., & Poortman, C. L. (2019). Study on data use in Indonesian primary schools. *Journal of Professional Capital and Community*, *4*(3), 198–215. https://doi.org/10.1108/JPCC-11-2018-0029

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, *1986*(23-28), 2.

Barry, M. J. (2006). *A school's use of data for teaching and learning: A case study of data's impact on instruction in an urban school.* ProQuest Dissertations Publishing.

Braun, V., & Clarke, V. (2022). Conceptual and design thinking for thematic analysis. *Qualitative psychology*, *9*(1), 3.

Carlson, D., Borman, G. D., & Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis, 33*(3), 378–398. https://doi.org/10.3102/0162373711412765

Carr-Hill, R., Rolleston, C. & Schendel, R. (2016). The effects of school-based decision-making on educational outcomes in low- and middle-income contexts. *Campbell Systematic Review*, *12*(1), 1-173.

Carrier, L. L., & Whaland, M. (2018). Left behind by policy: A case study of the influence of high stakes accountability policy on data-based decision making in one small, rural New Hampshire school. *The Rural Educator*, *38*(3), 12–26. https://doi.org/10.35608/ruraled.v38i3.217

Cheng, L. (1999). Changing assessment: Washback on teacher perspectives and actions. *Teaching and Teacher Education*, *15*(3), 253–271.

Cheng, L., & Curtis, A. (2004). Washback or backwash: A review of the impact of testing on teaching and learning. In L. Cheng, Y. Watanabe, & A. Curtis (Eds.), *Washback in language testing: Research contexts and methods* (pp. 3–17). Mahwah, NJ: Lawrence Erlbaum.

Connelly, M., & Clandinin, J. (1988). *Teachers as curriculum planner.* Toronto: OISE Press.

Copp, D. T. (2017). Policy incentives in Canadian large-scale assessment: How policy levers influence teacher decisions about instructional change. *Education Policy Analysis Archives*, *25*, 115-115.

Curry, K. A., Mwavita, M., Holter, A., & Harris, E. (2016). Getting assessment right at the classroom level: Using formative assessment for decision making. *Educational Assessment, Evaluation and Accountability*, *28*, 89-104.

Datnow, A. & Hubbard, L. (2015). Teachers' use of assessment data to inform instruction: Lessons from the past and prospects for the future. *Teachers College Record (1970)*, *117*(4), 1–26. https://doi.org/10.1177/016146811511700408

Dewey, J. (1916). Democracy and education: An introduction to the philosophy of education. New York: The Free Press.

DuFour, R., Eaker, R., & DuFour, R. (Eds.). (2005). *On common ground : the power of professional learning communities*. National Educational Service.

Dunn, K. E., Airola, D. T., Lo, J., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology*, *38*(1), 87–98.

Ebbeler, J., Poortman, C. L., Schildkamp, K., & Pieters, J. M. (2016). Effects of a data use intervention on educators' use of knowledge and skills. *Studies in educational evaluation*, *48*, 19-31.

Faber, J., Glas, C., & Visscher, A. J. (2018). Differentiated instruction in a data-based decision-making context. *School Effectiveness and School Improvement*, *29*(1), 43–63. https://doi.org/10.1080/09243453.2017.1366342

Flick, U. (2006). *An introduction to qualitative research* (3rd ed.). London: Sage Publications.

Freire, P. (1970). The adult literacy process as cultural action for freedom. *Harvard educational review*, *40*(2), 205-225.

Farhadi, B., & Winton, S. (2024). E-Learning for the Public Good? The Policy Trajectory of Online Education in Ontario, Canada. *Educational Policy (Los Altos, Calif.)*, *38*(7), 1676–1712. https://doi.org/10.1177/08959048241267953

Galway, G., & Sheppard, B. (2015). Research and evidence in education decision-making: A comparison of results from two pan-Canadian studies. *Education Policy Analysis Archives*, *23*(109), 1–41. http://dx.doi.org/10.14507/epaa.v23.1905

Gudivada, V. N., Rao, D. L., & Ding, J. (2019). Evolution and facets of data analytics for educational data mining and learning analytics. In *Responsible analytics and data mining in education* (1st ed., pp. 16–42). Routledge. https://doi.org/10.4324/9780203728703-3

Halverson, R. (2014). Data-driven leadership for learning in the age of accountability. In A. J. Bowers, A. R. Shoho, and B. G. Barnett (Eds.), *Using data in schools to inform leadership and decision making* (pp. 255–266). Information Age Pub Incorporated.

Haecker, B., Lane, F., & Zientek, L. (2017). Evidence-based decision-making: Influences on central office administrators' decision-making practices. *Journal of School Leadership*, *27*(6), 860–883. https://doi.org/10.1177/105268461702700604

Hebbecker, K., Förster, N., Forthmann, B., & Souvignier, E. (2022). Data-based decision-making in schools: Examining the process and effects of teacher support. *Journal of Educational Psychology*, *114*(7), 1695.

Heinrich, C., & Good, A. (2018). Research-informed practice improvements: Exploring linkages between school district use of research evidence and educational outcomes over time. *School Effectiveness and School Improvement*, *29*(3), 418–445. https://doi.org/10.1080/09243453.2018.1445116

Hoogland, I., Schildkamp, K., van der Kleij, F., Heitink, M., Kippers, W., Veldkamp, B., & Dijkstra, A. M. (2016). Prerequisites for data-based decision making in the classroom: Research evidence and practical illustrations. *Teaching and Teacher Education*, *60*, 377–386.

Huntington-Klein, N. (2022). *The effect: an introduction to research design and causality* (First edition.). CRC Press.

Jick, T. D. (1979). Mixing qualitative and quantitative methods: Triangulation in action. *Administrative Science Quarterly, 24(*4), 602–611.

Kapoor., A. (2019). *Connecting to success: Technology in Ontario schools.* Toronto, ON: People for Education. https://peopleforeducation.ca/wp-content/uploads/2019/04/PFE_TechnologyReport_Apr2019-online-final.pdf

Kelly, A., & Downey, C. (2011). Professional attitudes to the use of pupil performance data in English secondary schools. *School Effectiveness and School Improvement*, *22*(4), 415–437. https://doi.org/10.1080/09243453.2011.600525

Kempf, A. (2015). The school as factory farm: All testing all the time. In *The Pedagogy of Standardized Testing* (pp. 13–28). Palgrave Macmillan US. https://doi.org/10.1057/9781137486653_2

Keuning, T., van Geel, M., Visscher, A., & Fox, J. P. (2019). Assessing and Validating Effects of a Data-Based Decision-Making Intervention on Student Growth for Mathematics and Spelling. *Journal of Educational Measurement*, *56*(4), 757–792. https://doi.org/10.1111/jedm.12236

Kimbrel, L. (2019). Teacher hiring: The disconnect between research based best practice and processes used by school principals. *Administrative Issues Journal: Education, Practice, and Research*, *9*(2), 12-27. https://doi.org/10.5929/9.2.2

Kim, J., & Mueller, C. W. (1978). *Factor analysis statistical methods and practical issues*. SAGE.

Kovanovic, V., Mazziotti, C., & Lodge, J. (2021). Learning analytics for primary and secondary schools. *Journal of Learning Analytics*, *8*(2), 1-5.

Lai, M. K., Wilson, A., McNaughton, S., & Hsiao, S. (2014). Improving achievement in secondary schools: Impact of a literacy project on reading comprehension and secondary school qualifications. *Reading Research Quarterly*, *49*(3), 305–334. https://doi.org/10.1002/rrq.73

Lai, M. K., & McNaughton, S. (2016). The impact of data use professional development on student achievement. *Teaching and Teacher Education*, *60*, 434–443. https://doi.org/10.1016/j.tate.2016.07.005

Lee, M., Louis, K. S., & Anderson, S. (2012). Local education authorities and student learning: The effects of policies and practices. *School Effectiveness and School Improvement*, *23*(2), 133–158. https://doi.org/10.1080/09243453.2011.652125

Levacic, R., & Glatter, R. (2001). “Really good ideas?” Developing evidence-informed policy and practice in educational leadership and management. *Educational Management and Administration, 29* (5), 5–25.

Lyon, A., Bruns, E., Weathers, E., Canavas, N., Ludwig, K., Stoep, A., Cheney, D., & McCauley, E. (2014). Taking evidence-based practices to school: Using expert opinion to develop a brief, evidence-informed school-based mental health intervention. *Advances in School Mental Health Promotion*, *7*(1), 42–61. https://doi.org/10.1080/1754730X.2013.857903

Maier, U. (2010). Accountability policies and teachers' acceptance and usage of school performance feedback - A comparative study. *School Effectiveness and School Improvement*, *21*(2), 145–165. https://doi.org/10.1080/09243450903354913

Means, B., Toyama, Y., Murphy, R., & Baki, M. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teachers college record*, *115*(3), 1-47.

Malin, J., & Brown, C. (2019). What we want, why we want it: K-12 educators' evidence use to support their grant proposals. *International Journal of Education Policy and Leadership*, *15*(3), (1-19). https://doi.org/10.22230/ijepl.2019v15n3a837

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). Making sense of data-driven decision making in education (1-18). In *Policy File*. RAND Corporation.

Marsh, J. A. (2012). Interventions promoting educators' use of data: Research insights and gaps. *Teachers College Record*, *114*(11), 1–48.

McIntosh, K., Ellwood, K., McCall, L., & Girvan, E. (2018). Using discipline data to enhance equity in school discipline. *Intervention in School and Clinic*, *53*(3), 146–152. https://doi.org/10.1177/1053451217702130

Ministry of Education. (2024). Online and remote learning. Retrieved from: https://www.ontario.ca/document/ontario-schools-kindergarten-grade-12-policy-and-program-requirements-2024/online-and-remote-learning#:~:text=PPM%20167%3A%20Online%20learning%20graduation,out%20or%20been%20exempted%20in

Moussavi, M., Amannejad, Y., Moshirpour, M., Marasco, E., & Behjat, L. (2020). Importance of data analytics for improving teaching and learning methods. In *Data Management and Analysis* (pp. 91–101). Springer International Publishing. https://doi.org/10.1007/978-3-030-32587-9_6

Nardi, P. M. (2003). *Doing survey research: A guide to quantitative methods*. Boston, MA: Pearson Education.

Nilsen, P. (2015). Making sense of implementation theories, models and frameworks. *Implementation Science*, *10*(1), 1–13. https://doi.org/10.1186/s13012-015-0242-0

Nuland, S., Mandzuk, D., Tucker Petrick, K., & Cooper, T. (2020). COVID-19 and its effects on teacher education in Ontario: A complex adaptive systems perspective. *Journal of Education for Teaching 46*(4), 442–451. https://doi.org/10.1080/02607476.2020.1803050

Omoso, E., Schildkamp, K., & Pieters, J. (2019). Data use in Kenyan secondary schools. *Journal of Professional Capital and Community*, *4*(3), 216–231. https://doi.org/10.1108/JPCC-11-2018-0027

Pagan, S., Magner, K., & Thibedeau, C. (2019). Supporting data-driven decision making in a Canadian school district. *Int. J. Digit. Soc, 10,* 1510-1515.

Piaget, J. (1977). The role of action in the development of thinking. In *Knowledge and development* (pp. 17–42). Springer US.

Potts, J. (2022). *An analysis of elementary educators' use of student data in making instructional decisions*. ProQuest Dissertations Publishing.

Prinsloo, P., & Slade, S. (2019). Mapping responsible learning analytics: A critical proposal. In *Responsible analytics and data mining in education* (1st Ed., pp. 63–79). Routledge. https://doi.org/10.4324/9780203728703-5

Rangel, V. S., Bell, E. R., & Monroy, C. (2017). A descriptive analysis of instructional coaches' data use in science. *School Effectiveness and School Improvement*, *28*(2), 217–241. https://doi.org/10.1080/09243453.2016.1255232

Saleh, A. (2021). The effectiveness of differentiated instruction in improving Bahraini EFL secondary school students in reading comprehension skills. *REiLA*, *3*(2), 135–145. https://doi.org/10.31849/reila.v3i2.6816

Schildkamp, K., and Ehren, M. (2013). From "intuition" to "data"-based decision making in Dutch secondary schools? In K. Schildkamp, M. K. Lai, and L. Earl (Eds.), *Data-Based Decision Making in Education*, 49–67, New York, NY: Springer Netherlands.

Schildkamp, K., Poortman, C., & Handelzalts, A. (2016). Data teams for school improvement. *School Effectiveness and School Improvement*, *27*(2), 228–254. https://doi.org/10.1080/09243453.2015.1056192

Schildkamp, K., Poortman, C., Luyten, H., & Ebbeler, J. (2017). Factors promoting and hindering data-based decision making in schools. *School Effectiveness and School Improvement*, *28*(2), 242–258. https://doi.org/10.1080/09243453.2016.1256901

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia and Analgesia*, *126*(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Tayem, A., & Bourgeois, I. (2025). Data-based decision-making by teachers in K-12 schools: A scoping review. *Canadian Journal of Learning and Technology 50*(3), 1–23.

Tomlinson, C. A. (2017). *How to differentiate instruction in academically diverse classrooms* (3rd ed.). ASCD.

Tsai, Y., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *50*(6), 2839–2854. https://doi.org/10.1111/bjet.12846

van Geel, M. J. M., Keuning, T., Visscher, A. J., & Fox, G. J. (2016). Assessing the effects of a school-wide data-based decision-making intervention on student achievement growth in primary schools. *American Educational Research Journal*, *53*(2), 360–394. https://doi.org/10.3102/0002831216637346

van Geel, M., Visscher, A. J., & Teunis, B. (2017). School characteristics influencing the implementation of a data-based decision making intervention. *School Effectiveness and School Improvement*, *28*(3), 443–462. https://doi.org/10.1080/09243453.2017.1314972

van Geel, M., Keuning, T., Visscher, A., & Fox, J. (2019). Changes in educational leadership during a data-based decision making intervention. *Leadership and Policy in Schools*, *18*(4), 628–647. https://doi.org/10.1080/15700763.2018.1475574

Wayman, J. C., Wilkerson, S. B., Cho, V., Mandinach, E. B., & Supovitz, J. A. (2016). Guide to using the Teacher Data Use Survey. REL 2017-166. *Regional Educational Laboratory Appalachia*.

Weller, M. (2020). 2014 Learning analytics. In *25 years of ed tech (1st Eds)* (pp.143-150). Athabasca University Press.

Wilcox, G., Fernandez Conde, C., & Kowbel, A. (2021). Using evidence-based practice and data-based decision making in inclusive education. *Education Sciences*, *11*(129), 1–11. https://doi.org/10.3390/educsci11030129

Ylimaki, B., & Brunderman, L., (2019). School development in culturally diverse U.S. schools: Balancing evidence-based policies and education values. *Education Sciences*, *9*(84), 1–15. https://doi.org/10.3390/educsci9020084

Appendices

Appendix A: Shapiro-Wilk W test for normality.

