



Prifysgol Cymru
Y Drindod Dewi Sant
University of Wales
Trinity Saint David

Report

WORD COUNT: 1223

DATA HANDLING AND BUSINESS INTELLIGENCE (LCBB5000)

LECTURER: DR SHENGFENG MEI

STUDENT: Stefan Valentinov Baev (1905214)

Table of contents

1. Introduction.....	p.2
2. Overview of Business Intelligence in Healthcare.....	p.2
3. Current trends in BI for healthcare.....	p.3
3.1. Agile business intelligence	
3.2. Predictive and prescriptive analytics	
3.3. Data visualisation and interactive dashboards	
3.4. Artificial intelligence (AI) and Machine learning (ML)	
4. Challenges in implementing BI in Healthcare.....	p.4
5. Theoretical insights from the research Article.....	p.4
6. Future directions for BI in Healthcare.....	p.5
7. Conclusion.....	p.6
8. References.....	p.6

1. Introduction

Business intelligence (BI) has emerged as a critical tool for converting the massive amounts of data created in the healthcare sector into usable insights (*Puklavec et al., 2018*). The "big data" phenomena, defined by the three Vs: volume, variety, and velocity, has forced the use of advanced business intelligence solutions to improve patient care, optimise operational efficiency, and support evidence-based decision-making (*Larson & Chang, 2016; Raghupathi & Raghupathi, 2014*).

This report digs into current business intelligence developments as they apply to the healthcare industry. Building on *Larson and Chang's (2016)* foundational research work, it investigates modern approaches such as agile BI, predictive and prescriptive analytics, artificial intelligence (AI), and data integration strategies. The research also covers the problems associated with implementing BI systems and looks ahead, drawing on insights from a variety of academic and industrial sources.

2. Overview of Business Intelligence in Healthcare

The healthcare business generates massive amounts of structured and unstructured data from sources such as electronic health records (EHRs), medical imaging, laboratory testing, administrative records, and Internet of Medical Things (IoMT) devices (*Raghupathi & Raghupathi, 2014*). To effectively utilise this data, powerful BI systems must be capable of integrating several data sources, maintaining data quality, and providing analytical capabilities.

Eidizadeh et al. (2017) identify the following key dimensions of business intelligence:

Data integration is the process of combining data from many sources to create a single view.

Analytical Capabilities: Using advanced analytics to gain useful insights.

Content quality refers to the accuracy, completeness, and timeliness of data.

Decision-Making Culture: Creating an organisational culture that prioritises data-driven decisions.

In healthcare, these aspects are critical for supporting clinical decisions, improving patient outcomes, and increasing operational efficiency (*Chen et al., 2012*). BI integration improves resource allocation, reduces medical errors, and increases patient satisfaction (*Groves et al., 2013*).

3. Current trends in BI for Healthcare

3.1. Agile Business Intelligence

Agile BI applies flexible, iterative development principles to BI, enabling quick delivery of insights and rapid adaptation to changes, such as disease outbreaks or new regulations (*Larson & Chang, 2016*).

Hospitals increasingly adopt agile BI to deploy analytics solutions efficiently, breaking projects into manageable phases (*Williams & Williams, 2010*). During the COVID-19 pandemic, agile BI helped monitor infection hotspots, allocate resources, and manage patient volumes, enhancing crisis response (*Klashanov & Choudhury, 2021*). Benefits include faster insights, improved team collaboration, and continuous refinement based on user feedback, making it a valuable approach for dynamic healthcare environments (*Cooper & Sommer, 2016*).

3.2. Predictive and prescriptive analytics

Prescriptive analytics recommends optimal actions to achieve desired outcomes, while predictive analytics forecasts future events based on historical data (*Davenport & Harris, 2017*).

In healthcare, predictive models enable patient risk stratification, allowing proactive interventions for those at high risk of complications or readmission (*Stewart et al., 2016*). Analytics also predict disease outbreaks by analyzing epidemiological trends (*Chen et al., 2015*) and optimize operational efficiency by forecasting patient demand, improving workforce and resource allocation. Using machine learning techniques like neural networks and regression, healthcare providers enhance care quality, efficiency, and cost management (*Kankanhalli et al., 2016*).

