

Original Article

Transforming Healthcare Decision-Making Through Business Intelligence: A Practical Framework for Data-Driven Clinical and Operational Excellence

Sachin Girdhar

Kurukshetra University, Kurukshetra (Haryana), India

Received Date: 27 September 2026

Revised Date: 02 October 2026

Accepted Date: 07 October 2026

Abstract: Healthcare business intelligence has progressed from reporting on past performance to integrated infrastructures that can aid in clinical decisions, operational coordination, resource allocation and organizational learning. This review summarizes the components of business intelligence architectures, dashboards and visualization systems, data analytics, and clinical decision support capabilities, and how each of these elements can help drive data-driven clinical and operational excellence. The evidence suggests that the value of analytics lies in the ability to integrate data, visualize it meaningfully, align it with workflow, respond within the appropriate timeframe, and convert information into measurable action. Dashboard studies report improvements in information availability and situational awareness, while analytics research indicates potential benefits for risk stratification, resource management, and organizational performance. Causal conclusions are limited, however, by heterogeneous evaluation designs, the lack of controlled outcome studies, limited reporting of implementation costs, interoperability concerns, and human factors concerns. A realistic model is presented in which the above capabilities integrate data quality, analytics, decision interfaces, workflow integration, and outcome feedback. There is a need for further advancements in comparative evaluation, explicit governance, prospective validation and clinically meaningful decision quality measurement.

Keywords: Business Intelligence, Clinical Decision Support, Data Analytics, Healthcare Dashboards, Operational Excellence

I. INTRODUCTION

Business intelligence in healthcare has become a more prominent link between health information infrastructure and impactful clinical or managerial actions. Business intelligence is differentiated not merely by the collection of large amounts of data, but by its ability to transform data from a variety of clinical, administrative, financial, and operational sources into information that can be utilized at the appropriate organizational decision-making level. Empirical and conceptual studies have shown that, while healthcare analytics can aid in the understanding of processes, facilitate a more systematic use of resources, and guide the identification of high-risk populations, it will only be of value to the organisation if the data is of high quality, the organisation has the necessary implementation capability and if there is a successful alignment of the data with the processes within which it is used. Therefore, business intelligence maturity is more of an organizational capability dealing with data integration, data governance, analytic capability, delivery channels and decision processes rather than the simple deployment of specific dashboard technologies [2].

This ability has been increasingly relevant as larger volumes of electronic health record data, monitoring streams, laboratory results, and utilization information have become available for analysis. In cardiovascular care, for instance, advanced analytics has been suggested to have a beneficial effect on risk estimation, population monitoring, comparative effectiveness evaluation, and quicker clinical action, while significant concerns remain regarding bias, data origin, interpretability, and generalisability of the results [3]. The wider health-care analytics literature highlights similar use cases, diagnosis, prognosis, operational management, population health and cost control, and points to the lack of a unified landscape and the marked differences in the maturity of analytics across various healthcare settings [4]. However, technical capacity does not necessarily guarantee improved decisions.

One of the largely unanswered questions is how business intelligence brings clinical or operational value to the enterprise. Most studies assess the usability of the user interface, the usefulness of the information, or the availability of information, but not changes in the accuracy of the decisions that are made, the timeliness of the treatment or the use of resources, patient outcomes or cost. While dashboard interventions can bridge the gap between data and action, inappropriate choices of indicators can lead to information overload or may induce local optimization at the system level. Value is lost when outputs are delivered outside the relevant workflow and/or the value is not explained. Operational analytics can help identify throughput constraints, but it is only helpful if the authority has been granted to take action on identified constraints. The



above observations indicate that healthcare business intelligence should be considered a sociotechnical decision architecture as opposed to a stand-alone software intervention.

This review critically analyses evidence published in peer-reviewed publications on the business intelligence-based clinical and operational decision-making. The focus is on four interrelated areas: (1) analytics capability and organizational maturity, (2) dashboard and visualization design, (3) clinical decision support, and (4) operational performance management. The review also lays the groundwork for a hands-on approach towards connecting data foundations with analytics, decision interfaces, workflow execution and outcome feedback. Comparative results, methodological limitations, evidence gaps, and design principles that can differentiate between information display and actual decision improvement are discussed in particular.