Variable Construction and Validity

The table below presents the results of the Shapiro-Wilk test, which evaluates whether the distribution of each variable in the dataset deviates from normality. The test generates a W statistic, with values closer to 1 indicating distributions closer to normal. The p-value (Prob > z) helps determine statistical significance, where a p-value less than 0.05 suggests the variable deviates from normality. The table suggests that usage, leadership, collaboration, access, and data quality have p-values greater than 0.05, indicating that their distributions do not noteably deviate from normality. However, support (p = 0.012), anxiety (p = 0.009), and perceptions (p = 0.005) exhibit deviations from normality, as their p-values are below 0.05.

Distribution Shapiro-Wilk W test for normal data

Variable	Obs.	W	V	z	Prob>z
usage	102	0.99665	0.281	-2.816	0.99757
leadership	87	0.97415	1.901	1.414	0.07868
support	97	0.96572	2.76	2.248	0.01228
collaboration	96	0.97824	1.736	1.221	0.11096
access	94	0.97553	1.919	1.441	0.07483
Data quality	95	0.99313	0.543	-1.35	0.91147
anxiety	95	0.96294	2.932	2.38	0.00867
efficacy	93	0.9854	1.134	0.279	0.39019
perceptions	91	0.95823	3.188	2.559	0.00525

Appendix B: Binary analysis of data

Correlation Using Binary Variables – Simple Average Weight

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) usage	1.000								
(2) leadership	0.358	1.000							
(3) support	0.197	0.329	1.000						
(4) collaboration	0.504	0.269	0.198	1.000					
(5) access	0.390	0.374	0.432	0.232	1.000				
(6) data_quality	0.362	0.553	0.468	0.259	0.490	1.000			
(7) anxiety	-0.197	-0.241	-0.169	-0.140	-0.221	-0.158	1.000		
(8) efficacy	0.461	0.499	0.321	0.264	0.396	0.553	-0.475	1.000	
(9) perceptions	0.186	0.331	0.117	0.084	0.153	0.166	-0.379	0.189	1.000

Spearman rho = 0.189

Notes Binary variables were created by recoding responses as follows: For frequency, "Always," "Usually," and "Often" = 1; "Sometimes" and "Rarely" = 0. For agreement, "Srongly agree " and "Agree" = 1; "Disagree" and "Strongly disagree" = 0.

Regression Using Binary Variables – Simple Average Weigh

usage	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
efficacy	.551	.18	3.06	.003	.191	.91	***
leadership	.075	.09	0.83	.411	-.105	.255	
support	-.078	.11	-0.71	.478	-.298	.141	
collaboration	.435	.11	3.95	0	.215	.654	***
access	.118	.093	1.27	.208	-.067	.302	
data_quality	-.088	.13	-0.68	.501	-.346	.171	
anxiety	.117	.093	1.26	.212	-.068	.302	
perceptions	.188	.125	1.51	.135	-.06	.437	
Constant	-.335	.156	-2.15	.035	-.646	-.024	**

Mean dependent var	0.646	SD dependent var	0.343
R-squared	0.425	Number of obs	79
F-test	8.698	Prob > F	0.000
Akaike crit. (AIC)	28.491	Bayesian crit. (BIC)	49.816

**** p<.01, ** p<.05, * p<.1*

Notes Binary variables were created by recoding responses as follows: For frequency, "Always," "Usually," and "Often" = 1; "Sometimes" and "Rarely" = 0. For agreement, "Srongly agree " and "Agree" = 1; "Disagree" and "Strongly disagree" = 0.

Correlation Using Binary Variables – Factor Analysis Weight

```
Number of observations:
                      min =  80
                      avg =  92
                      max = 102
```

	usage_~r	leader~r	suppor~r	collab~r	data_a~r	data_q~r	anxiet~r	effica~r	perce~or
usage_factor	1.0000								
leadership~r	0.2918	1.0000							
support_fa~r	0.1772	0.3260	1.0000						
collaborat~r	0.4965	0.2091	0.1614	1.0000					
data_acces~r	0.3281	0.3563	0.4090	0.1599	1.0000				
data_quali~r	0.3310	0.4974	0.3935	0.2115	0.4480	1.0000			
anxiety_fa~r	-0.2152	-0.2088	-0.1542	-0.1496	-0.2091	-0.1238	1.0000		
efficacy_f~r	0.4356	0.4945	0.2809	0.1537	0.3735	0.4715	-0.4568	1.0000	
perceptio~or	0.2294	0.3230	0.1624	0.1553	0.1529	0.1755	-0.3867	0.2362	1.0000

Notes Binary variables were created by recoding responses as follows: For frequency, "Always," "Usually," and "Often" = 1; "Sometimes" and "Rarely" = 0. For agreement, "Srongly agree " and "Agree" = 1; "Disagree" and "Strongly disagree" = 0.

Linear Regression Using Binary Variables – Factor Analysis Weight

```
Linear regression                               Number of obs     =         79
                                                F(8, 70)          =       7.52
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4028
                                                Root MSE          =     .80879
```

usage_factor	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
leadership_factor	.106027	.1059471	1.00	0.320	-.1052779	.3173318
support_factor	-.0720688	.1220833	-0.59	0.557	-.3155562	.1714186
collaboration_factor	.3904178	.1032275	3.78	0.000	.1845371	.5962985
data_access_factor	.1006131	.0952735	1.06	0.295	-.089404	.2906301
data_quality_factor	-.0930453	.1283578	-0.72	0.471	-.3490469	.1629562
anxiety_factor	.1224516	.1095731	1.12	0.268	-.0960851	.3409884
efficacy_factor	.4173156	.1385706	3.01	0.004	.1409454	.6936859
perceptions_factor	.1182928	.1060398	1.12	0.268	-.0931969	.3297824
_cons	-.053722	.0925669	-0.58	0.564	-.2383408	.1308969

Notes Binary variables were created by recoding responses as follows: For frequency, "Always," "Usually," and "Often" = 1; "Sometimes" and "Rarely" = 0. For agreement, "Srongly agree " and "Agree" = 1; "Disagree" and "Strongly disagree" = 0.

Chapter 4: Exploring Secondary Teachers’ Needs for Effective Data Use in Ontario’s Online Classrooms

Abstract

Effective data use in education is widely recognized as a key factor in enhancing instructional decision-making (Pott, 2022; Schildkamp et al., 2019). This study examines the data-based decision-making (DBDM) needs of Ontario online secondary school teachers and explores how these needs can inform professional learning opportunities. It employs a mixed methods design to identify key enablers and barriers to DBDM practices. Findings reveal that while teachers value data, gaps in their data literacy skills hinder effective use. Addressing these gaps requires professional development that also integrates organizational support and enhances data accessibility. Teachers highlight that key training areas, which include leveraging AI use for tailored instruction, DBDM subject-specific training led by experienced educators, and hands-on scenario-based learning, are essential for strengthening DBDM practices. By aligning professional learning with these needs, this study offers insights for strengthening DBDM practices and improving student outcomes.

Keywords: Data-Based Decision-Making, Teacher Professional Development, Online Secondary Education, Data Literacy, Ontario

Introduction

Over the past decade, online learning has become an integral component of Ontario's secondary education system, mainly driven by national policy reforms (Farhadi & Winton, 2024). While the initial expansion of online learning was accelerated by the COVID-19 pandemic (Spadafora et al., 2023), online education has since become a permanent fixture embedded within Ontario's education system rather than an emergency measure (Ministry of Education, 2024). This shift towards the digitalization of education has necessitated a reimagining of instructional practices, with data-based decision-making (DBDM) emerging as a crucial approach for enhancing teaching and learning outcomes (Botvin et al., 2023).

DBDM refers to the systematic use of student data to inform and improve teaching practices, identify learning gaps, and tailor instructional strategies to meet diverse student needs (Marsh, 2006; 2012). These data can be qualitative (e.g., teacher observation data) or quantitative (e.g., demographic, assessment data, student survey data) (Voithofer & Golan, 2019). Data can also be derived from learning analytics, produced through student interactions within digital learning environments (Siemens, 2013). Learning analytics leverage real-time data from learning management systems, online assessments, and engagement metrics (e.g., time spent on tasks, clickstream data, and discussion forum participation) to provide insights into student learning behaviors and progress (Sin & Muthu, 2015).

However, the effective use of DBDM relies heavily on several factors that are related to the teaching environment and to the data literacy of teachers, which depend on institutional support and access to ongoing learning opportunities (Schildkamp et al., 2013, Schilkamp et al., 2016; Marsh, 2012). Despite DBDM's potential in enhancing pedagogical decision-making and student academic outcomes (Curry et al., 2016; Hebbecker et al., 2022; Peters et al., 2021; van der Scheer et al., 2016), the adoption of DBDM in online secondary education presents unique challenges (Kovanovic et al., 2021). Teachers must navigate a complex landscape of data systems, technological tools, and student engagement metrics, all while adapting to the asynchronous and often impersonal nature of online teaching (Fischer et al., 2020; Gudivada et al, 2019; Kew & Tasir, 2022; Rosenberg et al., 2022).

These challenges are particularly relevant in Ontario's online education system, which consists of three main models (Government of Ontario, 2025). First, remote learning provides K-12 students with online instruction during emergencies, such as pandemics or natural disasters. It is delivered synchronously, with real-time teacher-led instruction and regular interaction between students and educators. Second, the Independent Learning Centre (ILC), operated by TVO for English-language students and TFO for French-language students, offers self-paced, asynchronous courses for independent learners, adults, and students seeking additional Ontario Secondary School Diploma (OSSD) credits. These courses have minimal teacher interaction and assessment is conducted through self-directed assignments and standardized final exams. The third model is the online classes offered by school boards for students enrolled in Ontario secondary schools as they fulfill the mandatory online credit requirement. These courses may be synchronous, asynchronous, or blended, and they maintain regular teacher interaction, ongoing assessments, and structured support. Together, these three models reflect a complex and evolving digital education ecosystem that poses both opportunities and challenges for educators and learners alike.

Given the growing prominence and complexity of these online learning models, understanding the specific DBDM needs of Ontario's secondary school teachers who deliver online courses has become increasingly important. Gaining insight into these needs is essential for designing professional learning opportunities that enable educators to effectively integrate data into their instructional practices and ultimately enhance student outcomes.

This article aims to address two main research questions:

1. What competencies are needed by Ontario online secondary school teachers to use DBDM to inform their instructional practices?
2. How can these competency needs be transformed into professional learning opportunities?

By exploring these questions, this study seeks to provide actionable insights that inform the development of targeted professional development programs, which can ultimately enhance the quality of online education in Ontario secondary schools.

Literature Review

The potential uses and applications of data to improve instructional decisions are unlimited. Teachers can use data to set appropriate student learning goals, monitor progress towards these goals, set the pace of lessons, give students feedback, identify relevant instructional content, understand student errors, and support students in self-assessment and monitoring (Schildkamp & Ehren, 2013; Schildkamp et al., 2017). A systematic and consistent use of DBDM involves a proactive modification of teaching methods and approaches to address the broad range of learners' readiness levels, interests, and modes of learning to create interactional feedback loops between students and teachers (Faber et al., 2018). This helps teachers rethink education, decentralize it by providing student-centered education, and create an environment that gives individual students a voice and an opportunity to express themselves (Saleh, 2021).

Recent large-scale and nationwide studies have demonstrated a clear connection between using DBDM to enhance instruction and substantial improvements in academic outcomes across diverse educational settings. Such settings include, for instance, small rural elementary schools in New Hampshire (Carrier & Whaland, 2018); culturally and socioeconomically diverse schools across the United States (Carlson et al., 2011; Hoover & Abrams, 2013; Lee et al., 2012; Ylimaki & Brunderman, 2019); public schools in the Netherlands (Keuning et al., 2019; Schildkamp et al., 2016; Schildkamp et al., 2017); elementary and secondary schools in New Zealand (Lai et al., 2014; Lai & McNaughton, 2016), and secondary schools in Bahrain (Saleh, 2021).

It is important, though, to acknowledge that while several studies identified a link between data use and enhanced pedagogical decision making and academic outcomes (e.g., Faber et al., 2018; van Geel et al., 2017;), this is not always the case. The effects of a DBDM intervention on student outcomes can vary depending on the type of intervention and the setting in which it is implemented (Carr-Hill et al., 2016). Understanding that data alone will not guarantee effective use, DBDM researchers advocate for designing interventions based on process and determinant frameworks to maximize effectiveness (Nelsen, 2015). Process frameworks articulate the required competencies to identify, interpret, and create instructional strategies based on data (Sun et al., 2016). These frameworks help define what teachers need to know and be able to do in order to use data effectively. In contrast, determinant frameworks focus on the conditions under which data use occurs (Schildkamp et al., 2017). They help situate teacher competencies within the broader school environment, recognizing that even the most well-developed skills can be constrained or enabled by external factors.

DBDM Competencies Using Process Frameworks Lens

Researchers have proposed models to assist educators in the DBDM process that can ultimately build their DBDM competencies and serve as the basis for DBDM training programs (Mandinach et al., 2008; Marsh, 2012; Marsh et al., 2006; Schildkamp & Poortman, 2015). For example, Boudett, City, and Murnane (2006) introduced a specific "Data Wise" process, which is an 8-step structured process that guides teachers through DBDM, starting with teacher collaboration and continuing with cycles of data introduction and examination, instructional change action steps, and implemented change assessments. However, one shortcoming of this model is its over-reliance on quantitative data, which prioritizes standardized assessment results over qualitative insights such as teacher observations and student reflections. Schildkamp et al. (2016) developed the Data Teams model largely used in DBDM interventions (e.g., Andersen, 2020; Datnow et al., 2018; Hebbecker et al., 2022; Lai et al., 2014; Lai & McNaughton, 2016; Michaud, 2016; Ylimaki & Brunderman, 2019). In this model, a team composed of a data expert, four to six teachers, and one or two school administrators addresses an administrative or school-wide issue rather than focusing solely on instructional purposes. Therefore, the Data Teams model is not suited to daily use by teachers seeking to improve their pedagogical approaches. Another example is the Data Inquiry model (Marsh, 2012), which is a data analysis process that may be better suited for adoption by teachers for DBDM at the classroom level. This model focuses on the following steps: 1) access and collect data, 2) organize, filter, and analyze data to elicit information, 3) integrate information with expertise to extract knowledge, 4) adjust action and practice, and 5) assess the effectiveness of the intervention and provide feedback. This model is more flexible in terms of users and data, which can be both qualitative and/or quantitative.

Building on the above-mentioned frameworks, we identify four core competencies essential for effective data-driven instruction:

- **Data Identification**: The ability to recognize and select relevant data sources aligned with instructional goals.
- **Data Analysis and Interpretation**: The capacity to analyze and derive meaningful insights from data to inform decision-making.
- **Instructional Application**: The skill to translate data insights into actionable teaching strategies that enhance student learning.
- **Data Tools Efficacy**: Proficiency in utilizing data systems and tools to facilitate accurate identification, analysis, and application of data.

In order to enhance teachers' DBDM use, targeted professional development opportunities that emphasize DBDM competencies are essential, as the ability to interpret and use data effectively is not an innate skill, but rather one that needs to be developed over time (Bocala & Boudett, 2015; McCombes-Tolis & Spear- Swerling, 2011). Despite the convenience of modern technology facilitating easy access to data, utilizing it effectively requires specific skills that are not currently covered as part of in-service professional development for Ontario teachers (Pagan et al., 2019).

