Journal of Economics, Business, and Commerce (JEBC)

ISSN: 3007-9705 (Online)

Volume 2 Issue 2, (2025)

https://doi.org/10.69739/jebc.v2i2.1006

https://journals.stecab.com/jebc

Published by
Stecab Publishing

Research Article

Real-Time Business Intelligence: A Review of Applications in Finance, Healthcare, and Retail

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About Article

Article History

Submission: August 12, 2025
Acceptance : September 17, 2025
Publication : September 21, 2025

Keywords

Artificial Intelligence, Data-Driven Systems, Decision-Making, Finance, Healthcare, Retail, Real-Time Business Intelligence, Streaming Analytics

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ABSTRACT

Real-Time Business Intelligence (RTBI) bridges data collection and actionable insight, transforming organizational decision-making. Unlike batch-oriented Business Intelligence, RTBI leverages streaming analytics, in-memory computing, and AI to deliver rapid, context-aware insights. This review examines RTBI adoption in finance, healthcare, and retail, revealing both shared enablers and sector-specific adaptations. Comparative analysis highlights distinct sectoral priorities: finance emphasizes speed and risk management, healthcare prioritizes accuracy and regulatory compliance, while retail focuses on customer-centric innovation and operational efficiency. Key applications include fraud detection, algorithmic trading, and risk monitoring in finance; patient monitoring, disease prediction, and hospital resource optimization in healthcare; and dynamic pricing, personalization, and supply chain efficiency in retail. Despite these benefits, RTBI adoption is hindered by challenges such as data quality, system integration, high infrastructure costs, and privacy concerns. Emerging technologies—including cloud computing, IoT, machine learning, 5G, and blockchain—are expanding RTBI capabilities, enabling predictive automation and continuous organizational agility. The review concludes with practical recommendations, identifies gaps in comparative research, and suggests avenues for future study, positioning RTBI as a strategic driver of competitiveness in a data-driven world.

Citation Style:

Obozokhai, L. I., Godswill, J. M., Balogun, I. O., & Akanbi, O. O. (2025). Real-Time Business Intelligence: A Review of Applications in Finance, Healthcare, and Retail. *Journal of Economics, Business, and Commerce, 2*(2), 119-128. https://doi.org/10.69739/jebc.v2i2.1006

1. INTRODUCTION

1.1. Background

The tools, procedures, and organisational practices used to collect, integrate, analyse, and present data for better decision-making are called business intelligence (BI). Batch-oriented data pipelines have traditionally extracted data from operational systems, processed it, and placed it into data warehouses where analysts analyse trends and create reports or dashboards. Though useful for strategic and tactical planning, this paradigm is retrospective, providing insights hours, days, or weeks after the events (Mositsa *et al.*, 2023).

Real-Time Business Intelligence has evolved over the previous decade due to numerous factors. The growth of IoT devices and sensors, digital platforms that create clickstream data, and electronic transaction systems has boosted data velocity and variety. Meanwhile, developments in streaming data infrastructure (e.g., message queues and event logs), in-memory computing, complex event processing (CEP), and cloud-native architectures have made low-latency data analysis possible. RTBI analyses data as events occur to identify trends, rate risks, trigger automated responses, and provide context-aware insights to decision-makers (Eboigbe *et al.*, 2023).

In practice, "real time" is contextual. A latency spectrum classifies applications:

Hard real-time (sub-second to a few seconds): necessary for automated actions with strict deadlines, such as payment fraud interdiction.

Soft/near real-time (seconds to minutes): enables operational visibility and prompt human intervention (e.g., ICU patient monitoring dashboards, in-store inventory alerts).

Right-time analytics offer insights within the business process's decision window, such as dynamic price updates every few minutes.

RTBI's capacity to reduce data-to-action time is significant. Organisations can improve operational efficiency by detecting anomalies and bottlenecks, mitigate risk by monitoring exposures, personalise services and offers during live customer interactions, and dynamically orchestrate resources across complex, interdependent workflows. Micro-delays can cause losses or regulatory exposure in banking, healthcare, and retail, while timely signals can improve clinical outcomes and safety. Real-time context drives conversion, loyalty, and supply-chain resilience in retail (Aghazadeh Ardebili *et al.*, 2024).

