REVIEW

Data-Driven Instructional Decision-Making Models: A Literature Review

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***Abstract**: In recent years, the application of big data technology in education has attracted wide attention in academia. How to leverage big data to reach scientific instructional decision-making has become a topical issue. Based on a literature review of relevant studies, this article gives an overview of the evolution of data-driven instructional decision-making models in order to provide educators with a broad perspective on this subject. It also makes a comparative analysis of certain representative models, aiming to provide teachers with valuable insights for facilitating their application of big data technology to teaching decision-making.*

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Introduction

AMID THE ADVANCEMENT of information technology and the proliferation of digital data, human society has entered the era of big data. The ongoing waves of big data are fundamentally transforming all facets of society (United Nations Global Pulse, 2012; Zou & Yin, 2018). In the field of education, big data technology is bound to make a difference to the teacher's instructional decision-making. Instructional decision-making is a process in which the teacher explores, selects, and evaluates the teaching implementation schemes for the purpose of successfully reaching specific educational goals (Guan et al., 2019). It is the intermediate link between the educational ideas and teaching practices of the teacher (Borko et al., 2008). Traditional instructional decisions often rely on the teachers' personal experiences, which can lead to issues such as inadequate information collection during the preparation stage, an overreliance on individual experience in decision-making, and a lack of feedback during decision implementation (Li et al., 2023). These issues can compromise the quality and effectiveness of teaching decisions. The application of big data technology in education has the potential to ensure a more solid information foundation for evidence-based instructional decisions (Zhang, 2017) and to make the teacher more focused on the learning process and cognitive experiences of the individuals rather than those of a collective group (Zou & Yin, 2018; Li & Xia, 2020). Benefits like these have prompted many empirical studies on questions like "Is data-driven instructional decision-making really effective?" "What are its positive effects?" and "How significant are these effects?"

With the increase in empirical research on big data-driven instructional decision-making, a few meta-analytical studies have emerged in this area. Using meta-analytic techniques, Li et al. (2023) examined the impact of data-driven instructional decision-making on student learning outcomes based on relevant empirical studies published between 2003 and 2022. Their research findings show that data-driven instructional decisions could significantly promote students' learning outcomes by facilitating their knowledge retention and transfer, supporting their problem solving and engagement in learning, and elevating their motivation levels as well as learning satisfaction. On the basis of existing meta-analytic studies, Liu et al. (2022) used the method of umbrella review to comprehensively analyze the impacts of data-driven instructional decision-making from the standpoints of impact scope, impact cycle, and intervention measures. The study emphasizes the necessity of further exploring specific procedures of the decision-making process to optimize the effects of data-driven instructional decisions and notes that a data-driven decision-making model can provide actionable guidelines for decision-making practices of the teacher.

Currently, despite the many big data-driven instructional decision-making models advanced by researchers, systematic analyses of these models are relatively scarce. This study gives an overview of the evolution of data-driven instructional decision-making models and makes a comparative analysis of six representative big data-driven decision-making models with the intent to provide educators with valuable implications for teaching improvement.

Review of Relevant Concepts

The teacher's instructional decision-making is a process of judgment and selection in the uncertain and complex educational contexts (Zhang, 2009). It is an essential component of instruction, a key factor influencing other teaching behaviors (Ye, 2009). In the past, the teacher's educational notions, professional knowledge, and practical experience constituted reliable foundations for their instructional decisions (Borko et al., 2008; Song & Li, 2008). Yet, recent years witnessed different views among researchers. According to Feng (2020), the teacher's instructional decisions are not only impacted by their values, education levels, competences, and personality traits, but also by the accessibility of information; prior research failed to pay adequate attention to the value of information for instructional decision-making. Zou and Yin (2018) also argued that central to instructional decision-making is the teacher's mining, analysis, and evaluation of relevant data on key elements of teaching, based on which the teacher plans, implements, adjusts, and improves their teaching practices, whereas teaching decisions based on the teacher's personal experiences are insufficiently supported by objective evidence. Amid the change in the perspectives on this research area, more recent studies confirm that data-driven decision-making is effective in improving student learning outcomes (Schildkamp, 2019), which prompted increased integration of data into instructional decision-making. It has been expected that the introduction of big data can help realize more scientific, efficacious teaching decisions.

