BUSTECH 2026

The Sixteenth International Conference on Business Intelligence and Technology

ISBN: 978-1-68558-380-4

April 19 - 23, 2026

Lisbon, Portugal

BUSTECH 2026 Editors

Maik Drozdzynski, IU International University of Applied Sciences, Germany

BUSTECH 2026

Forward

The Sixteenth International Conference on Business Intelligence and Technology (BUSTECH 2026), held on April 19 – 23, 2026, continued a series of events covering topics related to business process management and intelligence, integration and interoperability of different approaches, technology-oriented business solutions and specific features to be considered in business/technology development.

Similar to the previous edition, this event attracted excellent contributions and active participation from all over the world. We were very pleased to receive top quality contributions.

We take here the opportunity to warmly thank all the members of the BUSTECH 2026 technical program committee, as well as the numerous reviewers. The creation of such a high quality conference program would not have been possible without their involvement. We also kindly thank all the authors that dedicated much of their time and effort to contribute to BUSTECH 2026. We truly believe that, thanks to all these efforts, the final conference program consisted of top quality contributions.

Also, this event could not have been a reality without the support of many individuals, organizations and sponsors. We also gratefully thank the members of the BUSTECH 2026 organizing committee for their help in handling the logistics and for their work that made this professional meeting a success.

We hope BUSTECH 2026 was a successful international forum for the exchange of ideas and results between academia and industry that will promote further progress in the area of business intelligence and technology. We also hope that Lisbon provided a pleasant environment during the conference and everyone saved some time to enjoy this beautiful city.

BUSTECH 2026 Steering Committee

Malgorzata Pankowska, University of Economics in Katowice, Poland
Pierre Hadaya, ESG-UQAM, Canada
Hans-Friedrich Witschel, University of Applied Sciences and Arts, Northwestern Switzerland
Maik Drozdzynski, IU International University of Applied Sciences, Germany

BUSTECH 2026 Publicity Chairs

Francisco Javier Díaz Blasco, Universitat Politècnica de València, Spain
Ali Ahmad, Universitat Politècnica de València, Spain
José Miguel Jiménez, Universitat Politècnica de València, Spain
Sandra Viciano Tudela, Universitat Politècnica de València, Spain

BUSTECH 2026

Committee

BUSTECH 2026 Steering Committee

Malgorzata Pankowska, University of Economics in Katowice, Poland
Pierre Hadaya, ESG-UQAM, Canada
Hans-Friedrich Witschel, University of Applied Sciences and Arts, Northwestern Switzerland
Maik Drozdzynski, IU International University of Applied Sciences, Germany

BUSTECH 2026 Publicity Chairs

Francisco Javier Díaz Blasco, Universitat Politècnica de València, Spain
Ali Ahmad, Universitat Politècnica de València, Spain
José Miguel Jiménez, Universitat Politècnica de València, Spain
Sandra Viciano Tudela, Universitat Politècnica de València, Spain

BUSTECH 2026 Technical Program Committee

Emna Ben Abdallah, University of Sfax, Tunisia
Unal Aksu, Utrecht University, Netherlands
Kiran Kumar Bandeli, Data Science | Walmart Inc., USA
Dariusz Barbucha, Gdynia Maritime University, Poland
Reza Barkhi, Virginia Tech, USA
Surendra Bhosale, Veermata Jijabai Technological Institute, India
Khouloud Boukadi, Faculty of Economics and Management of Sfax, Tunisia
Simone Braun, Offenburg.University, Germany
Karl Cox, University of Brighton, UK
Beata Czarnacka-Chrobot, Warsaw School of Economics, Poland
Jiamei Deng, Leeds Beckett University, UK
Giuseppe A. Di Lucca, University of Sannio - RCOST (Research Center on Software Technology), Italy
António Dourado, University of Coimbra, Portugal
Paweł Drąg, Wrocław University of Science and Technology, Poland
Maik Drozdzynski, IU International University of Applied Sciences, Germany
Helena Dudycz, Wroclaw University of Economics, Poland
Bedilia Estrada-Torres, Universidad de Sevilla, Spain
Jiri Feuerlicht, University of Economics, Prague, Czech Republic
Stefka Fidanova, IICT-BAS, Sofia, Bulgaria
Lixin Fu, University of North Carolina at Greensboro, USA
Faiza Ghozzi, University of Sfax, Tunisia
Todorka Glushkova, Paisii Hilendarski University of Plovdiv, Bulgaria
Manuel Gomez-Olmedo, Universidad de Granada, Spain
Foteini Grivokostopoulou, University of Patras, Greece
Pierre Hadaya, ESG-UQAM, Canada

Rawad Hammad, University of East London, UK
Mariem Haoues, Mir@cl Laboratory - University of Sfax, Tunisia
Uswatun Hasanah, Universitas Amikom Purwokerto, Indonesia
Hmida Hmida, Higher Institute of Technological Studies of Bizerte, Tunisia
Wladyslaw Homenda, Warsaw University of Technology, Poland
Wei-Chiang Hong, Asia Eastern University of Science and Technology, Taiwan
Wassim Jaziri, Taibah University, Saudi Arabia
Maria João Ferreira, Universidade Portucalense, Portugal
Jānis Kampars, Riga Technical University, Latvia
Mouna Torjmen Khemakhem, University of Sfax, Tunisia
Leoneed Kirilov, Institute of Information and Communication Technologies - Bulgarian Academy of Sciences, Sofia, Bulgaria
Alexandr Kormiltsyn, Estonian Research Information System, Estonia
Adrianna Kozierkiewicz, Wroclaw University of Science and Technology, Poland
Kyriakos Kritikos, ICS-FORTH, Greece
Hongxiu Li, Tampere University, Finland
Audrone Lupeikiene, Vilnius University, Lithuania
Andre Miede, University of Applied Sciences Saarbrücken, Germany
Anastasija Nikiforova, University of Tartu / European Open Science Cloud Task Force “FAIR Metrics and Data Quality”, Estonia
Alex Norta, Tallinn University of Technology, Estonia
Hanen Ochi, Efrei Paris, France
Malgorzata Pankowska, University of Economics in Katowice, Poland
Ronak Pansara, Tesla, USA
Marcin Paprzycki, Systems Research Institute | Polish Academy of Sciences, Poland
Ripon Patgiri, National Institute of Technology Silchar, Assam, India
Isidoros Perikos, University of Patras, Greece
Erwin Pesch, University in Siegen / HHL - Leipzig Graduate School of Management | CASiM - Center for Advanced Studies in Management, Germany
Stavros Ponis, National Technical University Athens, Greece
Patricio Ramírez-Correa, Universidad Católica del Norte, Chile
Franck Ravat, IRIT - Toulouse University, France
Federica Rollo, University of Modena and Reggio Emilia, Italy
Gunter Saake, Otto-von-Guericke-University of Magdeburg, Germany
Luis Enrique Sánchez Crespo, University of Castilla-la Mancha, Spain
Isabel Seruca, Portucalense University, Porto, Portugal
Paweł Skrzypek, 7bulls.com - SME IT company, Poland
Stanimir Stoyanov, Plovdiv University "Paisii Hilendarski", Bulgaria
Zoltán Szabó, Corvinus University of Budapest, Hungary
Dominik Ślęzak, QED Software & University of Warsaw, Poland
Mohan Tanniru, University of Arizona / Henry Ford Health System, Detroit / Oakland University, Rochester, USA
Francesco Tedesco, University of Calabria, Italy
Joseph G. Vella, University of Malta, Malta
Henrique Vicente, University of Évora, Portugal
Krzysztof Węcel, Poznań University of Economics and Business, Poland
Katarzyna Wegrzyn-Wolska, EFREI Paris | AlliansTIC & MINES ParisTech, France
Janusz Wielki, Opole University of Technology, Poland

Hans-Friedrich Witschel, FHNW University of Applied Sciences and Arts, Northwestern Switzerland
Krzysztof Wnuk, Blekinge Institute of Technology (BTH), Sweden
Shaomin Wu, Kent Business School - University of Kent, Canterbury, UK
Sira Yongchareon, Auckland University of Technology, New Zealand
Zornitsa Yordanova, University of National and World Economy, Sofia, Bulgaria

Table of Contents

Concept of a Business Intelligence Architecture for Digital Shopfloor Management

Christian Simon Magnus
IU International University of Applied Sciences
Erfurt, Thuringia, Germany
e-mail: christian.magnus@iu.org

Maik Drozdzynski
IU International University of Applied Sciences
Erfurt, Thuringia, Germany
e-mail: maik.drozdzynski@iu.org

***Abstract*—Digitalization in manufacturing increases both the diversity of data sources and the time sensitivity of information needs. Classical Business Intelligence architectures remain valuable for integrating enterprise data and for decoupling analytics from operational systems, but they are typically optimized for batch-oriented refresh cycles and day-level latency. This latency is sufficient for many controlling domains, including finance, sales, and Human Resources (HR), where reconciled and governed figures are often more important than minute-level responsiveness. Digital Shopfloor Management (dSFM), however, depends on timely transparency on the shopfloor, because leaders and teams must detect deviations early and intervene during the shift across key performance dimensions, such as quality, cost, delivery, safety, and workforce-related metrics. To address this gap, this paper proposes a domain-specific BI reference architecture for digital shopfloor management that integrates IT and OT data through an integration backbone, combines curated warehouse structures with low latency ingestion paths, and supports stakeholder specific consumption patterns from operators to executives. The architecture connects established reporting and planning capabilities with event driven analytics, thereby aligning different time horizons and data granularities within a unified design.**

***Keywords*-Business Intelligence; Digital Shopfloor Management; IT/OT integration; reference architecture; near-real-time analytics; data warehouse; streaming data pipelines; manufacturing analytics; Industry 4.0.**

I. Introduction

The ongoing digitalization of manufacturing has led to a substantial increase in the demand for data, extending far beyond classical enterprise systems, such as Enterprise Resource Planning (ERP) and traditional Business Intelligence (BI) front-ends. Alongside this development, both the number and the heterogeneity of data sources and data sinks are continuously growing. Modern manufacturing environments must integrate data originating not only from business-oriented systems but also from Manufacturing Operations Management (MOM) systems and shop-floor/control domain technologies [1]. Consequently, information requirements in manufacturing enterprises are not limited to a pure business perspective. Instead, they must incorporate production-related views in a consistent and integrated manner.

At the same time, the increasing adoption of assistance systems, artificial intelligence, and higher degrees of self-organization in the evolution towards smart factories further intensifies the need for timely and context-aware information derived from diverse and distributed data sources. To reduce redundant system integrations and avoid isolated data silos in subsystems, a common architectural framework is necessary that satisfies the varying functional and temporal requirements. In the context of IT (Information Technology) / OT (Operational Technology) convergence, Venanzi et al. [2] summarize different reference architectures like the Reference Architecture Model Industrie 4.0 (RAMI 4.0) [3] or the Industrial Internet Reference Architecture (IIRA) [4]. They conclude that asset digitization and communication, along with systems safety, resilience, and security are highly relevant aspects. Nevertheless, the absence of a deployable reference implementation necessitates the development of a context-specific IT architecture for Industry 4.0 applications [5].

Although classical BI architectures remain fundamentally valuable due to their ability to consolidate heterogeneous data and to offload operational systems, they are not inherently designed to accommodate the differing temporal requirements of operational levels within manufacturing organizations. From a technical perspective, IEC 62264-1:2013-05 defines five hierarchy levels, having time frames between ”seconds and faster” and ”months, weeks, and days” [6]. While a general model evolution from hierarchical pyramid structures to network structured architectures is observed [7], the stated time frames still give an idea about the different requirements. This paper focuses on digital Shopfloor Management as an exemplary use-case in the operational domain.

Against this background, an evolution towards a modern BI reference architecture tailored specifically to the manufacturing domain becomes necessary to address the growing complexity, heterogeneity, and time-sensitivity of data-driven decision-making [8].

