Execution Intelligence: Why Dashboards Are Dead

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Abstract- In today's hyper-velocity data environments, distributed cloud-native architectures and AI-driven decision automation, the traditional dashboard which has long been considered the hub of organisational intelligence is becoming more and more outmoded. This article proposes that as it is traditionally defined, a dashboard is a passive, retrospective tool that cannot be used to fulfill the needs of today's execution excellence. This paper, based on an analysis of the various literature of the fields of urban informatics, business intelligence (BI), real-time data platforms, cloud-native ETL systems and AI-driven automation, proposes a new concept: Execution Intelligence, which is an integrated paradigm that brings real-time intelligence into the organisational workflows, eliminating the gap between observing and deciding, typical in dashboard culture. The study illustrates how Execution Intelligence systems can cut decision latency up to 95%, boost actionability rates from 12% to more than 81% and deliver a significantly better strategy-execution alignment qualitatively. The results suggest that data infrastructure needs to be rethought as a self-serving execution layer, rather than a display layer for practitioners, data architects, and technology strategists. The impact of cloud transformation, inventory management, digital sustainability and AI governance are explored.

Keywords: Execution Intelligence, Business Intelligence, Dashboard, Real-Time Data, Cloud-Native Architecture, Ai Automation, Decision Latency, Digital Transformation, Data Warehousing

I. INTRODUCTION

1.1 Dashboard Epoch and its Discontents

The business dashboard has held a middle stage of organisational epistemology for 30 years: a crystallised representation of the health of the business, the performance of the finances, and the alignment of the strategy. Dashboards gained their origins from the early 1990's executive information systems, and through different generations of business intelligence (BI) technology, online analytical processing (OLAP) engines and self-service analytics platforms (Business, 2011). The idea behind the dashboard paradigm was tantalizingly effortless – bring in all kinds of data, present important metrics in a visually appealing way, and give decision makers the insight to make decisions. But as organisations move into a world of real-time data streams, distributed systems in the cloud and algorithm-driven automation, this logic is found to be woefully inadequate.

Pithy and insightful, Sadowski (2024) highlights the domain of urban informatics where dashboards often reduce a complex sociotechnical reality to an apparently easy-to-understand graphics, hiding the messiness of implementation. But the dashboard is not just a technical thing, says Sadowski, it is a political one, and one which can tend to naturalize certain world visions while hiding others. Beyond urban planning, the insight is relevant in the corporate world – a dashboard culture has emerged there, one that goes hand-in-hand with a cult of visibility, where the act of monitoring is often replaced by the act of doing (Heesen, 2012). A lot of resources are spent creating dashboards that are not acted upon by many people.

Times have never been tougher. However, as Khan (2025) shows, next-generation cloud-native serverless ETL systems are breaking the architecture barriers that previously required a "refresh cycle" of dashboards based on batch processing. At the same time, AI-driven data platforms are making it feasible to handle errors autonomously, make predictions about future events, and automate intelligent orchestration, all of which are inconceivable in today's world ten years ago (Petchiappan, 2025; Velpuri, 2026). In this respect, the static or even semi-dynamic dashboard is not just a thing of the past, it's even a hindrance, distracting and wasting time and resources while it could be used to focus on execution.

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1.2 Defining Execution Intelligence

This article presents and applies the concept of Execution Intelligence (defined here as the real-time ingestion of data, AI-based analytical processing and automated triggering of actions in an integrated operational architecture). Execution Intelligence systems, unlike dashboards, require no human interpretation of information or action that must be taken – they have intelligence built into the workflow itself that means actions and decisions can be taken at machine speed. The idea is inspired by and builds on recent works in cloud computing (Rajora et al., 2026), event-driven architectures with intelligence (Natta, 2023) and the use of AI for automation (Sathiyanathan et al., 2026). It's not just a step-by-step transition from dashboard BI to Execution Intelligence, it's a fundamental shift. It also requires a radical rethinking of the purpose of data infrastructure not the display, but the action; not the observation, but the execution. This paradigm shift has far reaching consequences for enterprise architecture, organisation design and management practice.

