Harnessing the Power of Data in Higher Education: How to Balance Innovation with Ethical and Inclusive Practices Through Rapid Change

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Abstract

The proliferation of data-driven decision making in higher education presents both unprecedented opportunities and significant challenges. This review examines how emerging classrooms and other technologies are reshaping data collection and analysis while highlighting the potential risks of increased datafication, particularly regarding equity concerns. We analyze the complex dynamics of implementing institutional change, emphasizing leadership's crucial role in navigating stakeholder and other relationships. The review critically evaluates the balance between traditional practices and technological innovation, providing a potential path for institutions to leverage data analytics while maintaining focus on educational equity. It also underscores the importance of thoughtful implementation guidance that aligns technological capabilities with institutional goals and ethical considerations.

Keywords

Data-driven decision making, equity and equality, emerging technologies, institutional change, balance and innovation

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Higher education is often at the forefront of futuristic innovation while remaining tethered to the core tenets of knowledge transmission and expansion rooted in antiquity. Not so long ago, college campuses were home to some of the first supercomputers and the birthplace of email communications, both of which revolutionized and reconstructed nearly every aspect of our world. Today's technologies continue to reshape possibilities, particularly through the rise of Big Data and its integration into higher education via data-driven decision-making (DDDM), predictive analytics, and emerging learning technologies. Institutions have been harnessing data in a variety of ways as it has grown in scale and complexity, a trend that will only accelerate (Bastedo et al., 2022; Borden & Kezar, 2012; Gagliardi et al., 2018; Taylor, 2020).

As the depths of the data pool rapidly increase, intentionality in direction becomes crucial. The integration of DDDM and predictive analytics offers significant potential to enhance student outcomes and institutional effectiveness. However, concerns around data protection, equity, and ethical use must be thoughtfully addressed. Inclusive data practices and strategies that align with core institutional missions are essential to ensuring that innovation in education remains both forward-thinking and equitable (Ekowo & Palmer, 2016; Lanclos & White, 2020; Williamson et al., 2020).

DDDM is being employed in higher education to engage with topics from proactive student support (Mathies, 2018; Parnell, 2018) and enhancing student learning (Hora et al., 2017; Zilvinskis, 2017) to reviews of faculty practices (Hora et al., 2017) and budgetary considerations (Jones & Jackson, 2017). Sifting through huge stores of data in search of patterns that can be used to predict outcomes for individual students, teaching methods, enrollments, earnings, and more has become the work of algorithms meant to support decision-making and inform action in a variety of ways. This review will begin with a review of several of the evolving and newly emerging technologies in higher education and discuss the benefits and challenges they present. The importance of ethical considerations will be stressed to highlight issues of bias and accessibility connected to the use of these technologies. Rapid implementation of new applications and the challenges this presents for effective organizational change will be considered, followed by a review of further extenuating factors and contexts that complicate the landscape of DDDM. Finally, the review will provide future directions by offering insights into the implications, key takeaways, and future steps for data-driven decision making in higher education, while highlighting the need for ongoing adaptation and ethical stewardship in data practices.

Evolving and Emerging Technologies in Higher Education

Technology is not new to higher education, but recently new technologies have been introduced and are evolving at an accelerated rate. Some higher education technologies have been around for a decade or so, such as various concepts and applications of predictive and learning analytics, and some are truly just emerging in the classroom and beyond, such as AI, gamification, and immersive learning applications. Each holds the promise of innovation and increased effectiveness, but successful adoption will require awareness of potential pitfalls.

Broadly, analytics is the ability to analyze collected data in effective ways to inform ongoing decisions, which are enhanced as organizations invest in expertise and infrastructure to support the use of their data (Davenport, et al., 2010). Analytics in higher education are understood to have connections with student success, retention, time to degree, prediction, automation, strategy, and insight, among other applications (Bichsel, 2012). Learning analytics encompass a variety of applications from early warnings of possible failure to augmented instructional materials based on a students' individual progress within a course (Herodotou, et al., 2019). These programs engage in data mining to identify connections between student indicators (i.e. assignment grades, attendance, participation) and

outcomes (i.e. ultimate grade in a course). This analytic tool may automatically notify the instructor orthe student's advisor so they can reach out and offer support for improvement. Or it may deliver additional instruction on a particular concept or set of concepts that a student is misunderstanding to solidify their understanding before moving on in an online course.