Accordingly, this paper aims to contribute to answering the following research question: *How can a modern reference architecture for manufacturing companies be designed to integrate increasing data diversity, differing temporal requirements, as well as business and production management perspectives?*

The remainder of this paper is organized as follows. Section II reviews the conceptual foundations of dSFM and BI, including the presentation of existing research in context of the research question. Section III derives the requirements for a modern BI architecture in the context of dSFM, considering stakeholder roles and temporal information needs. Section IV presents the proposed architecture and describes its components and application across different stakeholder groups. Section V discusses the implications and limitations of the proposed approach. Finally, Section VI concludes the paper and outlines directions for future research.

II. Foundations

A. Digital Shopfloor Management

Shopfloor Management (SFM), rooted in the principle of Genchi Genbutsu, is a leadership approach that improves processes directly at the point of value creation through on-site presence, structured communication, and systematic problem-solving [9]. It emphasizes supportive leadership and is based on four core elements: visual management, structured communication routines, standardized problem-solving processes, and standard-based process control, enabling transparent performance monitoring and continuous improvement. Hertle et al. [10] identified several necessery competencies in the four areas of Key Performance Indicators (KPIs), participation (shop floor operators) or leadership (team leaders), problem solving, and continuous improvement.

For SFM-routines regular leadership and communication sequences are organized with team leaders, line operators, and representatives of service functions, like maintenance or quality management. Following a multi-level structure, these meetings are often-times organized on shopfloor-level (per production line/cell), area level and factory level, serving the different stakeholders' needs. Depending on the level, also the frequency of the shopfloor-meetings is differing. For visual management, Shopfloor Management boards are used.

A Shopfloor Management board requires the systematic collection and visualization of operational performance data across the core dimensions of ”SQCDP”: safety (S), quality (Q), costs (C), delivery (D), people (P; in some sources also called moral [9]). This includes quantitative KPIs, such as disturbance rates, output volumes, scrap and savings figures, as well as safety incidents and employee satisfaction metrics. In addition, process-oriented data, such as project flow information, capacity constraints, and machine failures must be captured. Beyond performance indicators, structured information on current priorities, weekly focus topics, and action management data with status tracking is required to enable transparent deviation management and operational control. From a data perspective, this sums up to master, production execution, time-series/sensor, event & incident, KPI & aggregation, workflow/action management, planning & scheduling and HR/people metrics data.

It becomes evident that Lean and Industry 4.0 represent two distinct, yet potentially complementary approaches to the design and optimization of production systems. Empirical studies indicate that achieving higher levels of Industry 4.0 maturity requires a prior maturity in Lean Management [11]. Companies with established lean practices are more likely to be advanced in Industry 4.0, and digital technologies tend to amplify the benefits of lean structures [12].

While analog SFM relies primarily on printed or manually completed documents, digital SFM (dSFM) utilizes digitally captured data and automated processing. This enables time savings, access to historical data, cross-site transparency, and near real-time availability of current information. By reducing data, analysis, and decision latency, dSFM shortens overall reaction times and enhances the value contribution of deviation management [13].

B. Business Intelligence

BI has evolved from a set of isolated reporting practices into an integrated socio-technical capability that combines data integration, analytics, and decision-oriented information delivery. There is a need to transform the fast-growing operational business data into decision-relevant information and knowledge to eliminate cognitive overload and provide meaningful and directed reports to decision makers [14, p. 1519]. Until today, there is no generally accepted definition of BI. In this paper BI is defined

> [...] as the concept of aggregating and preparing data and information in order to improve the quality, speed, and effectiveness of decision-making for corporate steering, planning, and control [8, p. 484].

This definition positions BI explicitly as a decision-support concept that is outcome-oriented (decision quality, speed, effectiveness) and management-oriented (steering, planning, control). In that sense, BI is not merely a technology stack. Moreover, it is a purposeful arrangement of processes and systems that transforms data into managerial actionability.

The literature distinguishes a narrow and a broad understanding of BI. The narrow understanding focuses on user-facing applications, especially reporting, analyses, and planning tools that provide information to managers and analysts [15]. The broad perspective of BI goes beyond the visible applications and includes the end-to-end pipeline required for reliable decision support. In general, data acquisition from source systems, integration, transformation, quality assurance, governance, semantic harmonization, and the provision of consistent data layers make analytics trustworthy and repeatable.

The development of BI can be interpreted as a sequence of capability expansions: from descriptive reporting (what happened), to diagnostic analysis (why it happened), toward predictive and prescriptive approaches (what will happen and what should be done). This sequence can also be translated into an understanding from manually generated information in the 1990s to automated machine-generated insights from 2020 [16, p. 4]. This trajectory is reflected in the integration trends observed in BI systems, where formerly separate components become increasingly integrated and industrialized. To operationalize the broad BI definition, a reference architecture is required that structures the end-to-end flow from operational data to decision support. That leads to a five-layer architecture with a technical back-end and a user-oriented front-end [8], [17, p. 11], [18, p. 756].

1) Operational Systems: Operational subsystems are the transactional systems where business events are executed and recorded, for example ERP, Customer Relationship Management (CRM), point of sale, production, and finance systems.

2) Staging Area: The staging area is an intermediate landing zone that receives data extracted from the operational subsystems before it is loaded into analytical storage. It is used to isolate the warehouse from source volatility and to run ingestion and transformation steps, such as cleansing, standardization, and basic conformance checks.

3) Data Warehouse: The data warehouse is the integrated, persistent storage layer that consolidates data from multiple sources into a coherent enterprise view.

4) Evaluation Database: Evaluation databases or data marts are subject oriented or purpose oriented subsets derived from the enterprise warehouse, typically designed for specific domains, such as finance, sales, or controlling.

5) BI-Frontend: The BI-frontend is the consumption and interaction layer where users access reports, dashboards, ad hoc analysis, planning, and visual analytics. It translates curated datasets into decision-ready information products by providing filtering, drill paths, KPI views, and guided narratives aligned with managerial questions.

Classical BI architectures were historically designed around batch-oriented refresh cycles with a dedicated loading window, often during the night, to avoid stressing operational source systems, which implies that decision makers frequently work with data that is fresh on the next day [19]. For many controlling domains, this latency is acceptable because managerial steering problems, such as finance, sales, or HR controlling typically do not require minute level reaction, but rather reliable and reconciled figures with strong governance and auditability. In digital shopfloor management, however, the value proposition shifts toward timely operational awareness and rapid intervention, which increases the importance of low latency data acquisition, contextualization, and delivery. A shopfloor-focused information system architecture is therefore expected to deliver the right information to the right place at the right time, which is difficult to achieve with long running batch Extract, Transform, Load (ETL) chains and day level refresh cycles. From an architectural perspective, this supports the argument that classical ETL centric BI stacks need to be complemented by near real-time integration patterns, such as incremental loading and change propagation, or by streaming-based pipelines that can sustain continuous updates for time-critical shopfloor use cases.

C. Existing Research

Besides the rather abstract and generalized reference architectures IIRA and RAMI 4.0, that were already mentioned in the introduction, further manufacturing-focused architectures exist. Kaiser et al. [20] reviewed and classified 78 models which were referred to as 'reference architectures' by their authors. As Kaiser et al. [20] found a lack of a clear distinction between the terms 'reference architecture', 'system', 'system architecture', 'Framework', 'platform', and 'meta abstraction', they provided distinct definitions. Also, they suggest that domain-specific and interoperable reference architectures are generally easier to adopt in digital manufacturing than highly generic ones. Furthermore, combining complementary reference architectures and grounding them in appropriate standards and technologies enhances applicability, simplifies system design, and supports more practical and structured implementation.

Kassner et al. [21] discuss and compare existing architectures with their 'Stuttgart IT Architecture for Manufacturing (SITAM)'. Powered by middleware for integration, analytics and mobile use, they take into account data of the full product lifecycle and provide it for role-based applications, using value-added services for both machines and human users. For specific life-cycle phases and for overall integration, Enterprise Service Buses (ESB) are used for integration of all applications and services of the individual phases. Data quality, governance and security & privacy are introduced as cross-architectural components.

Based on categories for data and data processing requirements of Industry 4.0 from Gölzer et al. [22], Weber et al. [5] suggest architectural concepts with a focus on data processing. Structured by increasing latency, they suggest to introduce a speed layer and a batch layer. The speed layer allows for real-time analysis, Complex-Event-Processing (CEP), and streaming data processing, focusing on fast and incremental algorithms, only taking into account new data and no historical data. Hard real-time requirements for controlling manufacturing equipment is left to the Programmable Logic Controllers (PLCs). The batch layer shall be used for enhanced analyses of historic data for knowledge processing. It has no real-time-processing, but takes into account large datasets to generate views. The focus of the batch layer is on robustness, scalability, generality, support for ad hoc querying, low maintenance overhead, full traceability of data modifications, recalculation of results upon data updates, and comprehensive queryability across all available data.

Moghaddam et al. [23] also discuss an IBM Industry 4.0 reference architecture as well as a Service-Oriented Smart Manufacturing System Architecture from employees of the U.S. National Institute of Standards and Technology (NIST). The IBM architecture differentiates between Edge, Plant and Enterprise and follows an equipment/device layer and hybrid cloud platform approach. It is based on OT/IT gateways as middlemen between smart devices and tools and plant and enterprise elements. The Service-Oriented Smart Manufacturing System Architecture is introduced in detail by Lu et al. [24]. It is using a single Manufacturing Service Bus (MSB), integrating the manufacturing ecosystem, including IT and OT systems. Interactions with customers, suppliers and logistics shall be done by using a 'collaborative' BI service. The specific setting of the collaborative BI service is not described in detail. Also, the MSB is not described in detail, but it is mentioned that the IT-facing integration is similar to the ESB approach, using event-driven and standards-based middleware with message queues. The OT-facing integration shall be supported by Open Platform Communications Unified Architecture (OPC UA). Overall, Lu et al. [24] see six key implementation challenges in their proposed architecture: enabling a scalable manufacturing service bus that supports both real-time and high-volume data exchange, modeling real-time services in OT environments, ensuring secure and

TABLE I. TIME FRAMES AND PRACTICAL APPLICATIONS.

Stakeholders	*Primary Interests*	*Information Granularity*	*Time frames*
operators, support functions	reactive problem resolution; stable process flow; current tasks	event-level; machine states; individual deviations	minutes to shifts
team leaders	deviation transparency; workload balancing; resource availability	event-level; machine states; individual deviations; KPIs	minutes to days
area managers	cross-line performance; cost control; resource allocation; root causes	day KPIs, trend charts	days to weeks
factory manager/s	factory performance; target achievement; long-term resource planning	performance summaries	weeks to quarters
executive manager/s	strategic competitiveness; investment prioritization; productivity improvement	performance summaries	months to quarters

safe IT–OT integration, integrating high-fidelity models and simulations into real-time control environments, managing and contextualizing heterogeneous data for knowledge management, and advancing integration standards to facilitate broader interoperability.

A joint publication of MESA, IBM and Capgemini describes that an MSB extends the traditional ESB by providing manufacturing-specific capabilities [25]. In addition to standard ESB functions, it supports modeling of process events and corresponding actions via a production workbench, device access services for manufacturing device integration, standards-based manufacturing services (e.g., Work in Process tracking), and support for applicable manufacturing integration standards.

III. REQUIREMENTS FOR A MODERN BI-ARCHITECTURE IN DSFM

A. *Stakeholders*

It must be acknowledged that the number and frequency of meetings may differ depending on organizational size. The following outlines a typical structure.

Following a general bottom-up approach, the SFM-cascade starts on shopfloor-level with one meeting per production line/cell at the beginning of each shift, or sometimes even combined with a shift handover [26]. Usually, operators, team leaders and support functions (if specific problems occur) join these meetings. On area-level, all team leaders of a specific area escalate problems and give status updates to the respective area manager [26]. On factory-level, all area managers escalate problems and give status updates to the factory manager [26], who reports to the executive manager/s. Table I lists the stakeholders, their primary interests, the required information granularity and the respective time frames.

