Revolutionizing IT Service Process Monitoring with AI

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Abstract: This exploratory case study examines the implementation of a proprietary AI-based reporting and monitoring tool in the Hungarian subsidiary of a multinational IT service provider. The tool integrates an observability platform with machine learning–driven analytics to automate process monitoring, metric creation, and statistical reporting, minimizing manual intervention. Offered as a consult-led service through periodic "bring your own data" (BYOD) assessments and continuous deployments, it supports diverse IT environments across infrastructure, applications, and business services. Drawing on a literature review and six expert interviews with senior managers and IT operations specialists, the study investigates how the AI tool enhances process monitoring efficiency and KPI management and compares its perceived advantages and disadvantages with traditional reporting. Thematic analysis reveals that the tool centralizes observability, reduces manual reporting effort, and enables the definition and tracking of SMART KPIs, such as targeted incident reduction, increased automation potential, and enhanced compliance. First-year project KPIs include a 30% reduction in incidents, a 50% increase in corrective automation potential, 90% compliance adherence, and a 75% decline in incidents for selected services. Human expertise remains essential for defining KPIs, configuring data sources, and interpreting AI insights. Challenges include integration and licensing costs, data governance, trust in AI recommendations, and changes in reporting roles. The study concludes with recommendations for designing AI-enabled monitoring around SMART KPIs, clarifying human–AI task allocation, and proactively managing organizational risks and trade-offs.

Keywords: AI, efficiency, measurement

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1 Introduction

In the contemporary business landscape, organizations increasingly rely on complex, distributed IT services to deliver value to internal and external customers. Ensuring the availability, security, and cost-efficiency of these services requires continuous monitoring, timely reporting, and reliable key performance indicators (KPIs). Traditional reporting methods are often based on fragmented data sources and manual consolidation, which are time-consuming, error-prone and poorly suited to today's high-velocity data streams.

This paper introduces and examines an innovative AI-based reporting and monitoring tool designed to improve IT service process monitoring and KPI management. The tool aims to reduce reporting time, provide real-time visibility of critical KPIs, and free human resources from repetitive reporting tasks so they can focus on customer excellence and higher valued work. Functionally, the tool integrates data from multiple observability sources, applies AI and machine learning (ML) algorithms to detect anomalies and patterns, and presents prioritized incidents and metrics through a unified user interface.

The solution is implemented in the Hungarian subsidiary of a multinational IT company and is offered to customers as a paid, consult-led service. It is applicable across several business areas, such as IT operations, information security, risk and resilience management, and financial and executive decision-making. The tool supports different "classes" of monitoring, including infrastructure and application availability, incident and problem management, cost and resource utilization, and compliance-related indicators.

Regulatory developments further increase the pressure on organizations to establish robust monitoring. The new ISO/IEC 27001:2022 standard includes explicit requirements related to monitoring (Annex A.8.16), while Directive (EU) 2022/2555 and Regulation (EU) 2024/1689 strengthen cybersecurity and resilience obligations. Together with the emerging AI Act of the European Commission, these frameworks create a context in which AI-driven monitoring must not only improve efficiency but also support compliance and responsible use of AI technologies.

Given this background, the purpose of this study is to explore how the AI reporting and monitoring tool can contribute to more efficient IT service process monitoring and how it is perceived in comparison with traditional monitoring and reporting approaches. Because the empirical basis of the study is a small, qualitative sample from a single organizational setting, the intention is not to generalize statistically but to generate in-depth, practice-oriented insights. To ensure a clear focus, two research questions guide the analysis and are specified in the "Research objectives and questions" section. The paper proceeds with a literature review, followed by the research objectives and questions, methodology, results, and conclusion.

2 Literature review

2.1 AI, machine learning and IT service monitoring

Continuous efficiency improvement in IT services monitoring has become a central theme in recent research. Sharifani and Amini (2023) emphasize that machine learning and deep learning techniques can significantly enhance anomaly detection, capacity planning and performance optimization in complex IT environments. Stamp (2022) discusses applications of machine learning in information security, highlighting how AI-based models can detect threats and security incidents more effectively than traditional rule-based approaches. Mitchell's (1999) foundational work on machine learning and data mining provides the conceptual basis for many of these developments, emphasizing the importance of learning from historical data to improve decision-making.

