Integrating Business Analytics into Public Health Management: A Data-Driven Approach

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Abstract

Background: Public health organizations worldwide implement business analytics (BA) for better decision-making and resource optimization as well as health trend prediction. The United States confronted rising influenza alongside COVID-19 and RSV case numbers in December 2023. Methods: The research executed a descriptive cross-sectional study between May and July 2025 to collect data from 110 healthcare staff members working in hospitals and public health organizations and NGOs. Researchers used structured questionnaires to record demographic information together with BA implementation status and organizational readiness alongside perceived advantages and implementation barriers. Data analysis was performed using SPSS version 27 which utilized descriptive statistics along with chi-square tests and percentage distributions. Results: The survey findings indicated that 74% of participants gained faster decision-making through Business Analytics while 68% gained better outbreak prediction capabilities and 59% achieved better resource allocation. The survey results showed 72% of respondents reported staff shortages and 64% expressed data privacy issues while 58% had budget limitations and 52% experienced limited IT infrastructure and 47% had organizational resistance to change. Statistical evaluation revealed that organizations with larger employee counts showed substantially greater adoption rates of Business Analytics ($p = 0.05$). The integration of Business Analytics strengthens public health management by enabling faster and accurate decision-making. Conclusion: adoption of Business Analytics requires dedicated investments in workforce training and ethical data governance together with targeted resource support for smaller organizations to achieve equitable implementation.

Keywords: Business Analytics, Public Health Management, Data-Driven Decision-Making, Predictive Analytics, Healthcare Technology

Significance | Business analytics enhances decision speed, prediction accuracy, and resource allocation, improving public health crisis preparedness and management.

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Editor Luna Leoni, Ph.D., And accepted by the Editorial Board Dec 08, 2023 (received for review Oct 02, 2023)

1. Introduction

Healthcare digital transformation has established unmatched possibilities for data-driven public health management. Health information systems and cloud computing and artificial intelligence have revolutionized health data collection and storage and analysis processes during the past twenty years (Boyce et al., 2014). Electronic health records (EHRs) together with mobile health (mHealth) applications and laboratory information systems and disease surveillance networks produce large amounts of data every day which covers patient interactions and diagnostic information and vaccination statistics and disease prevalence data (Brown-Liburd et al., 2015). Healthcare big data streams provide

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Please cite this article.
Chowdhury, N., Mia, M. S., Hossain, M. I., Papia, S. K., Nashid, S. (2023). "Integrating Business Analytics into Public Health Management: A Data-Driven Approach", Business and Social Sciences, 1(1),1-7,10346

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exceptional potential for health improvement if they become actionable insights. The conversion process demands sophisticated analytical instruments which handle complexity with speed at scale (Wang et al., 2019).

Business analytics (BA) functions as a long-established corporate strategy tool that delivers capabilities for business operations (Detmer, 2003).Business analytics (BA) is consistent of three essential forms, which include descriptive analytics assessing historical data to interpret past situations using descriptive summaries, predictive analytics utilizing statistical models and machine learning techniques to predict future events, and prescriptive analytics providing prediction data with limitations and objectives in order to inform decision-making processes (Varda, 2011). The possibilities for using BA methods to change public health operations are astonishing. The combination and visualization of disease surveillance data with descriptive analytics gives people a way to look back at past outbreaks and how interventions performed in response to those outbreaks. Predictive analytics is often used by health professionals to model disease transmission and plan for the expected need in health facilities or even to evaluate the effect of an intervention (Dey et al., 2008). Prescriptive analytics can be used to optimize allocations of resources, as geopolitical circumstances force public health agencies to use them efficiently, or when prioritizing response strategies while designing unique public health outreach. The United States encountered a significant epidemiological dynamic in December 2023, as three respiratory illnesses rose and intensified throughout healthcare in a catastrophic manner.