B. *Time frames*

Time frames in dSFM in general span from minutes to quarters. These time horizons shape what the BI architecture must deliver and they are stakeholder-specific (see Table I). For operators and support functions, the dominant horizon is minutes to shifts, where information is required at the event level and at the machine level to support reactive problem resolution, stable process flow, and current tasks. Team leaders operate from minutes to days and require a similar level of granularity, including KPIs, to create transparency into deviations, balance workloads, and ensure resource availability. Area managers typically steer from days to weeks and rely on daily KPIs and trend charts to assess cross line performance, cost control, resource allocation, and recurring root causes. Factory managers use weeks to quarters to steer target achievement and medium-term resource planning, so they primarily need performance summaries that are comparable across areas and periods. Executive managers focus on months to quarters and consume performance summaries that support strategic competitiveness, investment prioritization, and long-term productivity improvement. These differentiated horizons explain why dSFM requires both high-frequency operational views and aggregated management views within one coherent BI architecture.

IV. CONCEPTS FOR A MODERN BI-ARCHITECTURE IN DSFM

A. *Target Architecture*

Figure 1 depicts a layered BI architecture for dSFM that integrates OT and IT data sources through a manufacturing integration backbone and provides different decision and control views for stakeholder groups.

1) Source and operations: At the bottom, operational source systems provide both OT signals and IT transactions. OT sources include PLCs, Supervisory Control and Data Acquisition (SCADA) systems, sensor-gateways, and edge components. IT sources include Manufacturing Execution Systems (MES) and ERP, Product Data Management (PDM), and other operational application systems, such as Supply Chain Management (SCM) and CRM. This mix is typical for enterprise control integration and creates the need for harmonized interfaces and contextualization across layers.

2) Integration and staging: An MSB acts as the main integration mechanism, enabling system-to-system connectivity and decoupling producers and consumers of shopfloor information. A staging area sits above this bus and supports both ETL and ELT patterns. ETL supports classic curated loading for structured data into the Data Warehouse. ELT supports loading into analytical databases and data lake-style storage, where transformation can occur closer to the target systems. This dual path is consistent with the requirement to serve both stable management reporting and more exploratory or high-frequency analytics workloads. Some Operational Application Systems (OAS), such as Financials, Customer Relationship Systems, and Human Resources, take a shortcut directly to

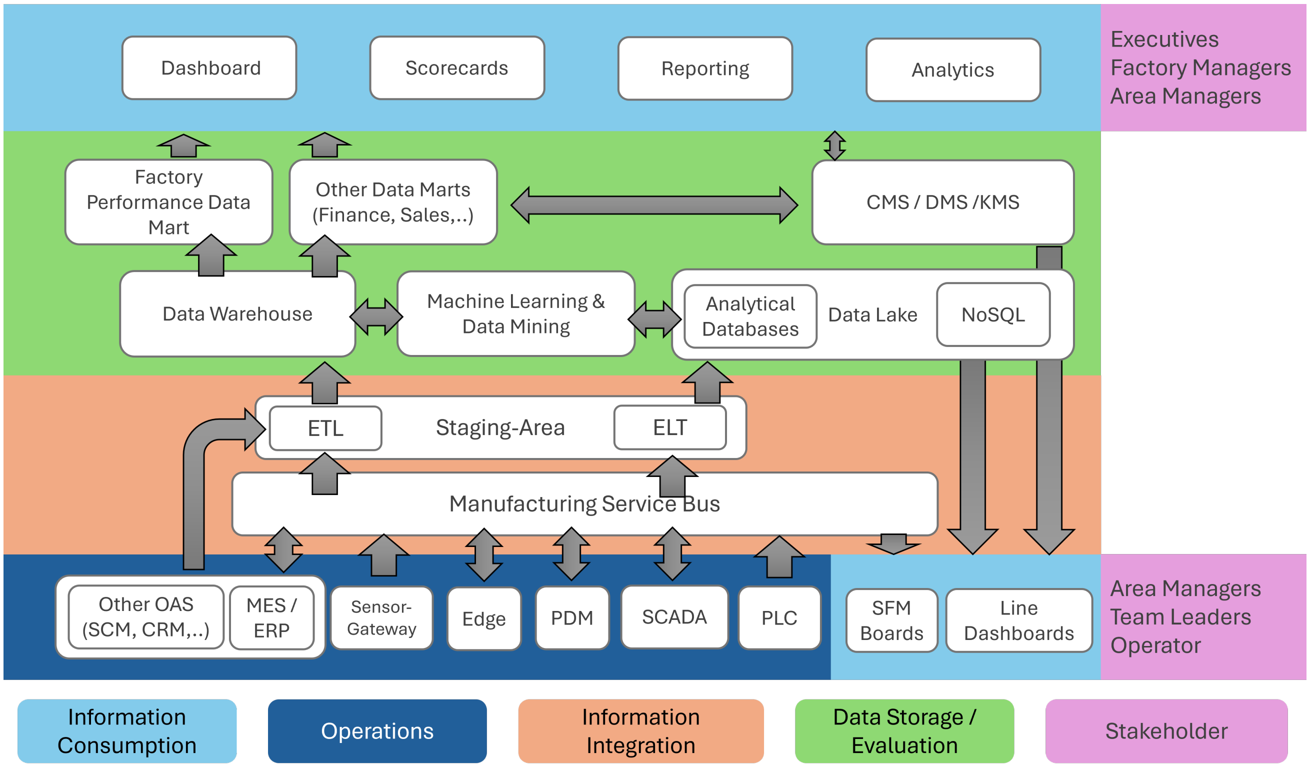

Figure 1. Target BI-Architecture for dSFM

the staging area because there is no need to interact with the MSB.

3) Data Warehouse and Data Marts: The Data Warehouse provides integrated, quality-assured, and historized data as the backbone for consistent reporting. On top of that, the Factory Performance Data Mart provides production performance steering, while other marts offer cross-functional perspectives, such as finance and sales. Standardized manufacturing operations KPIs and consistent KPI semantics are critical here, because misaligned KPI definitions lead directly to inconsistent steering. ISO 22400 provides a recognized KPI reference for manufacturing operations management [27].

4) Data Lake and NoSQL storage: A Data Lake with a NoSQL (Not only SQL) component represents storage for high-volume, high-variety, and high-velocity shopfloor data, such as event streams, logs, and semi-structured sensor data. This path supports rapid ingestion and flexible analytics, which are useful for short-term deviation analysis and advanced analytics that require raw, granular traces.

5) Analytical databases and advanced analytics: Analytical databases sit within the data lake as well and connect to Machine Learning and Data Mining. This reflects a split between curated warehouse-based analytics and faster, iterative analytical workloads operating on large, granular datasets. The bidirectional arrows between ML and the storage components indicate that models can be trained on curated or raw data and that scoring results can be persisted back to analytical stores to support consumption in reports and dashboards. In the dSFM context, Machine Learning and Data Mining are not intended as isolated data science activities, but as specialized analytical services that extend operational decision support. Typical use cases include anomaly detection on machine and sensor streams, short-term prediction of quality deviations or downtime risks, pattern mining on recurring stop reasons, and classification of disturbance constellations across shifts or lines. These methods primarily operate on granular event data, time series, and contextual production data from the data lake and analytical databases, while curated warehouse data can complement model training for cross-period comparisons and validation. The resulting outputs, such as anomaly flags, risk scores, predicted defect probabilities, or recurring loss patterns, are written back to analytical stores and exposed through dashboards and shopfloor boards. This enables operators and team leaders to react earlier to deviations, while area and factory managers can use the results to prioritize improvement actions and investigate structural causes.

6) Knowledge and content layer: A Content Management System (CMS), Document Management System (DMS), and Knowledge Management System (KMS) component is bidirectionally connected to the data mart landscape. This enables linking structured performance information with procedures, work instructions, and lessons learned. In dSFM practice, this supports the idea that deviation handling is not only about measurement but also about guided execution and standard work. The shopfloor operations need access to knowledge and content, such as manufacturing plans and documented escalation checklists.

7) Consumption layer: At the top, dashboards, scorecards, reporting, and analytics represent the main BI frontends for management stakeholders. The arrows from the data mart layer to the consumption layer indicate that executive and factory management views are primarily mart-driven, curated, and governed. BI front-end software can also convert reports and analyses into a format that is useful for distribution (i.e. PDF) and push them into the knowledge base.

B. Usage and Application

Across all stakeholder groups, the architecture supports target alignment by linking role-specific views to a common KPI logic and escalation structure, so that local decisions contribute to shared production goals rather than isolated individual evaluation [28].

From a BI-oriented point of view, there is a special focus on stakeholder-specific steering options, usage, and application with regard to the mentioned requirements along time frames.

1) Operators and team leaders: The lower right shows SFM Boards and Line Dashboards as dedicated operational frontends. The vertical data flow from the NoSQL component to these frontends provides a fast path for near-real-time shopfloor steering. Typical steering options include monitoring current states and alarms, reacting to deviation events, drilling from a KPI signal to the underlying event trace, and initiating immediate corrective actions in the shift. This aligns with digital shopfloor management research that emphasizes faster access to production data, a deviation-oriented approach, and improved execution of shopfloor routines.

2) Area managers: Area managers operate between real-time line control and daily performance coordination. In this architecture, they can use both the operational boards for short-cycle control and the Factory Performance Data Mart for shift and day aggregation, recurring loss patterns, and prioritization of improvement actions. The key steering option is closed loop deviation management across lines, supported by consistent KPI definitions and drill down capability from aggregated losses to granular stop reasons and quality events.

3) Factory managers: Factory managers mainly consume dashboards, scorecards, reporting, and analytics built on curated marts. Their steering focus is tactical and performance-oriented, for example, Overall Equipment Effectiveness (OEE)-related performance, throughput, scrap trends, maintenance-driven availability, and constraint management across the plant. ISO 22400-based KPI definitions serve as suitable anchors to ensure these views remain consistent across production areas and time windows.

4) Executives: Executives require cross-site and cross-functional steering, which the architecture supports through additional data marts, such as finance and sales, that connect to the production marts. Their steering options include strategic performance governance, investment justification, and network-level comparisons.

V. Discussion and Outlook

The proposed architecture translates insights from existing Industry 4.0 and BI reference models and stakeholder-specific requirements into a unified approach. By combining near-real-time integration with curated warehouse structures, it aligns heterogeneous IT/OT data sources with differing decision horizons and information granularities across operational and managerial levels.

While developed with a focus on dSFM, the architecture is adaptable to other operational scenarios, such as supporting production assistance systems, condition monitoring use-cases and further applications. However, hard real-time and safety-critical control functions must remain within deterministic control architectures. The proposed architecture can provide supervisory analytics and contextualization, but cannot replace certified control or safety mechanisms.

The architecture represents a generalized reference and may require adaptation for specific manufacturing contexts. Implementing the architecture may require significant technical and organizational effort, while the effectiveness strongly depends on the availability and quality of operational data.

VI. Conclusion and Future Work

This paper introduced a Business Intelligence reference architecture for digital Shopfloor Management that integrates heterogeneous IT and OT data sources while addressing differing temporal and stakeholder-specific requirements. By combining near-real-time processing with curated warehouse structures, the architecture extends classical BI principles to manufacturing environments characterized by mixed latency constraints. Practically, it provides a structured blueprint for role-based decision support and consistent KPI integration. Future work should investigate cloud and hybrid edge-cloud deployments to enhance scalability and resilience, and evaluate their cybersecurity and governance implications. Additionally, empirical validation in real production environments is part of ongoing research work with manufacturing companies in the dental industry. This next research step aims to assess the architectural assumptions under practical conditions and evaluate the approach's transferability to related manufacturing use cases beyond dSFM. The main foreseen obstacles include avoiding overloading operational systems, adequately considering organizational and workforce-related effects during implementation, and managing the inherently interdisciplinary nature of such projects.

References

[1] C. S. Magnus, "Smart factory mapping and design: methodological approaches," *Production Engineering*, vol. 17, no. 5, pp. 753–762, Jan. 2023.

[2] R. Venanzi, G. Di Modica, L. Foschini, and P. Bellavista, "Towards IT/OT integration in industry digitalization: A comprehensive survey," *Journal of Network and Computer Applications*, vol. 245, pp. 1–39, Jan. 2026.

[3] DIN SPEC 91345:2016-04, "Referenzarchitekturmodell Industrie 4.0 (RAMI4.0) [Reference Architecture Model Industrie 4.0 (RAMI4.0)]."