DBDM Competencies Within the Broader Context Using the Determinant Framework Lens

In addition to DBDM core competencies, various factors related to organizational context (e.g., leadership support, a collaborative culture, and clearly articulated vision and norms), user characteristics (e.g., teachers' attitudes, self-efficacy in DBDM, and practical experience with the inquiry process), and data characteristics (e.g., the quality, timeliness, and usability of the data) all play critical roles in determining whether data use translates into improved educational outcomes (Schilkamp et al, 2017). This combined consideration of both process and determinant elements provides a more comprehensive understanding of the potential needs of teachers involved in DBDM, by balancing the focus on individual competencies (data literacy skills) with the broader structural and contextual factors that influence the success of data use in educational settings. It also provides the conceptual foundation of this study, as this dual perspective is essential for designing effective professional development initiatives and policy interventions that not only enhance teachers' ability to use data but also in creating an enabling environment that maximizes its impact on student learning.

Building on this broader understanding, the present article focuses on the specific context of Ontario's online secondary school teachers. It aims to identify the particular competencies these educators require to effectively implement DBDM in their instructional practices and to examine how these competency needs can be translated into meaningful professional learning opportunities.

Methods

Research Design

This study employed an explanatory sequential mixed methods design to assess the needs of Ontario online secondary school teachers in incorporating DBDM into their instructional practices. The purpose was to identify gaps between current practices and recommended approaches to DBDM, as well as to identify the barriers and enablers influencing teachers' ability to engage in data-informed instruction. While the dataset was originally collected to examine the relationship between DBDM determinants (e.g., leadership, support, collaboration, access to data of good quality) and data use in online teaching (Authors, manuscript in preparation), the present study extends this work by analyzing teachers' professional development needs.

Participants

The study draws on data collected from Ontario secondary school teachers who taught online courses between 2021-2022 and 2023-2024. The dataset includes survey responses from 102 teachers (92 English-speaking, 10 French-speaking) and eight follow-up interviews (seven English-speaking, one French-speaking). Responses were reanalyzed to identify the gap between the current state (teachers' self-reported practices) and the desired state (recommended DBDM approaches in the literature).

Procedures

To facilitate participant recruitment, an external research application was submitted to all English school boards in Ontario, with approvals granted by nine boards. To enhance the study's reach, the Ontario Secondary School Teachers' Federation (OSSTF) was engaged, which enabled the distribution of an invitation to all secondary school teachers delivering English-language online courses in Ontario.

Recruitment of French-speaking teachers followed a different approach due to the labour action that affected certain school boards at the time of data collection. Instead of relying on institutional approvals, publicly available contact details of educators in French-language schools were identified through online sources. This direct email-based outreach method ensured the inclusion of French-speaking teachers in the study.

All participants who consented to follow-up interviews as part of the survey were subsequently contacted. A semi-structured interview guide was employed to explore key survey findings, providing an opportunity to triangulate and enrich the quantitative data (Jick, 1979). Both the survey and interviews took place during the 2023-2024 academic year.

Instruments

A comprehensive review of the literature identified several well-established, field-tested survey questions from prior research studies, including Dunn et al. (2013), Moussavi et al. (2020), Schildkamp et al. (2017), and Wayman et al. (2016). These studies provided validated measures related to DBDM. In addition to incorporating items from existing instruments, new survey questions were developed to ensure a comprehensive alignment with the study's objectives. These items were rigorously reviewed by experts in the field, who provided feedback on their clarity, coherence, and relevance to the research goals. The final survey instrument included nine key themes: data use, leadership, support, collaboration, access to data, quality of data, DBDM anxiety, DBDM efficacy, DBDM perceptions. However, the present study specifically focused on the DBDM efficacy theme, which assessed four core competencies essential to effective data-driven decision-making. These competencies, as outlined in the conceptual framework above, include 1- data identification, 2- data interpretation, 3- data application to instruction, and 4- the use of technological tools.

In addition to the quantitative survey items, an open-ended question was included to gather teachers' perspectives on their preferences and needs for future DBDM-related professional development opportunities. To gain deeper insights into these responses, follow-up 30-minute interviews were conducted online with willing participants. These interviews provided a more nuanced understanding of teachers' experiences with DBDM and their specific training needs, complementing the survey findings and enriching the overall analysis.

Analytical Approach

Quantitative Analysis. Survey data were analyzed using univariate analysis, as it allows for a detailed examination of individual variables (Royse et al., 2009). Descriptive statistics, including mean scores and standard deviations, were calculated to assess teachers' efficacy for five items distributed against the four key areas of DBDM: data identification, data interpretation, instructional application and data tools efficacy. The instructional application items were calculated using simple average weight. (See Table 1).

Table 1

Survey Items that Measured DBDM Competencies

Competency	Survey item
Efficacy for data identification	I am confident in my ability to determine which data are beneficial to me and which data are not.
Efficacy for data technology use	I am confident that I can use the tools provided by the learning management system to retrieve charts, tables or graphs for analysis.
Efficacy for data analysis and interpretation	I am confident in my ability to interpret student data to determine student strengths and weaknesses in a content area.
Efficacy for application of data to instruction	I am confident that I can use data to group students with similar learning needs for instruction.
	I am confident that I can use assessment data to provide targeted feedback to students about their performance or progress.

The survey items were measured on a 4-point Likert scale, and the mean for each variable was computed to summarize participants' self-reported competencies. To facilitate interpretation, the following thresholds were established: mean scores between 1.00 and 1.90 were categorized as low, indicating limited confidence or engagement in the given competency; scores between 2.00 and 2.90 were considered moderate, reflecting developing or inconsistent proficiency; and scores between 3.00 and 4.00 were classified as high, signifying strong confidence and engagement. Missing data were omitted from the analysis to ensure accuracy in the reported statistics.

Qualitative Analysis. The qualitative data from both the open-ended survey question and the interviews were analyzed using thematic analysis with NVivo. Responses were coded under the four key competencies outlined in the conceptual framework—data identification, data tools efficacy, data interpretation, and instructional application—while also allowing for the emergence of new themes related to the challenges teachers face and the training needs they articulated. The analytical approach combined deductive and inductive methods: predefined categories (as shown in Table 1) guided the initial coding process, while additional themes were identified as they emerged from the data (Flick, 2006). This dual approach ensured that the analysis captured both theoretically-driven patterns and participant-driven perspectives on professional development needs.

The findings from both quantitative and qualitative analyses were synthesize, highlighting key areas where intervention is required. This profile informs recommendations for professional learning and institutional support strategies to enhance teachers' DBDM capabilities.

Limitations

While this study provides valuable insights into teachers' DBDM needs, the dataset was originally collected for a broader exploration of DBDM determinants. Additionally, the sample may not fully represent all online secondary teachers in Ontario, particularly French-speaking educators. Future research could expand this approach to a larger, more diverse sample and incorporate additional stakeholder perspectives (e.g., school administrators, policymakers).

Findings

This section outlines key findings on Ontario secondary teachers' competencies and support needs for DBDM training, structured around our two research questions. First, the analysis focuses on teachers' competencies related to DBDM, which are conceptualized through elements taken from the process framework of Marsh (2012). These competencies fall under the broader construct of DBDM efficacy, which encompass four key competencies: (1) efficacy for data identification, (2) efficacy for data technology use, (3) efficacy for data analysis and interpretation, and (4) efficacy for the application of data to instruction. Second, we describe teacher preferences related to DBDM professional learning.

1- What competencies do Ontario online secondary school teachers need for using DBDM to inform their instructional practices?

The descriptive statistics highlight variations in teachers' self-reported efficacy across different DBDM competencies while teaching online, following the sequential process of data use. As shown in Table 2, teachers reported high confidence in interpreting data accurately (M = 3.07, SD = 0.73), suggesting relative comfort in making sense of student data. However, their confidence was moderate in earlier and later stages of the process: identifying relevant data (M = 2.91, SD = 0.83), applying data to instructional planning (M = 2.75, SD = 0.84), and effectively using technological tools to facilitate data analysis (M = 2.57, SD = 0.97). These findings suggest that while teachers can analyze data once it is available, challenges remain in selecting the right data sources, integrating insights into instructional decisions, and leveraging digital tools to streamline the process. The variation in reported efficacy, as indicated by the standard deviations, may reflect differences in teachers' experience, training, and institutional support for data use. These results suggest that targeted professional development could help strengthen teachers' capabilities at each stage of data use, from identification to application, with a particular emphasis on technology integration.

Table 2

Descriptive Statistics - Self-reported DBDM competencies (n = 93)

Variable	Mean	Std. Dev.	Min	Max
Data identification	2.914	.83	1	4
Data tools efficacy	2.57	.971	1	4
Data interpretation	3.075	.726	1	4
Instructional application	2.753	.843	1	4

The qualitative data further contextualized these quantitative results, revealing the nuanced challenges teachers face in data-driven instruction. One prominent theme was the **difficulty in accessing data**. Many participants expressed frustration with navigating student information systems (SIS) and virtual learning environments (VLEs). Some noted that their school boards frequently change data platforms without providing sufficient training, leaving them to locate relevant information. As one teacher explained, “Our board is switching our SIS platform, so I hope to learn how to access data easily and efficiently.” Another teacher highlighted how restrictions on data access limit their ability to support students: “We used to be able to impersonate students to see their progress in other courses, but privacy regulations now prohibit that, making it harder to understand their overall performance."

Beyond access, teachers also struggled with identifying relevant data and ensuring its accuracy. Several respondents believe that the data they receive from standardized assessments, such as EQAO reports, is often unreliable or difficult to interpret. A math and technology teacher noted, "We do view a lot of data in PD, but it's not always accurate. It's important to me that data truly reflects what we are trying to measure." Another teacher provided additional context: "Online eLearning formats in the secondary system, as the Ontario government are [sic] currently using, follow a business model, not an educational model. Student needs are not addressed through data generation, when teachers are not trained on how to use the data, let alone how to create/find the data effectively".

In addition, teachers requested more training on data analysis and visualization techniques. Many reported lacking the technical skills needed to use data effectively. One teacher mentioned, "I'd like to be able to take the data I gather and create reports, graphs, and visual representations of student progress." Others emphasized the need for more subject-specific training, with one stating, "There needs to be a way to run comparison models and conduct multivariate analysis to make sense of student achievement trends."

A crucial concern among participants was the disconnect between data and instructional practice. Several teachers questioned how data-driven approaches genuinely enhance student learning, noting that administrative perspectives on data usage do not always align with classroom realities. One teacher explained, "The data derived from academic achievement is often viewed through the lens of administration, which doesn't always reflect the day-to-day challenges of teaching." Others called for more practical training on integrating data insights into lesson planning and assessment design, with one stating, “I want to learn how to better assess progress using informal assessments and data models.”

Finally, time constraints emerged as barrier to effective data use. Teachers reported that analyzing data requires dedicated time, which is often unavailable due to their heavy workloads. One participant expressed this frustration succinctly: “Just more time to sit and analyze data and learn how to use it properly—right now, it feels like an added burden rather than a helpful tool.”

2- How can these needs be transformed into professional learning opportunities?

Participants highlighted shortcomings in past training on data use, describing it as superficial, inconsistent, or entirely absent. Many reported that most training sessions focused on locating data rather than interpreting or applying it effectively, leaving them to rely on trial and error or informal peer support. Looking ahead, educators emphasized the need for structured, hands-on training that goes beyond basic navigation. They want to learn how to integrate AI to analyze data efficiently and save time, as well as receive more contextualized, subject-specific training. Additionally, they see data use as a way to move beyond feeling anonymous in digital learning environments, which can help them connect more meaningfully with students and support their well-being.

Prior Training: What Was Missing?

The feedback from participants highlights several critical shortcomings in past training sessions on data use in education. Many educators reported receiving minimal or ineffective training, often limited to basic instructions.

Minimal and Surface-Level Training

A recurring theme in the interview responses was frustration with the quality of training. Many educators noted that the training they received was inadequate. One teacher explained: “I've only had a little bit of training on the use of data. Mostly they just show us where the data can be found, like for example, in the Markbook in D2L”. Another teacher shared this sentiment: “Honestly, most of the training we get is disappointing. Like you'll be excited to go and get this training, and then the person knows way less than you do about it.” This was also echoed by another teacher: “Most professional development in Ontario schools is done by people who’ve never stepped into a classroom in their life... we would need to learn something where data is helpful in a classroom and without taking too much time because teachers don’t have any time.”

Informal Learning and Peer Support

In the absence of formal training, educators often turned to colleagues for guidance. One teacher described their reliance on informal peer networks: “Mostly everything I've learned, I just kind of ask people. So, setting up meetings with people that I know are really good. And a lot of times, you set up a meeting with this person because they know like a little bit and then they tell you who they learned it from.” Some educators even took on training roles themselves, despite not receiving formal instruction. One participant shared: “I was having conference calls with teachers, teaching them how to use D2L and find the data they need.”

No Training at All

Most educators reported receiving no formal training on data use. One teacher expressed this reality: “I haven’t received any training. I think just being a teacher you would use data regardless to determine how your students are doing, where they’re having trouble, how do you help them.” Another participant emphasized the expectation that teachers figure things out independently: “The problem with this profession is that most things that you get told to do, you spend all your time learning to do it yourself. I’ve not really had any formal training in data. My degree is in English”. Echoing this challenge, another teacher pointed out that even basic guidance on data tools was missing: “It’s not like anyone taught me how to use Brightspace or extract data from there. It’s not like anyone ever set aside time to teach us.”

Future Training Needs

Participants expressed a strong desire for future professional development that is directly relevant to their subject areas, practical in application, and responsive to emerging technological advancements. Their responses highlighted the need for more individualized and hands-on training opportunities tailored to their instructional contexts.

Artificial Intelligence (AI) Integration for DBDM

Several participants reflected on the potential role of AI in analyzing student performance data to inform instructional practices. As one teacher noted: “Students have to write the Education Quality and Accountability Office (EQAO) and they have to write the Ontario Secondary School Literacy Test (OSSLT). And the AIs are getting pretty smart now that you could train them to go through all of these data to come up with better ways to engage our students or to improve their literacy and math skills.” Another teacher envisioned a more transformative role for AI in education, suggesting that in the future, AI could be responsible for personalized learning plans: “There’s no way a teacher would have time to do differentiated instruction to every student even when having sufficient data. However, if the teacher was an

AI... you probably will get a nice, tailored course to every student. In a classroom context, a teacher would just be a facilitator." While these perspectives suggest optimism about AI's potential, there was also recognition of the lack of training on how to effectively integrate the data AI has into teaching practices. As one participant stated: "But how to use it to change how you teach or how you design a class now? There's no training on that. No, that's just left to each individual teacher."

Subject-Specific and Modality of Training

Teachers expressed a need for professional development that is directly applicable to their specific subject areas. One participant emphasized: "If I was to say anything training-wise, I would love to have in-depth, specific training for our subject areas... if you could have a mentor come out and even work with us as a department to show us three or four things that would be applicable to our subject matter." Another teacher suggested that a more effective model of training would combine asynchronous learning with live support: "We should be trained on how to do these things... having pre-recorded videos that we can pause and then go back in with also live assistance when we get stuck would be super helpful."