Public health agencies that have developed BA platforms have demonstrated the ability to correlate hospital data in a seamless fashion with existing yet simultaneous data from testing centers and surveillance within an appropriate timeframe (Forbes, 2005). This allowed them to quickly identify patterns of outbreaks, quantify hospital bed occupation, and execute geo-targeted vaccination campaigns. In contrast, agencies without strong analytics capabilities could not report cases in time, had minimal predictive capabilities, and deployed medical personnel and supplies in ways that did not reflect the true needs of communities (Farid et al., 2005). This difference illustrates the opportunities for BA to provide recovery capacity, alleviate system-wide pressures, and enhance health outcomes. However, it should be recognized these benefits have yet to lead to widespread implementation of BA in public health. In high income country settings, examples of BA as part of a health system often rely on a strong information technology infrastructure, trained analysts, and a policy environment that supports BA (Tzeng et al., 2007). In low- and middle-income countries (LMICs), the uptake of such technology may be limited due to structural or resource limitations. Barriers include limited digital infrastructure, lack of interoperability of health information systems, restricted trained workforce, possible data security and privacy issues, and competing demands on the budgetary process (Wickramasinghe & Schaffer, 2018). Health crises, whether seasonal epidemics, newly-emerging infectious diseases, or environmental health threats, require coordinated responses that are often rapid in succession and based upon evidence-based data. Agencies needing currency or real-time analytics are destined to make decisions that are delayed, their resources probably less optimal or miss-allocated, and likely the health outcomes for the populations they serve will suffer (Simpao et al., 2014). The experience during the December 2023 health crisis in the USA provides a timely illustrative reminder that preparedness is not only a factor of resource allocation, but also of data capability and analytics capabilities. This research has been undertaken in order to describe the current state of BA use in public health management, with a focus on adoption rates, perceived benefits, and perceived barriers to BA use by healthcare professionals (Detmer, 2003). By combining survey data from 110 participants along with observations from global best practices and some recent experiences in US public health, this research attempts to delineate opportunities for accelerating equitable BA use adoption. Ultimately to inform both policy and practice, and ensuring the transformation opportunities of analytics is adopted to improve health outcomes in diverse contexts.

2. Materials and Methods

2.1 Study Design

The research utilized a survey design that combined descriptive cross-sectional elements to analyze business analytics (BA) adoption within public health management systems. The cross-sectional method was chosen because it presents current practices and barriers and perceptions in one timeframe which enables efficient data collection of the present state (Spring, 2007). The study design enabled both measurement of BA adoption rates along with healthcare professional attitudes toward its supposed advantages and difficulties. Public health research benefits most from this methodology because it avoids the high costs and extended durations of longitudinal studies (Glickman et al., 2007). The descriptive part of the research study enabled researchers to detect data patterns which revealed important insights about organizational factors affecting BA implementation across different organizational sizes. The design receives widespread recognition in health services research because it produces evidence which supports policy development and resource distribution and interventions across multiple healthcare settings (Simpao et al., 2014. The research framework based on cross-sectional design allowed the study to determine relationships between organizational factors and BA adoption while keeping research costs low and methodology straightforward.