[4] IIC. (2022) The Industrial Internet Reference Architecture. Accessed: 2026-03-15. [Online]. Available: https://www.iiconsortium.org/wp-content/uploads/sites/2/2022/11/IIRA-v1.10.pdf

[5] C. Weber, M. Wieland, and P. Reimann, “Konzepte zur Datenverarbeitung in Referenzarchitekturen für Industrie 4.0 [Concepts for data processing in reference architectures for Industry 4.0],” *Datenbank-Spektrum*, vol. 18, no. 1, pp. 39–50, Mar. 2018.

[6] IEC 62264-1:2013-05, “Enterprise-control system integration. part 1: Models and terminology (IEC 62264-1:2013),” 2013.

[7] D. Brandl and C. Johnsson, “Beyond the Pyramid: Using ISA95 for Industry 4.0 and Smart Manufacturing,” Oct. 2021, accessed: 2026-03-15. [Online]. Available: https://www.isa.org/intech-home/2021/october-2021/features/beyond-the-pyramid-using-isa95-for-industry-4-0-an

[8] D. Schön and M. Drozdzynski, *Planung und Reporting im BI-gestützten Controlling: Grundlagen, Business Intelligence, Mobile BI, Big-Data-Analytics und KI [Planning and Reporting in BI-Based Controlling: Fundamentals, Business Intelligence, Mobile BI, Big Data Analytics, and AI]*, 5th ed. Wiesbaden: Springer Gabler, 2025. [Online]. Available: https://doi.org/10.1007/978-3-658-47496-6

[9] K. Suzaki, *New Shop Floor Management: Empowering People for Continuous Improvement*. Simon and Schuster, 1993.

[10] C. Hertle, M. Tisch, H. Kläs, J. Metternich, and E. Abele, “Recording Shop Floor Management Competencies – A Guideline for a Systematic Competency Gap Analysis,” *Procedia CIRP*, vol. 57, pp. 625–630, Jan. 2016.

[11] M. Rossini, F. Costa, G. L. Tortorella, and A. Portioli-Staudacher, “The interrelation between Industry 4.0 and lean production: an empirical study on European manufacturers,” *The International Journal of Advanced Manufacturing Technology*, vol. 102, no. 9, pp. 3963–3976, 2019.

[12] G. L. Tortorella and D. Fettermann, “Implementation of Industry 4.0 and lean production in Brazilian manufacturing companies,” *International Journal of Production Research*, vol. 56, no. 8, pp. 2975–2987, Apr. 2018.

[13] L. Longard, S. Bardy, and J. Metternich, “Towards a Data-driven Performance Management in Digital Shop Floor Management,” *Proceedings of the Conference on Production Systems and Logistics: CPSL 2022*, pp. 111–120, 2022.

[14] E. Adeniran, Osundare, P. Abhulimen, and A. Abhulimen, “Integrating business intelligence and predictive analytics in banking: A framework for optimizing financial decision-making,” *Finance & Accounting Research Journal*, vol. 6, no. 8, pp. 1517–1530, 2024.

[15] H.-G. Kemper, H. Baars, and W. Mehanna, *Business Intelligence – Grundlagen und praktische Anwendungen: Eine Einführung in die IT-basierte Managementunterstützung [Business Intelligence – Fundamentals and Practical Applications: An Introduction to IT- Based Management Support]*, 3rd ed., ser. SpringerLink. Wiesbaden: Vieweg+Teubner, 2010.

[16] A. L. Antunes, E. Cardoso, and J. Barateiro, “Incorporation of Ontologies in Data Warehouse/Business Intelligence Systems - A Systematic Literature Review,” *International Journal of Information Management Data Insights*, vol. 2, no. 2, p. Art. 100131, 11 2022.

[17] R. J. Mositsa, J. A. Van der Poll, and C. Dongmo, “Towards a Conceptual Framework for Data Management in Business Intelligence,” *Information*, vol. 14, no. 10, p. 547, Oct. 2023.

[18] B. K. Gaddam, “Data warehousing architecture and implementation for enhanced financial reporting: A systematic review,” *International Journal of Computer Engineering and Technology (IJCET)*, vol. 15, no. 6, pp. 751–759, 2024.

[19] F. de Assis Vilela, V. C. Times, A. C. de Campos Bernardi, A. de Paula Freitas, and R. R. Ciferri, “A non-intrusive and reactive architecture to support real-time ETL processes in data warehousing environments,” *Heliyon*, vol. 9, no. 5, p. e15728, 2023.

[20] J. Kaiser, D. McFarlane, G. Hawkridge, P. André, and P. Leitão, “A review of reference architectures for digital manufacturing: Classification, applicability and open issues,” *Computers in Industry*, vol. 149, pp. 1–15, Aug. 2023.

[21] L. Kassner et al., “The Stuttgart IT Architecture for Manufacturing,” in *Enterprise Information Systems*, S. Hammoudi, L. A. Maciaszek, M. M. Missikoff, O. Camp, and J. Cordeiro, Eds. Cham: Springer International Publishing, 2017, pp. 53–80.

[22] P. Gölzer, “Big Data in Industrie 4.0. Eine strukturierte Aufarbeitung von Anforderungen, Anwendungsfällen und deren Umsetzung [Big Data in Industry 4.0 - A structured preparation of requirements, use cases and implementation],” 2017, accessed: 2026-03-15. [Online]. Available: https://open.fau.de/handle/openfau/8106

[23] M. Moghaddam, M. N. Cadavid, C. R. Kenley, and A. V. Deshmukh, “Reference architectures for smart manufacturing: A critical review,” *Journal of Manufacturing Systems*, vol. 49, pp. 215–225, Oct. 2018.

[24] Y. Lu, F. Riddick, and N. Ivezic, “The Paradigm Shift in Smart Manufacturing System Architecture,” in *Advances in Production Management Systems. Initiatives for a Sustainable World*, I. Nääs, O. Vendrametto, J. Mendes Reis, R. F. Gonçalves, M. T. Silva, G. von Cieminski, and D. Kiritsis, Eds. Cham: Springer International Publishing, 2016, pp. 767–776.

[25] MESA, “SOA in Manufacturing Guidebook. WHITE PAPER 27 - A MESA International, IBM Corporation and Capgemini co-branded white paper. 05.21.08,” 2008, accessed: 2026-03-15. [Online]. Available: https://public.dhe.ibm.com/software/plm/pdif/MESA_SOAinManufacturingGuidebook.pdf

[26] F. Bertagnolli, *Shop Floor Management*. Wiesbaden: Springer Fachmedien, 2022, pp. 327–348.

[27] International Organization for Standardization, *ISO 22400-2:2014 Automation systems and integration — Key performance indicators (KPIs) for manufacturing operations management — Part 2: Definitions and descriptions*, International Organization for Standardization International Standard ISO 22 400-2:2014, 2014.

[28] M. Franco-Santos, L. Lucianetti, and M. Bourne, “Contemporary performance measurement systems: A review of their consequences and a framework for research,” *Management Accounting Research*, vol. 23, no. 2, pp. 79–119, 2012.

Self-Service Business Intelligence Adoption and Value Realization: A Mixed-Methods Analysis of Drivers, Barriers, and Governance Implications

Maik Drozdzynski
IU International University of Appl. Sc.
Erfurt, Thüringen, Germany
email: maik.drozdzynski@iu.org

Alexander Lawall
IU International University of Appl. Sc.
Erfurt, Thüringen, Germany
email: alexander.lawall@iu.org

Olajide Idowu
Jireh Computer Solutions
Lagos, Nigeria
email: olajideidowu@jirehcomputers.com

***Abstract*—Self-Service Business Intelligence (SSBI) is widely promoted as a means to accelerate decision-making and democratize analytics beyond centralized IT units, yet cross-industry empirical evidence on adoption mechanisms and governance constraints remains limited. This study investigates the conditions under which SSBI is sustainably adopted and how value is realized across sectors in an emerging market context. Grounded in the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI), the research examines adoption drivers, implementation challenges, measurable performance effects, and effective integration strategies. A convergent mixed-methods design combines a stratified survey (N=101) with qualitative case studies and thematic analysis. Results identify perceived usefulness, particularly improved agility and decision-making speed, as the primary adoption driver. However, diffusion intensity is shaped by governance maturity, legacy integration, and regulatory constraints. The findings extend TAM and DOI by embedding individual acceptance within governance-constrained BI environments and provide actionable guidance for structured enablement, semantic governance, and phased architectural roll-out.**

Keywords-self-service business intelligence; data democratization; technology acceptance model; diffusion of innovations; data governance.

I. INTRODUCTION

In today's data-driven era, organizations increasingly rely on technology to foster innovation, improve efficiency, and sustain competitive advantage. Business Intelligence (BI), which emerged from early decision support and data processing systems, has evolved substantially over the past decades. A pivotal milestone in this evolution was the emergence of data warehousing, which established centralized data integration to enable systematic analysis of historical information for strategic decision-making [1]. By the 1990s, BI ecosystems matured further, but many implementations positioned IT departments as gatekeepers of data access, reporting, and dashboard development. While these centralized approaches improved robustness and standardization, they were also associated with delayed reporting cycles, limited accessibility for non-technical users, and organizational bottlenecks stemming from IT dependency [2]. As globalization and market dynamics intensified in the 2000s, organizations increasingly demanded more agile analytics capabilities. This demand contributed to the shift toward SSBI, which this study conceptualizes as a set of tools and practices enabling users, regardless of technical background, to access, visualize, and analyze data with reduced reliance on central IT functions. In contrast, self-service analytics can be viewed as a subset emphasizing advanced techniques, such as predictive analytics and interactive dashboards. From an architecture point of view, SSBI is the user-facing frontend part of an entire BI-solution and hides the technical backend containing especially database structures from the user and encapsulates technical functions in a good working user interface [3].

This distinction highlights that SSBI represents a broader organizational approach to democratizing data access and accelerating decision-making [4] [5].

The remainder of this paper is structured as follows. Section II articulates the research gap and positions the study within the existing body of SSBI and adoption literature. Section III develops the theoretical foundation by synthesizing the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), and the concept of data democratization. Section IV presents the research methodology, detailing the convergent mixed-methods design, data collection procedures, and analytical approach. Section V reports the empirical results across the four research questions. Section VI interprets the theoretical and practical findings, deriving implementation implications and a structured Strengths, Weaknesses, Opportunities, and Threats (SWOT) synthesis. Section VII discusses limitations and avenues for future research. Finally, Section VIII concludes the paper by summarizing the central contributions and outlining strategic directions for sustainable SSBI adoption.

II. RESEARCH GAP AND CONTRIBUTION

BI has long been shaped by centralized data warehousing and IT-mediated reporting, which provide standardization but often create bottlenecks, delayed information availability, and limited accessibility for non-technical users [1] [2]. In response, SSBI has gained traction as organizations seek faster decision cycles and broader access to insights, supported by platform trends, such as cloud delivery and AI-enabled analytics. However, the literature still shows relevant gaps because cross-industry comparative evidence remains limited. Socio-technical constraints, such as governance, security, training and legacy integration, are frequently discussed but not consistently connected to adoption mechanisms. Finally, the translation from adoption theory to actionable, validated implementation strategies is still underdeveloped [6] [7]. This paper addresses the overarching question: under which conditions is SSBI sustainably adopted, which benefits and barriers emerge across industries, and which design and implementation measures (e.g., training, governance, integration and change enablement) are required to realize value? Building on the TAM to explain individual acceptance and DOI to explain organizational diffusion, we structure the study around four research questions:

RQ1 What drivers influence SSBI adoption (individual and organizational)?
RQ2 Which benefits and implementation challenges dominate (e.g., governance, security, training, legacy integration)?
RQ3 Which measurable effects are associated with SSBI use in terms of decision-making and collaboration?
RQ4 Which strategies support effective implementation and integration across contexts?