Zaki et al. (2020) offer a comprehensive overview of data mining and machine learning algorithms, many of which can be applied to IT service monitoring for tasks such as classification of events, clustering of incidents and prediction of failures. Sharma and Srinath (2018), and Bharadiya (2023), discuss the use of machine learning and data mining techniques in business intelligence, underlining the value of AI for transforming raw operational data into managerial insight. Shu and Ye (2023) further explore knowledge-discovery methods from data mining and machine learning, which underpin many AI-driven monitoring tools.

2.2 AI, big data and efficiency in various domains

AI and big data analytics have been studied in a variety of domains with strong links to efficiency and sustainability. Bozsik, Fűrész, and Szeberényi (2025) analyze the role of AI in improving energy efficiency, showing how AI-driven optimization can minimize energy waste. Hossain et al. (2019) and Koshy et al. (2021) examine the application of big data and machine learning in smart grids, demonstrating how large-scale monitoring and predictive analytics can enhance grid reliability and efficiency. Himeur et al. (2023) review AI-big data analytics for building automation and management systems, again highlighting the central role of monitoring, anomaly detection and automated control.

In the broader context of digitalization, Salkuti (2020) provides a survey of big data and machine learning applications, while Rathore et al. (2021) discuss the role of AI, machine learning and big data in digital twins. Carlos, Kahn and Halabi (2018) describe how data science, big data and AI contribute to new forms of data-driven decision-making in fields such as radiology, where monitoring and reporting are also critical.

2.3 AI, governance and business value

From a managerial and governance perspective, Almaqtari (2024) analyses how IT governance influences the integration of AI into accounting and auditing operations, emphasizing the need for appropriate structures to ensure reliability and accountability. Wamba-Taguimdje et al. (2020) explore the influence of AI on firm performance and argue that AI-based transformation projects can generate significant business value, provided that organizational processes and capabilities are adapted accordingly. Leitner-Hanetseder and Lehner (2023) discuss regulatory issues related to AI-powered information and big data in financial reporting, signaling the importance of compliance and transparency.
Nguyen, Sermpinis and Stasinakis (2023) discuss the transformative symbiosis of big data, AI, and machine learning in financial technology, where high-frequency data and automated decision-making are central. Equbal et al. (2025) examine machine learning in additive manufacturing, offering another example of AI-enabled optimization in complex technical systems. Lampropoulos (2023) situates artificial intelligence, big data and machine learning within the broader Industry 4.0 context, which also affects IT service management.

2.4 Technical foundations for AI-enabled monitoring

At the technical level, several works address the challenges of machine learning with big data. Qiu et al. (2016), L'heureux et al. (2017), Zhou et al. (2017) and Al-Jarrah et al. (2015) discuss scalability, model performance and big data architectures. Rahmani et al. (2021) and Zaripova et al. (2023) provide systematic overviews of AI approaches and mechanisms for big data analytics, while Sun and Huo (2021) summarize the spectrum of big data analytics techniques. Punia et al. (2021) compare machine learning algorithms for big data classification, highlighting trade-offs that are also relevant when selecting models for IT monitoring.
Further contributions focus on data management, privacy and user interfaces. Bernabé et al. (2024) examine FAIR data practices in Bring Your Own Data (BYOD) workshops, a concept related to the BYOD engagement model used in the present case study. Sahebolamri et al. (2023) discuss data structures in Datalog, relevant for scalable rule-based querying. Tong et al. (2024) analyze natural language interfaces for Grafana dashboards, illustrating how AI can make complex monitoring data accessible to non-technical users. Parra-Ullauri et al. (2024) propose a privacy-preserving framework for federated learning in Kubernetes-based cloud–edge environments, which is closely related to modern infrastructure for observability solutions.

2.5 Regulatory context and AI reporting guidelines

Regulation is an increasingly important driver of monitoring and reporting. ISO/IEC 27001:2022 sets requirements for information security management systems, including the monitoring of security controls. Directive (EU) 2022/2555 and Regulation (EU) 2024/1689 define cybersecurity and resilience obligations for critical entities within the EU, intensifying the need for timely, accurate reporting on incidents and controls. The AI Act (European Commission, 2024) establishes a risk-based framework for AI systems, which requires companies to classify and manage AI risks.

Within the AI and reporting literature, Klontzas et al. (2023) provide guidance on selecting AI reporting guidelines, while Turzo et al. (2022) review non-financial reporting practices and their evolution. Khatoon, Ullah and Qureshi (2024) discuss AI models and data analytics in the context of next-generation language models and research workflows. These works underscore that AI-enabled monitoring and reporting must not only be technically robust but also align with regulatory and ethical expectations.