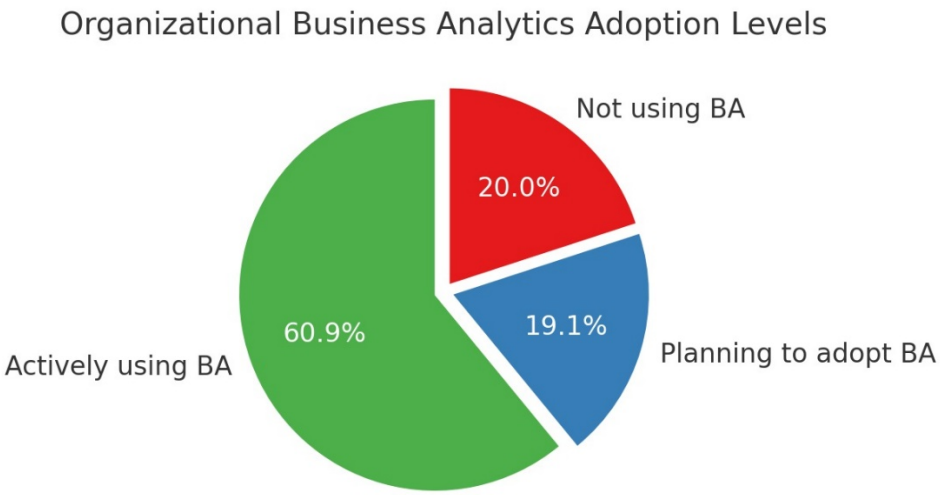

Figure 1. Organizational Business Analytics Adoption Levels

2.2 Study Population and Sampling

The research study targeted 110 health professionals who manage public health activities within hospitals and government health agencies as well as non-governmental organizations (NGOs). The participants consisted of hospital administrators together with public health officers and data analysts along with epidemiologists and program managers who hold managerial and technical responsibilities (He et al., 2018). To enhance the research validity, the investigators selected participants using purposive sampling based on their experience with BA implementation. Through purposive sampling the researchers obtained participants from both small clinics that had less than 100 staff members and large institutions with more than 500 employees. The methodology enabled researchers to conduct comparative studies between different organizational types which remains fundamental for studying the influence of structural elements and available resources on BA implementation (Kohli et al., 2001). All recruitment processes adhered to strict ethical standards which protected participant autonomy and obtained their informed consent. The study guaranteed participant anonymity and confidentiality to stimulate open disclosure about organizational methods and observed obstacles (Tzeng et al., 2007). The sampling method was strategically developed to achieve an equilibrium between practicality and participant variety and study relevance to deliver findings that mirror actual public health operational settings.

2.3 Data Collection Tool

The data collection process used a structured questionnaire which was created specifically for this research study. The questionnaire contained four primary sections for its structure. The initial section gathered demographic information about respondents by asking their age and gender and their organizational role and work experience together with their organization size to establish contextual understanding (Ward et al., 2014). The second section evaluated BA adoption status by determining if respondents' organizations currently use BA or plan to adopt it or if they do not use it at all. The third section examined BA adoption benefits and barriers through a 5-point Likert scale which allowed respondents to express their level of agreement from strong disagreement to strong agreement thus enabling measurement of subjective perceptions (Li et al., 2002). The fourth section assessed organizational readiness through evaluation of technological infrastructure and leadership support and analytics staff competency. Public health and data analytics experts examined the questionnaire to validate its content (Politi et al., 2007). The pilot testing included 15 professionals who evaluated the questionnaire for clarity and relevance before making minor modifications based on their feedback. The questionnaire development process created a tool which effectively measures both numerical data and descriptive information about BA integration in public health settings.

2.4 Data Analysis

The responses were processed using SPSS version 27 to perform statistical analysis. The analysis of respondent demographics together with BA adoption rates and perceived benefits and reported barriers utilized descriptive statistics including frequencies percentages means and standard deviations (Luo et al., 2016). The study used cross-tabulations to analyze how organizational characteristics affected BA adoption while chi-square tests determined the statistical importance of observed associations. The results showed meaningful relationships because researchers used a p-value threshold of 0.05 to distinguish