In the education world, "data-based decision making (DBDM)," "data-driven decision making (DDDM)," and "data-informed decision making (DIDM)" are the three comparable terms used to represent the process of making educational decisions using educational data. DBDM denotes the process in which teachers, school administrators, and other stakeholders gather, analyze, and interpret educational data (such as education evaluation data, classroom observation data, and research data) and use the extracted information as evidence for decision-making and for evaluating the students' academic progress and other expected educational outcomes (Feng, 2020). DDDM and DIDM, deemed similar concepts to DBDM, involve systematic processes of collecting and analyzing various types of data (e.g., teaching process data, outcomes data, and educational actor satisfaction data) on the part of administrators and teachers, which serve as justifications for their educational decisions (Ikemoto & Marsh, 2007; Feng, 2020). Some researchers contended that there are certain differences between the two, claiming that DDDM has a greater emphasis on the use of machine intelligence for data analysis, thereby reducing the involvement of human subjective judgments and personal biases in the decision-making process, while DIDM is more about leveraging data to reach meaningful conclusions and warrants high levels of data literacy in teachers (Guan et al., 2019). Despite the nuances between the three terms, they are basically identical, with the same emphasis on systematically collecting and analyzing data resources and using information gathered to improve teaching and learning. Unless otherwise specified, this article considers DBDM, DDDM, and DIDM to be synonymous.

An Overview of the Evolution of Data-Driven Instructional Decision Models

This survey sources literature from China National Knowledge Infrastructure (CNKI) and Google Scholar, using as search terms “big data,” “data-based decision making,” “data-driven decision making,” “data-informed decision making,” “instructional decision making,” and “decision-making model or framework” to retrieve relevant journal articles. Our analysis is pivoted around six big data-based instructional decision-making models or frameworks from four studies in the literature.

Traditional Data-Driven Instructional Decision Models

Our purpose in discussing the traditional data-driven instructional decision models is two-fold: to give a broader picture of the development of data-driven instructional decision-making models and to facilitate the understanding of the basic components of big data-driven instructional decision-making models.

The DIKW (data, information, knowledge, and wisdom) model, advanced by Ackoff (1989), represents how data is progressively transformed into teachers’ wisdom that underpins their instructional decision-making. Mandinach et al. (2006) were the earliest researchers experimenting with the data-driven instructional decision-making model, drawing on the basic ideas of the DIKW model. This model includes decision-making scenarios at three levels: school district, school, and classroom, and spans the following specific processes: collecting and organizing data; analyzing and synthesizing data and converting it into information; transforming information into decision-making knowledge

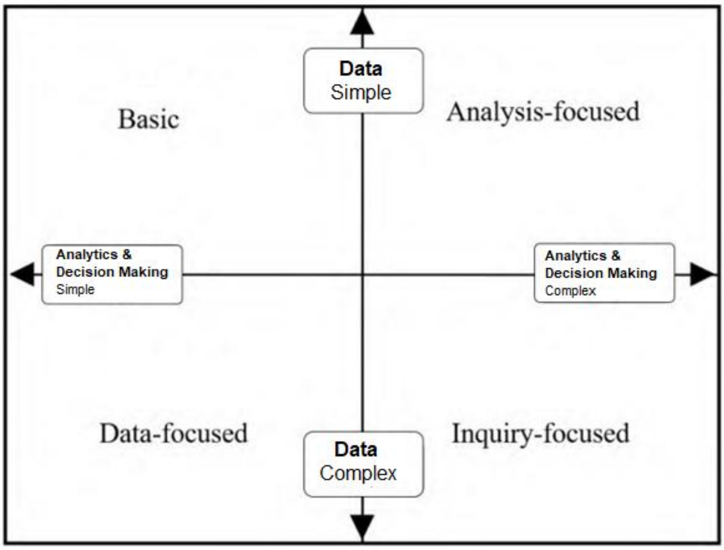

Figure 1. A Quadrant Diagram of the DDDM's Complexity.

using prescribed rules; formulating and implementing instructional decisions; and evaluating the effectiveness and impact of these decisions. Ikemoto and Marsh (2007) modified the above model by adding a quadrant diagram to represent the DDDM's complexity (**Figure 1**) to address the issue of oversimplistic description of DDDM processes. The diagram abstracted chief elements from DDDM, with the Y-axis representing the types of data and the X-axis signaling analytics and decision-making, aiming to offer guidance for the use of different types of DDDM in educational decision-makers.

