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Integrating High-Performance Computing and Business Information Systems for Intelligent Decision-Making

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ABSTRACT

The rapid growth of digital information, artificial intelligence, cloud computing, and real-time analytics has created many difficulties regarding BIS development in terms of coping with huge amounts of complicated information. The traditional information system functions well for transactions, reports, and managerial processes, but modern information systems require more computational capacities and real-time analytics capabilities. The High-Performance Computing technology gives access to advanced computation facilities that can improve BIS by providing faster data processing, analytics, modeling, optimization, simulation, and decision support tools. This paper explores the use of HPC and BIS together as an innovative solution in the field of organization decisions and business performance. The conceptual research design of this paper is based on the literature review and quantitative secondary data provided by HPC benchmarks. A conceptual framework is proposed including seven interrelated elements: data sources and data acquisition, data management and integration, high-performance computing technologies, business intelligence and analytics, Business Information Systems, intelligent decision-making, and business performance. Secondary data on HPC show that computational capacity is growing rapidly, with the November 2025 TOP500 list showing four exascale systems and the number one system, El Capitan, delivering 1.809 exaflop/s on the HPL benchmark test. This research indicates that these computational capacities can be used to process increasingly complex business loads that include big data forecasting, optimization, artificial intelligence, simulation, risk assessment, and real-time analysis. Besides, the paper presents challenges related to the cost of infrastructure, cybersecurity, data governance, interoperability, energy usage, technical expertise, and organizational implementation. In this case, the suggested framework highlights the idea that HPC technology should not be viewed only as infrastructure but also as computational capacity incorporated into organization's information systems and decision-making processes.

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Introduction

The rising digitalization of business processes has made information one of the critical resources within organizations. Organizations create and gather information using ERP systems, CRM systems, financial systems, online transaction systems, mobile applications, IoT devices, social media, sensors, and external databases. With the rise in the amount, speed, and diversity of information, organizations encounter the need to convert vast amounts of data into knowledge [1, 2].

Information Systems within Business have historically formed the technological backbone of information creation, storage, processing, and communication within organizations. Enterprise systems handle transactions and operations, whereas MIS and decision-making systems provide managers with information for their work. Most recently, business intelligence and analytics have broadened the scope of information systems allowing organizations to analyze past trends, discover the reasons behind those trends, predict future events, and offer possible solutions [3].

The proliferation of big data has impacted the computational needs for these tasks. Databases may include billions of records of transactions, interactions with customers, observations made by sensors, photos, documents, or any other object containing information. Moreover, contemporary enterprises often rely on machine learning and artificial intelligence systems that may have significant computational needs. Therefore, the performance of the computing systems becomes a factor influencing the speed and volume of business analytics.

Historically, High-Performance Computing has been used for scientific computations, engineering tasks, weather forecasts, computational physics, and other computationally intensive fields. High-Performance Computing systems utilize parallel processing, distributed computing, accelerators, fast networks, large-scale storage, and special software to run complex workloads. Nevertheless, the same approaches to computations have become applicable to business problems that involve analytics, optimization, simulations, AI, financial models, supply-chain management, and risk assessment [4, 6].

The November 2025 TOP500 list shows the continued growth of HPC capability. Four machines demonstrated exascale capabilities in terms of HPL tests; El Capitan took first place with 1.809

exaflop/s performance, Frontier got second place with 1.353 exaflop/s performance, Aurora took the third place with 1.012 exaflop/s performance, and JUPITER Booster received the fourth place with 1.000 exaflop/s performance. The examples show that in the modern computing environment, the processing capabilities of machines can far exceed those needed for regular enterprise computation.

The key research question here is not only whether HPC can do fast computations. Instead, the question is how computational capability can be combined with Business Information Systems for value creation. An HPC system operating separately from business processes can be of little use for organizations. At the same time, a BIS with insufficient computational capabilities cannot utilize advanced analytical methods.