Fostering Student Well-Being and Student-Teacher Connection

Teachers expressed a desire to better understand student well-being, particularly in online learning environments, recognizing that academic success and well-being are deeply interconnected. One participant emphasized: "When it comes to data related to student well-being, I'd like to broaden my knowledge in that area because it varies from student to student. And often, since it's online, all I see is the work produced. I have no idea what's happening at school or at home when the student is working on it." This highlights the need for professional development that integrates instructional strategies with insights into students' emotional and psychological well-being. By using data not only to inform teaching but also to foster stronger connections with students, educators can create more supportive and responsive learning environments.

Discussion

The findings reveal critical gaps in the competencies of Ontario secondary school teachers related to DBDM, particularly within online learning environments. While teachers demonstrate confidence in data interpretation, they struggle with key stages of the process, including identifying relevant data sources, navigating digital platforms, and applying data insights to instructional decision-making. These challenges are exacerbated by systemic barriers such as inconsistent access to high-quality data, inadequate training, and platform instability. Existing DBDM frameworks, such as the one proposed by Marsh (2012), do not fully account for the complexities of online education, where data collection is often automated, and teachers must synthesize pre-existing digital data rather than generate it themselves. This gap in the literature has been previously identified by Tayem and Bourgeois (2025), emphasizing the need for a revised DBDM process model tailored to online contexts. To address these challenges, we propose an adapted DBDM model that integrates an initial inquiry phase, streamlines data interpretation, and aligns with the realities of virtual teaching. This model not only addresses the limitations of existing frameworks but also serves as a foundation for designing professional development initiatives that equip teachers with the necessary skills and support structures to implement DBDM effectively in online settings. The following points explore the rationale for this new model, its improvement over existing approaches, and its implications for teacher training and policy reform.

Introducing a New DBDM Process Model for Online Education

Instructors in online environments often struggle with the overwhelming volume of available data, the complexity of interpretation, and the difficulty of translating insights into actionable teaching strategies (Kim & Asbury, 2020; van Leeuwen et al., 2021). To address these challenges, we propose a revised DBDM model specifically designed for online education. This model enhances efficiency by streamlining data identification, integrating system-generated analytics with pedagogical expertise, and incorporating AI to support data interpretation and instructional application. (See Figure 1).

Phase I: Intentional Data Use, Before, During, and After Instruction

The new model begins with an inquiry-driven phase, where teachers formulate a guiding question or instructional goal that directs their data use. Attaran et al. (2018) emphasize that data use should always be purpose-driven; teachers need a clear rationale for why they are engaging with data. The specific reason for referring to data depends on the stage at which it is being utilized.

Designing Stage. If teachers analyze data before a course, their focus is typically on curriculum design, identifying the needs of their future students, and planning instructional strategies (Holmes, 2019; Mangaroska & Giannakos, 2018). For example, if data from engagement indicators reveal that a particular topic is popular among students and has a high engagement rate, it suggests that future students are also likely to find the topic engaging (Lockyer, 2013).

Delivery Stage. While an online course is being administered, thousands of digital traces get recorded that allows instructors to monitor students' performance and use it to provide timely and relevant feedback to students (Attaran et al., 2018; Harism, 2019; Lockyer et al., 2013). These data can also be used to understand how individuals engage in the online course, which, in turn, can help instructors tailor activities to suit each student's needs (Scott & Nicholes, 2017).

Feedback Loop Stage. After the course, data is used for evaluation, informing long-term improvements and refining future instructional approaches. Teachers can use data to determine how engaging the design and the sequence of activities were to improve consecutive iterations of the course by measuring the impact on learning outcomes and provide a benchmark on the performance of the course (Lockyer et al., 2013).

Phase II: Data Identification in Online DBDM

In traditional DBDM models, like Marsh (2012), the data collection phase emphasizes gathering and organizing information from multiple sources. However, in online teaching, learning management system and learning analytics tools automatically generate structured data, such as engagement metrics, quiz scores, and discussion activity. Our model streamlines this process by introducing a direct pathway from inquiry to data identification, enabling educators to bypass redundant data handling and focus on synthesizing relevant information. By integrating system-generated data with pedagogical expertise, educators can efficiently extract meaningful insights, ensuring that decision-making remains both data-informed and instructionally relevant in digital learning environments.

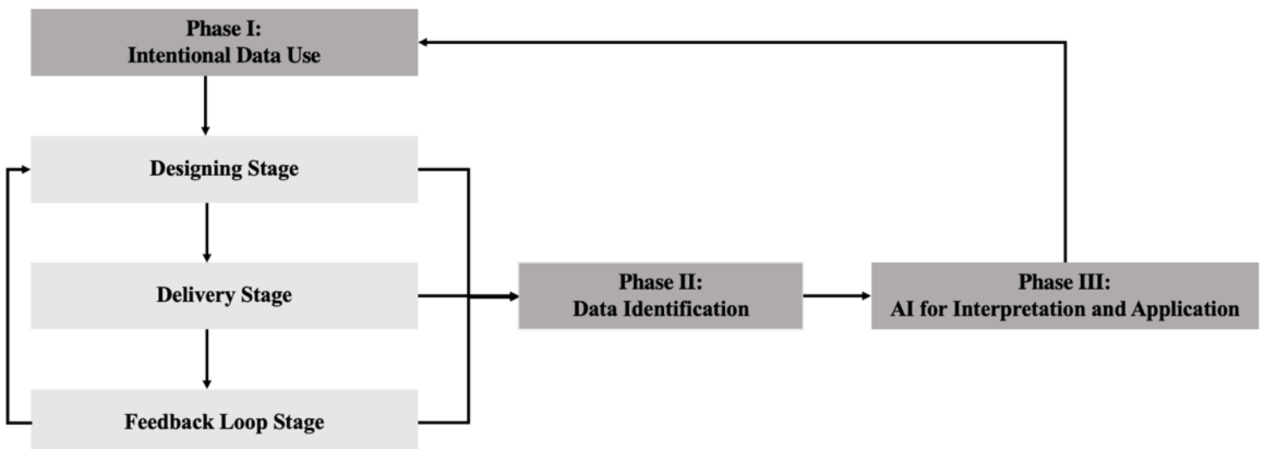
Phase III: AI for Data Interpretation and Instructional Application

The third phase of the online DBDM process model focuses on interpreting data and applying insights to instructional decisions. The findings of this study, backed up by recent work (Authors, in press) indicate that this stage is both the most time-consuming and the most challenging for educators. Teachers often struggle with interpreting complex datasets, identifying patterns, and translating findings into actionable teaching strategies. In online learning environments, where large volumes of system-generated data are available, this challenge is even more pronounced (Fischer et al., 2020; Rosenberg et al., 2022). However, AI can significantly support educators in this phase by automating data analysis, identifying trends, and providing predictive insights. AI-driven tools can generate personalized learning recommendations, highlight at-risk students based on engagement metrics, and suggest adaptive interventions tailored to student needs.

Recent federal initiatives underscore the growing relevance of AI in supporting data analysis for decision support in the federal government, such as public health monitoring, environmental monitoring, and economic forecasting, as outlined in *Consultations on the AI Strategy for the Federal Public Service: What We Heard* (Government of Canada, 2024). The strategy highlights AI's potential to analyze large datasets, predict trends, and offer insights that inform decision-making. However, despite the growing interest from educators in integrating AI to support real-time data interpretation, student profiling, and differentiated instruction, there is still **no formal policy or guidance** at the federal or provincial level regarding AI use for data analysis in education. This gap presents a critical next step: the development of an education-specific AI policy that prioritizes transparency, ethical use, data privacy, and teacher capacity-building. As the broader public service moves toward responsible AI adoption, education systems must be included in these efforts to ensure that AI-supported data use enhances equity, professional judgment, and student learning outcomes rather than undermining them. Such a policy would not only safeguard responsible implementation but also enable school systems to adopt the new Online DBDM Process Model introduced in this study with greater confidence, coherence, and trust.

Figure 1

Online DBDM Process Model



Like traditional DBDM models, the proposed online DBDM process retains a cyclical structure that ensures continuous improvement in instructional decision-making. Similar to models such as Marsh (2012) and Schildkamp et al. (2017), this framework follows an iterative loop where data aresystematically collected, analyzed, applied to instruction, and reassessed to refine teaching strategies. Each phase (i.e., intentional data use, data identification, and data interpretation and application) feeds into the next, creating an ongoing process of inquiry and adjustment. This cycle allows educators to continuously assess student needs, recognize patterns in the data, and adjust their instruction based on what works best, which creates a more flexible and informed approach to online education.

Integrating the New DBDM Model into Targeted Professional Development for Ontario's Online Secondary Educators

To enhance teacher competencies in DBDM, professional training must align with the stages of the **DBDM online process model** while addressing the specific barriers identified in Ontario secondary schools. Table 3 outlines key competencies required at each stage of the process, the challenges teachers face, and the targeted professional development strategies needed to bridge these gaps.

Table 3

Professional Learning Needs Aligned with the DBDM Online Process Model

DBDM Process Phase	Key Teacher Competencies	Challenges Identified by Ontario Teachers	Professional Training Needs
1- Intentional Data Use	- Determine when and why to use data (Attaran et al., 2018) - Align data use with instructional goals (Moore, 2019)	- Lack of clarity on the purpose of data-driven decisions - Disconnect between administrative expectations and classroom realities	- Case studies demonstrating effective data use (Lockyer et al., 2013) - Professional learning communities for peer discussion on best practices (DuFour et al., 2005)
2- Data Identification	- Recognizing relevant data sources (Voithofer & Golan, 2019). - Assessing data quality (Picciano, 2012) - Navigating different systems and using different tools (Dunn et al., 2013)	- Difficulty accessing SIS/VLE data - Frequent platform changes without training - Low confidence in using digital tools for data - Lack of formal training on data extraction - Limited time to explore tools	- Hands-on training on navigating and extracting SIS/VLE data (Garet et al., 2001). - Subject-specific data identification strategies (Desimone, 2009) - Blended learning: asynchronous tutorials + live support (Muljana et al., 2020; Schildkamp et al, 2017)
3- Data Interpretation & Application	- Interpreting student performance	- Lack of training on understanding student data	- AI integration for automated data analysis and application to instruction (Roessingh et

	trends (Marsh, 2012) - Using data to inform lesson planning, adapt instruction, and assessment. (Lockyer et al., 2013) - Using data to support student well-being (Balkis et al., 2024)	- and applying it to inform instruction - Lack of time for deep data analysis - Online learning environments create teacher-student disconnect - Teachers lack training in well-being-related data	al., 2019: Strielkowski et al., 2024) - Training delivered by experienced educators and subject-matter experts (Borko, 2004) - Case-based learning on applying data in instructional design (Sistermans, 2020). - PD on data-driven student well-being monitoring (Balkis et al., 2024)

As indicated previously, it is essential to highlight that effective professional development for DBDM must go beyond individual skill acquisition and address the broader systemic factors that shape data use in education. While training initiatives should enhance teacher competencies in data interpretation, selection, and application, their success is contingent on institutional enablers such as leadership support, access to high-quality data, and collaborative structures. Without addressing these determinants, even well-designed training programs may be ineffective (Schilkamp et al., 2017). Therefore, professional learning programs should incorporate strategies that promote a culture of data use, facilitate collaboration, and ensure that teachers have access to user-friendly data platforms. By aligning training with the structural realities of Ontario's online secondary schools, these initiatives can foster sustainable and meaningful data-informed instructional practices.

Conclusion

This study examined the needs of Ontario online secondary school teachers related to the use of DBDM for instructional purposes and explored how these needs can be translated into professional learning opportunities. The findings indicate that while teachers recognize the value of data in shaping instruction, their data literacy skills require further development. However, strengthening these skills must occur within a broader ecosystem that encompasses institutional support, leadership, collaboration, and access to high-quality, timely, and relevant data. To bridge these gaps, a structured online DBDM process model is developed to serve as a critical framework for addressing these needs. This model streamlines DBDM by integrating automated data collection, real-time visualization dashboards, AI-powered insights, to support instructional decision-making. This model can be integrated into teacher education programs for pre-service teachers and professional development for in-service teachers, to ensure that educators at all career stages develop essential data literacy skills.

References:

Attaran, M., Stark, J., & Stotler, D. (2018). Opportunities and challenges for big data analytics in US higher education: A conceptual model for implementation. *Industry & Higher Education*, *32*(3), 169–182. https://doi.org/10.1177/0950422218770937

Authors. (Manuscript in preparation). Data-based decision making in online classes: Exploring current practices and prevailing determinants.

Balkis, A. T., Bilikis, L. A., Imohimi, E., & Demilade, S. (2024). Data-driven approaches to mitigate academic stress and improve student mental health. *World Journal of Advanced Research and Reviews*, *24*(3), 2201-2206.

Bocala, C., & Boudett, K. P. (2015). Teaching educators habits of mind for using data wisely. *Teachers College Record*, *117*(4), 1-20.

Botvin, M., Hershkovitz, A., & Forkosh-Baruch, A. (2023). Data-driven decision-making in emergency remote teaching. *Education and Information Technologies*, *28*(1), 489–506. https://doi.org/10.1007/s10639-022-11176-4

Borko, H. (2004). Professional development and teacher learning: Mapping the terrain. *Educational Researcher, 33*(8), 3-15.

Boudett, K. P., City, E. A., & Murnane, R. J. (2006). The "Data Wise" Improvement Process. In *Principal leadership (Middle level ed.)* (Middle Level ed., Vol. 7, Number 2, pp. 53-). National Association of Secondary School Principals.

Bullock, S. (2011). *Inside teacher education: Challenging prior views of teaching and learning*. Sense Publishers. https://doi.org/10.1007/978-94-6091-403-4

Carlson, D., Borman, G. D., & Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis, 33*(3), 378–398. https://doi.org/10.3102/0162373711412765

Carr-Hill, R., Rolleston, C., & Schendel, R. (2016). The effects of school-based decision-making on educational outcomes in low- and middle-income contexts. *Campbell Systematic Review*, *12*(1), 1-173.

Carrier, L. L., & Whaland, M. (2018). Left behind by policy: A case study of the influence of high stakes accountability policy on data-based decision making in one small, rural New Hampshire school. *The Rural Educator*, *38*(3), 12–26. https://doi.org/10.35608/ruraled.v38i3.217

Copp, D. T. (2017). Policy incentives in Canadian large-scale assessment: How policy levers influence teacher decisions about instructional change. *Education Policy Analysis Archives*, *25*, 115-115.

Curry, K. A., Mwavita, M., Holter, A., & Harris, E. (2016). Getting assessment right at the classroom level: Using formative assessment for decision making. *Educational Assessment, Evaluation and Accountability, 28*, 89-104.

Desimone, L. M. (2009). Improving impact studies of teachers' professional development: Toward better conceptualizations and measures. *Educational Researcher*, *38*(3), 181-199.

DuFour, R., Eaker, R., & DuFour, R. (Eds.). (2005). *On common ground: The power of professional learning communities*. National Educational Service.