The answers to these research questions are followed by the derivation of a SWOT analysis of SSBI implementation for practical application. Beyond traditional BI adoption research, SSBI adoption increasingly intersects with broader digital transformation and data governance debates. Recent literature emphasizes that democratized analytics environments require new governance mechanisms, including semantic standardization, stewardship roles, and controlled data access frameworks. Consequently, SSBI adoption cannot be interpreted solely as a technological diffusion process, but rather as part of a wider organizational transformation toward data-driven decision-making capabilities.

We employ a mixed-methods design to capture both cross-sectional patterns and context-dependent mechanisms of SSBI adoption [8]. The qualitative strand uses multiple case studies across industries and semi-structured interviews to elicit drivers, realized benefits, and barriers, followed by thematic analysis to derive recurring themes and explanatory mechanisms [9]. The quantitative strand uses an online survey with Likert-scale items to measure adoption, perceived impact (e.g., decision-making speed, cross-functional collaboration) and challenges. Respondents are selected via stratified random sampling to represent both technical and non-technical roles (as operationalized in the study). Survey data are analyzed using descriptive statistics and correlation analysis to identify relationships between adoption-related constructs and outcome proxies. The findings are validated through methodological triangulation by integrating convergent and divergent evidence across qualitative and quantitative results.

III. Foundations in TAM, DOI and Data Democratization

A. Technology Acceptance Model - TAM

To explain adoption mechanisms, we draw on two established perspectives. The TAM links usage to Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which is especially relevant for SSBI tools designed for non-technical users [6]. PU is defined as the extent to which a user believes that using a particular technology will enhance their job performance. In the context of self-service BI, this might encompass how users view tools, such as Power BI or Tableau, in terms of improving decision-making processes and streamlining complex analytical tasks. PEOU refers to the degree to which a user finds a technology easy to operate. Tools that boast intuitive interfaces, short learning curves, and seamless integration are typically more readily adopted. For example, Malatji et al. [10] emphasize that PEOU plays a crucial role in reducing adoption resistance, particularly for non-technical users.

B. Diffusion of Innovations - DOI

The DOI model explains how innovations spread within social systems over time and highlights attributes, such as relative advantage, compatibility, complexity, trialability, and observability, as key drivers [7]. Together, TAM and DOI support an integrated view that covers both individual acceptance and organization-level diffusion of SSBI initiatives.

SSBI value realization is frequently constrained by socio technical barriers. Data governance and data quality become more critical as analytical autonomy increases, because inconsistent definitions and uncontrolled data preparation can undermine trust in results. Security and compliance requirements can restrict access and require role-based controls and auditability. Training and data literacy remain prerequisites for meaningful self-service usage. Integration with heterogeneous application landscapes, especially legacy environments, can add technical friction that interacts with governance and capability constraints. These barrier categories are widely discussed in SSBI research and practice and they provide a structured lens to interpret adoption challenges and derive implementation strategies.

C. Data Democratization

Data democratization, describes the deliberate shift from centralized, IT controlled access to broader, role appropriate access to data and analytics across the organization [2]. Its purpose is to shorten the path from business question to actionable insight by enabling users to explore and visualize trusted data without constant IT mediation. This shift has been accelerated by modern BI platforms and delivery models that emphasize usability, scalability, and cloud enabled distribution of analytics capabilities. Democratization matters because centralized BI delivery can become a bottleneck when demand for insights grows faster than the capacity of central teams, which can slow decision cycles and reduce responsiveness.

The main benefits typically include higher flexibility in analysis and faster insight generation (see Figure 1), which can improve coordination across functions and support quicker operational decisions [11]. However, democratization also increases the need for stronger data governance, since broader autonomy can lead to inconsistent definitions, uncontrolled data preparation, and reduced trust in results if ownership and standards are unclear [12]. Security and compliance requirements can become more challenging because wider access expands the potential attack surface and increases the

Copyright (c) IARIA, 2026. ISBN: 978-1-68558-380-4

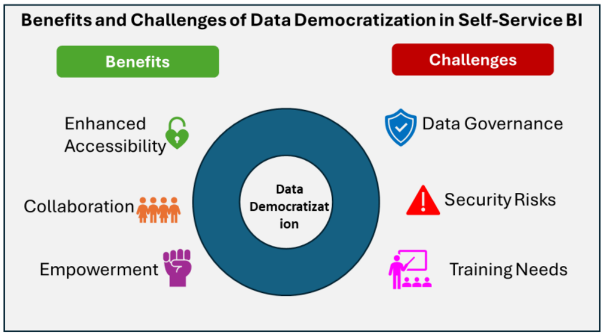

Figure 1. Benefits and Challenges of Data Democratization

importance of access control, auditing, and policy enforcement [13]. Another recurring challenge is capability building, since effective self-service depends on data literacy and tool proficiency, which often requires structured training and ongoing enablement [14]. Taken together, the findings suggest that SSBI implementation reshapes decision rights, accountability structures, and data ownership practices within organizations. Rather than functioning purely as a technological enhancement, SSBI alters how analytical responsibilities are distributed and governed across departments [12]. A practical way to frame the trade-off is that democratization increases speed and autonomy, but it must be paired with governance, security by design, and training to keep data valid, trusted, and compliant [14].

D. Operationalization of Technology Acceptance Model and Diffusion of Innovations Constructs

The study operationalized key constructs from TAM and DOI using multi-item Likert scales (1 = strongly disagree, 5 = strongly agree) to empirically ground the theoretical framework.

PU was measured using items assessing the extent to which SSBI improves decision-making speed, operational efficiency, and analytical effectiveness.

PEOU was operationalized through items measuring usability, learning effort, and interface intuitiveness.

From DOI, the following constructs were operationalized:

- Relative Advantage: perceived performance and agility improvements,
- Compatibility: alignment with existing workflows and data environments,
- Complexity: perceived integration and governance difficulty,
- Observability: visibility of benefits across departments.

All items were adapted from validated TAM and innovation diffusion scales and contextualized for SSBI environments. Composite scores were computed by averaging respective item groups.

IV. RESEARCH METHODOLOGY

We use a mixed methods design to study SSBI adoption because the topic involves both measurable adoption patterns and context-dependent organizational mechanisms [15]. Integration follows a convergent logic in which qualitative and quantitative evidence are compared and interpreted together to strengthen inference through triangulation [16].

The qualitative part consists of multiple case studies and semi-structured interviews with BI stakeholders to capture sector-specific drivers, benefits, and implementation barriers. Case study logic supports analytic generalization across contexts rather than statistical generalization [17]. Interview data and case notes are analyzed using thematic analysis, moving from familiarization to coding and theme development to produce cross-case patterns that map to the research questions. The semi-structured interviews lasted between 30 and 60 minutes and were conducted with BI managers, data analysts, and operational decision-makers. Thematic analysis followed the six-step procedure proposed by Braun and Clarke [9]: familiarization with the data, initial coding, theme identification, theme review, theme definition, and reporting. Two researchers independently coded a subset of transcripts to ensure interpretative consistency. Discrepancies were discussed and resolved to refine the coding scheme and strengthen analytic reliability. Cross-case comparison was then performed to identify recurring adoption patterns and sector-specific contextual mechanisms.

The quantitative strand uses an online survey with Likert-type items to measure adoption status, proxies for perceived usefulness and ease of use, perceived benefits, and barriers, such as governance, security, training, and legacy integration. Likert instruments are widely used for attitudinal measurement, though they can introduce information loss and bias that must be considered when interpreting the results [18]. To ensure coverage of diverse perspectives, participants are selected through stratified random sampling, ensuring representation of both technical and non-technical roles [19]. Data are analyzed using descriptive statistics and association analysis to identify patterns and relationships relevant to the research questions [20]. Participation is voluntary and based on informed consent. Data are anonymized and reported in aggregate form to protect participants and organizations, consistent with established qualitative research ethics practice [21].

Reliability and Validity Assessment: The internal consistency of the multi-item constructs was examined to ensure coherent measurement of the theoretical dimensions. The results indicate that the survey items demonstrated satisfactory consistency across constructs. Construct validity was assessed by evaluating whether items aligned clearly with their intended conceptual dimensions. The analysis confirmed that items were predominantly associated with their respective constructs, supporting the conceptual clarity of the measurement model. Given the exploratory design and the moderate sample size, the analysis emphasizes methodological transparency and robustness while avoiding unnecessary model complexity. In addition to descriptive statistics, exploratory correlation analysis was performed to examine relationships between TAM constructs (PU, PEOU) and perceived performance outcomes, such as decision-making speed and collaboration. The analysis

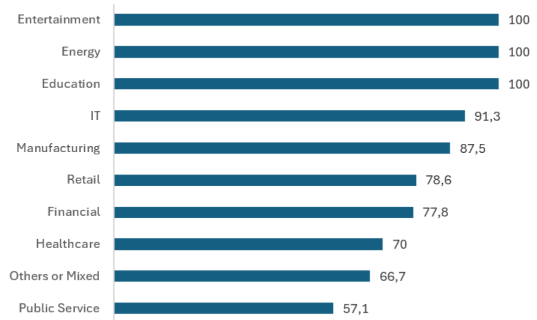

Figure 2. User Adoption Rate across Sectors

indicated positive associations between perceived usefulness and reported decision-making improvements, supporting the theoretical expectations derived from TAM.

V. Research Results

A. Sample and overall Adoption

The quantitative dataset includes 101 completed survey responses across multiple industries, including Fast-Moving Consumer Goods (FMCG), Healthcare, Manufacturing, IT, Financial Services, Retail, Public Service, Energy, and others. Sectoral differences were examined using descriptive comparisons of adoption rates and reported challenges across industry categories. This exploratory comparison approach allows identification of patterns and contextual differences, although the limited sample size prevents robust statistical testing of sector effects.

A large majority of respondents reported active use of self-service BI tools, with overall adoption exceeding 80% in the sample. Figure 2 illustrates the distribution of adoption rates across sectors, highlighting higher diffusion levels in IT and Manufacturing and comparatively lower adoption in Public Service and Healthcare.

B. Results for RQ1–Drivers of SSBI adoption

Respondents reported that the most important adoption driver was the need for agility, cited by 74%, followed by technological advancements at 68%, cost reduction at 53%, and competitive pressures at 37% (see Table I).

TABLE I
Drivers of SSBI Adoption

Driver	*Percentage of Mentions (%)*
Competitive Pressure	37
Cost Reduction	53
Technology Advancements	68
Need for Agility	74

These driver patterns are consistent with the high share of organizations reporting active SSBI use and with case based descriptions that emphasize operational agility and forecasting in FMCG and manufacturing settings.

C. Results for RQ2–Benefits and Implementation Challenges

A key reported benefit is faster decision-making after SSBI adoption, reflected in a strong shift in decision speed ratings from pre-adoption to post adoption. In addition, respondents reported operational improvements, including reductions in waste of 15-25% and a productivity increase of around 20% post-adoption, as summarized in the quantitative results. These performance improvements are based on self-reported managerial estimates comparing perceived pre- and post-adoption conditions. While indicative of operational gains, these figures should be interpreted cautiously due to potential response bias and the absence of audited financial validation.

TABLE II
Challenges in SSBI Adoption

Challenge	*Percentage of Mentions (%)*
Training Gaps	58
Legacy System Integration	45
Data Governance	41
Resistance to Change	32
Security Concerns	27

Regarding challenges among adopters (see Table II, respondents reported training gaps (58%), legacy system integration (45%), data governance (41%), resistance to change (32%), and security concerns (27%). The results also note sector differences in perceived severity, with lower challenge severity in FMCG and Retail contexts that reported structured onboarding, and greater difficulty in healthcare and financial services contexts that face tighter regulation and legacy constraints. In general, those findings correlate with the challenges of data democratization mentioned in Figure 1 and discussed by Achanta et al. [11].

D. Results for RQ3–Effects on decision-making and collaboration

The Decision-making speed improved significantly after SSBI adoption. Ratings of the decision quality category “Poor” decreased from 30% to 5%, and ratings of “Fair” decreased from 25% to 10%. Ratings of “Very Good” increased from 15% to 35%, and ratings of the category “Excellent” increased from 10% to 30%, while “Good” remained at 20%. The findings also report that 75% of users rated decision-making speed as “Very Good” or “Excellent” following adoption. The results indicate that the use of SSBI leads to a transition from poor decision quality to substantially improved decision quality.