This paper fills the research gap by providing an integrated HPC-BIS framework. The HPC-BIS framework links together data collection, data management, HPC, BIS, information systems, decision making, and business performance. The research objectives of the study are:

- To investigate the connection between HPC and Business Information Systems.
- To determine applications which could be enhanced through HPC enabled analytics.
- To construct a theoretical HPC-BIS framework.
- To examine secondary data on HPC performance related to development of computational power.
- To consider the potential benefits and problems associated with integration of HPC and BIS.
- To outline an implementation strategy for companies seeking data driven decision-making capabilities.
- This study adds to the existing literature on the link between the computational technology and business information system and decision-making process.

Related Works

A. Business Information Systems and Business Intelligence

Business Information Systems are comprised of people, processes, information and technologies that help the organization conduct its activities. Information systems can be used for transaction processing, managerial reporting, strategic planning, customer relationship management, financial activity, logistics operations, and many other organizational functions. The development of Business Intelligence is one of the key developments within this field. Chen, Chiang and Storey listed business intelligence and analytics as one of the key research areas that emerged due to growing complexity and abundance of organizational data [3]. BI systems help organizations convert data into information that can be used for conducting business analysis and making decisions.

According to Davenport and Harris, analytics can be used as a powerful means of gaining competitive advantage in case organizations conduct their activities using data and analytical models [4]. However, the use of analytics goes far beyond having appropriate technologies. Appropriate processes, analytical capabilities, data quality and managerial capabilities are also needed for achieving benefits. Popovič et al. found that maturity of BI environments and organizational culture impact analytical decision-making [7]. Trieu stressed that proper organizational and technological preconditions should be met for deriving benefits from BI systems [8]. These researches point out the necessity for the evaluation of business information technologies based on their involvement in organizational decision-making processes instead of being limited to technical criteria only.

B.High-Performance Computing

HPC is defined by the application of computational architectures used to perform computationally complex tasks. The possibility of parallel computing makes it possible to divide complex tasks into many subtasks that can be performed simultaneously. Distributed computing applies the same idea to multiple interconnected computing devices.

The recent advances in the development of HPC have led to creation of exascale computer systems. The statistics of the TOP500 November 2025. proves the scale of HPC infrastructure developed today. El Capitan leads and has 11,340,000 cores and HPL performance of 1,809 petaflop/s. The second place is taken by Frontier with 9,066,176 cores and 1,353 petaflop/s performance. Aurora ranks third and has 9,264,128 cores and 1,012 petaflop/s performance.

They are not business systems, however, their technical characteristics illustrate the computational capabilities that organizations can apply.

C. Large Dataset Processing and Distributed Computing

With the advent of distributed computing, processing of large datasets has become quite possible. MapReduce architecture by Dean and Ghemawat showed that large scale datasets could be split and processed using clusters [9]. On the other hand, the Apache Spark framework helped in the unification of data processing in large-scale environment and helped in handling data analytics and machine learning workloads [10].

The integration between HPC and large dataset processing is becoming increasingly significant as a lot of analytical workloads use large datasets and require complicated algorithms. Ejarque et al. studied the integration between HPC, data analytics, and artificial intelligence and stressed on the importance of integrated workflow processes [5].

D. Artificial Intelligence and HPC

Another field where the need of computational capability has increased is that of artificial intelligence. Machine learning and deep learning algorithms might contain large-scale datasets and mathematical calculations as well. Hence, the integration between HPC and artificial intelligence has resulted in fast model training, inference, optimization, and simulation [6]. For BIS, it is relevant in areas like demand forecasting, customer segmentation, fraud detection, recommendation systems, predictive maintenance, risk analysis, and automatic anomaly detection.

Research Methodology

In the current research, a conceptual approach, combined with secondary data collection is used. The research makes no claims about collecting any primary survey or experimental data on organizations. Rather, the study integrates three types of evidence. First, the academic literature on relevant topics such as Business Information Systems, business intelligence, analytics, big data, HPC, cloud computing, and artificial intelligence was reviewed to understand what are the existing concepts for each of those. Second, secondary quantitative data were gathered from the TOP500 list, which shows the extent of the development of HPC in recent years. Third, the results of both types of evidence were synthesized to develop a conceptual HPC-BIS framework. The process of analysis included four main steps:

Step 1: Identifying the major HPC and BIS capabilities.