II. LITERATURE REVIEW

Three overlapping areas of healthcare business intelligence research can be identified: dashboard-based performance intelligence, visualization-mediated clinical intelligence, and enterprise analytics capability. The dashboard literature offers the clearest insights into the transfer of processed information into operational practice. Dowding et al. identified that it was a common practice to create a healthcare dashboard that would bring together performance indicators and increase awareness of performance issues, though there was limited evidence of the relationship between dashboard exposure and patient outcomes [5]. Franklin et al. furthered this notion with the use of real-time visualization of throughput creating a dashboard-like display which helps identify bottlenecks and coordination requirements in an acute-care setting [6]. Ghazisaeidi et al. highlighted the following factors as practical considerations for dashboard usefulness: indicator selection, data quality, interface design, and management engagement [7]. In all these studies, there is a consistent comparison between information availability and the effectiveness of decisions made: If the responsibility, timing, interpretation, or action pathways are unclear, then the display of accurate indicators is not enough.

The latter group deals with visualization of complex clinical data. West et al. found significant innovation in EHR visualization, with a few reports indicating that new visualization methods had a positive impact on clinical outcomes [8]. Similarly, Gotz and Borland suggested that interactive visualization could be useful for clinicians to understand complex longitudinal and multivariate datasets, and that scalability, cognitive load, provenance, and workflow integration are significant human factors and technical challenges [9]. These concerns are echoed in systematic reviews of big data efforts in the healthcare sector. Along with privacy, security, interoperability, and data-quality challenges, Kruse et al. found decision support and population management opportunities [10]. They observed widespread acceptance of the use of analytics, but significant variation in the applications, the data environment, and measures of success used [11]. Despite emerging technical capacity for processing high-volume health data, Dash et al. reported that there were ongoing challenges in data integration, standardization, storage, privacy and translation into routine practice [12].

Table 1: Summary of key findings

Ref	Focus	Key Findings
[5]	Clinical and performance dashboards	Dashboards improve visibility of selected indicators, but robust evidence for patient-level outcome improvement is limited and evaluation designs are heterogeneous.
[6]	Real-time hospital throughput visualization	Context-specific visual displays can improve situational awareness and support identification of operational constraints requiring timely coordination.
[7]	Healthcare performance dashboard development	Effective deployment depends on relevant indicators, reliable data, visual clarity, organizational engagement, and alignment with management objectives.
[8]	Electronic health record visualization	Visualization methods can reduce information-search burden and expose temporal patterns, although clinical-effectiveness evidence remains underdeveloped.
[9]	Interactive healthcare visualization	Interactive analytics can support exploration of complex clinical data but introduces challenges involving cognition, scalability, provenance, and workflow fit.
[10]	Big-data opportunities and barriers	Decision-support potential is substantial, while interoperability, security, privacy, governance, and data quality constrain implementation.
[11]	Healthcare analytics evidence	Applications span clinical and managerial domains, but inconsistent methodologies and outcome definitions restrict comparative assessment.
[12]	Health-data management and analytics	Technical advances expand analytic capacity, yet heterogeneous data structures and weak integration complicate translation into operational value.

As shown in Table 1, the literature is more consistent on enabling conditions than on the measured impact of these conditions. Technically different studies share similar characteristics of data reliability, meaningful indicator selection, visualization quality, interoperability, and alignment of workflows. It is significant because it indicates that business intelligence performance is dependent upon the limiting factor in any decision chain, whether it is poor-quality data or a poorly defined metric that does not directly relate to the decision.

There is also a significant dichotomy between centralization and contextualization in the literature. While enterprise architectures often prefer to adhere to standardized data definitions and common performance measures, clinical decisions often require a specialty-specific context, temporal detail, and patient-level interpretation. Too much standardization can take away clinically meaningful nuance, and too much customization can reduce comparability and complicate governance. Past research has tended to focus on how to meet these demands in the short term. In addition, deployment studies often report on successful deployments in individual sites, creating potential for selection and context biases. Higher quality evidence demands a multisite assessment that separates out the impacts of technology from local leadership, staffing, workflow redesign and baseline digital maturity.