Schildkamp and Poortman (2015) expanded Mandinach et al.'s model by adding the process of setting objectives for decisions and managed to create a more workable and applicable instructional decision-making model. The model specifies the following processes: (1) Pinpoint the objective of data collection as well as the types and uses of data to be collected; (2) gather data pertaining to the objective; (3) draw information from data via data mining and analytics, such as information on problems with teaching; (4) combine the teacher's professional expertise with obtained information to generate knowledge for decision-making; (5) leverage the newly generated knowledge to assist with decision-making and the implementation of decisions; (6) evaluate the effects of decision implementation. To improve the objectivity and neutrality of decision-making, Dodman et al. (2021) created the critical data-driven decision-making (CDDDM) model by combining Ikemoto and Marsh's model and Duncan-Andrade and Morrell's (2008) "cycle of critical praxis." With this model, the teacher is required to remain critical throughout the processes of data collection, data interpretation, and decision-making and encouraged to screen out institutional data (such as social network data) that can potentially instigate and maintain inequality within the school to guarantee that school decision-making is driven by fairness and justice (Dodman et al., 2021; Zhang et al., 2021).

The above review reveals that the essence of traditional DDDM is that meaningful information closely related to teaching situations is extracted from data via the teacher's analysis and processing to aid in their instructional decision-making. Common procedures of traditional DDDM include gathering data, analyzing data, establishing evidence for decision-making, and formulating and implementing decisions (Qi, 2021). Big data-driven instructional decision-making models share the same essence and procedures, but with further developments.

Big Data-Based Instructional Decision-Making

In the era of big data, the emergence of educational technology of all forms, such as the large-scale online learning platform, classroom teaching diagnosis tool, wearable learning-assisting device, and smart classroom, has resulted in an exponential increase in educational data. To address the huge volumes of educational data, data analytics is used to discern relations between various factors, diagnose teaching problems, and predict trends in student learning (Zhong & Hou, 2017), acting as a valuable instrument for the teacher's decision-making. In this context, a variety of big data-based instructional decision-making models have been developed in reaction to the increased impact of big data on teaching decisions.

To address issues with the teacher's decision-making, such as overdependence on subjective judgments, a lack of adjustment to classroom dynamics, and inadequate real-time evaluation, Zhong and Hou (2017) created a big data-based decision-making model (**Figure 2**) by introducing educational data into the process to improve the instructor's teaching design, interaction, and evaluation. With this model, the teacher gathers instructional data from the content management system (CMS), learning management system (LMS), school information system, and other data sources using technological tools. In the procedure of teaching design, the teacher analyzes the gathered data with analytics software to generate information as the groundwork for pinpointing learning objectives, deciding on teaching materials, and preparing teaching resources. In the procedure of teaching interaction, the teacher and students communicate through the information exchange platform, which records and analyzes data in real time.

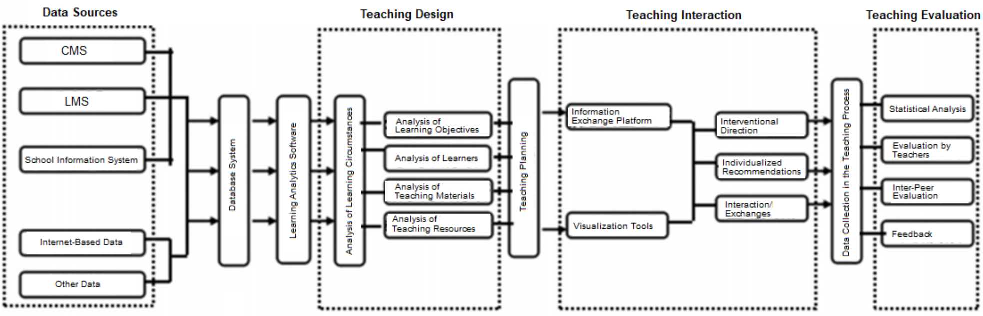

Figure 2. An Educational Data-Based Instructional Decision-Making Model.