Dunn, K. E., Airola, D. T., Lo, J., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology*, *38*(1), 87–98.

Faber, J., Glas, C., & Visscher, A. J. (2018). Differentiated instruction in a data-based decision-making context. *School Effectiveness and School Improvement*, *29*(1), 43–63. https://doi.org/10.1080/09243453.2017.1366342

Farhadi, B., & Winton, S. (2024). E-Learning for the Public Good? The Policy Trajectory of Online Education in Ontario, Canada. *Educational Policy (Los Altos, Calif.)*, *38*(7), 1676–1712. https://doi.org/10.1177/08959048241267953

Fischer, C., Pardos, Z. A., Baker, R. S., Williams, J. J., Smyth, P., Yu, R.,... & Warschauer, M. (2020). Mining big data in education: Affordances and challenges. *Review of Research in Education*, *44*(1), 130-160.

Garet, M. S., Porter, A. C., Desimone, L., Birman, B. F., & Yoon, K. S. (2001). What makes professional development effective? Results from a national sample of teachers. *American Educational Research Journal*, *38*(4), 915-945.

Government of Canada (2024). Consultations on the AI Strategy for the Federal Public Service: What We Heard. Retrieved from: https://www.canada.ca/en/government/system/digital-government/digital-government-innovations/responsible-use-ai/consultations-ai-strategy-federal-public-service-what-we-heard.html#toc-6

Gudivada, V. N., Rao, D. L., & Ding, J. (2019). Evolution and facets of data analytics for educational data mining and learning analytics. In *Responsible Analytics and Data Mining in Education* (1st ed., pp. 16–42). Routledge. https://doi.org/10.4324/9780203728703-3

Gummer, E., & Mandinach, E. (2015). Building a conceptual framework for data literacy. *Teachers College Record (1970)*, *117*(4), 1–22.

Harasim, L. (2019). Learning about learning online: The methodology of discourse analytics. In *Responsible analytics and data mining in education* (1st ed., pp. 119–137). Routledge. https://doi.org/10.4324/9780203728703-9

Hawn, M. A. (2019). *Data-wary, value driven: Teacher attitudes, efficacy, and online access for data-based decision making*. ProQuest Dissertations Publishing.

Hebbecker, K., Förster, N., Forthmann, B., & Souvignier, E. (2022). Data-based decision-making in schools: Examining the process and effects of teacher support. *Journal of Educational Psychology*, *114*(7), 1695.

Holmes, W., Nguyen, Q., Zhang, J., Mavrikis, M., & Rienties, B. (2019). Learning analytics for learning design in online distance learning. *Distance Education*, *40*(3), 309–329. https://doi.org/10.1080/01587919.2019.1637716

Hoover, N. R., & Abrams, L. M. (2013). Teachers' instructional use of summative student assessment data. *Applied Measurement in Education*, *26*(3), 219-231.

Jick, T. D. (1979). Mixing qualitative and quantitative methods: Triangulation in action. *Administrative Science Quarterly, 24*(4), 602–611.

Kennedy, M. M. (2016). How does professional development improve teaching? *Review of Educational Research*, *86*(4), 945-980.

Keuning, T., van Geel, M., Visscher, A., & Fox, J. P. (2019). Assessing and validating effects of a data-based decision-making intervention on student growth for mathematics and spelling. *Journal of Educational Measurement*, *56*(4), 757–792. https://doi.org/10.1111/jedm.12236

Kew, S. N., & Tasir, Z. (2022). Developing a learning analytics intervention in e-learning to enhance students' learning performance: A case study. *Education and Information Technologies*, *27*(5), 7099–7134. https://doi.org/10.1007/s10639-022-10904-0

Kim, L. E., & Asbury, K. (2020). "Like a rug had been pulled from under you": The impact of COVID-19 on teachers in England during the first six weeks of the UK lockdown. *British Journal of Educational Psychology, 90*(4), 1062–1083. https://doi.org/10.1111/bjep.12381

Kovanovic, V., Mazziotti, C., & Lodge, J. (2021). Learning analytics for primary and secondary schools. *Journal of Learning Analytics*, *8*(2), 1-5.

Lai, M. K., & McNaughton, S. (2016). The impact of data use professional development on student achievement. *Teaching and Teacher Education*, *60*, 434–443. https://doi.org/10.1016/j.tate.2016.07.005

Lai, M. K., Wilson, A., McNaughton, S., & Hsiao, S. (2014). Improving achievement in secondary schools: Impact of a literacy project on reading comprehension and secondary school qualifications. *Reading Research Quarterly*, *49*(3), 305–334. https://doi.org/10.1002/rrq.73

Lee, M., Louis, K. S., & Anderson, S. (2012). Local education authorities and student learning: The effects of policies and practices. *School Effectiveness and School Improvement, 23*(2), 133–158. https://doi.org/10.1080/09243453.2011.652125

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *The American Behavioral Scientist (Beverly Hills)*, *57*(10), 1439–1459. https://doi.org/10.1177/0002764213479367

Mangaroska, K., & Giannakos, M. (2018). Learning analytics for learning design: A systematic literature review of analytics-driven design to enhance learning. *IEEE Transactions on Learning Technologies*, *12*(4), 516-534

Marsh, J. A. (2012). Interventions promoting educators' use of data: Research insights and gaps. *Teachers College Record, 114*(11), 1–48.

Marsh, J. A., Bertrand, M., & Huguet, A. (2015). Using data to alter instructional practice: The mediating role of coaches and professional learning communities. *Teachers College Record, 117*(4), 1-40.

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). Making sense of data-driven decision making in education (1-18). In *Policy File*. RAND Corporation.

Mccombes-Tolis, J., & Spear-Swerling, L. (2011). The preparation of preservice elementary educators in understanding and applying the terms, concepts, and practices associated with response to intervention in early reading contexts. *Journal of School Leadership*, *21*(3), 360-389.

Ministry of Education. (2024). Online and remote learning. Retrieved from: https://www.ontario.ca/document/ontario-schools-kindergarten-grade-12-policy-and-program-requirements-2024/online-and-remote-learning#:~:text=PPM%20167%3A%20Online%20learning%20graduation,out%20or%20been%20exempted%20in

Moore. R. L. (2019). The role of data analytics in education: Possibilities and limitations. In *Responsible analytics and data mining in education* (1st ed., pp. 101–118). Routledge. https://doi.org/10.4324/9780203728703-8

Moussavi, M., Amannejad, Y., Moshirpour, M., Marasco, E., & Behjat, L. (2019). Importance of data analytics for improving teaching and learning methods. In *Data Management and Analysis* (pp. 91–101). Springer International Publishing. https://doi.org/10.1007/978-3-030-32587-9_6

Muljana, P. S., Luo, T., Watson, S., Euefueno, W. D., & Jutzi, K. N. W. (2020). Promoting Instructional Designers' Participation in Free, Asynchronous Professional Development: A Formative Evaluation. *Journal of Formative Design in Learning*, *4*(2), 74–87. https://doi.org/10.1007/s41686-020-00044-4

Nilsen, P. (2015). Making sense of implementation theories, models and frameworks. *Implementation Science, 10*(1), 1–13. https://doi.org/10.1186/s13012-015-0242-0

Pagan, S., Magner, K., & Thibedeau, C. (2019). Supporting data-driven decision making in a Canadian school district. *Int. J. Digit. Soc, 10*, 1510-1515.

Peters, M. T., Förster, N., Hebbecker, K., Forthmann, B., & Souvignier, E. (2021). Effects of data-based decision-making on low-performing readers in general education classrooms: Cumulative evidence from six intervention studies. *Journal of Learning Disabilities, 54*(5), 334-348

Picciano, A. (2012). The evolution of big data and learning analytics in American higher education. *Online Learning (Newburyport, Mass.)*, *16*(3), 9–20. https://doi.org/10.24059/olj.v16i3.267

Potts, J. (2022). *An analysis of elementary educators' use of student data in making instructional decisions*. ProQuest Dissertations Publishing.

Roessingh, J. J., Poppinga, G., van Oijen, J., & Toubman, A. (2019). Application of artificial intelligence to adaptive instruction-combining the concepts. In *Adaptive Instructional Systems: First International Conference, AIS 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings 21* (pp. 542-556). Springer International Publishing

Rosenberg, J., Schultheis, E. H., Kjelvik, M. K., Reedy, A., & Sultana, O. (2022). Big data, big changes? The technologies and sources of data used in science classrooms. *British Journal of Educational Technology, 53*(5), 1179–1201. https://doi.org/10.1111/bjet.13245

Royse, D., Staton-Tindall, M., Badger, K., & Webster, M. (2009). *Needs assessment* (1st ed.). Oxford University Press.

Saleh, A. (2021). The effectiveness of differentiated instruction in improving Bahraini EFL secondary school students in reading comprehension skills. *REiLA, 3*(2), 135–145. https://doi.org/10.31849/reila.v3i2.6816

Schildkamp, K. (2019). Data-based decision-making for school improvement: Research insights and gaps. *Educational Research (Windsor), 61*(3), 257–273. https://doi.org/10.1080/00131881.2019.1625716

Schildkamp, K., & Ehren, M. (2013). From "intuition" to "data"-based decision making in Dutch secondary schools? In K. Schildkamp, M. K. Lai, and L. Earl (Eds.), *Data-Based Decision Making in Education*, 49–67, New York, NY: Springer Netherlands.

Schildkamp, K., Poortman, C., & Handelzalts, A. (2016). Data teams for school improvement. *School Effectiveness and School Improvement, 27*(2), 228–254. https://doi.org/10.1080/09243453.2015.1056192

Schildkamp, K., Poortman, C., Luyten, H., & Ebbeler, J. (2017). Factors promoting and hindering data-based decision making in schools. *School Effectiveness and School Improvement, 28*(2), 242–258. https://doi.org/10.1080/09243453.2016.1256901

Scott, J., & Nichols, T. P. (2017). Learning analytics as assemblage: Criticality and contingency in online education. *Research in Education (Manchester), 98*(1), 83–105. https://doi.org/10.1177/0034523717723391

Siemens. (2013). Learning Analytics: The emergence of a discipline. *The American Behavioral Scientist (Beverly Hills), 57*(10), 1380–1400. https://doi.org/10.1177/0002764213498851

Sin, K., & Muthu, L. (2015). Application of big data in education data mining and learning analytics: A literature review. *ICTACT Journal on Soft Computing, 5*(4), 1035–1049. https://doi.org/10.21917/ijsc.2015.0145

Sistermans, I. J. (2020). Integrating competency-based education with a case-based or problem-based learning approach in online health sciences. *Asia Pacific Education Review, 21*(4), 683–696. https://doi.org/10.1007/s12564-020-09658-6

Spadafora, N., Reid-Westoby, C., Pottruff, M., Wang, J., & Janus, M. (2023). From Full Day Learning to 30 Minutes a Day: A Descriptive Study of Early Learning During the First COVID-19 Pandemic School Shutdown in Ontario. *Early Childhood Education Journal*, *51*(2), 287–299. https://doi.org/10.1007/s10643-021-01304-z

Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2024). AI-driven adaptive learning for sustainable educational transformation. *Sustainable Development*.

Sun, J., Przybylski, R., & Johnson, B. J. (2016). A review of research on teachers' use of student data: From the perspective of school leadership. *Educational Assessment, Evaluation and Accountability*, *28*(1), 5–33. https://doi.org/10.1007/s11092-016-9238-9

van der Scheer, E. A., & Visscher, A. J. (2016). Effects of an intensive data-based decision making intervention on teacher efficacy. *Teaching and Teacher Education*, *60*, 34-43.

van Geel, M., Visscher, A. J., & Teunis, B. (2017). School characteristics influencing the implementation of a data-based decision making intervention. *School Effectiveness and School Improvement*, *28*(3), 443–462. https://doi.org/10.1080/09243453.2017.1314972

van Leeuwen, A., Knoop-van Campen, C. A., Molenaar, I., & Rummel, N. (2021). How teacher characteristics relate to how teachers use dashboards: Results from two case studies in K-12. *Journal of Learning Analytics*, *8*(2), 6-21.

Voithofer, R. & Golan, A. M. (2019). Data sources for educators: Mining meaningful data for course and program decision making. In *Responsible analytics and data mining in education* (1st ed., pp. 83–100). Routledge. https://doi.org/10.4324/9780203728703-7

Wayman, J. C., & Jimerson, J. B. (2014). Teacher needs for data-related professional learning. *Studies in Educational Evaluation*, *42*, 25-34.

Wayman, J. C., Wilkerson, S. B., Cho, V., Mandinach, E. B., & Supovitz, J. A. (2016). Guide to using the Teacher Data Use Survey. REL 2017-166. Regional Educational Laboratory Appalachia.

Ylimaki, B., & Brunderman, L. (2019). School development in culturally diverse U.S. schools: Balancing evidence-based policies and education values. *Education Sciences*, *9*(84), 1–15. https://doi.org/10.3390/educsci9020084

Chapter 5: Integrated Summary of Findings and Conclusion

In this final chapter, I synthesize the key findings from the three articles that comprise this dissertation by drawing connections across the studies and highlighting their collective contributions. While each article addressed distinct research questions, they all explore complementary dimensions of DBDM in education. Taken together, the studies present a layered and nuanced portrait of how teachers interact with data in secondary and online learning contexts, the conditions that enable or constrain them, and the broader implications for policy, professional development, and future research. This chapter organizes the findings thematically to capture these insights and articulate the overarching narrative emerging from the research.

Major Themes

1- Data Use Practices: Reactive vs. Strategic Engagement

Across the three articles, a central pattern emerged: teachers engage with data primarily in reactive ways rather than using it strategically for long-term instructional planning. The systematic review in Article 1 (Chapter 2) revealed that while a substantial body of research explores the factors that shape teacher engagement with data, such as data literacy, accessibility, and perceptions, there is a marked absence of studies examining how these factors translate into sustained changes in practice or improved student outcomes. This suggests a lack of attention in the literature to strategic data use and indicates that the field has not yet fully explored how teachers might integrate data into proactive instructional design. Article 2 (Chapter 4) builds on this by providing empirical evidence of teachers' predominantly reactive engagement with data in online secondary classrooms. The findings revealed that 77% of Ontario secondary teachers use data to solve immediate challenges, while only 57% apply it proactively. As one teacher affirms, “Often, using data ends up being kind of when a student’s struggling or something like that, that’s when you would dig into a specific student”. This reactive use reflects a broader pattern in the literature where teachers often rely on data in response to problems rather than as part of an embedded, anticipatory planning process (Datnow & Hubbard, 2015; Mandinach & Gummer, 2016). This theme also intersects with Article 3 (Chapter 5), where teachers expressed limited confidence in identifying and applying relevant data for instructional purposes. While they were relatively confident in interpreting provided data, earlier stages of the DBDM process, such as selecting and applying data, proved to be challenging. This suggests that despite widespread discourse on the importance of data literacy, many educators operate without the foundational competencies needed to make data use a meaningful and proactive aspect of pedagogy.

Together, these findings highlight that fostering strategic data use is not simply a matter of encouraging teachers to “use more data,” but rather requires equipping them with the tools, time, and support to integrate data into the full arc of instructional decision-making.