E. Results for RQ4–Non-adoption factors

Among non-adopters, findings indicate that high initial costs at 36%, security and data governance concerns at 29%, and limited internal expertise at 24% are the leading barriers, followed by lack of executive buy-in at 20% and scalability concerns at 15%. A sector-specific breakdown of non-adoption reasons (see Figure 3) shows that high costs are the overall top factor for not introducing SSBI, especially in healthcare at 30% and retail at 25%, and that security concerns reach 28% in financial and public service contexts.

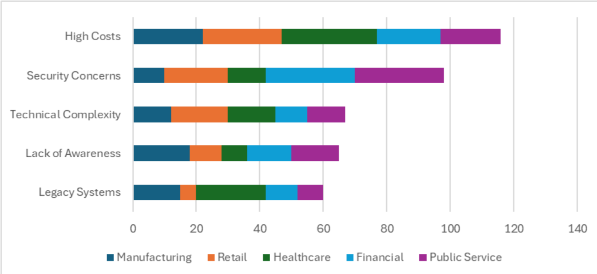

Figure 3. Factors for non-Adoption

VI. Discussion

1) Interpreting adoption drivers through TAM and DOI: The results indicate that SSBI adoption is primarily justified through agility, technology advancement, and cost-related expectations. From a TAM perspective, this pattern aligns with perceived usefulness as the dominant acceptance mechanism, as respondents associate SSBI with faster decision-making and operational improvements rather than with technical novelty. From a DOI perspective, agility and competitiveness map to relative advantage, while the sector differences in adoption suggest that compatibility with existing processes and data environments influences diffusion across industries. The sector view also indicates that diffusion is not only a tool decision, it is also shaped by organizational readiness and by how visible the benefits become to potential adopters, which relates to observability and trialability.

2) BI democratization as value promise and as operating model change: The findings support the view that BI democratization is pursued primarily to reduce analytical bottlenecks and enable faster decision-making closer to operational contexts [2]. However, democratization introduces governance challenges that must be addressed to maintain data trust and analytical consistency. This implies that strategic steering instruments, such as multidimensional controlling frameworks that integrate performance and cyber-risk perspectives, can support this governance shift and provide C-level transparency in democratized BI environments [22]. Increased autonomy requires clearly defined metric ownership, standardized semantic layers, and robust data stewardship mechanisms [12]. Thus, SSBI should not be interpreted merely as a technological capability but as an organizational operating model that redistributes analytical responsibilities across business units.

3) Barriers as socio technical constraints and how they explain sector differences: The most frequently reported implementation challenges cluster around training, legacy integration, and governance. These barriers align with the socio-technical nature of SSBI, where user experience and organizational environment jointly determine success. Training gaps directly limit perceived ease of use and reduce confidence in independent analysis, thereby weakening acceptance even when tools are intuitively designed. Legacy integration and governance complexity increase perceived complexity and reduce compatibility, slowing diffusion across units and creating uneven scaling within organizations. Security concerns, while not always the top barrier, remain structurally important because broader access increases exposure and the need for role-based controls and auditing to maintain compliance. Taken together, these constraints explain why some sectors show higher non-adoption rates despite the general attractiveness of SSBI: regulated contexts and legacy-heavy environments face a higher burden of governance and integration work before democratization becomes safe and trusted.

4) Practical implications for implementation and SWOT Analysis: The results suggest that implementation should focus on three linked workstreams. The first is enablement. Organizations should establish tiered training that starts with core data literacy and tool basics, then progresses to advanced analytics patterns for power users. This directly addresses training gaps and supports sustainable self-service usage. The second is governance. A pragmatic governance setup should define metric ownership, approved datasets, and standard semantic definitions, and support lightweight stewardship roles that enable democratization while protecting trust. The third is architecture and integration. Organizations should adopt a phased rollout that starts with a limited number of high-value use cases and expands once data pipelines and access controls are stable, thereby increasing trialability and observability and supporting faster diffusion. Where security and compliance constraints are strong, the governance workstream must include role-based access controls, logging, and auditability as baseline requirements for democratized analytics. Industry trend reports also indicate that modern platform capabilities, including cloud delivery and AI-enabled features, can lower friction, but they do not replace the need for governance and enablement as core success factors. The major findings are summarized in a SWOT Analysis chart in Figure 4, which helps to develop an SSBI approach in a company.

5) Theoretical Contribution: This study provides one of the first cross-industry empirical examinations of SSBI adoption in an emerging market context and embeds individual acceptance mechanisms within governance-constrained BI environments. While TAM explains adoption primarily through perceived usefulness, the results indicate that diffusion across sectors depends on structural conditions, such as governance arrangements, regulatory intensity, and legacy system compatibility.

Furthermore, in regulated industries, compatibility and complexity attributes from DOI appear more influential than relative advantage alone, contextualizing innovation diffusion within compliance-intensive environments.

VII. Limitations and Future Research

This study employs a cross-sectional mixed-methods design, limiting causal inference. While analysis identifies significant associations, longitudinal designs would be required to establish directionality. The quantitative data relies on self-reported measures, which may introduce response bias. Future research should incorporate objective performance metrics. Although the sample spans multiple industries, the empirical context is limited to Nigeria. Institutional and regulatory

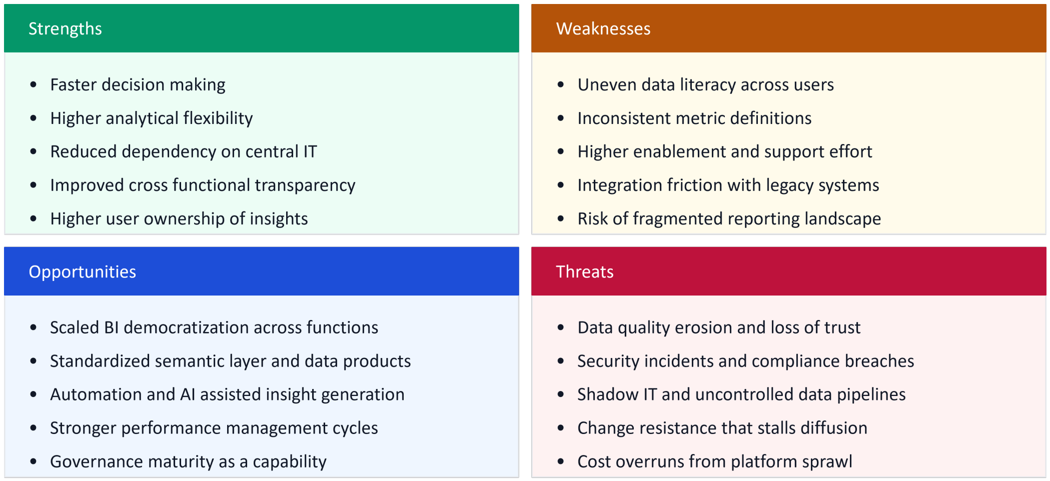

Figure 4. Final SWOT Analysis

differences may limit generalizability. This suggests several methodological and theoretical extensions. Future research should apply confirmatory factor analysis (CFA) and structural equation modeling (SEM) to validate theoretical relationships and explore governance maturity as a measurable moderating construct.

VIII. Conclusion

This study examined SSBI adoption and value realization across industries in an emerging market context using a convergent mixed-methods design (N = 101). The results demonstrate that perceived usefulness is the primary driver of adoption, while implementation challenges cluster around training, governance, and legacy integration constraints.

In synthesis, SSBI adoption represents a socio-technical transformation that reshapes how analytical responsibilities, decision authority, and governance mechanisms are distributed within organizations. While individual acceptance factors explain initial uptake, sustainable diffusion depends on structured enablement, consistent semantic governance, and security-by-design principles. The strategic challenge is therefore not whether to democratize analytics, but how to institutionalize controlled autonomy within a scalable governance architecture.

References

[1] W. H. Inmon, *Building the Data Warehouse*, 4th ed. John Wiley & Sons, 2005.

[2] H. J. Watson and B. H. Wixom, "The Current State of Business Intelligence," *Computer*, vol. 40, no. 9, pp. 96–99, 2007.

[3] D. Schön and M. Drozdzynski, *Planung und Reporting im BI-gestützten Controlling: Grundlagen, Business Intelligence, Mobile BI, Big-Data-Analytics und KI [Planning and Reporting in BI-supportet Controlling. Foundations, Business Intelligence, Mobile BI, Big-Data-Analytics]*, 5th ed. Wiesbaden: Springer Fachmedien Wiesbaden, 2025.

[4] R. Kandaswamy et al., "Top trends for tech providers for 2023," Gartner, Tech. Rep. G00779442, Jan. 2023.

[5] Gartner, "Magic quadrant for analytics and business intelligence platforms," Gartner, Tech. Rep., 2023.

[6] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989.

[7] E. M. Rogers, *Diffusion of Innovations*, 5th ed. New York: Free Press, 2003.

[8] J. W. Creswell and J. Creswell, *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage Publications, 2017.

[9] V. Clarke and V. Braun, "Thematic analysis," *The Journal of Positive Psychology*, vol. 12, no. 3, pp. 297–298, 2017.

[10] W. R. Malatji, R. V. Eck, and T. Zuva, "Understanding the usage, Modifications, Limitations and Criticisms of Technology Acceptance Model (TAM)," *Advances in Science, Technology and Engineering Systems Journal*, vol. 5, no. 6, pp. 113–117, 2020.

[11] A. Achanta, "Data democratization: Empowering non-technical users with self-service bi tools to access and analyze data without heavy reliance on it teams," *International Journal of Computer Trends and Technology*, vol. 71, no. 8, pp. 39–46, 2023.

[12] J. Stamp and S. Mwapwele, "Examining data governance to determine how democratic data management can be achieved in organizations," in *Annual Conference of the South African Institute of Computer Scientists and Information Technologists*. Springer Nature, 2024, pp. 421–436.

[13] S. Kumar, W. M. Lim, R. Sureka, C. J. C. Jabbour, and U. Bamel, "Balanced scorecard: Trends, developments, and future directions," *Review of managerial science*, vol. 18, no. 8, pp. 2397–2439, 2024.

[14] T. M. Takang and A. Amaechi, "Considerations for a planned democratizing data framework for valid and trusted data," *Journal of Data Analysis and Information Processing*, pp. 240–261, 2023.

[15] S. Bischoff, S. Aier, M. K. Haki, and R. Winter, "Understanding continuous use of business intelligence systems: A mixed methods investigation," *Journal of Information Technology Theory and Application (JITTA)*, pp. 5–38, 2015.

[16] M. D. Fetters, L. A. Curry, and J. W. Creswell, "Achieving integration in mixed methods designs: Principles and practices," *Health Services Research*, vol. 48, no. 6 Pt 2, pp. 2134–2156, 2013.

[17] R. K. Yin, *Case Study Research: Design and Methods*, 4th ed. SAGE Publications, 2009.

[18] J. C. Westland, "Information loss and bias in likert survey responses," *PLOS ONE*, vol. 17, no. 7, pp. 1–17, 2022.

[19] K. Iqbal, S. M. M. Raza, T. Mahmood, and M. Riaz, "Exploring mixture estimators in stratified random sampling," *PLOS ONE*, vol. 19, no. 9, pp. 1–21, 2024.

[20] A. Bryman, *Social Research Methods*, 4th ed. Oxford University Press, 2012.

[21] J. W. Creswell and C. N. Poth, *Qualitative Inquiry and Research Design: Choosing Among Five Approaches*, 4th ed. SAGE Publications, 2016.

[22] A. Lawall and M. Drozdzynski, "The Balanced Chance & Cyber-Risk Card: Extending Reichmann's Multidimensional Controlling Framework for C-Level Steering in SMEs," in *The Nineteenth International Conference on Emerging Security Information, Systems and Technologies (SECURWARE) 2025*, 2025, pp. 76–82.