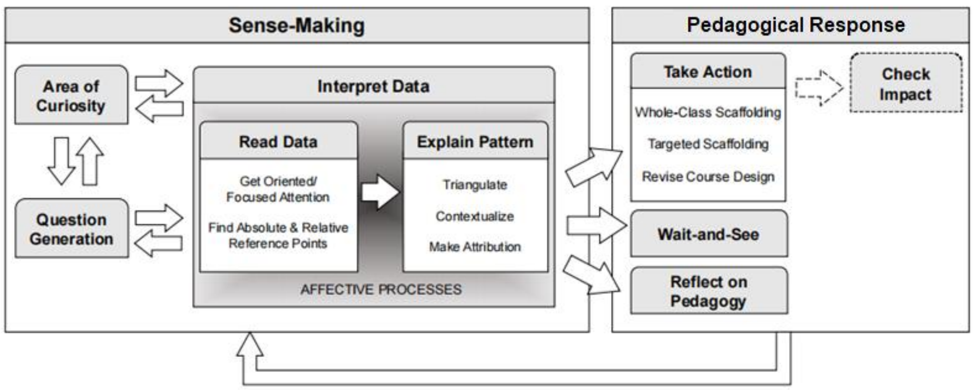

Figure 3. Wise and Jung's Situated Model of Instructional Decision Making.

Visualization tools are adopted to present the results of data analytics in a timely manner to facilitate the teacher's understanding of the students' mastery of knowledge and progress in learning as well as their provision of individualized intervention and tailored learning resources. In addition, the data gathered throughout the teaching process supports the teacher in reflecting on their own teaching behavior and evaluating the students' learning outcomes.

Guan et al. (2019) developed a data-driven instructional decision-making model targeting smart classroom environments. This model represents an evidence-focused process, including three procedures: conception of evidence, formation of evidence, and evidence-based decision-making. In the first procedure, the teacher needs to consider the correspondence between the objectives of decision-making and the data to be gathered. They must define the teaching focuses and establish and operationalize the objectives of decision-making first and subsequently select data acquisition routes and appropriate observation/measurement tools accordingly. The second procedure of evidence formation includes a few specific steps: gathering data, screening data, extracting information, generating new knowledge for problem identification, analyzing causes of problems, and directing decision-making actions. In addition, for the data generated in the smart classroom environment, the teacher can visualize learning data using intelligent tools, such as statistical analysis graphs of exercise/test results. Based on the first two procedures, the teacher can ultimately formulate the decision, implement it, and evaluate its effects in practice.

Wise and Jung (2019) investigated the experiences of five university teachers working with a learning analytics dashboard in authentic teaching settings. The findings were integrated to generate a situated model of instructional decision-making (**Figure 3**), which consists of two main parts: sense-making and pedagogical response. Data interpretation involved two distinct activities: reading data to identify noteworthy patterns and explaining their importance in the course using contextual knowledge, often along with affective reactions to data. Pedagogical responses to the analytics included whole-class scaffolding, targeted scaffolding, and revising course design, as well as two new non-action responses: adopting a wait-and-see posture and engaging in deep reflection on pedagogy.

Yan and Wang (2023) developed three DDDM models based on three different entry points to analytics, namely the platform, data, and question. Drawing on Ikemoto and Marsh's (2007) categories of decision-making, they named the three models as the analysis-focused decision-making model, the data-focused decision-making model, and the inquiry-based decision-making model. The analysis-focused decision-making model uses the platform as the entry point, which refers to the intelligent data analytics platform that can gather, process, and present data. Such a platform can lighten the burden of collecting teaching data on the teachers, but they may encounter additional difficulties in interpreting the analytic results generated by the platform. This model comprises six steps: creating a basic platform environment, defining data sources, examining data quality, identifying problems, discovering their causes, and generating solutions. The data-focused decision-making model also has six steps, namely, collecting and presenting data, analyzing strengths and gaps, establishing objectives, clarifying indicators of outcomes, selecting intervention tactics, and reflecting on practices. With this model, teachers are primarily responsible for data collection and analysis. Without the limitations of the platform, teachers can gather a wider variety of data. Regarding data analysis and decision-making, they do not need to depend heavily on specialist advice, team support, and large amounts of empirical evidence. Instead, they use ordinary descriptive analysis, correlation analysis, difference analysis, and other methods to explore patterns, trends, or relations in teaching data for developing action knowledge for teaching improvement or teaching strategy adjustment. The inquiry-based decision-making model, using the question as the entry point to analytics, warrants comparatively more complex data and actions concerning an iterative process entailing eight clearly defined steps: establishing the question, proposing hypotheses, gathering data, examining the quality of data, analyzing data, interpreting data and drawing conclusions, implementing improvement measures, and evaluating the decision.