Step 2: Categorization of possible business applications by their computational and information needs.

Step 3: Comparing traditional BIS capabilities with HPC-based BIS capabilities.
Step 4: Synthesizing an integrative framework between computation and intelligence decision-making.

Since the research is purely conceptual in nature, the business performance numbers used for illustration throughout the paper are clearly labeled as "scenario values" instead of empirical data. This is necessary since hypothetical performance numbers should never be used as empirical results of real-life companies.

Secondary Data Analysis

A. Current HPC Capability

The development of exascale computing provides useful evidence regarding the increasing availability of computational capacity. Table 1 summarizes selected systems from the November 2025 TOP500 ranking.

Table 1: Selected Top500 Hpc Systems, November 2025

Rank	System	Cores	Rmax (PFlop/s)	Rpeak (PFlop/s)	Power (kW)
1	El Capitan	11,340,000	1,809.00	2,821.10	29,685
2	Frontier	9,066,176	1,353.00	2,055.72	24,607
3	Aurora	9,264,128	1,012.00	1,980.01	38,698
4	JUPITER Booster	4,801,344	1,000.00	1,226.28	15,794
5	Eagle	2,073,600	561.20	846.84	—
6	HPC6	3,143,520	477.90	606.97	8,461
7	Fugaku	7,630,848	442.01	537.21	29,899
8	Alps	2,121,600	434.90	574.84	7,124
9	LUMI	2,752,704	379.70	531.51	7,107
10	Leonardo	1,824,768	241.20	306.31	7,494

Source: TOP500, November 2025.

There is considerable variability in architectural style, number of cores, computing performance and power usage. Four of the leading exascale computers show that we have now moved to another stage in terms of computing performance. For instance, El Capitan has a performance of 1.809 exaflop/s using the HPL benchmark and has over 11.3 million cores. It needs to be noted that computing performance does not necessarily indicate the level of business value. In particular, the HPL benchmark focuses on a certain kind of computing performance. Some other characteristics of business applications could include database access, networking capability, data movement, memory management, latency, security and user interactions.

B. HPC Benchmark Comparison

Table 2 presents selected HPL and HPCG results. HPCG is intended to represent a different class of computational workload from the HPL benchmark.

Table 2: Selected Hpc And Hpcg Performance

System	HPL Rmax (PFlop/s)	HPCG (PFlop/s)
El Capitan	1,809.00	17.41
Fugaku	442.01	16.00
Frontier	1,353.00	14.05
Aurora	1,012.00	5.61
LUMI	379.70	4.59
CHIE-4	135.40	3.76
Alps	434.90	3.67
Leonardo	241.20	3.11
Discovery 6	164.20	2.58
ABCI 3.0	145.10	2.45

Source: TOP500/HPCG, November 2025.

The disparity between HPL and HPCG performance highlights because companies must never measure computational capacity based solely on one indicator of efficiency. The computational needs for various tasks vary across the capabilities of the processors, memory, storage, and interconnects. With respect to BIS tasks, this point becomes especially significant. The computation task in business analytics can require extensive data transfers, database manipulation, machine learning, or real-time computation, instead of HPL dense math computations.

Proposed HPC-Bis Integration Framework

The proposed framework contains seven major components:

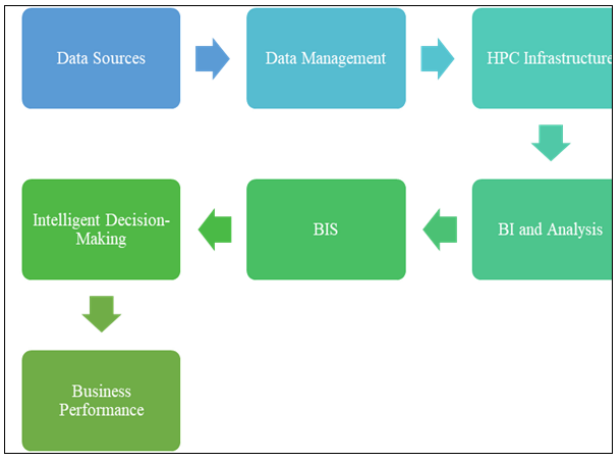

Figure 1: The Proposed Framework

A feedback mechanism connects business performance to subsequent data collection and analytics.