Copyright (c) IARIA, 2026. ISBN: 978-1-68558-380-4

What Drives Business Intelligence Satisfaction and Expansion? An Empirical Study of Swiss Companies

Viktoriia Apakova
School of Management Fribourg
University of Applied Sciences and Arts Western Switzerland
Fribourg, Switzerland
e-mail: viktoriia.apalkova@hefr.ch

***Abstract*—Business Intelligence (BI) tools are widely adopted to support decision-making and operational efficiency; however, empirical evidence on the factors driving BI satisfaction and future expansion remains limited, particularly in small and open economies, such as Switzerland. This study examines the technological and organizational determinants of BI user satisfaction and intentions to expand BI usage in Swiss companies. Drawing on the Technology–Organization–Environment (TOE) framework, the study analyzes data from a quantitative survey of employees in Swiss firms across multiple industries. Correlation and multiple regression analyses show that BI satisfaction is primarily driven by real-time data access, data visualization, mobile usability, and strategic alignment focused on decision-making, while excessive alerts and notifications have a negative effect on satisfaction. In contrast, BI expansion intentions are influenced by data visualization, cost-effectiveness, system integration, and industry technology intensity, whereas training and support challenges act as barriers to further adoption. The findings demonstrate that BI satisfaction and BI expansion are distinct but related post-adoption outcomes shaped by different drivers. The study contributes region-specific empirical evidence and offers practical implications for BI investment and alignment decisions.**

Keywords-business intelligence; analytics adoption; Switzerland

I. Introduction

Business Intelligence (BI) remains a core component of organizational analytics, supporting structured data analysis for decision-making, performance monitoring, and operational control. Global spending on BI and analytics software exceeded USD 23 billion in 2023, underscoring the sustained strategic relevance of BI solutions across industries [1]. Despite rapid advances in artificial intelligence and advanced analytics, BI tools continue to constitute the foundation of analytics maturity by enabling transparency, governance, and standardized reporting.

Switzerland consistently ranks among global innovation leaders [2]. However, high technological capability does not automatically translate into effective BI use. Empirical evidence from other advanced economies, including Germany and the United States, highlights persistent challenges related to system integration, customization, user training, and the alignment of BI tools with organizational strategy [3]–[5]. It remains unclear whether Swiss companies face similar constraints or whether BI outcomes in this context are shaped by different technological and organizational factors.

To address this gap, the objective of this study is to identify and empirically analyze the key technological and organizational factors that influence BI user satisfaction and future BI adoption or expansion intentions in Swiss companies. By focusing on post-adoption outcomes rather than binary adoption decisions, the study provides empirical evidence to support more effective and context-sensitive BI investment and alignment decisions.

The remainder of the paper is organized as follows. In Section II, the literature overview and theoretical background are presented. In Section III, the research questions are formulated. In Section IV, the methodology, variables, and data collection and analysis procedures are described. In Section V, the empirical findings are presented. In Section VI, the main conclusions are summarized and directions for future research are outlined. The paper concludes with acknowledgments, disclosure of interests, and references.

II. Literature Overview

Business Intelligence (BI) analytics tools are information systems designed to collect, integrate, analyze, and present structured organizational data to support managerial decision-making and performance management [6]–[8]. Traditionally, BI focuses on descriptive and diagnostic analytics using structured data from enterprise resource planning (ERP), customer relationship management (CRM), and financial systems to generate reports, dashboards, and key performance indicators [9]–[11]. Although advanced analytics and artificial intelligence (AI) increasingly attract attention, BI remains the entry point and stabilizing layer of organizational analytics architectures [12]–[14].

Prior research shows that BI success depends not only on technical quality but also on organizational acceptance and strategic alignment. Information systems success studies consistently identify perceived usefulness, usability, and relevance to business goals as key drivers of user satisfaction and continued use [15][16]. In the BI context, alignment between BI functionalities—such as data visualization, integration, real-time reporting, and collaboration—and strategic objectives significantly enhances perceived value and satisfaction [17]. Conversely, misalignment leads to underutilization, dissatisfaction, and resistance to further analytics investments [18][19].

Several theoretical perspectives have been used to explain information systems adoption and use, including the Technol-

 ISBN: 978-1-68558-380-4

ogy Acceptance Model (TAM) [20], the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Resource-Based View (RBV). However, these approaches primarily focus on individual user perceptions or firm-level capabilities. In contrast, the Technology–Organization–Environment (TOE) framework [21] provides a more comprehensive perspective by integrating technological characteristics, organizational conditions, and environmental context. This makes TOE particularly suitable for analyzing post-adoption outcomes, such as user satisfaction and expansion decisions, which are shaped by multiple interacting factors.

The TOE framework has demonstrated strong explanatory power in BI and analytics research across organizational sizes and industries [22]. Recent studies further emphasize that local and regional contexts influence technology outcomes through regulatory regimes, industry structures, and organizational characteristics [23]. Switzerland's regulated environment, strong data protection norms, and small and medium-sized enterprise (SME)-dominated economy suggest distinct trade-offs in BI adoption and expansion decisions [24].

Despite its relevance, prior research has predominantly focused on initial technology adoption rather than post-adoption outcomes, and has often been conducted in large economies or specific industries. As a result, there is limited empirical evidence on how technological and organizational factors jointly shape BI satisfaction and expansion in small, highly developed economies, such as Switzerland. Furthermore, existing studies rarely distinguish between different post-adoption outcomes, such as user satisfaction and expansion intentions, which may be driven by different mechanisms.

This study addresses these gaps by applying the TOE framework to examine the determinants of BI satisfaction and expansion in Swiss companies, thereby providing context-specific insights and contributing to a more nuanced understanding of post-adoption dynamics.

III. Research Questions

Based on the research objective outlined in the Introduction, the study addresses the following research questions:

- **RQ1:** Which technological and organizational factors most strongly influence user satisfaction with Business Intelligence (BI) tools in Swiss companies?
- **RQ2:** Which technological and organizational factors most strongly influence future BI adoption or expansion intentions in Swiss companies?

IV. Method

This study employs a quantitative, cross-sectional survey design. This approach is appropriate for the research objective, as it enables the identification and statistical assessment of relationships between technological and organizational factors and BI outcomes across firms. A quantitative design allows for the measurement of multiple variables and the evaluation of their relative influence on BI satisfaction and expansion intentions. The cross-sectional design provides a snapshot of current BI practices and perceptions in Swiss companies, which is suitable for examining post-adoption outcomes in a specific context.

TABLE I. Key variables and their measurement

Variable	Type	Description
BI Satisfaction (Y_1)	Dependent	5-point Likert scale
BI Expansion (Y_2)	Dependent	Yes / No
BI Feature Importance (X_1)	Independent	Feature importance scores
Strategic Alignment (X_2)	Independent	Alignment with business goals
Company Size (M_1)	Moderator	Firm size categories
Industry Sector (M_2)	Moderator	Industry classification
Technology Intensity (M_4)	Moderator	Low / Medium / High
Region (C_1)	Control	Company location
Respondent Role (C_2)	Control	Organizational role

The analysis focuses on two dependent variables: user satisfaction with BI tools (Y_1) and future BI adoption or expansion intent (Y_2). In line with the TOE framework, BI outcomes are modeled as a function of technological and organizational factors, while accounting for moderating and control variables.

The general regression model is specified as:

$$Y_n = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{j=1}^{p} \gamma_j M_j + \sum_{l=1}^{q} \delta_l C_l + \varepsilon \quad (1)$$

All variables and measurements are summarized in Table I.

Data were collected via Qualtrics between October 2023 and February 2024. After screening, 72 observations were retained for BI satisfaction analysis and 57 for BI expansion analysis. Statistical analyses were conducted using SPSS, including descriptive statistics, correlation analysis, and multiple regression modeling.

V. Results

A. Correlation analysis

Table II reports the bivariate correlations between BI satisfaction (Y_1), future BI expansion intentions (Y_2), strategic alignment variables, BI functionalities, and selected firm characteristics. Several statistically significant relationships emerge, offering preliminary insights into the drivers of BI outcomes.

BI satisfaction is positively associated with strategic alignment aimed at improving decision-making ($r = 0.289$, $p = 0.014$), suggesting that BI tools perceived as supporting managerial decision processes are evaluated more favorably by users. In addition, data visualization ($r = 0.309$, $p = 0.008$) and collaboration features ($r = 0.253$, $p = 0.032$) show significant positive correlations with satisfaction, indicating the importance of interpretability and shared use of BI outputs. In contrast, alerts and notifications ($r = -0.304$, $p = 0.009$) and BI tool categories ($r = -0.360$, $p = 0.002$) are negatively correlated with satisfaction, suggesting potential issues related to information overload or tool–user mismatch.

Future BI expansion intentions (Y_2) are most strongly correlated with data visualization ($r = 0.403$, $p = 0.002$), data integration ($r = 0.348$, $p = 0.008$), and integration with other systems ($r = 0.281$, $p = 0.034$). In addition, monitoring financial performance ($r = 0.276$, $p = 0.038$) and cost-effectiveness ($r = 0.272$, $p = 0.041$) are positively related to expansion plans, indicating that both strategic relevance and economic considerations shape forward-looking BI decisions.

Several features—such as predictive analytics, mobile access, scalability, and industry-level characteristics—do not exhibit significant correlations with either outcome, suggesting a more limited role in this sample. Overall, the correlation analysis indicates that different BI features matter for satisfaction and expansion, justifying separate multivariate models for Y_1 and Y_2.

TABLE II. BIVARIATE CORRELATIONS WITH BI SATISFACTION AND BI EXPANSION.

Variable	Y_1	Y_2
BI expansion plans (Y_2)	0.23	1.00
Improve decision-making	0.29*	0.04
Monitor financial performance	−0.06	0.28*
Data integration	0.20	0.35**
Data visualization	0.31**	0.40**
Alerts & notifications	−0.30**	0.16
Data security & compliance	0.24*	0.20
Cost-effectiveness	0.15	0.27*
System integration (CRM/ERP)	0.09	0.28*
Collaboration	0.25*	0.16
BI tools used	−0.36**	0.04

Notes: Pearson correlations reported. Y_1 = BI satisfaction ($N = 72$), Y_2 = BI expansion intention ($N = 57$). $^*p < 0.05$, $^{**}p < 0.01$.

B. Model 1: Determinants of BI tool satisfaction

Model 1 examines the determinants of user satisfaction with BI tools. The final specification explains 46.4% of the variance in BI satisfaction ($R^2 = 0.464$; Adjusted $R^2 = 0.386$), indicating substantial explanatory power (Table III).

TABLE III. REGRESSION RESULTS FOR MODEL 1 (BI SATISFACTION).

Variable	β (SE)	Std. Coef.	p
Constant	1.923 (0.310)	—	< .001
Improve decision-making	0.208 (0.119)	0.183	0.086
Data visualization	0.133 (0.062)	0.232	0.038
Mobile access	0.162 (0.063)	0.299	0.013
Alerts & notifications	−0.264 (0.071)	−0.461	< .001
Training & support	−0.133 (0.071)	−0.213	0.066
Customization	−0.118 (0.068)	−0.191	0.088
Real-time updates	0.278 (0.076)	0.466	< .001
Industry sector	0.129 (0.049)	0.253	0.012
BI tools used	−0.101 (0.069)	−0.155	0.151

Notes: Dependent variable: BI satisfaction (Y_1). Unstandardized coefficients reported with standard errors in parentheses.

Among technological factors, real-time updates and data refresh emerge as the strongest positive predictor of satisfaction ($\beta = 0.466$, $p < 0.001$), followed by mobile access ($\beta = 0.299$, $p = 0.013$) and data visualization ($\beta = 0.232$, $p = 0.038$). These results highlight the importance of timely, accessible, and interpretable information for positive BI user experiences.

In contrast, alerts and notifications have a strong negative effect on satisfaction ($\beta = -0.461$, $p < 0.001$), suggesting that excessive or poorly designed alert mechanisms may reduce perceived usefulness. Training and support and customization also display negative but marginally significant effects, indicating that implementation complexity or unmet expectations may undermine satisfaction.

From an organizational perspective, strategic alignment focused on decision-making improvement shows a positive, albeit marginal, effect ($\beta = 0.183$, $p = 0.086$). In addition, industry sector is a significant moderator ($\beta = 0.253$, $p = 0.012$), suggesting that satisfaction levels vary systematically across industries. Multicollinearity diagnostics confirm acceptable VIF values, supporting model robustness.