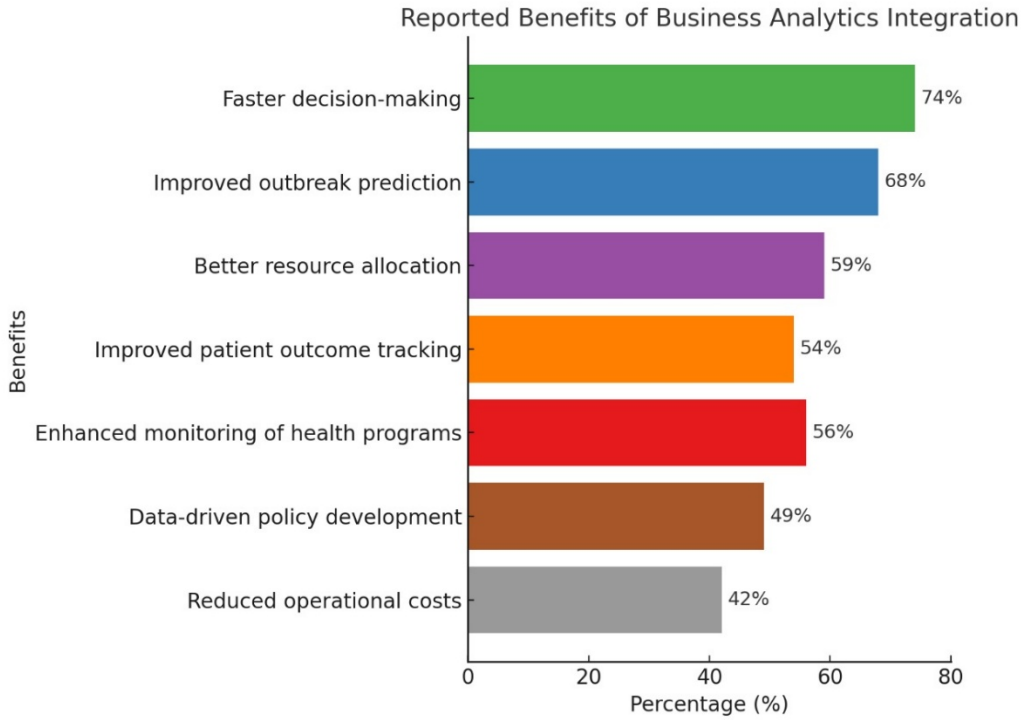

Figure 2. Reported Benefits of Business Analytics Integration

significant findings from random variation. The quantitative findings received contextual interpretation through thematic analysis of open-ended responses about challenges and facilitators (Sharma et al., 2014). The evaluation of BA integration utilized both descriptive and inferential statistical methods to identify adoption patterns together with key influencing factors (Ratia et al., 2019). The analytical approach was developed to combine statistical rigor with understandable results that deliver useful knowledge to public health policymakers and healthcare administrators and practitioners who implement BA in various contexts.

3. Results

3.1 Demographic Profile

The research sample consisted of 110 healthcare personnel working at hospitals together with public health agencies and non-governmental organizations. The study sample consisted of 52.7% male and 47.3% female respondents according to Table 1. The survey identified that most participants (41.8%) belonged to the 30–39 age range while 25.5% were in the 20–29 years' category, 21.8% belonged to the 40–49 group and 10.9% were above 50 years (Wang & Byrd, 2017). The study revealed that public health officers represented the largest group with 29.1% while medical officers followed with 23.6% and NGO program managers made up 18.2% while data analysts accounted for 16.4% and epidemiologists represented 9.1% and other roles made up 3.6% of the sample. The respondents showed different levels of professional experience with 34.5% having 5–10 years of service, 25.5% with 11–15 years, 23.6% with less than 5 years and 16.4% with more than 15 years. This varied demographic composition gives a complete understanding of BA implementation across multiple professional roles and age levels and experience ranges.

3.2 Business Analytics Adoption Status

The analysis of organizational adoption levels showed that 61% of respondents stated their institutions actively used BA tools which demonstrated widespread recognition of analytics value for public health management (Figure 1). These organizations implemented BA through tasks that included disease surveillance and outbreak prediction and resource allocation and healthcare program performance monitoring. The implementation of BA in these environments required the use of multiple software platforms including Tableau and SAS and Power BI together with trained data analysts and institutional support systems. The survey showed that 19.1% of respondents declared their organizations planned to implement BA tools within the next future period (Li et al., 2002). The data shows increasing awareness and commitment to data-driven decision-making across institutions which have yet to implement analytics fully. The organizations identified their future adoption of BA depends on budget allocation and staff training together with infrastructure development. The survey revealed that 20% of participants stated their organizations had not implemented BA which indicates ongoing difficulties with implementation (Rehman et al., 2021). The implementation barriers stem from technical knowledge gaps and financial constraints and IT system limitations and organizational opposition to transformation.

Table 1. Demographic Characteristics of Respondents (n = 110)

Variable	Category	Frequency	%
Gender	Male	58	52.7
	Female	52	47.3
Age Group	20–29	28	25.5
	30–39	46	41.8
	40–49	24	21.8
	50+	12	10.9
Professional Role	Public Health Officer	32	29.1
	Data Analyst	18	16.4
	Medical Officer	26	23.6
	NGO Program Manager	20	18.2
	Epidemiologist	10	9.1
	Other	4	3.6
Work Experience	<5 years	26	23.6
	5–10 years	38	34.5
	11–15 years	28	25.5
	15+ years	18	16.4

Table 2. Barriers Identified by Respondents

Barriers Identified by Respondents	**Agree with Respondents**
Skill shortage	72
Data privacy and security concerns	64
Budget constraints	58
Limited IT infrastructure	52
Organizational resistance to change	47
Lack of leadership support	39

3.3 Perceived Benefits of Business Analytics

The survey asked participants to list the advantages of integrating Business Analytics in public health operations. Most participants identified quick decision-making as the main advantage of BA integration with 74% followed by outbreak prediction at 68% and resource allocation at 59% Figure 2. Health program monitoring received 56% of mentions together with patient outcome tracking at 54% and policy development at 49% and operational cost reduction at 42%. The findings show that Business Analytics provides value through operational efficiency and strategic decision-making which validates its ability to improve public health management (Dey et al., 2008).