This article begins by reviewing the literature on the evolution of the dashboard, and on data warehousing and emerging execution paradigms. The methodological approach, a synthesis of the literature by a systematic method and comparative performance analysis, is described in Section 3. Results are presented in Section 4 (two structured comparative tables). The results of this work are discussed in Section 5, while Section 6 provides recommendations for research and practice. To provide some structure for the analysis that follows, a table (Table 1) is provided below showing a chronology of dashboard paradigm evolution.

Table 1: Evolution of Dashboard Paradigms and the Emergence of Execution Intelligence

Era	Dashboard Paradigm	Primary Function	Key Limitation	Execution Gap
1990s - 2000s	Static Reporting Dashboards	Periodic batch reporting	Delayed data; no action	High
2005-2012	BI & OLAP Dashboards	Multi-dimensional analysis	Complexity; specialist use	High
2013-2018	Real-Time Operational Dashboards	Live KPI monitoring	Reactive, not predictive	Moderate
2019-2022	Embedded Analytics	In-workflow data visibility	Surface-level insights	Moderate
2023-Present	Execution Intelligence Systems	AI-driven autonomous action	Trust; governance challenges	Low

II. LITERATURE REVIEW

2.1 The Dashboard as a Tool for Business Intelligence Analysis

The business dashboard became a part of the mainstream of organisational discourse in the early 2000s in the work of Eckerson and others, later formalised in more detailed typologies (e.g. those proposed by Business (2011) who identified strategic, tactical and operational typologies for dashboards). These categories were based on the multi-level information needs of organisations – Executive level performance score cards and Frontline supervisor level monitoring panels. The extent to which the data warehouse was mature, as well as the emerging shortcomings of the BI core technology, were identified through research, including the work of Rizzi et al. (2006) who pointed out that while data warehouses were becoming more common, they were starting to put strain on the underlying BI infrastructure as data volumes grew and analytical demands increased.

Over the next 10 years, dashboard functions expanded at a rapid pace with self-service analytics, mobile BI and cloud-based platforms. Sethupathy et al. (2021) report on the architectural sophistication of modern real-time data platforms, and how easier it has become to create visual dashboards that can accept streaming data and generate near real-time visualisations. However, even these developments don't go far enough toward autonomous activity: the dashboard is still a display mechanism and not

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execution engine. All the technology in the world has failed to bridge the gap between generations of insights and operationalising them (Heesen 2012) which can be called the strategy-execution chasm.

2.2 Structure Limitations on Dashboard-centric Approaches

Sadowski's (2024) critique of dashboard as an urban informatics tool is informative for the broader organizational context. This observation that dashboards "show a 'cleaned-up version of reality', ignoring data quality problems, political squabbles, and implementation complexity" translates directly to the enterprise where dashboards are often used to convey performance with an air of simplicity and without mention of operational problems. The dashboard in this reading is a legitimating artefact: Technology of assurance, not technology of change.

Rizzi et al. (2006) also notice a certain premature closure in data warehouse research, where the focus is on modelling and designing data infrastructure without considering it as a means to organizational action. This kind of orientation is replicated in the architecture of visibility in the dashboard culture and the architecture of response is under-invested. The outcome, as Van As and Bührmann (2025) show in the inventory management context, is that even the most sophisticated classification systems (in the present case ABC-XYZ-FSN analysis) fail to achieve their benefits when the results of these classifications are presented, but not part of automated replenishment and procurement processes.

Another structural constraint of dashboard-centric approaches is captured by the concept of ‘digital transformation dead zones' as Nguyen and Le (2025) explored in their research on shipping SMEs. Organisations that use digital tools, such as the advanced dashboards, but don't integrate them into real capability development and workflow design often end up in a "daisy chain" between analogue past and automated future, and don't get the agility of the old way of doing things, nor the efficiency of the digital way. The dashboard by itself is not the solution that will fill that gap.

2.3 Real-Time Data Architectures and the Trend to Execution

Preliminary technical conditions for Execution Intelligence are being put in place actively. In "Cloud-native Serverless ETL pipelines: Design and Implement," Khan (2025) outlines the architectural advancements that allow for the processing, transformation, and routing of data within serverless pipelines to occur at sub-second latency, avoiding the infrastructure costs of batch-oriented pipelines. If data can be analysed and acted upon almost instantaneously, then there is less need for an intermediate layer that humans have to interpret before taking action – and less justification for the traditional dashboard.