Data Sources and Acquisition

The first component consists of internal and external data sources. Internal Sources Include: ERP systems; CRM systems; financial systems; sales databases; inventory systems; production systems; employee information systems; and transaction-processing systems.

External Sources may Include: market data; economic information; social media; public databases; IoT data; competitor information; and third-party datasets. The objective is to provide a comprehensive data foundation for analysis.

Data Management and Integration

The second component involves preparing the data for computations. The data has to be cleansed, transformed, integrated, stored, and governed. The data preparation process encompasses data warehousing, data lakes, ETL operations, data quality measures, metadata management, access controls, and governance. Poor quality data could negate the effects of an advanced HPC setup. Consequently, data quality and computational performance should be considered complementary abilities.

HPC Infrastructure

The third component provides computational capacity.

It can include: multi-core CPUs; GPUs; HPC clusters; parallel computing; distributed computing; high-speed networks; specialized storage; and cloud-based HPC. The infrastructure can be deployed on-premises, through cloud services, or through a hybrid architecture.

Business Intelligence and Analytics

The fourth component converts computationally processed data into business insights.

It includes: Descriptive analytics, Diagnostic analytics, Predictive analytics, Prescriptive analytics, Machine learning, Artificial intelligence, Optimization, Simulation. The progression from descriptive to prescriptive analytics represents increasing analytical complexity.

Business Information Systems

Fifth component is where analytics connects to business users.

It consists of the following: management information systems; decision support systems; executive dashboards; ERP applications; CRM applications; and business intelligence tools. The BIS layer converts complicated analytics outputs into usable information.

Intelligent Decision-Making

This is the sixth dimension, which captures the primary organizational objective. Decision makers can apply HPC enabled analytics for: strategic planning; forecasting; resource allocation; risk assessment; inventory planning; marketing decisions; investment analysis; control; and scenario analysis.

Business Performance

The seventh factor will be organizational outputs.

Some examples may include: decision-making time; processing time; forecast accuracy; cost; productivity; customer satisfaction; revenue; resource utilization; and risk reduction. The output will create further data that will create a cycle of feedback.

Comparison of Conventonal and HPC-Enabled Bis

Table 3 provides the conceptual distinction between traditional BIS and HPC-enhanced BIS. Traditional BIS still suits many organizational workloads. On the other hand, HPC needs to be applied wherever computational complexity constitutes a business need.

Table 3: Conventional Bis Versus Hpc-Enabled Bis

Dimension	Conventional BIS	HPC-Enabled BIS
Data volume	Moderate to large	Very large and complex
Processing	Standard/centralized computing	Parallel and distributed computing
Processing speed	Suitable for routine workloads	Suitable for computationally intensive workloads
Analytics	Mainly descriptive and moderate predictive analytics	Advanced predictive and prescriptive analytics
AI/ML	Moderate computational capability	High computational scalability
Scenario analysis	Limited by processing time	Large-scale scenario analysis
Real-time analysis	Limited to moderate	High potential
Scalability	Dependent on enterprise infrastructure	High through clusters/cloud
Applications	Reporting, ERP, CRM, dashboards	Simulation, optimization, AI, large-scale analytics
Decision support	Routine and managerial	Complex, data-intensive, time-sensitive

Business Application of HPC-Bis Integration

Table 4 identifies major business areas in which the integration can potentially provide value. These applications demonstrate that HPC can contribute to business processes indirectly. The computational system performs large-scale processing, while BIS translates

the output into organizational information.