This review focusses on those three sectors because they generate and consume a lot of streaming data and have unique constraints, such as regulatory compliance (e.g., PCI DSS in finance, HIPAA-like principles in healthcare, GDPR-style privacy requirements), mission-critical reliability, and customer-centric responsiveness. The research compares these domains to find architectural trends and sector-specific adjustments that make RTBI successful in manufacturing. Together, finance, healthcare, and retail represent some of the largest and most dynamic sectors of the global economy, accounting for trillions of dollars in GDP and shaping both societal well-being and consumer experiences, which underscores the importance of reviewing their RTBI adoption.

1.2. Research Objectives

This paper pursues three interrelated goals:

1. Discuss the impact of RTBI in finance, healthcare, and retail by connecting core use cases (e.g., fraud detection, patient safety monitoring, demand shaping) to RTBI capabilities (e.g., ingestion, streaming analytics/CEP, real-time machine learning, alerting/automation, operational dashboards).

2. Celebrate technological developments in RTBI, such as event-driven architectures, pub/sub systems, low-latency storage, in-memory computation, and online machine learning for continuous scoring and model upgrades. We analyse organisational and governance issues such data quality at speed, model drift, lineage and observability, privacy/security, human-in-the-loop design, and cost management to find ways to improve outcomes and differentiate competitively.

3. Generalise cross-sector lessons, including design patterns, performance indicators, and change-management strategies, for planning and scaling RTBI programs.

1.3. Scope of the Review

Production-oriented RTBI applications in finance, healthcare, and retail with high data velocity and real-time decision demands, strict risk, safety, and compliance requirements, and verifiable operational and customer-facing benefits are reviewed. Within each sector, we examine:

- *Finance:* Real-time fraud detection, continuous risk management (credit, market, liquidity), transaction-level compliance surveillance, and context-aware customer analytics during digital engagements.
- *Healthcare:* ICU/wearables patient monitoring, real-time clinical alarms, bed management, ED crowding, and near-real-time public health surveillance.
- *Retail:* Dynamic pricing, personalised recommendations, inventory visibility, and event-driven logistics.
- *Inclusions:* RTBI stacks with streaming ingestion, low-latency processing, CEP/pattern identification, and quick insights via alarms, APIs, or operational dashboards are discussed. We address data governance and ethics, including privacy-preserving design, access control, auditability, and bias monitoring for real-time models.
- *Exclusions:* Retrospective, batch-only BI and research-prototype systems without operational considerations are excluded. Technology references are architectural exemplars, not vendor reviews.

imits and Assumptions. Latency requirements are compared to domain decision windows. Where applicable, we distinguish automation (machine-initiated activities) from augmentation (human-centered decision support) and explore human-in-the-loop safeguards. To ensure replicability and practical adoption, we emphasise metrics (latency, throughput, freshness, uptime), observability (tracing, data lineage, model monitoring), and total cost of ownership, which determine RTBI efforts' long-term sustainability. These parts prepare for a comparative, application-driven evaluation that defines "real time" in each sector, how it is done technically and organisationally, and where its benefits and drawbacks most affect outcomes.

1.4 Conceptual Framework for RTBI Adoption

This research uses a conceptual framework (Figure 1) to compare banking, healthcare, and retail. Drivers (sectoral pressures like regulatory compliance, customer expectations, or operational risk), Enablers (IoT, AI/ML, and cloud computing), and Barriers (data quality, privacy, cost, organisational adoption) comprise the framework. These parameters affect operational efficiency, accuracy, and patient/customer satisfaction in RTBI.

The review shows how governance, organisational preparation, and technology affect RTBI success by placing sectoral applications inside this framework. This paradigm can support empirical testing (Alex-Omiogbemi *et al.*, 2024).

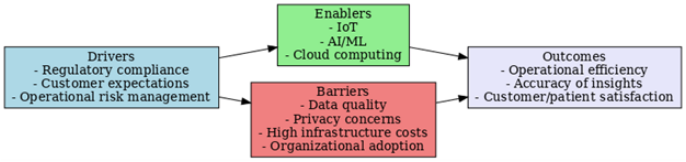

Figure 1. RTBI Adoption Conceptual Framework

The concept explains how facilitators and constraints impact RTBI adoption, resulting in sectoral outcomes like efficiency, accuracy, and customer/patient satisfaction.