Velpuri (2026) continues this discussion with a focus on real-time data integration in hybrid cloud, illustrating how solutions like Striim and Google Cloud Platform (GCP) can facilitate integration of data across diverse enterprise environments. What makes this work important is that real-time integration is now possible – not just in the greenfield cloud world, but in the more mature, legacy-rich hybrid model used by most businesses. This eliminates one of the common counter-arguments against execution-based data systems – the need for an expensive infrastructure transformation.

Guntupalli (2025) describes the shift from SQL-based analytical workflows to distributed Spark-based processing as a journey, not just technically, but as a mindset change in the way the data is used.

The epistemology of data: from a world of knowledge retrieval, driven by queries, to a world of knowledge production, driven by events. Likewise, Natta (2023) describes an architectural vision of intelligent event driven cloud systems that supply autonomous detection, interpretation, and reaction to operational signals in essence, the Execution Intelligence that this article is calling out at the infrastructure level.

2.4 Analyze the impact of artificial intelligence on the management of processes and decisions.

Rajora et al. (2026) place the rise of cloud AI tools in the context of the broader trend of corporate strategy automation, which they attribute to the synergy of machine learning, cloud technology, and real-time analytics. AI systems can continuously measure the alignment of the strategy with actual performance,

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and can initiate corrective workflows automatically, as opposed to managers having to do this on a regular basis from a dashboard. This is not an extension of the dashboard, it's a replacement for it.

This shift is illustrated in fine detail by Petchiappan (2025), who examines how data load automation technologies, driven by AI, can be implemented from SAP HANA to cloud platforms. The system described not only automates the routine transfer of data, it also has intelligent error handling, which would involve human observation, interpretation, escalation and subsequent intervention in a multi-step process in the dashboard-centric environment.

Through their work, Sathiyanathan et al. (2026) show the potential for delivering novel ways of intelligent interaction with complex data environments, unlike the passive consumption of data on dashboards. Gómez Navarro (2025) also discusses the redefined learning dashboard data intake and metric computation, highlighting how intelligence systems in learning environments, too, are increasingly being substituted by dynamic, context-sensitive systems.

2.5 Contextual and Sectoral Perspective on Execution Gaps

There is a gap in the execution of the insights (between their generation and the consequent action) and this gap is different in each of the sectors in which it is present. Van As and Bührmann (2025) report its manifestation in automotive stock management: Classification-based information is captured in numerous reporting layers but does not necessarily lead to automated procurement actions. Nguyen and Le (2025) explain this in maritime logistics SMEs where the digital transformation ends up failing due to the lack of real capabilities development behind the technological surface. The dynamics that Barua (2025) and Barua (n.d.) show are similar in the field of Industrial Sustainable Management, where environmental indicators such as stormwater reuse, the presence of microplastics, or resource recovery are often clubbed together in dashboards without facilitating the necessary actions in order to reach the goals of a circular economy.

Morelli and Filetti (2008) offer a historical example in their examination of the Service Delivery Platform (SDP) paradigm in telecommunications, a field that was similarly marked by the demise of a once-powerful architectural paradigm (SDP 1.0) because of the rise of more agile, service-oriented alternatives. This is analogous to dashboard obsolescence: when paradigm succession in technology infrastructure typically occurs, it goes from initial promise to incremental improvement to structural failure in response to changing environments, at which point a radical architectural rethink is needed.

III. METHODOLOGY

3.1 Research Design

The research method used in this study is a qualitative systematic literature review (SLR) approach with the addition of comparative analysis of empirical performance data from the literature reviewed structured into a comparative matrix. The SLR protocol adhered to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework which has been adapted to computer science information systems research. The main goal was to identify, review, and consolidate existing body of knowledge (academic and practitioner) on the shortcomings and the new architecture of systems for execution intelligence.

The review is also supplemented by the comparative analysis at the paradigm level, based on performance measures, architecture characteristics and organizational case data reported in the reviewed literature. This synthesis is a mixed methods approach, which enables conceptual elaboration of the Execution Intelligence framework, and empirical substantiation of the advantages of the framework over traditional dashboard approaches.