2- *Gaps in Training, Support, and Infrastructure*

All three articles point to a systemic lack of sufficient training and support for teachers in engaging with data meaningfully. On a global scale, Article 1 (Chapter 2) highlighted the absence of studies examining how the factors influencing data use can be translated into sustained changes in practice or improved student outcomes. This indicates that teachers may lack strategic, forward-looking engagement with data, largely due to insufficient systemic support. Articles 2 and 3 (Chapters 3 and 4) build on this by showing that in Ontario, even when digital tools like Brightspace were available, teachers struggled with their complexity as well as with school-level student information systems. Teachers expressed that they had received little or no structured training in DBDM. Many relied heavily on informal peer support for learning how to use data, revealing a critical gap in formal professional development. This lack of structured training contributed to teachers' limited ability to apply data in a meaningful and sustained way.

The literature on DBDM has long emphasized the need for capacity building through professional development opportunities (Marsh, 2012; Schildkamp et al., 2017). However, this thesis contributes an important nuance to the discussion: it is not merely the presence of training that matters, but its relevance, depth, and alignment with teachers' subject areas and instructional goals, as participants in this study called for hands-on, subject-specific, and ongoing training formats—needs that are often unmet in current professional development structures.

Moreover, the findings indicate a persistent disconnect between administrative mandates around data use and the realities of classroom teaching. Both Articles 2 and 3 (Chapters 3 and 4) revealed that secondary online teachers in Ontario often experience data use as an external demand rather than an internally driven practice. This tension mirrors concerns in the literature about the overemphasis on accountability at the expense of pedagogical relevance (Kempf, 2015; Schilkamp & Ehren, 2013). The findings of this thesis call for rethinking institutional approaches to DBDM that better align leadership expectations with classroom realities.

3- *Uneven Implementation Across Contexts and Levels*

Article 1 (Chapter 2) mapped the broader landscape of DBDM research and revealed stark imbalances in both geographical and educational coverage. Research is highly concentrated in the U.S. and the Netherlands, with Canada being significantly underrepresented. In terms of educational levels, elementary settings dominate the literature, leaving secondary education relatively understudied. This gap was directly addressed in Articles 2 and 3 (Chapters 3 and 4), which focused the experiences of Ontario secondary teachers in online learning environments. In doing so, the thesis makes a unique contribution to the literature by offering empirical insight into how DBDM plays out in contexts that have been largely overlooked. These findings suggest that assumptions derived from research in elementary or U.S.-based settings may not translate seamlessly into Canadian classrooms.

Furthermore, the limited research on DBDM in digital learning environments, flagged in Article 1 (Chapter 2), underscores the timeliness of this thesis. As teachers increasingly operate within virtual platforms, understanding how they navigate data in these spaces becomes critical. Articles 2 and 3 (Chapters 3 and 4) provide a grounded view of this reality, revealing both the potential and the limitations of current digital tools in supporting DBDM.

4- *Teachers' Aspirations and the Promise of AI*

While much of the discussion around DBDM focuses on gaps and challenges, participants also expressed forward-looking aspirations. Article 3 (Chapter 4) found that teachers are not only open to improving their data practices but are also eager to explore the role of artificial intelligence in streamlining data analysis and personalizing instruction.

This interest aligns with emerging scholarship on AI-enhanced education, which suggests that intelligent systems can support teachers in identifying patterns, predicting student needs, and recommending interventions (Runge et al., 2025; Wang et al., 203). However, realizing this potential will depend on designing AI tools that are transparent, ethical, and accessible to educators.

The findings suggest a readiness among teachers to engage with innovative solutions, provided they are supported by meaningful training and embedded in pedagogical practice. As such, this thesis positions teacher perspectives as central to shaping the next generation of data tools and systems.

Contributions to the Field

This research makes several contributions to the field of education and teacher professional development by addressing critical gaps in the literature and offering actionable insights for enhancing DBDM practices.

First and foremost, this thesis fills a crucial gap in existing research by investigating the underexplored area of how secondary school teachers in Ontario engage with data in online teaching environments. While much of the prior research has concentrated on elementary education or traditional classroom settings, and has been highly concentrated in the U.S. and the Netherlands, this study shifts the focus to secondary education and digital learning contexts. This shift opens up new perspectives on how teachers use data in contemporary, technology-driven classrooms and provides empirical insights that are essential for the evolving landscape of education.

The second major contribution of this research is the development of a practical framework for using data in online teaching settings (refer to Chapter 4, Figure 1 p. 150). This framework not only provides a structured approach for engaging with data in digital classrooms but also offers a valuable tool for designing DBDM interventions and professional development programs. By grounding the framework in the realities of Ontario secondary school teachers, it ensures its relevance and applicability in real-world settings, addressing both current challenges and emerging needs. Furthermore, the study highlights key barriers that teachers face in accessing, interpreting, and applying data effectively, while also identifying specific competency gaps. These findings provide clear direction for the development of targeted and meaningful professional development initiatives. By focusing on these areas of difficulty, this research advocates for a shift in teacher training that goes beyond generic, one-size-fits-all programs, emphasizing the need for more personalized, hands-on, and subject-specific professional development.

Finally, this study underscores the growing importance of integrating emerging technologies, such as artificial intelligence, into teacher training programs to enhance data accessibility and usability. By incorporating these innovations, the research offers a foundation for creating more effective and sustainable DBDM training strategies in secondary education, ultimately supporting both teacher development and improved student outcomes.

Limitations

While this research provides valuable insights into DBDM in secondary education, it is important to acknowledge its limitations.

One key limitation is the geographical scope of the study. The empirical findings are based on research conducted in Ontario, which, while informative, may not fully capture the experiences of teachers in other provinces or international contexts. Educational policies, access to technology, and institutional support structures vary across regions, which may influence how teachers engage with DBDM. Future research should explore how these findings compare across different educational systems to gain a more comprehensive understanding of DBDM practices globally.

Another limitation stems from the reliance on self-reported data. Both survey and interview responses reflect the personal experiences and perceptions of participants, which may be subject to recall bias or individual interpretations of their own data use. While self-reported insights are valuable for understanding teacher perspectives, they do not provide direct observational evidence of how data is used in practice. Future studies could benefit from triangulating self-reported data with classroom observations or system-generated data analytics to validate findings and capture more objective measures of DBDM engagement.

Finally, this research primarily focuses on teacher engagement with data and the barriers they face, without directly examining the impact of DBDM on student learning outcomes. While the thesis highlights the ways in which teachers use data to inform instruction, it does not measure whether these practices lead to improved student performance, engagement, or well-being. Future research should investigate the direct relationship between DBDM-informed instructional strategies and student success to provide a more holistic understanding of its effectiveness in education.

Directions for Future Research

Building on the findings of this thesis, several directions for future research can further expand the understanding of DBDM in education.

One important avenue for future inquiry involves conducting comparative studies across different provinces in Canada. Given that educational policies, professional development opportunities, and data accessibility vary between regions, comparative research could provide valuable insights into how these factors influence teacher engagement with DBDM. Such studies could highlight best practices, identify structural barriers, and offer recommendations for more effective policy and training implementation.

Another key area for exploration is the long-term impact of improved DBDM training on instructional quality and student outcomes. While this research has identified competency gaps and professional learning needs, further studies are needed to assess whether targeted training interventions translate into sustained improvements in teaching effectiveness and student achievement. Longitudinal research could track teachers who participate in structured DBDM training programs, examining how their instructional decision-making evolves over time and whether their students benefit from enhanced data-informed teaching strategies.

Finally, future research should examine the potential of emerging technologies in supporting DBDM. With the increasing availability of artificial intelligence and advanced analytics tools, there is an opportunity to explore how these technologies can streamline data interpretation, personalize instruction, and reduce the workload associated with data analysis. Investigating how AI-driven tools can be integrated into teacher training and classroom practices would provide valuable insights into the role of technology in enhancing data literacy and decision-making in education.

In conclusion, this thesis has made significant contributions in addressing the gaps in the existing literature on DBDM by highlighting the challenges teachers face, developing a framework for data use in digital classrooms, and offering practical recommendations for professional development. This research contributes to the ongoing dialogue on how to better equip educators with the skills and support needed to be better teachers. However, as this study has shown, there is still much to be explored. Future research should build upon these findings, exploring regional differences, the long-term effects of DBDM training, and the integration of emerging technologies such as artificial intelligence. Such inquiries will further refine our understanding of how to support teachers in becoming more data-literate and, in turn, enhance the quality of education for students across diverse learning contexts.

References:

Kempf, A. (2015). *The pedagogy of standardized testing: The radical impacts of educational standardization in the US and Canada*. Springer.

Schildkamp, K., & Ehren, M. (2013). From “intuition” to “data”-based decision making in Dutch secondary schools? In K. Schildkamp, M. K. Lai, and L. Earl (Eds.), *Data-Based Decision Making in Education*, 49–67, New York, NY: Springer Netherlands.

Runge, I., Hebibi, F., & Lazarides, R. (2025). Acceptance of Pre-Service Teachers Towards Artificial Intelligence (AI): The Role of AI-Related Teacher Training Courses and AI-TPACK Within the Technology Acceptance Model. *Education Sciences*, *15*(2), 167-. https://doi.org/10.3390/educsci15020167

Wang, X., Li, L., Tan, S. C., Yang, L., & Lei, J. (2023). Preparing for AI-enhanced education: Conceptualizing and empirically examining teachers’ AI readiness. *Computers in Human Behavior*, *146*, 107798-. https://doi.org/10.1016/j.chb.2023.107798

Appendices

Appendix A: Survey Email Invitation

Subject: The Use of Student Data in Online Courses to Enhance Teaching Practices

Dear Colleagues,

I am Areej Tayem, Ph. D. candidate at the University of Ottawa. As a teacher who taught online courses myself, I understand the struggle that some teachers face to accommodate the different needs of students while teaching virtually. One way to overcome this difficulty may be by using student data (e.g., grades, attendance, participation, tasks accomplishment, etc.) to tailor instruction by altering our teaching practices and strategies.

You are invited to participate in this Ph. D. research study on the use of data to determine students' needs and how to meet them by completing a 15-minute survey using the link below. The research aims to investigate the extent to which secondary teachers in Ontario who teach one or more online courses use data as part of their online teaching practices, as well as the barriers and facilitators they face in this process.

I am conducting this research under the supervision of Dr. Isabelle Bourgeois, Faculty of Education, University of Ottawa. The information you provide is confidential. Only the research team at the University of Ottawa will have access to the information collected. At your request, you will be provided with a copy of any research published as part of this study.

Thank you for considering this request.

Sincerely,
Areej Tayem

Appendix B: Survey consent forms (English and French)

Université d’Ottawa / University of Ottawa

Title of the study: Data-Based Decision Making in Online Classes: Prevailing Determinants and Current Practice.

Invitation to Participate: I am invited to participate in the above-mentioned Doctoral thesis study conducted by Areej Tayem under the supervision of Dr. Isabelle Bourgeois and funded by the Social Sciences and Humanities Research Council (SSHRC).

Purpose of the Study: The purpose of the study is to investigate the extent to which secondary teachers in Ontario who teach one or more online courses use students’ data as part of their online teaching practices, as well as the barriers and facilitators they experience.

Participation: My participation will consist of completing a 15-minute online questionnaire. During the questionnaire, I will be asked about data usage, the support I get to use student data efficiently, accessibility and usability of student data, the quality of data, my efficacy to use data, my attitude and opinion regarding the use of student data, the doubts or fears I have, and future data use training.

Risks: My participation in this study will entail that I volunteer information about my personal experience, opinions, and perception of using data and this may cause me to feel uncomfortable. I have received assurance from the researchers that every effort will be made to minimize these risks as I have the option to refuse to answer certain questions, I have the option to withdraw at any time, and I am aware that identities will not be revealed.

Benefits: My participation in this study will contribute to the advancement of data usage and data-based decision-making literature in an online context in Ontario. It will also serve as a concrete foundation for future training initiatives that could be created as a follow-up to this dissertation. At my request, I will also be provided with a copy of any research published as part of this study.

Confidentiality and Privacy: I have received assurance from the researchers that the information I will share will remain strictly confidential. I understand that the contents will only be used to further the knowledge around data usage in online teaching environment, and that my identity will be protected. My anonymity, however, cannot be fully protected. Snice participants will be asked to participate in a follow-up interview, the names of participants and their contact information are important. Nevertheless, there are no potential risks involved for my participation, since my identity will not be revealed in publications or the data analysis.

In order to minimize the risk of security breaches and to help ensure my confidentiality, it is recommended that I use standard safety measures, such as signing out of my account, closing my browser, and locking my device when I am no longer using it/when I have completed the study.

Conservation of Data: The data collected (i.e., survey datasets, consent forms) will be kept in a secure manner. Data will be stored on a secured password-protected laptop and will be destroyed after five years. Only the members of the above-mentioned research team will have access to the data.

Voluntary Participation: I am under no obligation to participate and if I choose to participate, I can withdraw from the study at any time and/or refuse to answer any questions, without suffering any negative consequences. If I choose to withdraw, all data gathered until the time of withdrawal will be removed from the dataset and not used in the study.

It is recommended that I *(keep/print/save)* a copy of this consent form for my records.

Acceptance: By selecting the consent statement below, I agree to participate in this research study.

- ☐ Yes, I want to participate.
  (Name): ____________________
  Email: ____________________
- ☐ No, I do not want to participate.

Université d’Ottawa / University of Ottawa

Formulaire de consentement

Titre de l'étude : Utilisation des données dans les cours à distance

Objectif de l'étude : Le but de l'étude est d'examiner dans quelle mesure les enseignants francophones du secondaire en Ontario qui donnent un ou plusieurs cours en ligne utilisent les données fournies par les plateformes d’apprentissage électroniques.

Participation : Ma participation consistera à remplir un questionnaire en ligne d'une durée de 15 minutes. Pendant le questionnaire, je serai interrogé sur l'utilisation des données, le soutien que je reçois pour utiliser efficacement les données des élèves, l'accessibilité et la facilité d'utilisation des données, la qualité des données, mon efficacité à utiliser les données, mes attitudes concernant l'utilisation des données, ainsi que mes besoins en formation par rapport à l'utilisation des données.

Risques : En participant à cette étude, je fournirai des informations sur mon expérience d’enseignement, mes opinions et ma perception de l'utilisation des données, ce qui pourrait me rendre mal à l'aise. J'ai reçu l'assurance des chercheuses que tout sera mis en œuvre pour minimiser ces risques, puisque j'ai la possibilité de refuser de répondre à certaines questions, que je peux me retirer à tout moment et que je sais que mon identité demeurera confidentielle.

Avantages : Ma participation à cette étude contribuera à l'avancement des connaissances sur l'utilisation des données et la prise de décision fondée sur les données pour l’enseignement en ligne. Elle servira également de base concrète à de futures initiatives de formation qui pourraient être créées à la suite de cette étude pour la communauté enseignante francophone. À ma demande, je recevrai également une copie de toute recherche publiée dans le cadre de cette étude.