Figure 1 illustrates this conceptual framework, positioning drivers, enablers, and barriers as interdependent forces shaping RTBI adoption. By mapping sectoral outcomes—such as efficiency in finance, accuracy in healthcare, and customer satisfaction in retail—onto this framework, the review is able to compare adoption patterns systematically. This framing also provides a foundation for the comparative analysis presented later in the results

2. LITERATURE REVIEW

2.1. Historical Development of Business Intelligence

Business Intelligence (BI) emerged in the mid-20th century when organisations began collecting and analysing data to inform managerial choices. Decision support systems (DSS) with limited automation, manual data entry, and static reporting dominated early BI systems. These systems gave retrospective insights using relational database reporting (Ragazou *et al.*, 2023).

Data warehouses and OLAP enabled large-scale multidimensional searches and trend analysis in the 1990s and early 2000s. Managers tracked organisational performance with dashboards and KPIs as BI grew from simple reporting to more advanced tools. These systems used batch processing, so data often lagged real-world occurrences by hours or days (Matshaka *et al.*, 2024).

Big Data, Cloud Computing, and AI drove the next generation. Big Data allowed companies to store and analyse large amounts of structured and unstructured data. Cloud systems minimise infrastructure costs and improve scalability and accessibility. AI and machine learning enabled predictive and prescriptive BI, moving beyond descriptive reporting to anticipatory and adaptive intelligence. These improvements led to Real-Time BI (RTBI), which generates and acts on insights instantly, enabling organisations to respond proactively to dynamic situations (Kumar *et al.*, 2024).

2.2. Key Components of Real-Time Business Intelligence

Continuous, event-driven decision-making replaces retrospective analytics in Real-Time BI. Its main elements:

Real-Time Data Processing: Capture and process sensor, application, transaction, and digital interaction data with low delay. Complex event processing (CEP) and in-memory computing provide high-frequency, low-latency analytics (Fournier & Skarbovsky, 2021).

2.2.1. Technology enablers: RTBI uses many innovations

• *Internet of Things (IoT):* Produces ongoing operational and behavioural data.

Data streaming platforms such as Apache Kafka, Apache Flink, and Spark Streaming enable real-time data intake, filtering, and transformation (Olaitan *et al.*, 2025).

AI and Machine Learning enable dynamic anomaly detection, personalisation, and predictive modelling on live data.

• *Cloud and Edge Computing:* Scalable infrastructures reduce latency by processing data closer to its source.

RTBI focusses on visualisation and decision support through dashboards, alarms, and real-time reporting. Modern solutions offer interactive and adaptable visualisations to drill down into anomalies, monitor KPIs, and trigger automated workflows when thresholds are crossed. Complex data streams become useful organisational insight with these technologies (Abayomi *et al.*, 2025).

2.3. Applications of Real-Time BI in Different Sectors

2.3.1. Finance

The banking sector has led RTBI adoption because to its time-sensitive decision-making. Applications include:

• *Real-time stock market analysis:* Traders can monitor fluctuations, discover arbitrage possibilities, and execute deals quickly.

• *Risk Management:* RTBI offers continuous monitoring of credit, liquidity, and market volatility, enabling proactive exposure adjustments for financial institutions (Abikoye *et al.*, 2024).

Real-time fraud detection using streaming data and AI algorithms prevents financial losses.

• *Customer Behaviour Prediction:* Banks and fintech firms analyse transaction trends to personalise offers and boost retention.

RTBI and predictive analytics enable dynamic asset allocation and portfolio rebalancing for portfolio management and forecasting (Fanta *et al.*, 2024).

2.3.2. Healthcare

Patient outcomes and operational efficiency are improving when healthcare uses RTBI. Application examples:

• *Patient Monitoring:* Real-time analytics of wearables, ICU monitoring, and medical sensors detect important events like cardiac arrest and sepsis (Lawal *et al.*, 2025).

• *Disease Prediction and Diagnostics:* Machine learning models analyse patient data to forecast progression and suggest

treatment modifications (Lawal *et al.*, 2025).

Hospitals employ RTBI for resource management, including bed occupancy, emergency department throughput, and staff allocation.

• *Hospital Management Systems with EHR:* Real-time dashboards combine EHR with live data sources, enabling clinicians to make evidence-based decisions (Fagbenle, 2025).