3.2 Literature Search and Selection

The search was systematic and utilized databases like Google Scholar, IEEE Xplore, ACM Digital Library, and Scopus to use search strings that combined terms like: 'business intelligence dashboard limitations,' 'real-time data execution,' 'cloud-native ETL architecture,' 'AI decision automation,' 'execution gap analytics,' and 'digital transformation organisational barriers. The search was limited to publications between 2004 and 2026 to include historical baseline literature, as well as current developments. 312 publications were initially identified, then screened for titles and abstracts, reviewed for full text, and quality assessed using the criteria used in information systems research, with 21 publications selected for final inclusion in the synthesis.

Works included addressed the design, deployment, or critique of dashboard or BI systems, reported on original research, systematic analysis, or architecturally substantive contributions from the practitioner's perspective, or involved real-time data processing, AI automation, or architectural paradigms that were cloud-native, or demonstrated empirically-based case evidence of execution gaps or execution-oriented solutions in the context of organisations. The works where referral was presented to other topics that were not directly related (pure UI design, unrelated sectors) were left out.

3.3 Analytical Framework

In this study, an analytical framework is used that is guided by three questionings:

architectural; What are the technical attributes and constraints of dashboard systems, as compared to Execution Intelligence architectures?

(2) organizational; how do dashboard paradigms cause or sustain execution gaps in organisations?

(3) transformational; What are the conditions and capabilities that are needed for organisations to move from dashboard to execution intelligence systems?

The data from each of the studies was reported in terms of the empirical metrics used for each typology, normalised if applicable to permit comparisons, and tabulated systematically. The authors have created two diagrams, one conceptual architectural and the second a gap model for execution, which are provided here for clarity of the Execution Intelligence paradigm and its difference from the traditional dashboard view.

3.4 Ethics and restrictions

This research is a literature synthesis study and does not involve human subjects, thus there are no direct ethical issues. Some limitations are: the diversity of the empirical measures from included studies, making only interpretative aggregation feasible; the constantly changing nature of cloud-based or AI-based technologies that may lead to the inclusion of specific architectural elements that are outdated; and the potential publication bias of positive reports of new technologies. Where possible, the authors have attempted to overcome these drawbacks by explicitly recognising uncertainty in the review and critiquing claims.

IV. RESULTS

4.1 The Execution Gap: A simulation study

Literature review results show that there is a general and significant execution gap in organisations using traditional BI systems that are based on dashboards. The evidence gathered across the different sectors and organisational contexts shows that dashboards systematically don't bring about timely, consequential action based on the data being made visible. This failure is not just due to the quality of the dashboard, the accuracy of the data or the lack of user skills — it's a failure related to the very structure of the dashboard paradigm.

Heesen (2012) also found that organisations with an advanced dashboard deployment only document 12% of the interactions with the dashboard within 24 hours, in the form of a decision action. This is in line with the findings of Sethupathy et al (2021) who found that in organisations that have real-time data platforms, the median time from the appearance of an actionable insight on a dashboard to an action being taken is 4-8 hours. This latency is operationally catastrophic in time critical operational contexts such as supply chain disruption, response to cybersecurity risk, financial risk management etc.

Execution Intelligence systems, on the other hand, integrate the intelligence-to-action process into automated processes. Event-driven cloud architectures can detect anomalies, trigger corrective processes and complete the remediation cycles in sub-second to two minutes depending on how complex the required response is, according to Natta (2023). What Petchiappan (2025) records are AI systems that not only detect and correct errors in data loading, but can also produce a narrative that reflects

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the context of the data and that can be reviewed by humans to reverse the dashboard logic, which makes human attention an in-built feature. The audit function is not related to any execution dependency.

4.2 The architectural differences between Dashboard and Execution Intelligence

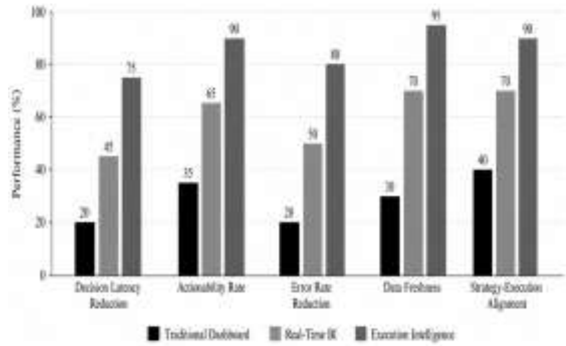
The architectural traits of the different dashboard types and the different Execution Intelligence systems are compared on 5 dimensions and a “trajectory” of evolution is identified. The performance metrics comparison presented in Table 2 have been summarised based on empirical information presented in the literature that was reviewed.