Table 4: Potential Business Applications

Business Area	Computational Requirement	HPC Contribution	BIS Decision
Marketing	Customer segmentation and prediction	Large-scale customer analytics	Campaign targeting
Finance	Risk and scenario modelling	Parallel simulation	Investment and risk decisions
Supply chain	Optimization	Large-scale optimization	Inventory and logistics
Retail	Demand forecasting	Predictive modelling	Stock allocation
Manufacturing	Predictive maintenance	Sensor-data processing	Maintenance scheduling
Banking	Fraud detection	Real-time analytics	Fraud alerts
Human resources	Workforce analytics	Large-scale data analysis	Workforce planning
Strategy	Scenario analysis	Multiple simulations	Strategic planning

Illustrative Performance Analysis

Table 5: Illustrative Hpc–Bis Performance Scenario

Indicator	Conventional BIS	HPC-Enabled BIS	Illustrative Change
Data-processing time	100 units	35 units	65% reduction
Analytical scenarios	100	1,000	10× increase
Forecasting cycle	24 hours	4 hours	83.3% reduction
Relative data volume	1×	5×	5× capacity
Decision-support response	60 min	10 min	83.3% reduction

By way of example, if an analysis needs 24 hours using the traditional architecture and 4 hours using the HPC architecture, then there is a reduction of about 83.3% in the processing time. Again, going from 100 scenarios to 1,000 scenarios means ten times more scenario processing capacity. The aim of this table is not to assert that every firm would achieve such results. It simply shows the kind of performance variables that can be examined in future empirical studies. A future empirical study may use real observations instead of illustrative figures and see if there are any statistically significant impacts on processing time, forecasting accuracy, decision latency, or financial performance due to the incorporation of HPC into the architecture.

Data – Information – Decision Analysis

The proposed framework can be understood through three transformation stages.

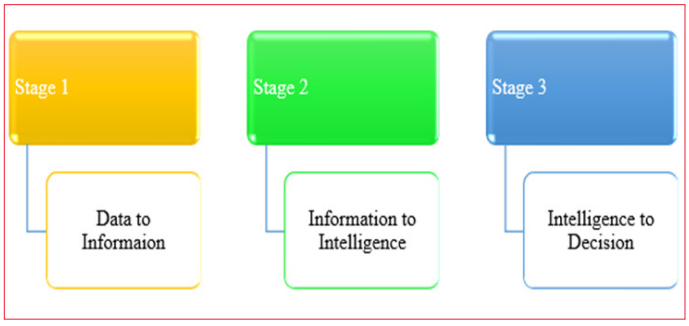

Figure 2: The Transformation stages

The integration of the proposed HPC-BIS can be defined as a transformation process consisting of three stages where raw organizational data is turned into business decisions. At the first stage, namely, Data to Information, large volumes of raw data are gathered from internal and external sources. Those include enterprise systems, customer transactions, financial databases, operation systems, Internet of Things devices, and external market information. This raw data is then cleansed, verified, combined, and properly managed using data management tools so that the raw data is turned into structured and usable information. The second stage, namely, Information to Intelligence, is associated with using HPC-based computational capabilities for analyzing this information. Statistical models, machine learning algorithms, artificial intelligence solutions, simulations, and optimization approaches can be used in order to process large and complex datasets and thus generate predictions, scenarios, patterns, and insights which cannot be generated quickly and efficiently using traditional computing resources. The third stage, namely, Intelligence to Decision, is associated with connecting the analytical results with Business Information Systems. The managers and employees can now analyze these results and take appropriate actions that can be strategic, tactical, or operational. Hence, the process is an ongoing process that starts from data gathering through analysis to decision making, while at the same time the results from the business performance can be used to enhance data gathering and analysis.

Benefits of HPC-Bis Integration

Below is the table outlining the main advantages offered by High-Performance Computing (HPC) for businesses and decision-making processes within companies. The mentioned advantages will help to see how HPC can increase computational capacity, analysis level, and decision-making speed.