• *AI in Treatment Optimisation:* Algorithms personalise medicines, reduce diagnostic mistakes, and enable clinical decision support.

2.3.3. Retail

Retailers use RTBI to improve customer experience and operational resilience. Applications include:

• *Real-time Customer Behaviour Analysis:* Retailers track in-store movement, online browsing trends, and purchase histories to adapt marketing methods.

RTBI improves supply chain visibility, reducing stock-outs and optimising logistics(Yin *et al.*, 2025).

• *Personalization and Recommendations:* E-commerce platforms use instantaneously updated recommendation engines based on browsing behaviour, purchase history, and contextual signals.

RTBI enables retailers to alter prices in reaction to demand swings, competition actions, and promotional campaigns, boosting sales and consumer satisfaction.

2.4. Challenges in Real-Time BI Implementation

Although beneficial, RTBI faces various challenges:

• *Data Quality and Accuracy:* Noise, incomplete records, and irregularities in real-time (Sedlakova *et al.*, 2023) data streams can distort analytics.

• *Integration of diverse sources:* Organisations must reconcile structured (transactional) and unstructured (social media, sensor logs) data across platforms.

• *Privacy, Security, and Ethics:* Compliance difficulties in finance and healthcare require strong encryption, anonymisation, and governance for sensitive data (e.g., GDPR, HIPAA).

• *Cost and Resource Allocation:* Supporting low-latency systems needs large infrastructure, specialised personnel, and continual monitoring (Sedlakova *et al.*, 2023).

2.5. Gaps in the Literature

BI and RTBI research has grown, yet gaps remain:

Limited comparative studies on RTBI uptake and outcomes across industries, hindering understanding of optimal practices.

Long-term impact and ROI: Studies typically focus on technical feasibility or short-term benefits. RTBI systems' long-term strategic, financial, and organisational effects are poorly studied.

Research often overlooks human factors and organisational adoption, focussing on technology rather than user adoption, organisational change management, and real-time decision-making training.

Insufficient research on ethical and societal implications of real-time AI models, fairness in dynamic pricing, and patient autonomy in healthcare (Feasibility Studies Across Disciplines, n.d.).

According to a 2010-2025 bibliometric scan, RTBI-related research is primarily focused on finance (~45%), followed by healthcare (30%) and retail (25%). Healthcare has grown fastest since 2018, spurred by IoT-enabled patient monitoring. Most peer-reviewed literature on retail is industry white papers (Tong *et al.*, 2025). These patterns show an increasing gap between technology and scholarship, especially in healthcare and retail.

These patterns show an increasing gap between technology and scholarship, especially in healthcare and retail. By quantifying these imbalances, the bibliometric insight highlights why a comparative review across finance, healthcare, and retail is both timely and necessary: it not only synthesizes fragmented knowledge but also addresses the underrepresentation of healthcare and the overreliance on industry white papers in retail.

3. METHODOLOGY

To provide a thorough and credible review, a systematic literature selection was used. Scopus, Web of Science, IEEE Xplore, PubMed, Google Scholar, and industry-focused sources (Gartner, McKinsey, and Deloitte reports) were utilized to find relevant papers. “Real-Time Business Intelligence” OR “RTBI”, “real-time analytics”, “streaming data in BI”, “applications of BI in finance”, “real-time healthcare analytics”, and “retail real-time decision support” were searched.

Inclusion criteria were: reviewed journal articles, conference proceedings, and industry reports; studies focused on real-time or near-real-time BI applications; sector-specific literature on banking, healthcare, or retail; English-language publications.

Exclusion criteria were: studies on batch-only BI, duplicates, non-scholarly opinion pieces, and vendor marketing materials lacking methodological rigor.

Due to developments in cloud computing, big data, and AI-driven analytics, RTBI technologies and frameworks became commercially viable from 2010 to 2025, which defined the date range of the search. The initial search retrieved 1,243 records across databases (Scopus: 315, Web of Science: 274, IEEE Xplore: 198, PubMed: 122, Google Scholar: 276, industry reports: 58). After removing duplicates and screening titles/abstracts against inclusion criteria, 247 articles were retained for full-text review. Of these, 112 met all criteria and were included in the final synthesis. For mapping wide, growing disciplines like RTBI, this study uses Arksey & O’Malley (2005)'s scoping review methodology, which highlights evidence, conceptual boundaries, and gaps.