Confidentialité et protection de la vie privée : J'ai reçu l'assurance des chercheuses que les informations que je partagerai resteront strictement confidentielles. Je comprends que les données recueillies ne seront utilisées que pour approfondir les connaissances sur l'utilisation des données dans un environnement d'enseignement en ligne, et que mon identité sera protégée. Les chercheuses auront accès à mon nom mais mon anonymat sera protégé dans toutes les publications ou diffusions de la recherche.

Afin de minimiser le risque de failles de sécurité et d'assurer ma confidentialité, il m'est recommandé d'utiliser des mesures de sécurité standard, telles que la déconnexion de mon compte, la fermeture de mon navigateur et le verrouillage de mon appareil lorsque je ne l'utilise plus/quand j'ai terminé l'étude.

Conservation des données : Les données recueillies au cours de l'étude (c'est-à-dire, les données de sondage, les formulaires de consentement, les transcription d'entretiens) seront conservées en toute sécurité. Elles seront stockées sur un ordinateur portable protégé par un mot de passe et seront détruites au bout de cinq ans. Seuls les membres de l'équipe de recherche susmentionnée auront accès aux données.

Participation volontaire : Je n'ai aucune obligation de participer et si je choisis de participer, je peux me retirer de l'étude à tout moment et/ou refuser de répondre à toute question, sans subir de conséquences négatives. Si je choisis de me retirer, toutes les données recueillies jusqu'au moment du retrait seront supprimées de l'ensemble des données et ne seront pas utilisées dans le cadre de l'étude.

Si j'ai des questions sur l'étude, je peux contacter les chercheuses principales. Si j'ai des questions concernant la conduite éthique de cette étude, je peux contacter le Bureau de l'éthique et de l'intégrité de la recherche par courriel (ethics@uottawa.ca) ou par téléphone (613-562-5387).

Il m'est recommandé de (conserver/imprimer/sauvegarder) une copie de ce formulaire de consentement pour mes dossiers.

Acceptation : En sélectionnant l'énoncé de consentement ci-dessous, j'accepte de participer à cette étude de recherche.

☐ Oui, je souhaite participer.
(Nom) : ____________________
Courriel : ____________________

☐ Non, je ne souhaite pas participer.

Appendix C: Survey Questions

1- What is your age?

☐ 18-24 ☐ 25-34 ☐ 35- 44 ☐ 55-64 ☐ 65+

2- What is your employment status as a teacher in Ontario?

- Full-time permanent teacher ☐
- Full-time contract teacher ☐
- Part-time permanent teacher ☐
- Part-time contract teacher ☐
- Occasional teacher ☐
- Retired teacher ☐
- Other (please specify) ☐

3- Which Grade level/s have you taught online? (Check all of the applicable boxes)

☐ Grade 9 ☐ Grade 10 ☐ Grade 11 ☐ Grade 12

4- How long have you been teaching online courses?

☐ Less than one year ☐ 1-3 years ☐ more than 3 years

5- What learning management system have you used the most when teaching online?

☐ Desire2Learn (D2L) Brightspace ☐ Google Classroom ☐ Other (specify)

6- Are your classes single level or multi-level classes?

☐ Single level ☐ multi-level

7- What is the average number of students in your online courses?

☐ 10-15 students ☐ 15-20 students ☐ 20-25 students ☐ more than 25

Usage	**During your online course, how frequently do you engage in the following?**

	8- How often do you refer to student data (e.g., grades, attendance, participation, task completion) to find a solution to a problem you are facing in class or with a specific student? (Never, Rarely, Sometimes, Often, Always) 9- How often do you refer to student data (e.g., grades, attendance, participation, task completion) when you need to make a decision regarding the basic/supplementary teaching materials, your teaching methods, or assignments? (Never, Rarely, Sometimes, Often, Always) 10- How often do you refer to student data (e.g., grades, attendance, participation, task completion) without a specific reason, merely to anticipate any issues that you did not notice? (Never, Rarely, Sometimes, Often, Always)
Leadership	**Please indicate how much you agree or disagree with the following statements:** 11- My principal or assistant principal(s) encourages data use (i.e., the use of student data to make decisions) as a tool to support effective teaching in an online class. (Strongly agree, Agree, Disagree, Strongly disagree) 12- My principal or assistant principal(s) is a good example of an effective data user. (Strongly agree, Agree, Disagree, Strongly disagree) 13- My principal or assistant principal(s) discusses data with me. (Strongly agree, Agree, Disagree, Strongly disagree)
Support	14- There is specific time set aside for me to use student data. (Strongly agree, Agree, Disagree, Strongly disagree) 15- There is someone who answers my questions about using data and can guide me on how to change my teaching practices based on data. (Strongly agree, Agree, Disagree, Strongly disagree) 16- My school board provides enough professional development about data use for online classes. (Strongly agree, Agree, Disagree, Strongly disagree)
Collaboration	17- I discuss students' data with other teachers to help me understand and interpret them. (Strongly agree, Agree, Disagree, Strongly disagree)

	18- I share and discuss my students' data with the students themselves, or with their parent or guardian. (Strongly agree, Agree, Disagree, Strongly disagree)
Accessibility of timely data	19- I can easily access student data from different resources (e.g., the learning management system used in my school board, MySIS) (Strongly agree, Agree, Disagree, Strongly disagree) 20- The data I have on my students are up to date. (Strongly agree, Agree, Disagree, Strongly disagree)
Usability and quality of data	21- I can examine various types of data at once for each student (e.g., attendance, achievement, demographics) (Strongly agree, Agree, Disagree, Strongly disagree) 22- I can easily navigate data using different systems (e.g., attendance, achievement, demographics) (Strongly agree, Agree, Disagree, Strongly disagree) 23- I can use data to generates displays (e.g., reports, graphs, tables) that are useful to me. (Strongly agree, Agree, Disagree, Strongly disagree)
DBDM anxiety	24- I am concerned that I will feel or look ‘‘dumb’’ when it comes to data-driven decision-making. (Strongly agree, Agree, Disagree, Strongly disagree) 25- I am intimidated by the process of connecting data analysis to my instructional practice. (Strongly agree, Agree, Disagree, Strongly disagree)
DBDM efficacy	**Efficacy for data identification:** 26- I am confident in my ability to determine which data are beneficial to me and which data are not. (Strongly agree, Agree, Disagree, Strongly disagree) **Efficacy for data technology use:** 27- I am confident that I can use the tools provided by the learning management system to retrieve charts, tables or graphs for analysis. (Strongly agree, Agree, Disagree, Strongly disagree) **Efficacy for data analysis and interpretation:** 28- I am confident in my ability to interpret student data to determine student strengths and weaknesses in a content area.

	(Strongly agree, Agree, Disagree, Strongly disagree) **Efficacy for application of data to instruction:** 29- I am confident that I can use data to group students with similar learning needs for instruction. (Strongly agree, Agree, Disagree, Strongly disagree) 30- I am confident that I can use assessment data to provide targeted feedback to students about their performance or progress. (Strongly agree, Agree, Disagree, Strongly disagree)
Attitudes and opinions regarding data	31- I like to use data. (Strongly agree, Agree, Disagree, Strongly disagree) 32- I find data useful. (Strongly agree, Agree, Disagree, Strongly disagree) 33- Using data helps me to be a better teacher. (Strongly agree, Agree, Disagree, Strongly disagree)
Perceptions of how useful data are to teacher practice	34- Students benefit when instruction is based on data. (Strongly agree, Agree, Disagree, Strongly disagree) 35- I think it is important to use data to inform my teaching practice. (Strongly agree, Agree, Disagree, Strongly disagree) 36- Data offer information about students that is not already known. (Strongly agree, Agree, Disagree, Strongly disagree) 37- Data help teachers know what concepts students are learning easily or with difficulty. (Strongly agree, Agree, Disagree, Strongly disagree)
Further training	38- What knowledge or skills would you like to acquire in terms of DBDM? -- --

If you are willing to be contacted for a follow-up interview related to this survey, please provide your name and email address below.

Name: ___________________________

Email address: ______________________________

Instrument de sondage

Section A : Expérience en enseignement de cours en ligne

À quel(s) niveau(x) scolaire(s) du secondaire avez-vous enseigné entièrement en ligne lors des trois dernières années ? (Veuillez sélectionner toutes les réponses qui s'appliquent)

- ☐ 9e
- ☐ 10e
- ☐ 11e
- ☐ 12e

Depuis combien de temps enseignez-vous des cours entièrement en ligne ?

- ☐ Moins d'un an
- ☐ Entre 1 et 3 ans
- ☐ 4 ans ou plus

Quel système de gestion de l'ap**prentissage avez-vous le plus utilisé pour enseigner en ligne ?**

- ☐ Google Classroom
- ☐ Apple Classroom
- ☐ Moodle
- ☐ Desire2Learn
- ☐ Canvas
- ☐ EAV
- ☐ Teams
- ☐ Miro
- ☐ ClasseDojo
- ☐ Seesaw
- ☐ Formative
- ☐ Autre (veuillez préciser) :

En moyenne, à combien d'élèves enseignez-vous dans chaque cours en ligne ?

- ☐Moins de 10

☐11 à 15

☐15 à 20

☐21 à 25

☐26 et plus

Section B : Utilisation de données pour informer l'enseignement en ligne

Pour chacun des énoncés ci-dessous, veuillez indiquer à quelle fréquence vous consultez les données relatives aux élèves fournies par la plateforme d'enseignement en ligne :

	Jamais	Rarement	Parfois	Souvent
Je consulte les données pour trouver une solution à un problème rencontré en classe.				
Je consulte les données pour prendre une décision concernant le matériel pédagogique, ma méthode d'enseignement ou les devoirs.				
Je consulte les données sans raison particulière, pour anticiper des problèmes ou des situations que je n'ai pas déjà remarqué.				

Section C : Climat et soutien à l'utilisation des données

Veuillez indiquer dans quelle mesure vous êtes d'accord avec les énoncés suivants en utilisant une échelle de 1 à 4, ou 1 indique que vous n'êtes « pas du tout d'accord », et 4 indique que vous êtes « tout à fait d'accord ».

	Pas du tout d'accord	Pas d'accord	D'accord	Tout à fait d'accord
Ma direction ou direction adjointe encourage l'utilisation des données (c'est-à-dire l'utilisation des données des élèves pour prendre des décisions) comme outil pour soutenir un				

enseignement efficace dans une classe en ligne.				
Ma direction ou direction adjointe donne l'exemple en matière d'utilisation des données.				
Ma direction ou direction adjointe discute des données avec moi.				
Je dispose du temps nécessaire pour utiliser les données.				
Je dispose du temps nécessaire pour analyser les données.				
Il y a quelqu'un qui répond à mes questions sur l'utilisation des données et qui peut me guider sur la façon de changer mes pratiques d'enseignement sur la base des données.				
Mon conseil scolaire fournit suffisamment de perfectionnement professionnel sur l'utilisation des données pour les cours en ligne.				
Je discute des données de mes élèves avec d'autres membres du personnel enseignant.				
Je partage et discute les données de mes élèves avec eux et elles, ou avec leurs parents ou tuteurs et tutrices.				

Section D : Accessibilité et qualité des données

Veuillez indiquer dans quelle mesure vous êtes d'accord avec les énoncés suivants en utilisant une échelle de 1 à 4, ou 1 indique que vous n'êtes « pas du tout d'accord », et 4 indique que vous êtes « tout à fait d'accord ».

	Pas du tout d'accord	Pas d'accord	D'accord	Tout à fait d'accord
Je peux facilement accéder aux données des élèves dans la plateforme d'enseignement				

électronique utilisée par mon conseil scolaire.				
Les données dont je dispose sur mes élèves sont à jour.				
La plateforme d'enseignement électronique utilisée dans mon conseil scolaire me permet d'examiner simultanément divers types de données pour chaque élève (par exemple, assiduité, résultats, données démographiques).				
La plateforme d'enseignement électronique utilisée dans mon conseil scolaire est facile à naviguer (pour l'utilisation des données).				
La plateforme d'enseignement électronique utilisée dans mon conseil scolaire génère des affichages (par exemple, des rapports, des graphiques, des tableaux) qui me sont utiles.				

Section E : Efficacité par rapport à l'utilisation des données

Veuillez indiquer dans quelle mesure vous êtes d'accord avec les énoncés suivants en utilisant une échelle de 1 à 4, ou 1 indique que vous n'êtes « pas du tout d'accord », et 4 indique que vous êtes « tout à fait d'accord ».

	Pas du tout d'accord	Pas d'accord	D'accord	Tout à fait d'accord
Je crains de me sentir ou d'avoir l'air " bête " lorsqu'il s'agit de prendre des décisions fondées sur des données.				
Je suis intimidé.e par le fait de relier l'analyse des données à ma pratique pédagogique.				

J'ai confiance en ma capacité à déterminer quelles données me sont utiles et lesquelles ne le sont pas.				
J'ai confiance en ma capacité à utiliser les outils fournis par le système de gestion de l'apprentissage pour extraire des diagrammes, des tableaux ou des graphiques à des fins d'analyse.				
J'ai confiance en ma capacité à interpréter les données des élèves pour déterminer leurs forces et leurs faiblesses dans un domaine particulier.				
J'ai confiance en ma capacité à utiliser les données pour regrouper les élèves ayant des besoins d'apprentissage similaires en vue de l'enseignement.				
Je suis sûr(e) de pouvoir utiliser les données d'évaluation pour fournir aux élèves un retour d'information ciblé sur leurs performances ou leurs progrès.				

Section F : Attitudes et opinions concernant les données

Veuillez indiquer dans quelle mesure vous êtes d'accord avec les énoncés suivants en utilisant une échelle de 1 à 4, ou 1 indique que vous n'êtes « pas du tout d'accord », et 4 indique que vous êtes « tout à fait d'accord ».

	Pas du tout d'accord	Pas d'accord	D'accord	Tout à fait d'accord
J'aime utiliser les données.				
Je trouve les données utiles				
L'utilisation des données m'aide à devenir un.e meilleur.e enseignant.e.				
Les élèves bénéficient d'un enseignement basé sur des données.				

Je pense qu'il est important d'utiliser les données pour informer ma pratique d'enseignement.				
Les données fournissent de nouvelles informations sur les élèves qui ne sont pas disponibles ailleurs.				
Les données aident les enseignant.es à savoir quels concepts les élèves apprennent.				

Section G : Autres commentaires et formation complémentaire

Avez-vous des commentaires ou des approfondissements à partager avec nous au sujet de l'utilisation des données pour informer les pratiques pédagogiques en mode virtuel?

Quelles connaissances ou compétences souhaiteriez-vous acquérir en matière d'utilisation des données ?

Merci beaucoup d'avoir complété notre sondage. Nous souhaitons, dans un avenir rapproché, réaliser des entretiens virtuels de 30-45 minutes auprès des membres du personnel enseignant qui donnent ou qui ont donné des cours en ligne afin d'approfondir les résultats de cette enquête. Si vous acceptez de participer à un entretien virtuel, veuillez indiquer votre nom et votre adresse électronique personnelle ci-dessous.