Table 6: Benefit of Hpc-Bis

Faster Processing	The most obvious benefit is increased computational speed. Parallel processing can reduce the time required for computationally intensive tasks. This can be particularly important when business conditions change rapidly.
Greater Analytical Scale	HPC can allow organizations to process larger datasets and evaluate more scenarios. This can support more comprehensive analysis.
Advanced Predictive Analytics	HPC can support machine learning and other computationally intensive predictive models.
Improved Scenario Planning	Organizations can evaluate multiple possible futures rather than relying on a single forecast.
Improved Responsiveness	Faster analytics can reduce the time between data generation and organizational action.
Support for Artificial Intelligence	The computational requirements of AI make HPC increasingly relevant to intelligent business systems.
Better Resource Allocation	Optimization models can help organizations allocate scarce financial, human, physical, and technological resources.

Challenges of HPC-Bis Integration

The combination of HPC and BIS offers great potential for analytical advantage, yet there are certain challenges that have to be dealt with by companies. Major challenges are listed in the table below.

Table 7: Challenges of HPC-Bis

Cost	HPC infrastructure can require substantial investments in computing equipment, storage, networking, cooling, electricity, software, and specialist personnel.
Technical Complexity	HPC environments require specialized skills in parallel computing, distributed systems, AI, data engineering, and systems administration.
Data Governance	Large-scale integration increases the importance of data quality, privacy, access control, and governance.
Cybersecurity	Connecting computational infrastructure with enterprise systems can increase the number of potential attack surfaces.
Interoperability	Organizations often have legacy systems developed using different technologies. Integrating these systems can be difficult.
Energy Consumption	The November 2025 TOP500 data demonstrate that high-performance systems can consume substantial electrical power. For example, El Capitan's reported power consumption is 29,685 kW, while Aurora's is 38,698 kW [17]. This means that computational performance should be evaluated together with energy efficiency.
Skills	Organizations need employees capable of understanding both computational technology and business requirements.
Human Trust	AI-generated recommendations may not always be transparent. Human oversight remains important, particularly for high-impact decisions.

Implementation Framework

A practical implementation strategy can be divided into seven phases.



Figure 1: The Seven phases

The development of HPC-driven Business Information Systems requires the completion of a structured and business-focused approach to guarantee that computing resources would be deployed in accordance with the needs of the organization and its decision-making goals. Step 1, Business Problem Definition, starts from detecting particular organizational challenges rather than from choosing the type of technology. Possible use cases include demand forecasting, optimization, fraud detection, risk assessment, simulations, predictive maintenance, and big artificial intelligence. Step 2, Data Readiness Analysis, checks the quality, availability, security, governance, integrity, and integration of the organizational data because the efficiency of HPC-based analytics highly depends on the presence of the reliable and properly structured data. Step 3, Infrastructure Choice, finds the most suitable computing infrastructure according to the nature of the load, scale, security, costs, and capabilities of the organization. Accordingly, an organization can choose either on-premises, cloud-based, or hybrid HPC systems involving CPUs, GPUs, high-speed networks, and scalable storage. Phase 4, Analytical Model Development, comprises of the choice and development of analytical techniques that fit the business problem under consideration, such as statistical models, machine learning, artificial intelligence, optimization, simulation, and predictive analytics. Phase 5, BIS Integration, involves the linkage of the analytical outputs obtained during the analysis conducted via HPC with Business Information Systems (BIS) through their inclusion in dashboards, reports, alerts, workflows, and decision support applications. Phase 6, Human Oversight, guarantees that managers and domain experts will continue to be in charge of interpreting the analytical outputs, taking into account organizational and contextual factors, and making necessary decisions, especially in case of recommendations from AI. Finally, Phase 7, Performance Evaluation, estimates the performance of the integrated system according to its technical, operational, and business parameters, such as processing time, decision latency,

forecast accuracy, system availability, user acceptance, operation costs, energy consumption, and business results. In this way, through the proposed seven phases, an organization is able to create a continuous process of system integration in which the business needs define the preparation of the data and the choice of the computational infrastructure, HPC contributes to advanced analytics, and analytical outputs are incorporated into BIS. This framework also highlights that HPC should not be viewed as a stand-alone technological tool, but rather as a computing capability that provides value to the organization through its integration with information/data and the decision-making process.