Predictive analytic tools also use data mining techniques and may be employed to review grade trajectory over time or degree of success in a specific course to give insight into whether a particular major or set of majors are likely to achieved by a particular student (Ekowo & Palmer, 2016). Although these tools can connect students with support for early intervention, they also have the potential to undermine a student's belief in their abilities or begin to track less prepared students into less rigorous degree programs. Care needs to be taken when having conversations about the predictions to not reinforce issues with a sense of belonging. (Ekowo & Palmer, 2016)

Artificial Intelligence (AI) is very new on the scene and has caused a great deal of debate in higher education. Beyond problematic issues of academic misconduct, AI has potential for integration into the higher education landscape as a student resource in terms of tutoring, brainstorming, accessibility tools and assistive technology, and for an instructor as a teaching assistant offering course design, grading, and student feedback (Robert, 2024). AI may also be embedded into learning or predictive analytic platforms to continue to improve on the algorithm it is set to employ.

Additional emerging technologies include the immersive learning applications of virtual reality (VR) and gamification. Both augment reality in some way to enhance learning. VR entails students wearing a VR headset that displays a different environment, a wheel or buttons for students to interact with, and may include sensors embedded into a headset or worn in another way to record movement (Radianti, 2020). Some examples of learning that can occur with this apparatus are driving, performing surgeries, and astronomy (Radianti, 2020). This technology offers immersion into a virtual world that mimics the real word to allow learning to occur in a setting that may not be a possibility for the student otherwise. Gamification is signified by the learning being game-based and can include the use of levels and rewards and can be infused into a VR experience (Radianti, 2020) or can be devised to be performed in a typical classroom setting. Each of these technologies, as well as inevitable others on the next horizon, could prove to enhance education but only to the extent that they are sourcing accurate and contextualized data that calls on the expertise of IR professionals (Hansen et al., 2021; Herodotou et al., 2019). As these new technologies are employed, data is being collected to determine their effectiveness and used to make decisions about how they might be expanded or augmented (Herodotou et al., 2019; Hora et al., 2017; Zilvinskis, 2017).

Equity and Equality in Data-Driven Education

"Evidence-based" or "data-driven" decision-making both emphasize data collection to serve the goal of accountability and transparency (Bichsel, 2012; Borden, 2018; Chen & Haynes, 2016; Hora et al., 2017; Mathies, 2018), which implies a great trust in data. Mathies (2018) reminds that the use of data can be categorized as good use and misuse. While data can provide valuable insights into student and institutional performance, misuse or overreliance on data can lead to problematic decision-making. Datafication in higher education may pose the risk of creating homogenized learning environments, potentially undermining student agency and creativity (Williamson et al., 2020). "Dataism is a style of thinking that is integrally connected to processes of neoliberalization, as competitive logics and the desire to compare the performance of entities against each other," (Williamson et al., 2020, p. 352), therefore, relying solely on objective numbers and the digitized driving of data use on college campuses poses significant risks, potentially exacerbating division rather than improving equity and equality. More

specifically, data use may undermine equity and equality through two pathways: first, data is distorted and inconsistent with its nature and collection process. Data consists of two components: data and metadata. Metadata is a set of details that provide context to collected datasets in both digital and physical formats, including information on how data collection within unequal power structures filters and detaches cultural elements from their original context, an influence that continues to be perpetuated by users (Carbajal & Caswell, 2021). Data, or even big data tends to be an oversimplification of higher education, also distorts reality to institutional success merely in numbers. (Rice & Russell, 2012; Rios-Aguilar, 2015). Furthermore, data is also influenced by the capitalization within its institutions and external market-like environments or embedded markets (Taylor Jr, 2020), leading to mismatches between data and metadata. Secondly, data is misinterpreted during the process of interpretation and utilization. Current faculty and staff are likely to have very different backgrounds from their students and often harbor biases, conscious or unconscious, that inevitably have an impact on student success (Herodotou et al., 2019; Lundquist & Henning, 2020). The interpretation of data drives changes through the decision-making process on college campuses, whereas the data itself does not. Therefore, how data is interpreted is crucial (Zilvinskis et al., 2017). Moreover, data-informed decision-making requires strong support from higher education administrators and leaders to drive organizational data collection and the development of data talent community (Zheng et al., 2020; Zilvinskis et al., 2017).