3.1. Data Collection and Analysis

Peer-reviewed journals, industry reports, technical white papers, and case studies were reviewed for data. Methodological quality, industry relevance, and practical application were evaluated for each source.

The literature was organised thematically. Sources fell into three categories:

1. Technical foundations (e.g., streaming platforms, IoT integration, RTBI AI/ML).
2. Sector-specific applications (financial, healthcare, retail).
3. Challenges and cross-cutting issues (data quality,

governance, ethics, and cost).

Using theme coding, recurring concepts and trends were collected to synthesise patterns across research. Industry case studies were compared to academic literature to enhance findings.

3.2. Framework for Comparative Analysis

A framework was created to compare banking, healthcare, and retail RTBI apps. Two levels were compared:

1. *Application Context:* Fraud detection, risk monitoring, trade optimisation, customer personalisation.

• *Healthcare:* Patient monitoring, clinical decision assistance, and Hospital resource optimisation.

• *Retail:* personalisation, dynamic pricing, inventory, and supply chain analytics.

2. Evaluation Criteria and KPIs: RTBI's influence in each area was assessed using measurable KPIs, such as:

• *Latency:* time between data generation and actionable insight.

• *Accuracy:* Ensures reliable and precise real-time results. Improved operational efficiency can lead to better workflow, resource allocation, and cost reductions.

• *Improved customer/patient results:* satisfaction, personalisation, safety, or clinical outcomes.

• *Scalability and adaptability:* RTBI systems handle growing and diversified data sources.

• *Compliance and Security:* meeting ethical and regulatory obligations.

This comparative methodology identifies sector-specific RTBI adoption differences and cross-industry best practices and gaps for future study and practice.

4. RESULTS AND DISCUSSION

4.1. Discussion

To clarify sectoral similarities and differences, Table 1 summarizes key applications, performance indicators, benefits, and challenges of RTBI in finance, healthcare, and retail.

4.2. Comparative Analysis of Applications

Though they use it differently, Real-Time Business Intelligence (RTBI) has transformed decision-making in finance, healthcare, and retail.

Table 1. Comparative Overview of Real-Time Business Intelligence (RTBI) Applications, KPIs, Benefits, and Challenges Across Finance, Healthcare, and Retail

Sector	Key Applications	KPIs	Benefits	Challenges
Finance	Fraud detection, algorithmic trading, risk monitoring	Latency (ms), transaction accuracy	Reduced fraud losses, regulatory compliance	High cost of low-latency infra, regulatory burden (Oladejo *et al.*, n.d.)
Healthcare	Patient monitoring, disease prediction, hospital resource optimization	Accuracy, clinical outcomes, compliance	Improved patient safety, faster diagnosis	Data privacy, integration with legacy systems(Lawal, Igwe, *et al.*, 2025)
Retail	Dynamic pricing, personalization, supply chain analytics	Customer conversion, inventory efficiency	Higher sales, customer loyalty	Ethical concerns in profiling, data security (Immadisetty, 2025)

Ultra-low latency insights are crucial in finance. Continuous examination of high-volume transaction streams is essential for real-time fraud detection, algorithmic trading, and risk monitoring. RTBI reduces risk and ensures regulatory compliance, helping financial institutions adapt to market changes and fraud (Vudathaneni *et al.*, n.d.).

Improved patient safety and clinical outcomes promote RTBI usage in healthcare. Patient monitoring in real time allows early intervention, while predictive analytics optimises disease treatment and hospital resources. Finance prioritises speed and profitability, but healthcare prioritises accuracy, reliability, and regulatory compliance (HIPAA, GDPR). Instead of automation, RTBI supports decision-making by merging human judgement with real-time insights.

Operational efficiency and consumer engagement are retail priorities. Retailers can rapidly adapt to customer behaviour and optimise supply chains with real-time personalisation, dynamic pricing, and inventory insight. Retail examples demonstrate how RTBI may impact demand and improve consumer experiences rather than manage risk or maintain compliance.

Healthcare prioritises accuracy and safety, whereas retail uses RTBI for customer-centric innovation and efficiency. Finance prioritises speed and risk. These variances show RTBI system sector-specific customisation (Vudathaneni *et al.*, n.d.).