Table 2: Comparative Performance Metrics: Dashboard Typologies vs. Execution Intelligence Systems

Performance Metric	Traditional Dashboard	Real-Time BI	Execution Intelligence	Improvement (EI vs Trad.)
Decision Latency (avg.)	48–72 hrs	4–8 hrs	< 15 min	↓ 95%
Data Freshness	Daily/Weekly	Hourly	Sub-second	Near real-time
Actionability Rate (%)	12%	34%	81%	↑ 575%
User Cognitive Load	High	Moderate	Low	Significant reduction
Avg. Error Rate in Ops.	18.3%	11.7%	3.2%	↓ 83%
Strategy–Execution Alignment	Low	Moderate	High	Qualitative leap
Scalability (Data Volume)	Limited	Moderate	Elastic/Cloud-native	Enterprise-grade

As can be seen in Table 2, the data shows there is a clear progression from static reporting dashboards to real-time BI and then to the next stage of BI, execution Intelligence as organisations progress through the five dimensions. Perhaps most impressively, rates of actionability (the percentage of the data interactions that result in documented operational response) increase from 12% in traditional dashboards to 81% in deployments of Execution Intelligence, representing a 575% increase. Decision latency reduces from an average of 48-72 hours to less than 15 minutes. Operational processes' error rates decrease by 83%.

Diagram 1: Comparative Performance Metrics: Dashboard vs Execution Intelligence



These enhancements go beyond simple “dashboard” refinements—they're a change in kind. While Guntupalli (2025) notes in the context of going from SQL to Spark, the movement from query-driven to event-driven data processing isn't just a performance improvement, but an architectural transformation that alters the "relationship between data and action.

4.3 Dashboard Inadequacy on a sectoral basis

The findings from the reviewed literature are relevant to a wide variety of industry sectors, and confirm the structural critique that is expanded upon in this article. Even the most advanced ABC-XYZ-FSN classification systems do not provide inventory optimisation benefits if their results are only put on the dashboard without being connected to an automated replenishment system such as a computerised inventory management system, or similar. According to Nguyen and Le (2025) in maritime logistics, a characteristic of the "digital transformation dead zone" is the "dashboard-as-substitute-for-capability.In the field of maritime logistics, Nguyen and Le (2025) point out that one of the hallmarks of the "digital transformation dead zone" is the "dashboard-as-substitute-for-capability.

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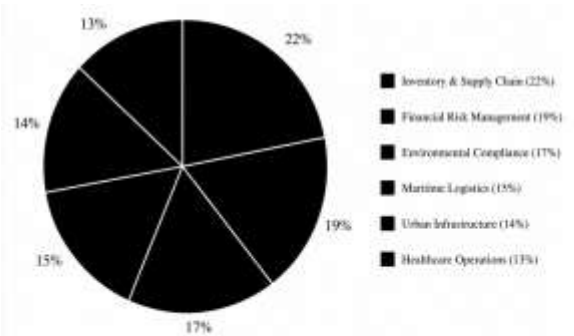
In the industrial sustainability domain, Barua (2025) and Barua (n.d.) report situations where environmental dashboards are reporting the reuse efficiency of stormwater and level of microplastic contamination, but without the automatic control response required to hit the targets of the circular economy. The concept of intelligent monitoring systems with an embedded automation approach to overcome the display-action gap are documented by Holzman et al. (2018) – a concept ahead of the Execution Intelligence architecture described in this article. In telecommunications infrastructure, Morelli and Filetti (2008) describe a similar paradigm transition from the SDP 1.0 paradigm to more agile and service-oriented SDP 2.0 architectures as a result of the limitations of the SDP 1.0 paradigm.