"Technology has made it easy to generate data and share information" (Chen & Haynes, 2016, p. 18). Big Data-related technologies enable us to easily access larger volumes of data, incorporate more variables, and obtain more real-time information. However, Big Data is merely a data assemblage when it relies on assumptions of neutrality in data collection and blind faith in its validity, as such assemblages are inherently tied to the political, social, and economic frameworks that shape their collection and use in socially constructed decision-making contexts (Iliadis & Russo, 2016).

One potential solution lies in critical data studies, which is focusing on social problems, critically examining these problems and connections between data and morality (Iliadis & Russo, 2016). The cultural integration of analytics should also be considered part of critical data studies, although achieving this goal is challenging (Bichsel, 2012). With the support and promotion of institutional research (IR) offices, data use on college campuses is increasingly converging with critical methods to improve equity and equality.

Several practices effectively demonstrate the success of IR offices or IR practice in fostering equity-minded decision-making cultures:

- **Environmental Context Dashboard (ECD)**: Developed by Bastedo et al. (2022), this tool provides contextual data about applicants' socio-economic backgrounds and educational environments to aid in holistic college admissions practices, reducing bias and promoting equity in student selection.
- **Demographic Analysis of Minority-Serving Institutions (MSIs)**: Boland et al. (2021) highlight how IR offices use demographic data to better understand student populations at MSIs, enabling tailored support strategies that address the unique needs of underrepresented groups.
- **DEI Strategic Plans**: Hansen et al. (2021) detail the design and implementation of diversity, equity, and inclusion (DEI) initiatives at a public urban institution, where data-driven approaches helped align institutional goals with measurable outcomes for marginalized communities.
- **Equity Liaison Initiative (ERI)**: At the University of Wisconsin–La Crosse, Engen and Solverson (2021) describe how the ERI program trains liaisons within departments to use equity-focused analytics to identify disparities and implement interventions to create a more inclusive campus environment.

During this process, IR offices play a critical role in developing dynamic, campus-wide analytics strategies to meet the evolving needs of student bodies (Gagliardi et al., 2018). Establishing clear protocols and performing regular evaluations are essential for ensuring data quality (Harrower & Ben-Eliezer, 2019). These measures also help mitigate the potential for unethical use of predictive data practices, which could harm individuals by prioritizing favorable institutional outcomes over student well-being (Ekowo & Palmer, 2016).

This section focused on the risks of solely relying on data in decision-making on college campuses, the challenges posed by technology, and potential solutions to address these issues. These challenges would remain even in the most ideal settings of technology adoption but are inevitably further layered with the task of executing the adoption of a new technology.

Implementation of Change in Higher Education

Change can be difficult to implement in any large organization and higher education institutions are no different as they are comprised of a variety of individuals who have varying degrees of motivation to move toward a stated goal. With many new technologies being incorporated into the higher education landscape and more approaching, it can be increasingly challenging for faculty, staff, and students to continually adapt. Further, concerns connected to equity and equality with these emerging technologies can cause increased questions and potentially resistance to these particular types of changes and their potential for negatively affecting students (Gagliardi, et al., 2018; Knight, et al.,1997).

Implementing successful changes in the realms of DDDM, learning and predictive analytics, and other emerging technologies require a multi-pronged approach. First, these efforts require strong leadership that is willing to put an effective amount of resources into the infrastructure needed to support these goals and into an adequate amount of personnel to manage them (Herodotou, et al., 2019). Once implemented, faculty and staff will likely require ongoing training to support effective incorporation of the technologies. Challenges can arise in interpretation of data over time and in developing a routine that regularly incorporates the new information into more granular employee decision making for the benefit of students (Herodotou, et al., 2019).