III. METHODOLOGY

In the literature, various methodological approaches are found, which include maturity models, systematic reviews, implementation studies based on observation, evaluation of interfaces, data-mining frameworks, and decision-support analyses. Research in clinical decision support focuses on the relationship between computable patient data and recommendations or alerts at the point of decision. Sutton et al. noted benefits such as consistency, preventive support, diagnostic assistance, medication safety, and highlighted alert fatigue, poor usability, inappropriate timing, maintenance burdens, and risks of automation [13]. Data-mining research in healthcare, on the other hand, follows a different methodology, as it identifies associations, classifications and predictions using large amounts of data, and Islam et al. observed that the applications are widespread across clinical and administrative problems, whereas the evaluations of implementation and theory are found to be inconsistent [14]. Organizational analyticity was defined by Wang et al. as a transformation mechanism between data resources, analytic process, analytic organizational practices and analytic performance outcomes [15].

These methods can be combined in a five-layer approach: data foundation, analytic transformation, decision interface, workflow action and outcome feedback. The first layer ensures completeness, timeliness, semantic consistency and provenance. The second transforms source data into descriptive, diagnostic, predictive or prescriptive information. The third one dictates the ways output is displayed on dashboards, alerts, drill-down views, scorecards, or other decision interfaces. The fourth relates to the timing of information entering a workflow where an authorized actor could intervene. The fifth examines whether an action has a clinically and operationally significant impact and yields information to governance and model improvement processes.

Table 2: Method Comparison

Ref	Method	Strengths	Limitations
[5]	Structured literature review of healthcare dashboards	Identifies recurrent design and evaluation patterns across dashboard applications.	Heterogeneous studies prevent strong causal attribution of clinical outcomes.
[6]	Applied dashboard design and evaluation in hospital throughput	Connects visualization requirements with real operational decisions and temporal constraints.	Context-specific deployment limits transportability across institutions.
[8]	Systematic review of electronic health record visualization	Provides a broad assessment of visualization techniques and clinical information tasks.	Outcome evidence is dominated by usability and task-performance measures.
[13]	Clinical decision-support framework and evidence review	Links information delivery with clinical workflow, risk, and implementation requirements.	Wide intervention scope complicates attribution to business intelligence components specifically.
[14]	Systematic review of healthcare data-mining approaches	Exposes diversity of analytic methods and application domains.	Variation in datasets, validation procedures, and targets limits comparability.
[15]	Organizational analytics-transformation model	Connects technical analytic capability with organizational performance mechanisms.	High-level constructs require context-specific operationalization for clinical settings.

The proposed architecture is made up of a closed decision cycle instead of a single report line (one way), as shown in Figure 1. This distinction is important because it affects data definitions, models, thresholds, interface design, and governance upon deployment for clinical and operational excellence by having measured outcomes to affect the definition. Healthcare data assets are linked to five measurable clinical and operational consequences. Observed outcomes provide feedback for recalibrating metrics, analytic logic, decision rules, and governance. The methodological comparison also reveals a measurement problem. Organizational studies tend to focus on adoption, perceived value, or performance transformation, while technical studies focus on model discrimination, data-processing capability, and/or visualization performance. A more informative evaluation process will link both levels by examining if a given analytic output leads to a change in a specific decision, if the changed decision results in a change in process performance, and if the changed process results in a clinically or economically meaningful outcome. Without evaluating this chain, it is difficult to attribute observed outcomes to a specific component of the business intelligence system.