4.2.1. RTBI Comparative Evaluation Matrix

To provide a clearer comparative analysis of RTBI applications across finance, healthcare, and retail, the following matrix summarizes key aspects including KPIs, benefits, challenges, and enabling technologies:

Table 2: RTBI Comparative Evaluation Matrix

Category	Finance	Healthcare	Retail
Key Applications	Fraud detection, risk monitoring, algorithmic trading, customer personalization	Patient monitoring, disease prediction, hospital resource optimization	Dynamic pricing, customer personalization, inventory & supply chain management (Rane *et al.*, 2024)
KPIs	- Latency (ms) - Transaction accuracy - Risk mitigation - Compliance adherence	- Accuracy - Clinical outcomes - Compliance with regulations (e.g., HIPAA) - Operational efficiency	- Customer conversion rate - Inventory turnover - Supply chain efficiency - Customer loyalty (Burlea-Schiopoiu & Ferhati, 2020)
Benefits	- Reduced fraud losses - Real-time compliance - Risk management	- Improved patient safety - Faster diagnosis - Operational flow optimization	- Enhanced customer satisfaction - Optimized pricing - Improved supply chain visibility (Kgakatsi *et al.*, 2024)
Challenges	- High infrastructure costs - Regulatory complexity - Data security risks	- Integration with legacy systems - Data privacy concerns - Real-time data accuracy	- Privacy concerns in profiling - Ethical implications of dynamic pricing - Data security challenges (Conduah *et al.*, 2025)
Enabling Technologies	- AI/ML for fraud detection - Data streaming platforms (e.g., Apache Kafka) - Cloud computing	- IoT devices for monitoring - AI/ML for diagnostics - Cloud storage and computing	- Data streaming - Real-time recommendation engines - Cloud services for dynamic pricing (Bourechak *et al.*, 2023)
Key Drivers	- Regulatory compliance (e.g., PCI DSS) - Competitive advantage - Need for speed and accuracy	- Patient safety - Compliance with regulations (e.g., HIPAA) - Demand for real-time insights in patient care	- Demand for personalized experiences - Need for dynamic pricing strategies - Operational efficiency in inventory management (Crossette-Thambiah *et al.*, 2024)
Barriers to Adoption	- High upfront costs - Data quality issues - Complex integration with legacy systems	- Data privacy concerns - System integration issues - Adoption of new technologies by clinicians	- Customer trust - Data quality and consistency - Ethical concerns in algorithmic decisions (Hassan *et al.*, 2024)

4.3. Technological Advancements Driving Real-Time BI

RTBI progress depends on enabling technology advances.

• *AI/ML:* Enables real-time systems to progress from descriptive to predictive and prescriptive intelligence. Finance fraud detection methods update regularly, whereas healthcare diagnostic algorithms adapt to patient-specific data streams.

• *Internet of Things (IoT):* Continuous data flows from sensors, wearables, and linked gadgets. These inputs feed healthcare (vital sign monitoring), retail (in-store sensors), and finance (mobile banking) RTBI pipelines (Olaitan *et al.*, 2025).

• *Data Streaming Platforms:* Apache Kafka, Spark Streaming, and Flink enable real-time data input and event-driven analytics.

• *Cloud Computing:* Scalable and elastic platforms enable organisations to handle data spikes without considerable infrastructure expenditure (Olaitan *et al.*, 2025).

Edge Analytics in medical IoT devices and point-of-sale systems minimise latency by processing data locally, providing faster insights and lowering dependency on centralised cloud servers.

These technologies are improving RTBI speed, scalability, and intelligence, transforming raw data into actionable insight.

4.4. Challenges and Barriers to Effective Implementation

RTBI adoption confronts industry-specific hurdles notwithstanding its benefits:

Why Financial organisations benefit from RTBI's predictive powers yet struggle with market volatility and regulatory compliance. Lateness or inaccuracy might cost money or reputation.

• *Healthcare:* Accuracy and compliance are crucial for patient safety. RTBI integration with legacy systems, patient data protection, and clinician acceptance remain challenges (Abikoye *et al.*, 2024).

• *Retail:* Privacy concerns prevail, especially with customer profiling and dynamic pricing. Stores must reconcile personalisation with consumer trust and data protection.