2.6 Research gap

Taken together, the reviewed literature shows that AI, machine learning and big data analytics offer powerful tools for monitoring and reporting across diverse domains. However, there is less empirical work on how a concrete AI-based monitoring tool is implemented in a real-world IT service context, how it supports the construction and operation of KPI schemes (e.g. SMART-type KPIs), and how organizational stakeholders evaluate its benefits and drawbacks compared with traditional approaches. This paper addresses this gap through an in-depth qualitative case study of an AI reporting and monitoring tool in IT services.

3 Research objectives and questions

The primary objective of this study is to explore the potential efficiency improvements and organizational implications associated with implementing an AI-based reporting and monitoring tool in IT service operations.

Given the exploratory nature and small qualitative samples, the study focuses on a limited number of research questions to enable coherent analysis and interpretation. Specifically, the empirical work addresses two overarching research questions:

- RQ1: How does the AI reporting and monitoring tool support more efficient, KPI-driven process monitoring in IT services, including the identification, construction and operation of SMART KPIs?

- RQ2: What benefits and drawbacks do organizational stakeholders associate with the AI-enabled monitoring approach compared with the previous, more traditional reporting and monitoring practices?

These questions are examined through a single case study of a Hungarian subsidiary of a multinational IT company and its collaboration with a banking sector client. The small sample size and qualitative design mean that the findings are not statistically generalizable; rather, they provide rich, context-dependent insights that can inform both practice and future research.

4 Methodology

4.1 Research method

The study adopts a qualitative, single-case method to investigate the implementation and perceived effects of the AI reporting and monitoring tool within a multinational IT company's Hungarian subsidiary. A qualitative approach is appropriate because the focus is on understanding stakeholders' experiences, interpretations and perceived trade-offs rather than measuring performance changes quantitatively at this stage of implementation.

4.2 Data collection

Primary data were collected through six in-depth, semi-structured interviews with key stakeholders. The interviewees were selected purposively to cover different roles involved in or affected by the AI tool, including senior leadership and operational experts. At a high level, the interviewees represented functions such as IT leadership (e.g. CIO/CTO roles), information security and resilience, service ownership and technical expertise in observability and AI. All interviewees had substantial experience in IT services in the case company and/or the banking sector partner, ensuring that they could provide informed perspectives on both traditional and AI-enabled monitoring approaches.
The interviews were conducted between 1 April 2025 and 28 July 2025 in individual sessions. The average duration was approximately 65 minutes, allowing sufficient time to explore experiences and viewpoints in depth. With the consent of participants, interviews were recorded and subsequently transcribed for analysis.

To ensure transparency, the semi-structured interview guide covered the following core themes and example questions:

- Current monitoring and reporting practices:
  - How do you currently monitor IT services and key performance indicators in your area?
  - What tools and processes are involved?
- Description and use of the AI tool:
  - How would you describe the AI reporting and monitoring tool and its main functionalities?
  - In which business areas or processes are you using it?
- KPI construction and SMART criteria:
  - Which KPIs do you monitor with the tool?
  - How are these KPIs defined in terms of specificity, measurability, feasibility, relevance and time horizon?
- Human–AI collaboration:
  - In which parts of the monitoring process do the AI tool provide the most value?
  - Where is human intervention still necessary or irreplaceable?
- Comparison with traditional approaches:
  - Compared with your previous monitoring and reporting practices, what do you see as the main advantages of the AI tool?
  - What disadvantages, risks or concerns do you perceive?
- Organizational implications and outlook:
  - How does the AI tool influence skill requirements, roles and workload in your team?
  - What developments would you like to see to increase the value of the tool?

These themes ensured that the interviews directly addressed the research questions and encouraged interviewees to reflect on both benefits and limitations of the AI-driven solution.

4.3 The AI tool and monitoring service

The AI reporting and monitoring tool examined in this study is a proprietary platform developed by the case company and offered as a paid service to existing customers. It integrates data from multiple sources (e.g. logs, metrics, traces) and uses AI and ML techniques to detect anomalies, correlate events and surface prioritized insights. The solution provides a unified user interface focused on critical incidents and KPIs, enabling stakeholders to address availability, performance, cost and resilience issues more systematically.