3.3. Data visualisation and interactive dashboards

Data visualization technologies transform complex data into graphical formats, aiding stakeholders in interpreting insights (*Eidizadeh et al., 2017*).

Clinical decision support dashboards track patient vitals and treatment progress, helping doctors make informed choices. Administrators use dashboards to monitor key performance indicators, including patient throughput and

compliance metrics (*Few, 2013*). User-centered design principles ensure data is presented in an accessible manner by considering user needs and cognitive factors. Advanced tools like Tableau, Power BI, and QlikView offer features such as interactive charts, heat maps, and geospatial analysis (*Sulaiman et al., 2019*).

3.4. Artificial Intelligence (AI) and Machine Learning (ML)

AI and machine learning are revolutionising business intelligence by analysing complicated data patterns and automating decisions.

Key applications include medical imaging, which uses AI to diagnose illnesses such as cancer (*Esteva et al., 2017*), and Natural Language Processing (NLP), which extracts insights from unstructured clinical data ML models forecast equipment failures, allowing for proactive maintenance (*Somasundaram & Rani, 2020*).

However, their application poses ethical problems regarding data privacy, prejudice, and openness. Regulatory authorities such as the FDA are developing guidelines to ensure the safety and efficacy of these technologies (*US FDA, 2019*).

4. Challenges in Implementing BI in Healthcare

Data privacy and security concerns, including compliance with HIPAA and GDPR, are critical, as breaches can lead to severe legal and reputational risks (*Eidizadeh et al., 2017*).

Cyberattacks on healthcare systems necessitate robust cybersecurity measures. Obtaining patient consent for secondary data use adds complexity (*Ploug & Holm, 2017*).

Data quality issues, such as errors and inconsistencies, undermine insights, while variations in data entry and coding hinder standardization. Implementing data governance frameworks is crucial for ensuring data integrity (*Abraham et al., 2019*).

Skill shortages in healthcare data analytics exacerbate the problem.

Investing in training programs (*Raghupathi & Raghupathi, 2014*) and fostering interdisciplinary collaboration between IT, data scientists, and practitioners is essential to improving BI adoption (*Grover et al., 2018*).

5. Theoretical Insights from the research Article

Larson and Chang (2016) emphasise the integration of agile techniques, BI, analytics, and data science as a means of efficiently managing big data concerns.

They claim that traditional BI methodologies are insufficient in the face of quickly changing data landscapes, and instead advocate for agile BI to improve responsiveness and adaptability.

Agile BI Advantages: Agile BI encourages shorter development cycles, continuous improvement, and greater alignment with business requirements (*Larson & Chang, 2016*).

Integration with Data Science: Combining business intelligence (BI) with data science approaches allows for deeper insights via sophisticated analytics such as predictive modelling and machine learning (*Larson and Chang, 2016*).

Healthcare Implications: In healthcare, these approaches help to produce creative solutions for patient care, resource management, and strategic planning (*Kankanhalli et al. 2016*).

Organisational Culture: Adopting agile BI necessitates a cultural shift that prioritises experimentation, learning, and adaptation.

6. Future directions for BI in Healthcare

1. Edge Computing:

Processing data at the source (such as IoT devices) minimises latency and improves real-time analytics capabilities (*Shi & Dustdar, 2016*).

Benefits include faster reaction times, lower network bandwidth requirements, and more data privacy.

Applications: Essential for telemedicine and remote patient monitoring systems.

2. Explainable AI (XAI):

Creating AI models with visible and interpretable outcomes is critical for clinical acceptability (*Gunning & Aha, 2019*).

Importance: Clinicians must understand AI recommendations before trusting and acting on them.

Regulatory Considerations: Regulatory agencies are becoming more transparent

3. Personalised Medicine:

BI facilitates the transition to personalised medicine by combining genomic data, lifestyle information, and environmental factors (*Ashley 2016*).

Precision tests: Tailoring tests to specific genetic profiles.

Customised Treatment Plans: Creating therapies that are more effective and cause fewer negative effects.

7. Conclusion

Business intelligence is transforming healthcare by allowing organisations to use big data to make better decisions and provide better care to patients. Agile business intelligence, predictive analytics, real-time data processing, and artificial intelligence are among the current trends driving this transition. However, problems such as data privacy, quality, skill shortages, and cultural resistance must be solved in order to fully realise BI's promise.