To recap, big data-driven instructional decision-making models have certain salient advantages over traditional DDDM ones. First, with a big data-driven decision-making model, the teacher can access a greater variety of data via technological tools and make instructional decisions that benefit every student (Wu, 2019). It not only expands the scope of evidence for the teacher's decision-making but also renders personalized instruction possible. Second, big data technology has the potential to magnify the teacher's capacity to process large datasets and to reshape the decision-making process (Hu, 2024). Traditional DDDM models typically predict teaching behavior based on existing data (Zhang, 2017) or focus on how to utilize summative assessment data to improve student academic performance (Schildkamp, 2019), whereas big data technology and visualization tools enable the teacher to collect and analyze data in real-time during the teaching process and to adjust teaching strategies accordingly. Third, the traditional DDDM model requires a predetermined objective for decision-making (Schildkamp & Poortman, 2015), which actually limits the possibilities of exploring other instructional decisions. In contrast, the big data-based instructional decision-making model allows the teacher to identify latent relations in larger amounts of data, sometimes without a preset objective; the direction of their decision-making may become clearer during the process of data analysis (Zhang, 2017). This approach gives the teacher a broader perspective in decision-making but may also make the process more complicated and uncertain.

A Comparative Analysis of Representative Big Data-Driven Instructional Decision-Making Models

Table 1 encapsulates details of the six big data-based instructional decision-making models. It shows that underpinning these models are prior experiences in DDDM model construction, teachers' in-situ practices, and relevant educational theories. All the models share a basic procedure, "from gathering data, to analyzing data, establishing evidence for decision making, and formulating/implementing instructional decisions," which indicates the

Table 1. A Comparison between Big Data-Driven Instructional Decision-Making Models.

	Zhong & Hou (2017)	Guan et al. (2019)	Wise & Jung (2019)	Yan & Wang (2023)
References	Evidence-based education; basic instructional procedures	Evidence-based education; the DIKW model	Teaching experiences based on educational data	Mandinach et al.'s DDDM model; Ikemoto and Marsh's Quadrant Diagram of the DDDM's Complexity
Purposes of the model	To provide guidelines for how to apply educational data to instructional decision making.	To guide the teachers in improving instructional decision making leveraging the smart classroom environment.	To conceptualize instructors' process of data analytics and make recommendations for analytics design and implementation.	To address issues with educational data application in decision making, such as the lack of explicit objectives and procedures in data use.
Application scenarios	Ordinary classroom teaching settings	Smart classroom environments	Ordinary classroom teaching settings	Ordinary classroom teaching settings
Technological use	Leveraging technological instruments to gather and analyze structured and non-structured data and present the results	Recording student learning data, assessment data, psychological and physiological data using the smart classroom's digital terminals, interactive system, assessment system and other devices; allowing the teacher to select data analytics software for data analysis.	Designing a learning analytics dashboard to present to the teacher various information about the activity and performance of their students in a specific course, such as student access of course site and resources, video viewership information, results of online quizzes, and student survey responses.	In the analysis-focused decision-making model, the technological tools are responsible for collecting and providing data as well as presenting the results of data analytics, while the teacher is not allowed the choice of the type of data or the method of analytics. In the data-focused decision-making model, the technological tools play a supporting role in assisting the teacher in gathering necessary data; the teacher has the right to choose the type of data needed. With the inquiry-based decision-making model, the teacher needs to identify the issue with their teaching and select legitimate data mining and analytics tools accordingly.
Outcomes	A theoretical model pending practical validation	Practical experiments with this model suggest that the teacher can enhance the effectiveness of teaching design by using data generated in the smart classroom environment.	A theoretical model pending practical validation	According to the survey results, the three models were relatively highly rated in terms of usability (4.07/5), effectiveness (4.10/5), and teacher satisfaction (4.19/5) but lower regarding learnability (3.90/5) on average.