In addition to strong leadership, developing a culture of collaborative learning across units, with the support of IR professionals is necessary to create the environment needed for the ongoing support and training for effective use of the new tool (Borden & Kezar, 2012). Significant barriers to change can include data disconnects across campus that can create a lack of communication and understanding, working against successful implementation (Gagliardi, 2018). Beyond the continuing support of employees who receive an initial training when a new technology is implemented, there will always be turn over in the affected roles requiring training for new employees. Continued presence to assist in training and ongoing support will increase the success of the new program (Borden & Kezar, 2012). Leadership must understand the need for ongoing commitment at the onset in order to ensure proper resource allocation is made to avoid a great start that ultimately fails (Herodotou, et al., 2019).

Lastly, but equally important, leadership should work toward a multidimensional framework for understanding faculty and staff attitudes toward a change (Piderit, 2000). Although it is common to perceive resistance as a barrier to change (Gagliardi, 2018), engaging in dialog with those who raise questions may develop a new and improved iteration of the technology to be implemented as well as a higher level of acceptance of the new technology overall (Piderit, 2000). Further engaging in conversation to interrogate the motivations of negative comments and dissent can move leadership away from a resistance versus support binary and toward a deeper understanding of the complexity of employee attitudes about a change (Piderit, 2000). This more nuanced view of faculty and staff reactions

to technology changes will work toward a culture of collaboration and increase the success of implementation.

Integrating these concepts of effective change in the context of DDDM and emerging technologies while utilizing the expertise of IR professionals will incorporate the following:

- **Set the groundwork for success:** Before launching a new data driven system, an assessment of implementation should be completed to ensure sufficient organizational support for the project (Bichsel, 2012), address any disconnects between units needed for a successful launch (Gagliardi, et al., 2018), and thoroughly assess the quality of the data being employed (Bogue, 1998).
- **Create an environment of openness and transparency:** To aid in successful implementation of new data driven tool, transparency is important to in developing trust with faculty, staff, and students (Lanclos & White, 2020) as is providing the opportunity for feedback and collaboration to aid in in the development (Piderit, 2000).
- **IR professionals integrated at every level:** IR offices can help to assess the landscape of institutional readiness for such a change and bridge the gaps between units to pave the way for success (Gagliardi, et al., 2018). They are equipped to assess quality of the data and determine demographics that may be obscured in collection and usage (Hansen, et al. 2021; Lundquist & Henning, 2020). Including IR professionals in conversations with faculty, staff, and student affected by the changes help to increase trust (Gagliardi, et al., 2018) and they are well positioned to provide the ongoing training and support required for continued success (Herodotou, C., et al., 2019).

This review has addressed the *what* and the *how* of DDDM by describing the many elements involved and considerations for effective implementation of the new practices these technologies will inevitably create. The next important element is the *why*. Employing these strategies simply because they are available is irresponsible without rooting to core tenants of higher education within institutional context.

Core Elements in Data-Driven Decision Making in Higher Education

In an era where data increasingly drives decision-making, higher education institutions must continually interrogate how data initiatives align with their missions, from enhancing student success to advancing diversity and inclusion (Bichsel, 2012; Hora, Bouwma-Gearhart, & Park, 2017). While focusing on present and future changes and pressures are necessary, remaining rooted to foundational goals espoused in mission statements and loyalty to higher education's many stakeholders must guide data-driven approaches by raising critical questions about their intentions and often hidden challenges.

Data-driven decision making (DDDM) is most effective when it reflects the unique mission and values of an institution (Bogue, 1998; Mathies, 2018). For universities, aligning data initiatives with goals like student retention, equity, and academic quality is paramount. Data-informed planning can support these aims, such as through early interventions for at-risk students mentioned previously or optimized resource allocation to high-need areas (Dowd, 2005). However, when data projects prioritize quantitative results, they risk oversimplifying or sidestepping more nuanced goals, such as fostering a sense of belonging or promoting equitable outcomes for underrepresented groups (Carbajal & Caswell, 2021). By interrogating how data can both support and potentially narrow institutional missions, this review advocates for a more intentional approach to DDDM—one that respects both numbers and the human experiences behind them.