The service is consult-led rather than fully managed and does not include custom software development. Customers are responsible for providing data access and configuration, while the provider delivers the observability platform, AI analytics and expert guidance. Two main engagement options are available:

- Bring Your Own Data (BYOD): customers periodically provide data (e.g. log exports, metrics) which are ingested into the platform using standard templates. The tool is then used to perform time-bound analyses and generate insights and recommendations.
- Continuous integration with available data: the platform is integrated into the customer's IT environment, enabling ongoing data ingestion and real-time insights. This model supports continuous monitoring and iterative optimization of KPIs and processes.

Technically, the tool supports deployment on multiple Kubernetes distributions, uses data segregation by residency to support data protection requirements, and offers single sign-on (SSO) integration for both IT staff and customer users. Kubernetes auto-scaling is employed to handle varying workloads. Observability tools such as OpenTelemetry and Grafana are standard components of the solution's monitoring and visualization stack.

Risk management for the tool follows the principles of the AI Act (European Commission, 2024). Based on the analysis performed by the company, the AI reporting and monitoring tool is not categorized under any of the high-risk or prohibited AI system classes. Figure 1 summarizes the risk management assessment.

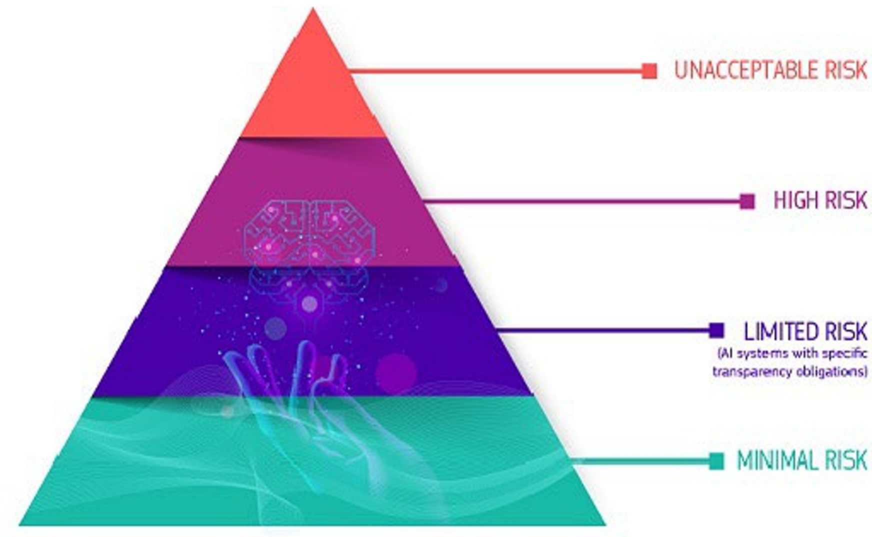

Fig. 1. Risk Management based on AI Act (European Commission, 2024)

4.4 Data analysis

The interview transcripts were analyzed using thematic analysis. The process involved several iterative steps:

1. Familiarization: the authors independently read the transcripts to gain an overall understanding of the material.
2. Initial coding: segments of text relevant to the research questions were coded, including references to efficiency, KPIs, human–AI collaboration, perceived benefits and disadvantages, compliance and organizational implications.
3. Theme development: codes were grouped into broader categories, such as "description and scope of the AI tool", "SMART-based KPI framework", "benefits compared with traditional monitoring" and "risks and limitations".
4. Refinement and synthesis: the themes were refined through discussion among the authors to ensure internal coherence and clear distinction between themes.
5. Linking to SMART model: statements related to KPIs, and target values were interpreted using the SMART model (Specific, Measurable,

Achievable, Relevant and Time-bound) to structure how the AI tool supports the construction and operation of a KPI scheme.

The thematic analysis was complemented by internal project documentation from the case company (e.g. high-level architecture descriptions and KPI definitions) to ensure an accurate understanding of the solution and its context.

5 Results

Given the qualitative nature of the study and the small number of interviews, the results should be interpreted as context-specific insights into stakeholder perceptions rather than as generalizable evidence. The findings are organized into five subsections: (5.1) characterization of the AI reporting and monitoring tool, (5.2) business areas, classes of use and user groups, (5.3) SMART-based KPI framework, (5.4) perceived benefits compared with traditional monitoring, and (5.5) perceived risks, costs and limitations.

5.1 Characterization of the AI reporting and monitoring tool

Interviewees consistently described the AI tool as an integrated observability and analytics platform that consolidates previously fragmented monitoring and reporting processes. Instead of relying on separate tools for logs, metrics and incidents and manually compiling reports, the AI tool ingests heterogeneous data into a unified environment. AI and ML algorithms then help detect anomalies, identify patterns and correlate events across systems and services.