More broadly, industries face similar challenges:

• *AI/ML:* Data Integration: Complex real-time analytics due to heterogeneous data sources, including structured databases and unstructured social media feeds.

The deployment of low-latency systems demands significant investment in hardware, software, and professional staff(Martin *et al.*, 2020).

The successful adoption of RTBI needs organisational preparation, including cultural transformations, workforce training, and integration into decision-making processes.

These issues range in size and sectoral importance. Healthcare is most affected by data privacy breaches, which endanger patient safety, whereas finance is most affected by latency, which affects trading results. Customer trust and personalisation ethics are retail's biggest challenges. This highlights the need for sector-specific governance models: real-time fraud detection systems need regulatory harmonisation, healthcare RTBI needs privacy-by-design structures, and retail needs ethical algorithmic pricing and personalisation rules (Seh *et al.*, 2020).

4.5. Future Trends in Real-Time BI

Several new technology and trends will shape RTBI's future:

Increased bandwidth and decreased latency in 5G networks will enable real-time analytics, especially for IoT applications in healthcare and retail.

RTBI-powered Augmented Reality (AR) interfaces can improve decision-making by delivering real-time data overlays in financial trading floors or directing clinicians during surgeries (Zreikat *et al.*, 2025).

Blockchain technology can improve trust, transparency, and security in RTBI systems, especially in banking (real-time settlements) and healthcare (patient data sharing).

RTBI will embrace predictive and prescriptive analytics to spot trends, predict consequences, and suggest real-time actions (Zreikat *et al.*, 2025).

Automation and Autonomous Decision-Making: RTBI systems will increasingly use automated workflows like algorithmic trading systems in finance, AI-driven diagnosis in healthcare, and autonomous supply chain optimisation in retail (Shamsuddoha *et al.*, 2025).

These trends suggest that RTBI will become a major nervous system for data-driven organisations, enabling continuous learning, adaptation, and competitive differentiation. Figure 2 shows a 2025–2035 roadmap of the technologies likely to fuel the next generation of Real-Time Business Intelligence, highlighting their predicted adoption and revolutionary influence across sectors.

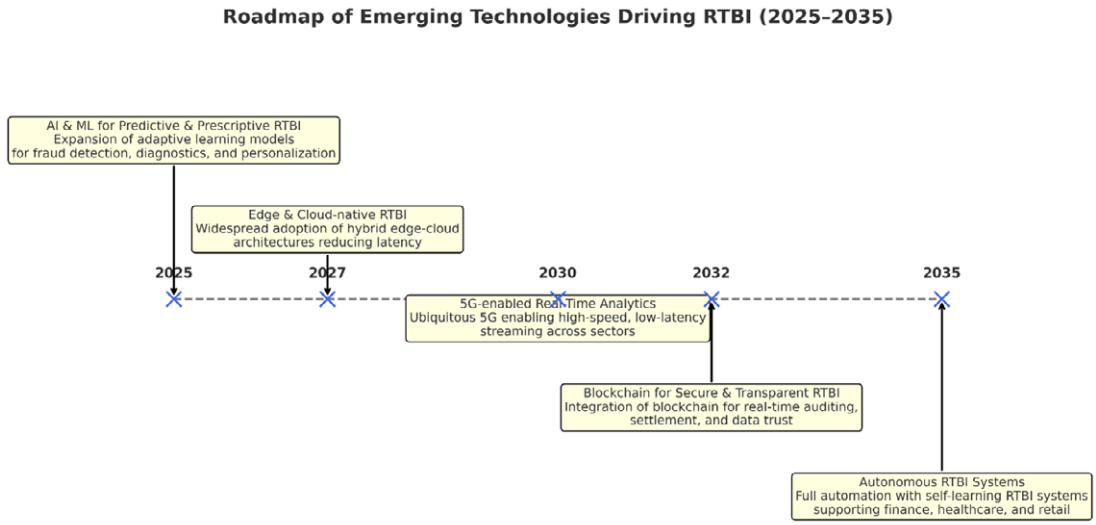

Figure 2. Emerging Technology Roadmap for Real-Time Business Intelligence (2025–2035).