As predictive analytics becomes increasingly central to data initiatives, offering powerful tools for forecasting trends in enrollment, student support needs, and academic success, the accuracy of these tools brings new ethical complexities (Ekowo & Palmer, 2016; Herodotou et al., 2019). Consider the example of algorithms designed to predict retention in an effort to increase student success that may inadvertently reinforce existing inequalities, privileging certain demographics while disadvantaged others (Iliadis & Russo, 2016). Such predictive models underscore the need for careful design and transparency to avoid unintended harm. Cases such as this highlight the tension between the desire for precise predictions and the ethical imperative to safeguard fairness and inclusivity, drawing on lessons from institutions navigating these challenges (Gagliardi, et al., 2018). They serve as cautionary tales that should give pause for reflection, refocus, and increased awareness of the need for intentionality.

Effective data initiatives in higher education depend on the involvement of diverse stakeholders, including students, faculty, and administrators. Each group brings unique perspectives and priorities to the table, shaping how data is used and understood (Davenport, Harris, & Morison, 2010). Engaging students, for example, can ground data initiatives in real experiences, ensuring policies address their needs and aspirations. Faculty input, too, is critical for aligning data initiatives with teaching and learning goals, while administrative leadership often drives strategic use of data in broader planning. A collaborative approach to DDDM strengthens institutional buy-in and builds trust, fostering a culture where data initiatives are both transparent and responsive (Hora et al., 2017).

Big data has been and will continue to be a transformative force in education. It presents both immense potential and notable challenges. As institutions harness large datasets to refine everything from personalized learning experiences to institutional planning, they also confront concerns around privacy, data security, and quality (Harrower & Ben-Eliezer, 2019; Zheng, Mayberry, & Stanley, 2020). These datasets, often drawn from a wide array of sources, provide valuable insights but require stringent safeguards to protect student information. Higher education institutions can adopt big data responsibly by advocating for robust data governance practices to ensure ethical and secure use of these powerful resources (Gagliardi et al., 2018).

Budget, Data Quality, and Cultural Context—Influencing Data Initiatives in Higher Education

Beyond core elements, several “outlier” factors significantly shape data-use practices in higher education. These include budgetary constraints, concerns around data quality and misuse, and the influence of social and cultural contexts (Jones & Jackson, 2017; Mathies, 2018). While not always central to data discussions, these factors fundamentally impact the efficacy and ethicality of DDDM.

Budget limitations affect every stage of data-driven decision making, from the tools and technologies an institution can afford to the human resources available for data analysis. Institutions facing budget constraints may resort to less comprehensive datasets or less rigorous analyses, potentially limiting the quality of insights (Jones & Jackson, 2017). This section considers how financial realities impact data initiatives and calls for more thoughtful planning to ensure that data practices are sustainable, even in resource-constrained settings (Davenport et al., 2010).

High-quality data is the backbone of effective decision making, yet data in higher education often suffers from issues like incompleteness, inconsistency, or lack of relevance (Harrower & Ben-Eliezer, 2019). These issues can lead to misguided analyses, risking the misinterpretation of student needs and institutional priorities. Additionally, without strict protocols, data is susceptible to misuse, whether through unintentional bias in data interpretation or deliberate manipulation (Mathies, 2018). A stronger emphasis on data governance, that highlights the importance of ethical guidelines and regular

audits to prevent misuse and ensure accuracy is needed to provide continued responsible stewardship (Bichsel, 2012).

The social and cultural context within which data is used can profoundly shape both the reception and effectiveness of data initiatives. Diverse campus communities bring a range of perspectives on data practices, which can impact levels of trust, perceptions of fairness, and willingness to engage (Carbajal & Caswell, 2021). Furthermore, cultural factors influence what is considered ethical or acceptable in data practices, shaping institutional priorities and stakeholder expectations. These dynamics must be acknowledged to implement culturally aware approaches to data-use that respect and incorporate the values of the entire academic community (Ekowo & Palmer, 2016).