Discussion

It is clear from the secondary sources and the literature analyzed in this study that computing capabilities continue evolving. There are now multiple exascale systems, which is a sign that there is continuous development of the boundaries of computational capability [17]. But the significance of these capabilities for business organizations can only become evident through the connections between computations and information/data and decisions. The framework presented provides such a connection.

First, this implies that high-performance computing needs to be regarded as an organizational capability, and not just a tool for computations. There is no point in having computing power if organizations cannot leverage it for solving their business problems. Second, the time-to-insight is crucial in data-intensive organizations. The information can become obsolete due to the delay. Thus, reducing the computation time can lead to more useful information. Third, HPC allows organizations to think about more complex analytics. They can run more scenarios, make more simulations, and build more complex models. Fourth, the framework underlines the significance of the quality of information/data. Consequently, data governance should be considered a basic element of architecture. Fifth, the framework assumes that human decision-makers play a vital role. An intelligent system can generate recommendations, predictions, and warnings, yet it is imperative to design proper means of interpreting the findings and taking control over the system.

The study offers three major theoretical contributions. First, it builds a connection between HPC research and Business Information Systems research. HPC research is conventionally analyzed through computational performance while BIS research focuses on organizational information and decision making. The framework combines both paradigms. Secondly, the framework highlights computational capacity as an enabling factor in business intelligence. The quality of analysis does not only depend on the algorithm itself and the quality of data used, but on computational capacity too. Lastly, the study places time-to-insight into the conceptual intersection between computational performance and decision value.

For managers, the framework suggests that investment decisions should begin with business requirements. Organizations should ask:

1. Which business processes currently experience computational limitations?
2. What datasets need to be processed?
3. Which analytical models are required?
4. How much faster must information become available?
5. What infrastructure is appropriate?
6. How will analytical outputs reach decision-makers?
7. How will business value be measured?

This approach prevents organizations from adopting HPC simply because it is technologically advanced. Instead, HPC becomes part of a broader business transformation strategy.

Conclusion and Future Research

This paper provided an overview of the combination of High-Performance Computing and Business Information Systems as a means to intelligent decision-making. The research suggested a seven-element framework including data sources, data management, HPC infrastructure, business intelligence and analytics, BIS, intelligent decision-making, and business performance.

Secondary data related to HPC show the impressive size of current computational infrastructure. The list of TOP500 from November 2025 listed four exascale systems, namely El Capitan that was measured at 1.809 exaflop/s, Frontier – 1.353 exaflop/s, Aurora – 1.012 exaflop/s, and JUPITER Booster – 1.000 exaflop/s on HPL benchmark [17]. This shows the ongoing growth of computational power.

However, computational power should not be equated with business value. The research shows that the strategic value of HPC for BIS comes only when computation is supported by good quality data, business analytics, and decision-making.

In doing so, the suggested framework places HPC as an enabling layer rather than an independent technology solution. It may be used for large-scale forecasting, optimization, simulation, artificial intelligence, risk assessment, and real-time analysis. At that point, BIS transforms those analytical results into useful information for management. The paper points out a number of issues associated with implementation of the technology, including cost, complexity, security issues, data management, interoperability, power consumption, skills, and human trust. As a result, successful HPC and BIS integration necessitates having appropriate technological, organizational, and managerial competencies.

To conclude, the convergence of HPC and BIS is considered to be an important opportunity for the development of intelligence-oriented organization. Future empirical research needs to use real organizational performance measures to replace the illustrative one and analyze the connection between computational performance, analytical competence, decision-making, and business performance.

Future research should aim to test the developed framework. In particular, the first step would involve gathering data about organizations using HPC-enabled business intelligence systems and comparing their performance prior to and after the adoption of such systems.

The second step could be to conduct quantitative studies about the relationships between HPC processing capability, time to insight, decision-making, and organizational performance. The third step involves comparing cloud HPC, on-premises HPC, and hybrid setups. The fourth area could be examining the use of generative AI in HPC-enabled Business Information Systems. Fifthly, research could look into energy-efficient and sustainable computing. Sixth, future research could develop maturity models for HPC-enabled BIS.

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