importance of the use of technological tools as well as the agency of the teachers as the decision makers. The models' purposes and application scenarios exhibit their focus on classroom-level decision-making but show disregard for school- and school district-level decision-making, which has been evidenced by the comments of those teachers who have applied these models (Yan & Wang, 2023). Some of these models lack practical validation, leading to the uncertainties of their effects. This hampers their popularization in the teaching community. Therefore, we need more experimental research to demonstrate their reliability and effectiveness.

Furthermore, Yan and Wang (2023) observed that the overgeneralization of decision-making procedures poses a challenge for teachers using these models, as they require subject-specific and education phase-specific guidelines for their instructional decision-making. To prompt the teachers' interest in big data-based decision-making, Wise and Jung (2019) suggest that the use of learning analytics should be aligned with teachers' pedagogical practices. In other words, information should be organized from the perspective of teachers, not data structures, and data ought to be updated in accordance with their instructional needs.

Discussion and Conclusion

From the earlier DIKW model to the more recent big data-based instructional decision models, ongoing are explorations of paths for reaching meaningful decision-making by leveraging educational data. The initial DDDM models had issues with data sources, such as overly focusing on student achievement data while disregarding other types of data (Hora et al., 2014). The advent of big data technology has made it easier to access multiple types of data in colossal volumes. Big data-based instructional decision-making models can provide multiple entry points to analytics for teachers while also presenting various routes to successfully harnessing data to inform decision-making (Zhong & Hou, 2017; Guan et al., 2019; Wise & Jung, 2019; Yan & Wang Wei, 2023).

On the other hand, certain researchers showed concerns about the effectiveness of big data-driven decision-making. Coburn et al. (2012) noted that underlying the interventions aimed at promoting data use was the belief that collecting and analyzing the right data would necessarily lead to valuable information, generating resolutions to chief educational problems and better educational outcomes. In effect, the application of DDDM is potentially affected by multiple factors. First off, the quality of data is the most critical factor. Whether the data is worth considering is contingent on its quality (Lin et al., 2021). For example, the student's self-report may contain insufficiently objective data, which may lead to the teacher's incorrect judgment if included in learning analytics. Thus, it is important to ensure the data incorporated in decision-making is valid, reliable, and pertinent (Agasisti & Bowers, 2017). Second, data abuse may cause severe ethical issues. There is the possibility that the teacher or data analyst may infringe on students' privacy in using their data. Hence, the access to and study of data must be based on the principle of transparency (Agasisti & Bowers, 2017). Third, the conversion of data into evidence for decision-making requires the development of data literacy or data wisdom in teachers. Gummer and Mandinach (2015) defined teacher data literacy as the ability to collect, analyze, and interpret various types of data and to transform the information extracted into actionable instructional knowledge to assist with teaching design. Lastly, the adoption of big data-based instructional decision-making involves cost-related factors. Teacher data literacy training and the deployment of technological tools essential for DDDM bring about additional costs to educational institutions. For many schools, the construction of a digital teaching environment like the smart classroom is still an unaffordable financial burden. Thus, to encourage investment in intelligent education environments from the government and non-governmental organizations, more empirical research is warranted to provide evidence that big data-based educational activities, including DDDM, can significantly improve educational outcomes.

Studies included in our review showcase the researchers' confidence in the positive effects of big data technology in facilitating the teacher's precise and productive decision-making. However, our search for big data-driven instructional decision models is far from exhaustive due to the limitations of the searching method. Future studies should rely on a broader scope of literature search to uncover more models in this area, providing a more comprehensive understanding of the application of big data technology in instructional decision-making. Also, researchers need to pay more attention to the outcomes of these models in teaching practices and focus on exploring more scientific paths for integrating big data technology into instructional decision-making.

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