Figure 1: Business Intelligence Decision Architecture for Clinical and Operational Excellence

IV. DISCUSSION

There is a consistent, if not stronger, relationship between the benefits of using health care business intelligence with enhanced information visibility, as found in the reviewed literature. Research in dashboards and visualization has shown that integrated displays can help to decrease the number of information sources and help spot deviations, bottlenecks, or temporal patterns [5], [6], [8]. Of particular interest to Franklin et al. is that operational evidence is relevant since throughput decisions are made in real time, not monthly, based on real-time information about patient flow [6]. This is a temporal dimension which differentiates operationally effective business intelligence from conventional reporting. When the intervention window is over, the information may be useful for an audit but has little value to affect the immediate decision. Clinical decision support literature comes to the same conclusion: information needs to be available at the right time and place in the workflow, in a form that facilitates rather than hinders clinical thinking [13].

Visualization quality is therefore a decision-performance variable, not merely an aesthetic consideration. West et al. reported visualization approaches for reorganizing the information in longitudinal, multidimensional EHR data around clinically interpretable patterns [8]. They pointed out interactive methods that allow filtering and exploration, but greater flexibility also leads to cognitive and interpretive challenges [9]. The real-world problem is that the highest level of information density does not equal the highest level of intelligence. Many indicators on a dashboard can drown out priority indicators, and over-simplified indicators can mask uncertainty, subgroup variation, or causal context. Indicator design, therefore, must clearly link every indicator displayed with a specific decision owner, action threshold, action time, and escalation pathway.

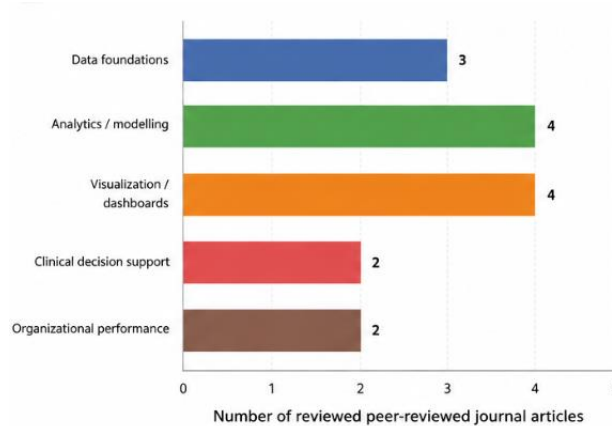


Figure 2: Distribution of Reviewed Evidence Across Business Intelligence Decision Functions

The capability of business intelligence also has multiple layers of dependency on the data infrastructure. Heterogeneous formats, missingness, semantic inconsistency, privacy constraints, and interoperability are all consistently cited as challenges

to successful big-data analytics in the literature [10]–[12]. These restrictions have repercussions for decisions that are made. A metric that seems to be accurate based on incomplete or delayed source data can give false confidence in the situation. The worry is exacerbated by the use of predictive systems; errors made in defining cohorts, timing of measurements, or coding can become part of model results. Data resources and analytic capabilities should thus not be seen as substitutes in an organizational transformation model [15]. Without reliable, up-to-date and repeatable calculations from underlying data pipelines, investments in visualization or predictive modelling make little sense.

Figure 2 classifies the evidence reviewed by each source based on the key decision function each addresses. The distribution shows that most of the literature focuses on enablers of infrastructure, analytics or information presentation, while fewer studies directly assess downstream clinical and operational outcome effects. Dominant contributions to the data foundation, analytics, visualization/dashboard delivery, clinical decision support, and organizational performance are coded to peer-reviewed sources. The concentration in enabling layers shows the relative lack of direct outcome evaluations.

The second significant finding is related to the difference between descriptive intelligence and action-oriented intelligence. Descriptive dashboards can create a common operating picture, especially for throughput, quality indicators and service utilization [6] and [7]. Extending the concept of supporting decisions beyond what is known, predictive and data-mining techniques attempt to forecast future outcomes or to classify patients based on their information [3, 14]. Prescriptive capability is comparatively less developed due to the added requirements of causal validity, safety, explainability and accountability in generating recommendations. A risk estimation by itself is not enough to decide which intervention is beneficial, feasible or cost-effective. The distinction is often confused in analytics maturity conversations and poses a risk of predictive accuracy being mistaken for clinical utility.