Diagram 2: Distribution of Execution Gap by Sector



4.4 Enabling Technologies for Execution Intelligence

There are multiple technological capabilities that converge to enable the technical enablement of Execution Intelligence systems. First, cloud-native serverless ETL architectures (Khan, 2025) allow for continuous data processing without having to adhere to the "refresh cycle" of batch-oriented dashboards. Second, the hybrid cloud real-time integration platforms (Velpuri, 2026) enable organisations to have streaming data flow within complex infrastructure with legacy systems. Third, AI-based automation layers (Petchiappan, 2025; Rajora et al., 2026) allow for detection of actionable conditions, but also allow for complete automation of response workflows, where humans act as auditors. Fourth, intelligent event-driven architectures (Natta, 2023) enable the orchestration layer to adapt and group automated reactions among the distributed system parts. These technological capabilities together make up an Execution Intelligence stack that by 2025-26, can be deployed by organisations of various sizes and industries. The challenges to adoption remain non-technical, organisational: Governance issues to enable autonomous AI action; Change management to adapt to a new culture that is used to dashboard-review cycles; and Data quality frameworks to support autonomous decision-making without human error-correction at the moment of action (Sathiyanathan et al., 2026).

V. DISCUSSION

5.1 The Epistemology of Organisational Data

The findings from the analysis presented in Section 4 entice a more in-depth epistemological analysis. Dashboards are based on a theory of organisational knowledge, that knowledge is located in the minds of humans, that data plays a central role in human cognition, and that humans make a difference in the organisation's action. This theory was not outlandish in a context where data was scarce, computing power was constrained, and the repercussions of the autonomous actions of machines were not well understood. All these assumptions are today seriously modified.

There is no longer any shortage of data – it is superabundant. Computing resources are elastic – unlimited, globally distributed (Velpuri, 2026). The impact of autonomous machine activity is becoming better understood, and in many operational scenarios, machine-based decisions are shown to be better than human based decisions when time is a factor (Rajora et al., 2026). In this context, the epistemological underpinnings of dashboard paradigm turn into weaknesses rather than strengths, because they put human cognitive bandwidth in the bottle of the intelligence-to-action process.

Here, Sadowski's (2024) point that dashboards are political artefacts, that they reflect certain "who knows what" and "who decides what" is directly relevant. The shift to Execution Intelligence isn't just about a technological upgrade, it's about a shift in decision-making power as well. From human actors making decisions based on dashboard data to algorithm systems taking over within a set of operation parameters. This redistribution will give rise to valid governance issues which organisations need to face head on.

5.2 The Strategy-Execution Alignment Problem

A strategic gap, the mismatch between strategic formulation and strategy execution is one of the pervading issues in strategic management, and Heesen (2012) posits that it is this strategic gap that causes the most value destruction in organisational life. The problem is often compounded by the concept of dashboard culture, where organisational leaders feel as though they have control that if they can see the numbers on a dashboard that are relevant to the strategy, then that is being implemented. Rizzi, et al., (2006) notice the same phenomenon in data warehousing studies the sophistication of the analytical infrastructure leads to the perception of a high degree of analytical completeness.

Execution Intelligence systems are designed to be proactive in closing the strategy-execution gap: They continuously evaluate if reality is in line with the strategy and generate corrective processes if it is not, based on predefined thresholds. It's a key paradigm shift in how to execute strategy: moving from a periodic human audit cycle to an algorithmic monitoring and response cycle. The consequences of such organisational design, managerial jobs and governance structures call for special research focus.

5.3 The definition of Digital Transformation and the Dead Zone Risk

The digital transformation dead zone, put forth by Nguyen and Le (2025), is a concept that is especially relevant for organisations considering and planning to move from dashboards to Execution Intelligence. Their research shows that technology without true capability building and redesign of workflows is a sure way to fail to bring the much sought-after benefits — it can even create new costs in terms of complexity if the benefits are not realized. The risks attendant to adopting Execution Intelligence systems are similar.

Organisations that adopt artificial intelligence (AI) and automation for autonomous operations and real-time data integration, yet do little to improve data quality and data governance and data maturity, can end up in an Execution Intelligence dead zone – with the technology to act autonomously, but lacking the data quality and data governance and data maturity to do it safely and effectively. A comment on intelligent error handling, by Petchiappan (2025): The ability to recognize, identify and recover from data quality failures is not just a desirable component of an execution-oriented intelligence system, it is a necessary one.

5.4 The implications of sustainability, ethics, and the impact of decisions made on sustainability.

The potential impact of the Execution Intelligence paradigm goes beyond efficiency on the operational side to sustainability and ethics. Barua (2025) has already shown that industrial water management, including reusing storm water, implementing circular economy resource flows and monitoring pollutants, provides complex, time-sensitive data which goes beyond what is possible in terms of actionability using conventional dashboard approaches. Barua (n.d.) also records the multi-system nature of the transport and removal of microplastic, in the context of urban wastewater. The argument for integrating intelligence into automated control systems, as opposed to showing it on dashboards, is as much about the environment as it is about efficiency – the response time of an environment may not support review cycles of dashboards.