3.4 Barriers to Adoption of Business Analytics

The study investigated various obstacles that prevent Business Analytics (BA) implementation. Most organizations faced difficulty in obtaining skilled staff members (72%) as their main hurdle yet data privacy and security matters (64%) and budget restrictions (58%) followed closely behind Table 2. Additional challenges to BA implementation emerged through weak IT systems (52%), organizational opposition to transition (47%) and absence of leadership backing (39%). The research demonstrates that building organizational capacity and digital infrastructure investments alongside supportive cultural environments are essential for BA implementation success (Rajkomar et al., 2018).

3.5 Adoption by Organization Size

The implementation of BA showed strong dependence on the organizational size of the institutions. Large institutions 78% which employ more than 500 staff members have implemented active BA adoption. Organizations with employee numbers between 100 and 500 demonstrated a 64% BA adoption rate yet only 42% of

organizations with fewer than 100 employees implemented BA as shown in Figure 3. The data shows that larger organizations tend to have the necessary financial resources together with technical infrastructure and personnel expertise needed to successfully implement BA. Smaller organizations encounter organizational structure problems and limited resources which create obstacles for adopting new practices.

4. Discussion

Business analytics (BA) integration in public health is growing yet organizations show uneven uptake according to this research. The survey analysis reveals that 61% of healthcare professionals use BA tools now while 19.1% plan to implement them shortly (Kohli et al., 2001). A fifth of participants revealed that their organizations lacked analytics implementation which demonstrates ongoing obstacles to complete integration (Orwat et al., 2008). The research demonstrates that although organizations increasingly value BA the implementation of its full adoption remains restricted by infrastructure limitations and resource availability and workforce development needs. According to respondents the main advantages of BA usage include quicker choices followed by superior outbreak prediction and more effective resource distribution (McGovern et al., 2017). The survey showed respondents recognized multiple advantages including better health program monitoring and improved patient outcome tracking alongside data-based policy development and decreased operational costs. The data shows BA brings value through operational effectiveness as well as through enhanced strategic planning capabilities which base decisions on evidence (Rew, 2000). The benefits mentioned by participants reflect actual results from the December 2023 U.S. respiratory illness surge when analytics-enabled agencies effectively handled influenza and COVID-19 and RSV outbreaks demonstrating real-world value of data-driven decision support.

Barriers to BA adoption discussed in the study suggest an organization faces both structural and human challenges when adopting BA identify. The most often cited barrier was lack of skills (72%), highlighting the significant need for trained people who can apply analytics in a public health context (Ranjan, 2008). Data privacy and security issues (64%) were also significant barriers and highlight the importance of meeting regulatory and ethical compliance to handle sensitive health information. Budget (58%), IT infrastructure (52%), and organizational resistance to change (47%), were additional structural barriers to BA adoption which indicates that adoption was influenced by financial, technical and cultural barriers (Musen et al., 2021). Also of note was lack of leadership support (39%) which indicates that commitment from above is typically required for successful implementation. There was also an observable relationship between organizational size and BA adoption in this study. Larger organizations (>500 employees) had the highest adoption rate of analytics (78%) followed by medium organizations (64%), and then small organizations (less than 100 employees) at 42%, thus confirming that resource availability, infrastructure capability, and staffing levels are significant factors to successful analytics integration (Mosa et al., 2012). Smaller organizations, in particular, will likely experience more difficulties with analytic integration due to lack of budget and specialized personnel, which further supports the need for systems of support such as collaborative development of analytics platforms, centralization of analytics support, and enhancements in capacity.

5. Conclusion

Business analytics can transform how public health operates with meaningful and timely, data-driven information to support decision-making, forecasting, and resource allocation. As the public health sector continues to transition to data-informed decision-making, there is an opportunity to address barriers to implementing BA, particularly for smaller organizations. Closing skill gaps, investing in data governance, and providing financial and infrastructural incentives will be vital for future and equitable opportunities. A systematic approach that balances investing in new technologies and workforce development and management systems will enable the benefits of analytics to be shared across different strata of the public health sector.

Author contributions

N.C. conceptualized the study and developed the methodology. M.S.M. and M.I.H. prepared the original draft and contributed to the review and editing of the manuscript. S.K.P. and S.N. performed data analysis and also participated in the review and revision of the writing.

Acknowledgment

Not declared

Competing financial interests

The authors have no conflict of interest.

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