Concept of a Business Intelligence Architecture for Digital Shopfloor Management

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***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.

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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

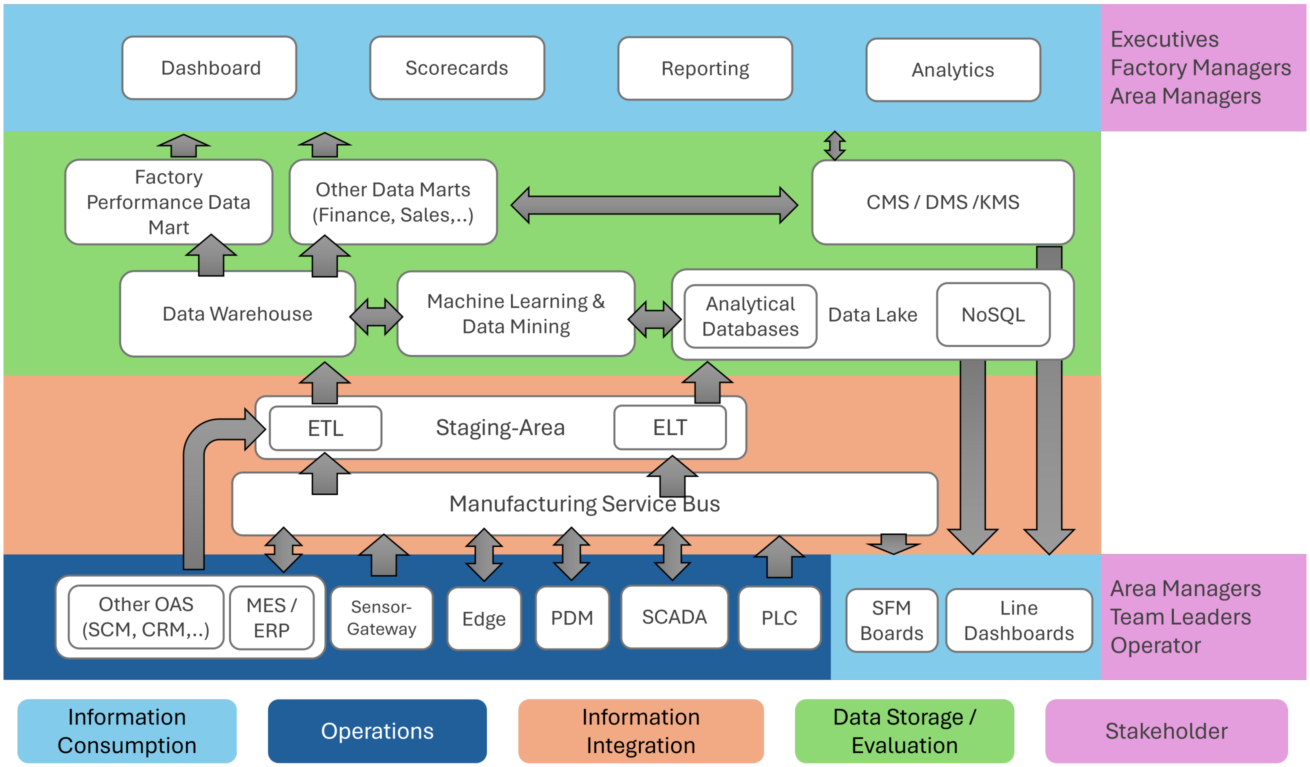

Figure 1. Target BI-Architecture for dSFM

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.

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