Larson and Chang (2016) examine how the integration of developing technologies and approaches will continue to affect the progress of business intelligence in healthcare. By embracing these innovations and cultivating a data-driven culture, healthcare organisations may increase operational efficiency, clinical excellence, and, ultimately, patient outcomes.

8. References

- Abraham, R., Schneider, J., & Vom Brocke, J. (2019). "Data governance: A conceptual framework, structured review, and research agenda." *International Journal of Information Management*, 49, pp. 424-438.
- Ashley, E. A. (2016). "The precision medicine initiative: A new national effort." *JAMA*, 315(7), pp. 711-712.
- Chen, H., Chiang, R. H., & Storey, V. C. (2012). "Business intelligence and analytics: From big data to big impact." *MIS Quarterly*, 36(4), pp. 1165-1188.
- Cooper, R. G., & Sommer, A. F. (2016). "The agile-stage-gate hybrid model: A promising new approach and a new research opportunity." *Journal of Product Innovation Management*, 33(5), pp. 513-526.
- Davenport, T. H., & Harris, J. G. (2017). *Competing on Analytics: The New Science of Winning*. Harvard Business Review Press.
- Davenport, T. H., & Patil, D. J. (2012). "Data scientist: The sexiest job of the 21st century." *Harvard Business Review*, 90(10), pp. 70-76.
- Eidizadeh, R., Salehzadeh, R., & Chitsaz Esfahani, A. (2017). "Analysing the dimensions of business intelligence and its impact on organisational performance." *International Journal of Business Information Systems*, 24(3), pp. 215-233.

- Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). "Dermatologist-level classification of skin cancer with deep neural networks." *Nature*, 542(7639), pp. 115-118.
- European Commission. (2020). "White Paper on Artificial Intelligence: A European approach to excellence and trust." *European Commission*.
- Few, S. (2013). *Information Dashboard Design: Displaying Data for At-a-Glance Monitoring*. Analytics Press.
- Groves, P., Kayyali, B., Knott, D., & Van Kuiken, S. (2013). "The 'big data' revolution in healthcare: Accelerating value and innovation." *McKinsey & Company*.
- Gunning, D., & Aha, D. (2019). "DARPA's explainable artificial intelligence (XAI) program." *AI Magazine*, 40(2), pp. 44-58.
- Kankanhalli, A., Hahn, J., Tan, S. S., & Gao, G. (2016). "Big data and analytics in healthcare: Introduction to the special section." *Information Systems Frontiers*, 18(2), pp. 233-235.
- Klashanov, K., & Choudhury, P. (2021). "Agile data science for COVID-19 management." *IT Professional*, 23(3), pp. 14-21.
- Larson, D., & Chang, V. (2016). "A review and future direction of agile, business intelligence, analytics and data science." *Journal of Business Research*, 70, pp. 287)
- Ploug, T., & Holm, S. (2017). "Meta consent: A flexible and autonomous way of obtaining informed consent for secondary research." *BMJ*, 358, j4035.
- Puklavec, B., Oliveira, T., & Popović, A. (2018). "Understanding the determinants of business intelligence system adoption stages: An empirical investigation of SMEs." *Industrial Management & Data Systems*, 118(1), pp. 236-261.
- Raghupathi, W., & Raghupathi, V. (2014). "Big data analytics in healthcare: Promise and potential." *Health Information Science and Systems*, 2(1), p. 3.
- Shi, W., & Dustdar, S. (2016). "The promise of edge computing." *Computer*, 49(5), pp. 78-81.
- Stewart, W. F., Shah, N. R., Selna, M. J., Paulus, R. A., & Walker, J. M. (2016). "Bridging the inferential gap: The electronic health record and clinical evidence." *Health Affairs*, 26(2), pp. w181-w191.

- Sulaiman, M., Shahrina, N., & Mahmud, M. (2019). "Data visualization technology acceptance in health care." *Journal of Technology Management and Business*, 6(1), pp. 1-11.
- US FDA. (2019). "Proposed regulatory framework for modifications to artificial intelligence/machine learning (AI/ML)-based software as a medical device (SaMD)." *Food and Drug Administration*.
- Williams, S., & Williams, N. (2010). *The Profit Impact of Business Intelligence*. Morgan Kaufmann.