The reported benefits also vary with respect to the level of decision-making. At the patient level, business intelligence can be used in risk identification, interpretation of longitudinal data, adherence with clinical protocols and prioritization of attention [3, 8, 13]. The most common applications at the unit/hospital level include throughput, capacity, quality metrics, service utilization, and performance monitoring [6, 7]. On the organizational level, the capability of analytics is conceptually associated with process and performance management changes [1] [15]. These levels are correlated and not mutually exclusive. An optimised departmental throughput indicator can shift resource pressure onto other parts of the system, and a prediction model for the population level can be of little use during an individual 'encounter' unless the result is translated into action for the individual patient.

Table 3: Results Comparison

Ref	System / Context	Metric / Basis of Comparison	Outcome
[6]	Real-time acute-care throughput dashboard	Timeliness and accessibility of operational status information	Improved visibility of flow constraints and support for real-time coordination decisions.
[7]	Healthcare performance dashboards	Indicator relevance, data reliability, usability, and management alignment	Dashboard value was contingent on metric quality and organizational implementation conditions rather than display technology alone.
[8]	Electronic health record visualization	Information organization, temporal representation, and clinical interpretation tasks	Visual approaches improved access to complex patient information, but evidence for downstream clinical outcome gains remained limited.
[11]	Healthcare analytics applications	Diversity of analytic methods, data sources, and reported outcomes	Broad decision-support potential was identified, accompanied by methodological heterogeneity that limited cross-study effect comparison.
[13]	Clinical decision-support systems	Workflow timing, alert relevance, usability, safety, and adoption	Benefits depended on delivery within clinical workflow; poorly configured systems risked alert fatigue and reduced acceptance.
[15]	Enterprise healthcare analytics capability	Linkage among data resources, analytic capability, organizational change, and performance	Performance value depended on organizational transformation mechanisms in addition to analytic technology.

As is demonstrated in Table 3, effectiveness reported is not uniform. The most plausible reasoning is that business intelligence is valuable when it is aligned with the four parameters of data integrity, analytic relevance, interface design, and workflow fit, and when business responds as well. This conditionality is one reason why systems that appear to be alike can be different in settings. Many of the circumstances in which organizations are implementing local staffing models, decision rights, baseline data maturity, clinical culture, and process constraints can moderate what is observed but these contextual factors are not often measured with great precision.

Contradictions in the literature are thus more apparent than absolute. There are two kinds of analytics reviews, with broad reviews focusing on the potential for transformation [1, 4, 11, 12] and dashboard reviews on the existence of relatively small evidence of outcomes [5, 8]. These roles can be aligned by separating capability potential from proven causal impact. While enterprise data architectures facilitate the ability to perform new classes of analysis, having the capability to perform these analyses does not prove that some implementation will improve patient outcomes. Likewise, clinical decision support systems are useful in specific tasks and susceptible to alert fatigue, automation bias, poor integration and maintenance issues [13]. For this reason, outcome models are needed that decompose the dimensions of technical performance, decision-process performance, operational performance, and patient-level effects from the research field.

Figure 3 shows the result of this by locating the major classes of business intelligence applications based on the two dimensions of decision latency and organizational scope. Representation is important because data refresh requirements, interface design, validation, governance and evaluation requirements vary greatly from real-time bedside support to enterprise performance management that takes time. Application classes are placed on the diagram by ordinal reviewer coding, where larger bubbles are evidence for wider evidence coverage reviewed in the literature. Low latency applications, such as real-time clinical, and throughput applications typically run over shorter decision windows and narrower organizational scope.