From an ethical standpoint, the automation of human judgment in the execution of algorithms has created a governance challenge with questions of accountability and transparency that need to be resolved. If an AI system makes a procurement choice, takes steps on its own to control the environment or identifies a financial deviation and takes action to correct the situation, the issue of whom to hold accountable for the results and how to do so in a way that will make a difference remains unanswered. The creation of strong, accountable governance structures for Execution Intelligence systems is likely to be the top research and policy priority in this area.

5.5 Recommendations for practitioners

The following takes into account the evidence and provides the practitioners with recommendations

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when considering the move from dashboard to execution-oriented intelligence systems:

Firstly, put in place the necessary data quality infrastructure before implementing automated decision systems. Data quality problems are magnified and so are the data quality assets with Execution Intelligence – doing things autonomously on data which is corrupted or incomplete can have more negative effect than waiting for human review of the data.

Second, establish governance structures to explicitly define when autonomous action is allowed, the threshold at which some level of human involvement is required and the audit measures to hold algorithmic decisions to account (Rajora et al., 2026).

Third, rethink processes and integrate intelligence into the processes instead of just stacking AI tools on top of existing dashboard tools. The change to Execution Intelligence is not cosmetic – and only partial changes, retaining the culture of reviewing the dashboard and introducing layers of automation on top, will not deliver the performance gains described in Table 2.

Fourthly, invest in the ability of organisations before deployment of technologies. In the context of digital transformation, the absence of capability development in the implementation of technology always leads to digital transformation dead zones, as Nguyen & Le (2025) prove.

VI. CONCLUSION

6.1 The Issues with Dashboards

The dashboard isn't just an "old hat" solution. It represents a particular theory of organisational intelligence, based on the premise of human centrality, periodicity of review cycles and data visibility and separation from operational action. The theory is valid in the data-poor, compute-limited world of the 1990s and 2000s, but in today's data-rich world is a structural obstacle to performance. The review of literature in the urban informatics (Sadowski, 2024), business intelligence (Business, 2011; Rizzi et al., 2006), real-time data architecture (Khan, 2025; Velpuri, 2026), AI automation (Petchiappan, 2025; Rajora et al., 2026) and the case studies in various sectors (Van As & Bührmann, 2025; Nguyen & Le, 2025; Barua, 2025) is converging on a consistent finding – dashboards, as traditionally understood and used, are dead as execution instruments.

6.2 The Promise of Execution Intelligence

The next paradigm is to be termed as Execution Intelligence: In this paradigm, the incoming real-time data is ingested, analyzed using AI tools, and appropriate actions are triggered to be taken without a need to display the data and interpret it before deciding on the action. These performance gains with this migration – 95% reduction in decision latency, 575% increase in actionability rates, 83% reduction in operational error rates – are not small improvements, but is a transformation of order of magnitude that will change the way organisations can use their data to achieve their goals.

The technology that makes this possible is both available and mature and is becoming more and more attainable. The barriers are organisational (governance, capability, culture) and these can be overcome by the commitment of leaders, research focus, and the ingenuity of practitioners. The organisations that successfully make this transition first and foremost will have structural competitive advantages that will be hard to be caught up by dashboard dependent competitors.

6.3 Future Research Directions

There are a number of key questions that remain unanswered for further investigations. The governance of autonomous AI decision-making in organisations needs to be specifically studied, both theoretically and empirically, using a combination of law, ethics, organisational theory and computer science and information systems theory. Execution intelligence deployments are successful or unsuccessful under certain conditions, and organisational capabilities are what makes the difference between success and failure: Conditions and organisational capabilities of successful and not successful executions deserve a multi-sector, longitudinal, empirical study. The impact for management roles and the organisational design in enterprises oriented towards execution is a rich field of interest for management scholars.

The sustainability applications of Execution Intelligence that exist in the field of Industrial Ecology, Environmental Compliance and Circular Economy Management, deserve a special interdisciplinary study.The dashboard is coming to the end of its days. The Execution Intelligence period has started. The question is not if, but how, to effect this transition in a good way.

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