C. Model 2: Factors influencing BI future expansion

Model 2 analyzes the determinants of future BI adoption or expansion intentions. The model explains 50.5% of the variance in expansion plans ($R^2 = 0.505$; Adjusted $R^2 = 0.370$), indicating slightly higher explanatory power than the satisfaction model (Table IV).

TABLE IV. REGRESSION RESULTS FOR MODEL 2 (BI FUTURE EXPANSION).

Variable	β (SE)	Std. Coef.	p
Constant	−0.313 (0.320)	—	0.333
Monitor financial performance	0.221 (0.113)	0.221	0.056
Identify growth opportunities	−0.295 (0.177)	−0.189	0.102
Data integration	0.102 (0.070)	0.218	0.154
Data visualization	0.217 (0.068)	0.461	0.003
Predictive analytics	−0.116 (0.067)	−0.228	0.091
Mobile access	−0.106 (0.054)	−0.251	0.058
Alerts & notifications	0.133 (0.059)	0.298	0.028
Cost-effectiveness	0.157 (0.061)	0.333	0.014
Training & support	−0.145 (0.062)	−0.299	0.024
Scalability	−0.120 (0.061)	−0.233	0.058
Technology intensity	0.122 (0.064)	0.221	0.062
Company region	−0.083 (0.070)	−0.136	0.244

Notes: Dependent variable: BI future expansion intention (Y_2). Unstandardized coefficients reported with standard errors in parentheses.

The most influential predictor is data visualization ($\beta = 0.461$, $p = 0.003$), underscoring its role not only in current satisfaction but also in motivating further BI investment. Cost-effectiveness ($\beta = 0.333$, $p = 0.014$) and alerts and notifications ($\beta = 0.298$, $p = 0.028$) also positively influence expansion intentions, suggesting that firms consider both economic feasibility and operational monitoring capabilities when planning BI growth.

In contrast, training and support negatively affect expansion decisions ($\beta = -0.299$, $p = 0.024$), indicating that perceived implementation or skill-related barriers may discourage further adoption. Several technological features—including predictive analytics, mobile access, and scalability—exhibit negative but marginal effects, suggesting that complexity or maturity requirements may delay expansion.

Among contextual factors, industry technology intensity shows a positive, marginally significant effect ($\beta = 0.221$, $p = 0.062$), implying that firms in more technology-intensive environments are more inclined to expand BI usage. Company region does not exert a significant influence.

D. Regression analysis summary

Table V summarizes the regression results for both models. Both Model 1 and Model 2 are statistically significant ($p < 0.001$), with Model 2 exhibiting slightly higher explanatory power. ANOVA results (Table VI) further confirm model robustness.

TABLE V. SUMMARY OF REGRESSION RESULTS FOR BI SATISFACTION AND BI FUTURE EXPANSION.

Model	R	R^2	Adj. R^2	SE	F
BI satisfaction (M1)	0.681	0.464	0.386	0.436	5.97***
BI future expansion (M2)	0.711	0.505	0.370	0.353	3.74***

Note: $^{***}p < 0.001$.

Moderation analysis indicates that industry sector plays a meaningful role in BI satisfaction, whereas technology intensity is more relevant for BI expansion decisions. Company size, BI tool category, respondent role, and region were excluded due to weak or insignificant effects, suggesting that strategic and functional factors outweigh structural characteristics once BI is in use.

TABLE VI. ANOVA SUMMARY FOR BI SATISFACTION AND BI FUTURE EXPANSION.

Model	Source	SS	df	F
BI satisfaction (M1)	Regression	10.206	9	5.97***
	Residual	11.781	62	—
BI future expansion (M2)	Regression	5.580	12	3.74***
	Residual	5.473	44	—

Note: $^{***}p < 0.001$.

VI. CONCLUSION AND FUTURE WORK

This study examines the technological and organizational drivers of Business Intelligence (BI) satisfaction and expansion in Swiss companies, contributing to the limited body of region-specific research on post-adoption analytics outcomes. The findings demonstrate that BI satisfaction and BI expansion are distinct but interrelated outcomes, shaped by different sets of factors.

The results show that BI satisfaction is primarily driven by usability-oriented features, particularly real-time data access, data visualization, and mobile availability. In contrast, excessive alerts and notifications negatively affect user experience, suggesting that information overload may reduce perceived usefulness.

BI expansion decisions are influenced by a different set of considerations. While data visualization remains a key driver, cost-effectiveness, system integration, and financial monitoring play a more prominent role, reflecting a strategic and investment-oriented perspective. The negative effect of training and support highlights the importance of organizational readiness and skills availability as potential barriers to further BI adoption.

The findings also indicate a limited role of advanced analytics features, such as predictive analytics, suggesting that many Swiss firms remain focused on core BI functionalities. This reflects a preference for reliability, governance, and compliance over analytical sophistication at the current stage of BI maturity.

This study contributes to the literature by providing empirical evidence from a small, innovation-driven economy, thereby extending existing BI and analytics adoption research beyond commonly studied large-market contexts. From a practical perspective, the results suggest that improving user satisfaction alone may not be sufficient to ensure continued BI investment. Organizations should also address cost considerations, system integration, and capability development to support BI expansion. From a theoretical perspective, the study highlights the importance of distinguishing between different post-adoption outcomes and accounting for contextual factors when analyzing analytics adoption.

Future research could extend this study in several directions. First, larger and more diverse samples across countries would improve the generalizability of the findings. Second, longitudinal studies could provide deeper insights into how BI satisfaction and expansion evolve over time. Third, further research could explore the role of artificial intelligence and advanced analytics capabilities in shaping BI outcomes, as well as the interaction between organizational culture, skills development, and analytics adoption.

ACKNOWLEDGMENTS

This study was conducted as part of the BISWISS project, supported by the School of Management Fribourg (HES-SO). The author used generative AI tools (ChatGPT) to support language editing, clarity improvement, and structuring of the manuscript. All content was critically reviewed and revised by the author, who takes full responsibility for the final version of the paper.

DISCLOSURE OF INTERESTS

The author has no competing interests to declare that are relevant to the content of this article.

REFERENCES

[1] IDC, "Worldwide business intelligence and analytics software market forecast," International Data Corporation, 2023.

[2] World Intellectual Property Organization, "Global innovation index 2025 at a glance," 2025, Accessed: Jan. 26, 2026. [Online]. Available: https://www.wipo.int/web-publications/global-innovation-index-2025/en/gii-2025-at-a-glance.html.

[3] C. C. Sellitto and P. Hawking, "A study of business intelligence strategy development by large organizations," in *Applying Business Intelligence Initiatives in Healthcare and Organizational Settings*, IGI Global, 2019, pp. 326–339. DOI: 10.4018/978-1-5225-5718-0.ch018.

[4] O. M. Faruk and M. S. Sultana, "Comparative analysis of BI systems in the US and Europe: Lessons in data governance and predictive analytics," *Journal of Sustainable Development and Policy*, vol. 1, no. 5, pp. 1–38, 2021. DOI: 10.37256/jsdp.1520211126.

[5] V.-H. Trieu, "Getting value from business intelligence systems: A review and research agenda," *Decision Support Systems*, vol. 93, pp. 111–124, 2017. DOI: 10.1016/j.dss.2016.09.019.

[6] M. M. Nazier, A. Khedr, and M. Haggag, "Business intelligence and its role to enhance corporate performance management," *International Journal of Management & Information Technology*, vol. 3, no. 3, pp. 8–15, 2013.
[7] M. Kowalczyk, P. Buxmann, and J. Besier, "Investigating business intelligence and analytics from a decision process perspective: A structured literature review," Darmstadt Technical University, Department of Business Administration, Economics and Law, Institute for Business Studies (BWL), 2013.
[8] L. Hurbean, F. Militaru, M. Muntean, and D. Danaiata, "The impact of business intelligence and analytics adoption on decision making effectiveness and managerial work performance," *Scientific Annals of Economics and Business*, vol. 70, no. SI, pp. 43–54, 2023. DOI: 10.47743/saeb-2023-0031.
[9] H. Chen, "Business and market intelligence 2.0, part 2," *IEEE Intelligent Systems*, vol. 25, no. 2, pp. 74–82, 2010. DOI: 10.1109/MIS.2010.31.
[10] H. Chen, "Trends & controversies," *IEEE Intelligent Systems*, vol. 26, no. 6, pp. 82–85, 2011. DOI: 10.1109/MIS.2011.111.
[11] S. Kothapalli, "Data analytics for enhanced business intelligence in energy-saving distributed systems," *Asia Pacific Journal of Energy and Environment*, vol. 9, no. 2, pp. 99–108, 2022.
[12] A. E. Ebule, "Leveraging artificial intelligence in business intelligence systems for predictive analytics," *International Journal of Scientific Research and Management*, vol. 13, no. 1, pp. 1862–1879, 2025.
[13] N. A. Alghamdi and H. H. Al-Baity, "Augmented analytics driven by AI: A digital transformation beyond business intelligence," *Sensors*, vol. 22, no. 20, p. 8071, 2022. DOI: 10.3390/s22208071.
[14] D. Edge, J. Larson, and C. White, "Bringing AI to BI: Enabling visual analytics of unstructured data in a modern business intelligence platform," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, ACM, 2018, pp. 1–9. DOI: 10.1145/3170427.3188519.
[15] R. Sabherwal, A. Jeyaraj, and C. Chowa, "Information system success: Individual and organizational determinants," *Management Science*, vol. 52, no. 12, pp. 1849–1864, 2006. DOI: 10.1287/mnsc.1060.0583.
[16] S. Matook and H. Van Der Heijden, "Goal abstraction, goal linkage dependency, and perceived utilitarian value of information systems: A mixed-method study," *Journal of Organizational and End User Computing*, vol. 25, no. 2, pp. 41–58, 2013. DOI: 10.4018/joeuc.2013040103.
[17] D. Kalishina and K. Bista, "Cognitive and strategic dimensions of data visualization in executive decision-making," *World Journal of Advanced Engineering Technology and Sciences*, vol. 4, no. 1, pp. 115–123, 2021.
[18] S. J. Andriole and N. P. Barsky, "Overdue diligence: Questioning the promise, not the premise, of analytics," *Communications of the Association for Information Systems*, vol. 50, no. 1, p. 42, 2022. DOI: 10.17705/1CAIS.05042.
[19] M. J. Liberatore, B. Pollack-Johnson, and S. H. Clain, "Analytics capabilities and the decision to invest in analytics," *Journal of Computer Information Systems*, vol. 57, no. 4, pp. 364–373, 2017. DOI: 10.1080/08874417.2016.1181497.
[20] M. Mikša and N. Sikirica, "The evolution and applications of the technology acceptance model," *Journal of Modern Civil Engineering*, vol. 4, no. 5-6, pp. 154–157, 2024.
[21] J. Baker, "The technology–organization–environment framework," in *Information Systems Theory: Explaining and Predicting Our Digital Society*, Y. K. Dwivedi, M. R. Wade, and S. L. Schneberger, Eds., Springer, 2011, pp. 231–245. DOI: 10.1007/978-1-4419-6108-2_12.
[22] S. Sun, C. G. Cegielski, L. Jia, and D. J. Hall, "Understanding the factors affecting the organizational adoption of big data," *Journal of Computer Information Systems*, vol. 58, no. 3, pp. 193–203, 2018. DOI: 10.1080/08874417.2016.1222891.
[23] T. Nilsen and R. Njøs, "Greening of regional industrial paths and the role of sectoral characteristics: A study of the maritime and petroleum sectors in an arctic region," *European Urban and Regional Studies*, vol. 29, no. 2, pp. 204–221, 2022. DOI: 10.1177/09697764211034326.
[24] M. Krey, M. Soriano Ramirez, M. Christen, and J. Candreia, "Development of a model for the implementation of business intelligence in SMEs," in *Proceedings of the 12th International Conference on Information Communication and Management*, ACM, 2022, pp. 61–68. DOI: 10.1145/3545322.3545332.