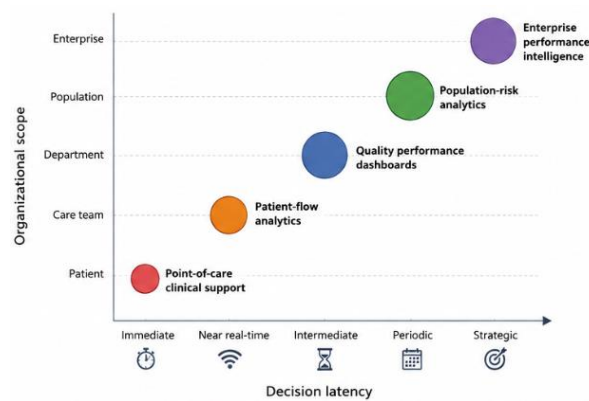


Figure 3: Relationship Between Decision Latency and Organizational Scope in Healthcare Business Intelligence

Another ongoing weakness is the lack of economic evaluation. Operational excellence is not just about improved visibility or satisfaction with the dashboard/system, it is also about measurable improvement in resource use, waiting time, managing capacity, cost avoidance, burden on staff, or process reliability. However, the costs to implement, requirements of data engineering, training, governance effort, maintenance and opportunity costs are not consistently documented. This neglect prevents evaluation of return on analytic investment and can also lead to an over-representation of technically successful implementations in the literature in resource-rich institutions. Studies comparing the performance gains and total burden of implementation should be reported in the future.

This is related to a limitation called generalizability. Local data dictionaries, EHR configurations, staffing, quality measures and regulatory environments are often crucial to healthcare business intelligence systems. It may be necessary to significantly redesign a dashboard that is validated in one institution before it can be used in another. A difficulty with predictive models is that patient case mix and clinical practice may change over time. Therefore, there should never be any assumption that evidence of local effectiveness will equate to evidence of universal effectiveness. Responsible adoption depends on external validation, monitoring for data drift, and explicit reporting of organizational context.

The key takeaway is that business intelligence should be managed on a decision basis instead of a data product basis. A set of dashboards, analytic models or scores should be linked to a specific decision problem, decision owner, refresh frequency, action threshold and evaluation metric. This enables the technical and operational impacts to close the shared gap. It also offers a tangible guide on eliminating low-value indicators, being those indicators that have no clear pathway of interpretation or action.

V. FUTURE DIRECTIONS

Prospective decision-centred evaluation should be prioritized in future research in the field of healthcare business intelligence. Research should identify the decision being targeted by an intervention, the baseline decision process, the analytic process, expected behavioural changes, the process outcome, and the patient or organizational consequence. When individual randomization is not feasible, cluster-randomized, stepped-wedge, interrupted time-series, and carefully designed quasi-experimental studies can bolster causal inference. Not only should evaluation be based on interface satisfaction or predictive discrimination [5], [13] but should also consider adoption, override behaviour, false-alert burden, data latency, missingness, model calibration, operational workload, maintenance requirements and cost.

The second priority relates to adaptive governance throughout the entire analytic life cycle. A variety of requirements are necessary for healthcare organizations, including version-controlled metric definitions, lineage documentation, monitoring of the performance of subgroups, change-management processes and procedures, and the ability to retire obsolete indicators or models. External validation and surveillance for temporal performance degradation should be added to predictive analytics, and dashboard metrics should be examined for unintended behavioural incentives. The importance of data quality assessment should be made clear in the validation of a decision system, since poor source data can lead to a quick dissemination of errors when automated in the analysis [10]–[12]

Greater integration of informatics, clinical expertise, operations research, human factors, implementation science and health economics are also required for interdisciplinary development. Research on visualization should include the cognitive load and accuracy of action in addition to usability [8, 9]. Operational studies should focus on the overall impact of the system, not just on departmental measures. Enterprise analytics research should link capability maturity to measures of patient safety, quality, throughput, workforce burden, and economic outcomes, all of which should be shared as common measurements [15]. On such work would lie the development of Healthcare Business Intelligence from a technology-driven assessment to a comparable reproducible evidence that analytic capability has a positive impact on the consequential decisions made, when, where, and in what way.

VI. CONCLUSION

Business intelligence can have a significant impact on healthcare decision making by being able to integrate data and support meaningful clinical and operational action. The collected evidence suggests that dashboards, visualization systems, analytic models and decision-support tools can enhance information accessibility, situational awareness, prioritization and coordination. But technology alone is not a criterion for excellence. As with all operations, reliable source data, appropriate analytic methods, interpretable presentation, timing of the workflow, decision authority, governance, and outcome feedback are all interdependent.