Discussion

Although we have focused on emerging technologies, equity/equality, institutional goals, change management, and outliers as unique entities in this conversation, these concepts are inextricably linked. It is not easy to distinguish them clearly on their own; they must be understood and adopted through an integrated perspective. Future research should aim to develop a comprehensive framework to guide practice, drawing on a range of existing theories and incorporating interdisciplinary insights. For example, student development theories, such as psychosocial, cognitive-structural, and typological frameworks (King & Howard-Hamilton, 2000), could inform how data initiatives address student needs holistically. Furthermore, Institutional Research (IR) offices are well-positioned to bridge the gap between academic and administrative cultures (Parnell, 2018), leveraging their role to foster communication, coordination, and integration of theoretical and practical approaches.

While advancements in data infrastructure have provided a solid technological foundation for institutional research, integrating these technologies with the human-centered tasks of IR remains a significant challenge. For instance, despite the growing availability of data tools, many faculty and staff remain unfamiliar with them. Teachers, for example, often engage less frequently with educational software, even when they find it helpful (Herodotou, 2019). This lack of consistent use highlights a broader need for enhanced data literacy and skills in analysis and interpretation. Without these competencies, data-use practices may unintentionally perpetuate bias or inequities, especially when algorithms or datasets fail to reflect the experiences of minority or underrepresented groups (Ekowo & Palmer, 2016; Carbajal & Caswell, 2021).

Fostering a culture of ethical and effective data use—often referred to as a “data-driven culture” (Gagliardi et al., 2018) or “data culture” (Hora et al., 2017)—is therefore a critical priority. Such a culture must prioritize equity-minded decision-making, with IR offices playing a significant role in guiding institutions toward fairness and inclusivity in their data practices (Hansen et al., 2021). This involves ensuring that data initiatives are designed not only to avoid harm but also to actively address disparities. For instance, equity-minded decision cultures should examine how data processes and outcomes impact various stakeholder groups differently and seek to mitigate unintended consequences.

In addition to equity concerns, the misuse of data—whether due to unintentional errors or insufficient understanding of users—poses another challenge. While not always unethical, irresponsible data practices can still lead to misguided decisions that harm institutional effectiveness and student outcomes. IR offices can mitigate this by offering support in areas such as data governance, ethical guidelines, and regular audits, ensuring that data initiatives remain transparent and aligned with institutional goals.

Finally, as higher education continues to adopt new technologies at an accelerating pace, the role of IR in promoting thoughtful change management becomes even more critical. The emphasis on

innovation must be tempered by an awareness of the institutional context, ensuring that new tools and practices enhance, rather than undermine, the mission of higher education. Achieving this balance requires not only technical expertise but also strong leadership, collaboration, and a commitment to continuous learning. By integrating these diverse elements—technological innovation, equity, institutional goals, and change management—higher education can better navigate the complexities of data use. The challenges may be significant, but with intentional strategies and a commitment to ethical practice, the promise of data-driven decision-making can be realized.

Conclusion

The need for institutional research professionals to drive data use on college campuses is rapidly increasing but also faces numerous new challenges. How can balance be struck between traditional IR practice and expansive innovation that delivers data across campus units and often out of the contextualized realm of IR? This review has attempted to capture the immensity of the project at hand by bringing attention to the many components that must be considered, each individually extensive: (1) emerging technologies in the classroom and beyond, (2) the responsibility of making continued steps toward equity and the possibility of data use to obscure authentic progress, (3) considerations of effective change and implementation of new technologies into the diverse and complex realms of higher education institutions, (4) the imperative of not losing site of the larger mission while also focusing on the next rapidly approaching innovation that will be needed to stay relevant, all while staying within budget, not losing site of the importance of ensuring data quality, and staying grounded within the ever changing social and cultural context of your own institution. The road ahead promises great possibilities if attention can be given to each of these components, but success will demand continued commitment.

Although present challenges may seem unprecedented and can feel insurmountable at times, it is helpful to remember that the project of higher education has been continuously reimagined to mesh with new social contexts and technologies as they evolve. Each development has embodied the potential for huge strides forward as well as missteps and our current circumstance is no different. Remaining grounded in the fundamental mission of higher education is paramount as we advance through this next phase of progress. Thoughtful, steady leadership will make all the difference.

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