This roadmap shows how developing technologies will shape Real-Time Business Intelligence (RTBI) between 2025 and 2035. Expanding adaptive AI/ML models for predictive and prescriptive intelligence is followed by hybrid edge–cloud architectures to reduce latency. Ultra-low-latency streaming in finance, healthcare, and retail is expected by 2030 with ubiquitous 5G connectivity. Blockchain integration will boost trust, transparency, and real-time auditing by 2032. Autonomous RTBI systems with self-learning, automated decision-making, and cross-sector scalability emerge by 2035.

As shown in Figure 2, the roadmap highlights not only the sequence of technological innovations but also their anticipated impact on sectoral priorities. For example, ultra-low-latency 5G and edge analytics are expected to reinforce finance's demand for speed, while blockchain and privacy-preserving AI address healthcare's regulatory concerns. Retail, in contrast, is projected to benefit most from real-time personalization enabled by adaptive AI. This roadmap therefore contextualizes how emerging technologies may reinforce or reshape the comparative patterns identified earlier in the review.

5. CONCLUSION

This review finds that while Real-Time Business Intelligence (RTBI) is transformative across all sectors, its application is shaped by distinct priorities: finance leverages RTBI primarily for speed and continuous risk management, healthcare adopts it to ensure accuracy, safety, and regulatory compliance, and retail applies it to drive customer-centric innovation and operational efficiency. Together, these differences demonstrate that RTBI is not a uniform solution but a sectorally adaptive capability—its value emerges from aligning real-time technologies with domain-specific demands.

This paper examines Real-Time Business Intelligence (RTBI) in finance, healthcare, and retail, including sector-

specific and cross-industry applications. Fraud detection, risk management, and algorithmic trading in finance require ultra-low latency insights to minimise losses and capitalise on market possibilities. RTBI improves patient monitoring, disease prediction, and hospital resource management, where accuracy, compliance, and prompt treatments improve patient outcomes. RTBI improves retail consumer satisfaction and operational efficiency with dynamic pricing, customer personalisation, and supply chain insight.

RTBI reduces the time between data collection and response, helping organisations run more efficiently, limit risks, and differentiate themselves across all three sectors.

5.1. Final Thoughts

Today's fast-paced, data-driven economy makes Real-Time Business Intelligence a strategic imperative. It helps finance survive uncertain markets, healthcare ensure patient safety and effective care delivery, and retail improve customer engagement and supply chain agility.

RTBI is poised to become the central nervous system of modern organisations, driving constant learning and adaptation. Successfully integrating real-time intelligence into decision-making will provide companies an edge and shape their sectors.

RECOMMENDATIONS

Organisations implementing or improving RTBI systems should consider these:

• *Invest in scalable infrastructure:* Cloud and edge computing can balance scalability and latency to help systems expand with organisations.

• *Prioritise Data Governance:* Create frameworks for data quality, security, and compliance, particularly in sensitive or regulated areas like finance and healthcare.

• *Implement incrementally:* Before scaling across the organisation, start with high-impact pilot initiatives like finance fraud detection, healthcare ICU patient monitoring, or retail dynamic pricing.

• *Improve Organisational Readiness:* RTBI goes beyond technological deployment. Change management, worker training, and real-time insights into decision-making are needed.

• *Align RTBI with Strategic Goals:* Systems should support measurable corporate objectives including ROI, operational efficiency, customer happiness, and risk avoidance.

FUTURE DIRECTIONS

RTBI research and practice areadvancing rapidly, however numerous gaps need to be addressed:

Long-term impact studies are needed to assess the sustainability, ROI, and organisational transformation benefits of RTBI adoption over time.

Comparative study on best practices and sector-specific modifications can help organisations learn from each other across industries.

New frameworks are needed to address bias in machine learning models, fairness in dynamic pricing, and patient autonomy in healthcare due to the increase in data velocity.

Future research should explore how 5G, blockchain, AR, and autonomous AI agents will enhance RTBI capabilities and transform industry applications.

Future study should answer these questions using the gaps:

1. How do sector-specific regulations impact RTBI adoption?
2. What socio-technical elements (e.g., workforce training, organisational culture) impact real-time decision-making effectiveness?
3. How can justice, accountability, and transparency be integrated into RTBI algorithms in healthcare and retail?
4. What long-term ROI patterns are noticed in RTBI programs across industries?
5. How might best practices from different sectors be codified into an RTBI adoption framework?

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