Literature continues to be more robust in proving analytic opportunity or information-process improvement, and less in patient outcomes, system efficiency or economic value. The prevalence of single-site studies, heterogeneous evaluation designs, limited external validation, inconsistent reporting of costs, and inclusion of intermediate endpoints limit the ability to draw generalizable comparisons. A decision-centred framework goes beyond these constraints by linking each analytic product to a specific decision, an accountable entity, an actionable window, an action path, and an observable effect.

Future progress will depend on prospective evaluation, lifecycle governance, more rigorous economic assessment, and systematic consideration of human interaction with analytic outputs. The true strength of business intelligence for clinical and operational excellence lies in treating it not as a set of dashboards or algorithms, but rather as a controlled, evidence-based infrastructure that translates trusted evidence into timely, accountable and measurable decisions.

VII. REFERENCES

- [1] Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, 126, 3–13.
- [2] Brooks, P., El-Gayar, O., & Sarnikar, S. (2015). A framework for developing a domain specific business intelligence maturity model: Application to healthcare. *International Journal of Information Management*, 35(3), 337–345.
- [3] Rumsfeld, J. S., Joynt, K. E., & Maddox, T. M. (2016). Big data analytics to improve cardiovascular care: Promise and challenges. *Nature Reviews Cardiology*, 13(6), 350–359.
- [4] Batko, K., & Ślęzak, A. (2022). The use of Big Data Analytics in healthcare. *Journal of Big Data*, 9, Article 3.
- [5] Dowding, D., Randell, R., Gardner, P., Fitzpatrick, G., Dykes, P. C., Favela, J., Hamer, S., Whitewood-Moores, Z., Hardiker, N., Borycki, E., & Currie, L. (2015). Dashboards for improving patient care: Review of the literature. *International Journal of Medical Informatics*, 84(2), 87–100.
- [6] Franklin, A., Gantela, S., Shifarrow, S., Johnson, T. R., Robinson, D. J., King, B. R., Mehta, A. M., Maddow, C. L., Hoot, N. R., Nguyen, V., Rubio, A., & Zhang, J. (2017). Dashboard visualizations: Supporting real-time throughput decision-making. *Journal of Biomedical Informatics*, 71, 211–221.

- [7] Ghazisaeidi, M., Safdari, R., Torabi, M., Mirzaee, M., Farzi, J., & Goodini, A. (2015). Development of performance dashboards in healthcare sector: Key practical issues. *Acta Informatica Medica*, 23(5), 317–321.
- [8] West, V. L., Borland, D., & Hammond, W. E. (2015). Innovative information visualization of electronic health record data: A systematic review. *Journal of the American Medical Informatics Association*, 22(2), 330–339.
- [9] Gotz, D., & Borland, D. (2016). Data-driven healthcare: Challenges and opportunities for interactive visualization. *IEEE Computer Graphics and Applications*, 36(3), 90–96.
- [10] Kruse, C. S., Goswamy, R., Raval, Y., & Marawi, S. (2016). Challenges and opportunities of big data in health care: A systematic review. *JMIR Medical Informatics*, 4(4), e38.
- [11] Mehta, N., & Pandit, A. (2018). Concurrence of big data analytics and healthcare: A systematic review. *International Journal of Medical Informatics*, 114, 57–65.
- [12] Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: Management, analysis and future prospects. *Journal of Big Data*, 6, Article 54.
- [13] Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. *npj Digital Medicine*, 3, Article 17.
- [14] Islam, M. S., Hasan, M. M., Wang, X., Germack, H. D., & Noor-E-Alam, M. (2018). A systematic review on healthcare analytics: Application and theoretical perspective of data mining. *Healthcare*, 6(2), Article 54.
- [15] Wang, Y., Kung, L., Wang, W. Y. C., & Cegielski, C. G. (2018). An integrated big data analytics-enabled transformation model: Application to health care. *Information & Management*, 55(1), 64–79.