Prénom et nom: ________________________
Adresse électronique: ___________________________

Appendix D: Recruitment of Interview Participants

Subject: Follow-up interview on the use of student data in online courses study

Dear participants,

Thank you for taking the time to complete the DBDM survey sent to you earlier this year. Hearing more about your experiences on how you use data to enhance your instruction and the steps you follow to do so will contribute to a robust description of the DBDM culture in secondary online classes in Ontario. Thus, I would like to invite you to participate in the second phase of this research project. As I mentioned previously, the purpose of this research study is to gain a comprehensive understanding of the DBDM practice in secondary online teaching and the factors that can contribute to its use or hinder it. This study will be carried out under the supervision of Dr. Isabelle Bourgeois at the University of Ottawa, Faculty of Education. The data will be collected for the purposes of my PhD thesis in education and for subsequent research articles.

This second phase consists of an interview which will take approximately 30 minutes and will occur virtually using software such as Zoom, or Microsoft Teams. If you prefer, the interview can be conducted over the telephone. If a participant requires an in-person interview on site, the I would need to evaluate whether it is feasible and safe to do so. Factors that would need to be considered include the location and accessibility of the site. With your permission, the interview will be audio recorded in order for me to fully engage in our conversation, without having to take detailed notes. Following the interview, I will transcribe the interview myself, and will offer you a copy for your records. Your participation in this study will include you responding to questions about your teaching practice and DBDM. You have my assurance that every effort will be made to respect your personal reflections in the writing and reporting of the research. If, at any time, you wish to end the interview, and/or withdraw from the study your request will be respected. Should you choose to withdraw from the study and prefer that I not use your interview data collected up to that point, I will remove it from the research.

If you are interested in participating in this research study, please review and sign the attached consent form and book a slot using the link below.

Sincerely,
Areej Tayem

Appendix E: Interview Consent Forms (English and French)

Université d'Ottawa / University of Ottawa

Title of the study: Data-Based Decision Making in Online Classes: Prevailing Determinants and Current Practice.

Invitation to Participate: I am invited to participate in the abovementioned Doctoral thesis study conducted by Areej Tayem under the supervision of Dr. Isabelle Bourgeois and funded by the Social Sciences and Humanities Research Council (SSHRC).

Purpose of the Study: The purpose of the study is to investigate the extent to which secondary teachers in Ontario who teach one or more online courses use students' data as part of their online teaching practices, as well as the barriers and facilitators they experience.

Participation: I will participate in a semi-structured conversation-style interviews. During the interview, I will be asked a few open-ended questions about my perceptions, opinions, and insights about data usage, the support I get to use student data efficiently, accessibility and usability of student data, the quality of data, my efficacy to use data, my attitude and opinion regarding the use of student data, the doubts or fears I have, and future data use training.

The interview will take place via Zoom or Microsoft Teams at a time that is most convenient to me. The researcher will ask that I select a location for the interview that is private and convenient for me. Areej Tayem will conduct the interview with me from a private office. The interview will take approximately **30 minutes** to complete. With my consent, the interview will be audio-recorded and transcribed by Areej Tayem for analysis.

Risks: My participation in this study will entail that I volunteer information about my personal experience, opinions, and perception of using data and this may cause me to feel uncomfortable. I have received assurance from the researchers that every effort will be made to minimize these risks as I have the option to refuse to answer certain questions, I have the option to withdraw at any time, and I am aware that identities will not be revealed.

Benefits: My participation in this study will contribute to the advancement of data usage and data-based decision-making literature in an online context in Ontario. It will also serve as a concrete foundation for future training initiatives that could be created as a follow-up to this dissertation. At my request, I will also be provided with a copy of any research published as part of this study.

Confidentiality and Privacy I have received assurance from the researchers that the information I will share will remain strictly confidential. I understand that the contents will be used only to further the knowledge around data usage in online teaching environment, and that my identity will be protected. My anonymity, however, cannot be fully protected. Since the interview will be conducted by Zoom or Microsoft Teams with Areej Tayem, my anonymity cannot be fully protected. Only Areej Tayem and her supervisor (Dr. Isabelle Bourgeois) will know my identity, and I will not be asked to state my name during the interview. Any information that could potentially reveal my identity will be erased from the video recording and transcript so that I cannot be identified in published reports or presentations.

In order to minimize the risk of security breaches and to help ensure my confidentiality, it is recommended that I use standard safety measures, such as signing out of my account, closing my browser, and locking my device when I am no longer using it/when I have completed the study.

Conservation of Data: The digital video-audio recording of the interview will be downloaded and erased from the audio-recorder immediately after the interview. Data (i.e. transcripts, consent forms, researchers' notes) will be stored in a secure manner. Data will be stored on a secured password-protected laptop and will be destroyed after five years. Only the members of the above-mentioned research team will have access to the data.

Voluntary Participation: I am under no obligation to participate and if I choose to participate, I can withdraw from the study at any time and/or refuse to answer any questions, without suffering any negative consequences. If I choose to withdraw, all data gathered until the time of withdrawal will be removed from the dataset and not used in the study.

If I have any questions about the study, I may contact the researcher or their supervisor. If I have any questions regarding the ethical conduct of this study, I may contact the Office of Research Ethics and Integrity via email (ethics@uottawa.ca) or telephone (613-562-5387).

It is recommended that I *(keep/print/save)* a copy of this consent form for my records.

Acceptance: By signing my name below, I agree to participate in this research study.

Participant's name: ________________________ Date: ___________________
Participant's signature: ________________________ Date: ___________________
Researcher's signature: ________________________ Date: ___________________

Université d’Ottawa / University of Ottawa

Formulaire de consentement

Titre de l'étude : Utilisation des données dans les cours à distance

Objectif de l'étude : Le but de l'étude est d'examiner dans quelle mesure les enseignants francophones du secondaire en Ontario qui donnent un ou plusieurs cours en ligne utilisent les données fournies par les plateformes d’apprentissage électroniques.

Participation : Je participerai à un entretien individuel. Au cours de l'entretien, on me posera quelques questions ouvertes sur mes perceptions, mes opinions et mes idées concernant l'utilisation des données, le soutien que je reçois pour utiliser efficacement les données des élèves, l'accessibilité et la facilité d'utilisation des données, la qualité des données, mon efficacité à utiliser les données, mes attitudes concernant l'utilisation des données et mes besoins en formation par rapport à l’utilisation des données.

L'entretien se déroulera via Zoom ou Microsoft Teams au moment qui me conviendra le mieux. Le chercheur me demandera de choisir un endroit privé et pratique pour l'entretien. L'entretien durera environ 30 minutes. Avec mon consentement, l'entretien sera enregistré et transcrit par l'équipe de recherche à des fins d'analyse. J’aurai l’occasion de lire la transcription et d’y apporter des révisions. Suite à mon approbation de la transcription, la vidéo de l’entretien sera détruite.

Risques : En participant à cette étude, je fournirai des informations sur mon expérience d’enseignement, mes opinions et ma perception de l'utilisation des données, ce qui pourrait me rendre mal à l'aise. J'ai reçu l'assurance des chercheuses que tout sera mis en œuvre pour minimiser ces risques, puisque j'ai la possibilité de refuser de répondre à certaines questions, que je peux me retirer à tout moment et que je sais que mon identité demeurera confidentielle.

Avantages : Ma participation à cette étude contribuera à l'avancement des connaissances sur l'utilisation des données et la prise de décision fondée sur les données pour l'enseignement en ligne en Ontario. Elle servira également de base concrète à de futures initiatives de formation qui pourraient être créées à la suite de cette étude. À ma demande, je recevrai également une copie de toute recherche publiée dans le cadre de cette étude.

Confidentialité et protection de la vie privée : Les chercheuses m'ont assuré que les informations que je partagerai resteront strictement confidentielles. Je comprends que le contenu ne sera utilisé que pour approfondir les connaissances sur l'utilisation des données dans un environnement d'enseignement en ligne, et que mon identité sera protégée. Étant donné que l'entretien sera mené par Zoom ou Microsoft Teams, mon anonymat ne peut pas être entièrement garanti. Seuls les membres de l'équipe de recherche connaîtront mon identité. Toute information susceptible de révéler mon identité sera effacée de l'enregistrement vidéo et de la transcription afin que je ne puisse pas être identifié dans les rapports ou présentations publiés.

Afin de minimiser le risque de failles de sécurité et d'assurer ma confidentialité, il m'est recommandé d'utiliser les mesures de sécurité standard, telles que la déconnexion de mon compte, la fermeture de mon navigateur et le verrouillage de mon appareil lorsque je ne l'utilise plus/quand j'ai terminé l'étude.

Conservation des données : L'enregistrement vidéo-audio numérique de l'entretien sera téléchargé et effacé de l'enregistreur audio immédiatement après l'entretien. Les données (c'est-à-dire les transcriptions, les formulaires de consentement, les notes des chercheurs) seront conservées en toute sécurité. Les données seront stockées sur un ordinateur portable protégé par un mot de passe et seront détruites au bout de cinq ans. Seuls les membres de l'équipe de recherche susmentionnée auront accès aux données.

Participation volontaire : Je n'ai aucune obligation de participer et si je choisis de participer, je peux me retirer de l'étude à tout moment et/ou refuser de répondre à toute question, sans subir de conséquences négatives. Si je choisis de me retirer, toutes les données recueillies jusqu'au moment du retrait seront supprimées de l'ensemble des données et ne seront pas utilisées dans le cadre de l'étude.

Si j'ai des questions sur l'étude, je peux contacter les chercheuses. Si j'ai des questions concernant la conduite éthique de cette étude, je peux contacter le Bureau de l'éthique et de l'intégrité de la recherche par courriel (ethics@uottawa.ca) ou par téléphone (613-562-5387).

Il m'est recommandé de (conserver/imprimer/sauvegarder) une copie de ce formulaire de consentement pour mes dossiers.

Acceptation : En signant mon nom ci-dessous, j'accepte de participer à cette étude de recherche.

Nom du participant : ________________________ Date : ___________________
Signature du participant : ________________________ Date : ___________________
Signature du chercheur : ________________________ Date : _________________

Appendix F: Interview Guides (English and French)

First and foremost, thank you for taking the time to meet with me today. I'd like to provide you with some context about the project I'm currently working on and explain how your valuable input can help us enhance online teaching in Ontario. Our project aims to investigate how secondary teachers in Ontario perceive the use of data in their online teaching practices. Specifically, we're interested in learning about the extent to which teachers employ data in their instruction and the challenges they encounter that may hinder their use of data.

Before we proceed with the interview, I would like to confirm that you have completed and signed the consent form. It contains my contact information, as well as the contact details of my supervisor, in case you have any questions or concerns after the interview. Please take your time to review the form and let me know if you have any questions before we begin.

Interview protocol

1- Tell me about how you ended up teaching online and what courses you normally teach online? Are they the same as the courses you teach in-person?
2- As I mentioned, I am interested in learning about how you use data to inform your teaching practices in online courses. Can you describe a time when you used data to make a decision about your online course? What data did you use, and how did you use it?
3- How do you think data can be useful in making decisions about student learning in online courses?

   ***Probing questions**:*

   a- Could you please give me examples of data you find useful?
   b- How do you measure student engagement and participation in your online courses?
   c- How do you use data to enhance the outcomes of students? (e.g., group students with similar learning needs for instruction, identify gaps in students learning, or to solve a problem that you were having).
4- Can you explain in detail what steps you usually follow when you want to use data?
5- Do you also teach in person? Have you used data in your in-person classes?
6- How is your experience in using data in an online course different from using data in in-person classes?

   Probing questions:

   a- In what ways could your experience in using data for an online course have been different? Can you provide a specific example?
   b- In your experience, what are some challenges to effectively use data in online courses, and how do you overcome them?
   c- Have you ever received training in using data to inform teaching in online courses (If yes: What was that training like? Do you feel that it helped you acquire new skills and knowledge in this area?)
   d- What knowledge or skills would you like to acquire in the future in terms of DBDM? What are you interested in learning about?
   e- Is there anything else you would like to add or any thoughts you would like to share? We've covered a lot of ground today, but I want to make sure that everyone has had the chance to share any final reflections or insights they may have.

Guide d’entretien

D'abord et avant tout, je vous remercie d'avoir pris le temps de me rencontrer aujourd'hui. J'aimerais vous présenter le contexte du projet sur lequel je travaille actuellement et vous expliquer comment votre précieuse contribution peut nous aider à améliorer l'enseignement en ligne en Ontario. Notre projet vise à étudier la façon dont les enseignants du secondaire en Ontario perçoivent l'utilisation des données dans leurs pratiques d'enseignement en ligne. Plus précisément, nous souhaitons savoir dans quelle mesure les enseignants utilisent les données dans leur enseignement et quels sont les défis qu'ils rencontrent et qui peuvent entraver leur utilisation des données.

Avant de commencer l'entretien, je voudrais m'assurer que vous avez bien rempli et signé le formulaire de consentement. Veuillez prendre le temps de lire le formulaire et me faire savoir si vous avez des questions avant que nous commencions.

1- Pour commencer, décrivez comment vous en êtes arrivé à enseigner en ligne et quels sont les cours que vous enseignez habituellement en ligne ? S'agit-il des mêmes cours que ceux que vous donnez en personne ?

2- Comme je l'ai mentionné, j'aimerais savoir comment vous utilisez les données pour informer vos pratiques d'enseignement dans les cours en ligne. Pouvez-vous décrire une occasion où vous avez utilisé des données pour prendre une décision concernant votre cours en ligne ? Quelles données avez-vous utilisées et comment les avez-vous utilisées ?

3- Comment pensez-vous que les données peuvent être utiles pour prendre des décisions concernant l'apprentissage des élèves dans les cours en ligne ?

Questions d'approfondissement :

a- Pourriez-vous me donner des exemples de données que vous trouvez utiles ?

b- Comment mesurez-vous l'engagement et la participation des élèves dans vos cours en ligne ?

c- Comment utilisez-vous les données pour améliorer les résultats des élèves ? (par exemple, regrouper les élèves ayant des besoins d'apprentissage similaires pour l'enseignement, identifier les lacunes dans l'apprentissage des élèves, ou pour résoudre un problème que vous rencontrez).

4- Pouvez-vous expliquer en détail les étapes que vous suivez habituellement lorsque vous souhaitez utiliser des données ?

5- Enseignez-vous également en personne ? Avez-vous utilisé des données dans vos cours en présentiel ?

6- En quoi votre expérience de l'utilisation de données dans un cours en ligne diffère-t-elle de l'utilisation de données dans des cours en présentiel ?

Questions d'approfondissement :

a- En quoi votre expérience de l'utilisation des données pour un cours en ligne aurait-elle pu être différente ? Pouvez-vous donner un exemple précis ?

b- D'après votre expérience, quels sont les défis à relever pour utiliser efficacement les données dans les cours en ligne, et comment les avez-vous surmontés ?

c- Avez-vous déjà reçu une formation sur l'utilisation des données pour informer l'enseignement dans les cours en ligne (si oui : comment s'est déroulée cette formation ? Pensez-vous qu'elle vous a permis d'acquérir de nouvelles compétences et connaissances dans ce domaine ?)

d- Quelles connaissances ou compétences aimeriez-vous acquérir à l'avenir en matière d’utilisation des données ? Qu'est-ce que vous aimeriez apprendre ?