Several interviewees emphasized that the tool's value lies not only in advanced analytics but also in its consult-led implementation. The provider's experts support the customer in defining relevant KPIs, configuring data sources and interpreting results. This consultative dimension is important for organizations that have limited internal expertise in AI, ML or complex observability stacks.

The BYOD and continuous integration engagement models were considered particularly useful because they allow different levels of commitment and maturity. BYOD engagements provide an entry point for organizations to "test" AI-enabled monitoring on selected data sets. Continuous integration, in contrast, supports real-time monitoring of critical systems and longer-term optimization of KPIs.

5.2 Business areas, classes of use and user groups

The interviews indicate that the AI tool is relevant across several business areas and "classes" of activities within the case company and its customers:

- IT operations and service management: monitoring infrastructure components, applications, services and dependencies; tracking availability, performance and incident trends.
- Information security and resilience: monitoring security-relevant events and resilience indicators, supporting compliance with ISO/IEC 27001:2022 and EU cybersecurity legislation.
- Risk and business continuity management: providing visibility into critical systems and failure modes, enabling more proactive risk management and continuity planning.
- Financial and executive decision-making: helping executives understand the value of IT investments, cost drivers and the business impact of incidents and downtime.

Primary users of the AI tool include C-level executives and senior managers such as Chief Technology Officers (CTOs), Chief Information Officers (CIOs), Chief Information Security Officers (CISOs), Chief Executive Officers (CEOs) and Chief Financial Officers (CFOs). These users rely on filtered alerts, aggregated views and high-level KPI dashboards to align IT initiatives with business goals and to support strategic decisions.
Secondary users include Service Owners, Chief Resilience Officers, Chief Risk Officers, Business Continuity Managers and Application Owners. For these roles, the tool offers detailed analytics and drill-down capabilities that support performance improvement, incident analysis, resilience planning and targeted training. Interviewees emphasized that the tool is particularly helpful in environments with complex, multi-vendor architectures where manual consolidation of monitoring data is very challenging.
The collaboration between the IT company and a banking sector client illustrates these use cases. Through observability-as-a-service arrangements and business application mapping, the bank gained continuous visibility into its IT infrastructure, including service performance and incident trends. A significant commercial outcome of this collaboration was a USD 100,000 deal secured during a modernization phase, in which the scope of the AI tool was expanded to the entire IT infrastructure and additional business insights were integrated.

5.3 SMART-based KPI framework

A central theme in the interviews was the establishment of a KPI framework around the AI tool. Stakeholders developed a set of first-year success metrics that explicitly follow the SMART logic:

- Specific: the KPIs focus on clearly defined outcomes in IT services, such as incident reduction, automation potential and compliance adherence.

- Measurable: the AI tool provides continuous measurement and reporting of the KPIs based on log, metric and event data.
- Achievable: the target values are considered ambitious but realistic given the current baseline and planned improvements.
- Relevant: KPIs are aligned with strategic priorities such as service reliability, cost optimization and regulatory compliance.
- Time-bound: the targets are defined for the first year of operation of the AI-enabled monitoring solution.

Four illustrative first-year success metrics, as discussed by the interviewees, are:

- 30% reduction in incidents by using AI and ML to improve anomaly detection, proactive alerting and root-cause analysis.
- 50% increase in corrective automation potential through analyzing logs, metrics and events to identify repeatable remediation actions that can be automated.
- 90% compliance adherence with internal policies and external regulatory requirements related to monitoring and reporting.
- 75% decline in incidents for selected services or environments where continuous monitoring, reporting and AI-driven action proposals are fully implemented.

At the time of the study, these values function as planned KPIs and design targets rather than measured outcomes. The AI tool plays a central role in the "M" of SMART (Measurable), ensuring that progress towards these targets can be tracked in near real time. However, the "S", "A", "R" and "T" dimensions still require strong human involvement: stakeholders must define what exactly is to be improved, assess whether target levels are realistic, ensure alignment with business and regulatory priorities, and specify the relevant time horizons.

Interviewees emphasized that the AI tool makes it easier to recalibrate KPIs iteratively because the effects of configuration changes and process improvements become visible quickly. Nevertheless, they highlighted that the design of the KPI scheme itself remains a strategic management task rather than a fully automatable function.

5.4 Perceived benefits compared with traditional monitoring

In relation to RQ1 and RQ2, interviewees identified several advantages of the AI-enabled approach compared with the previous monitoring and reporting practices, which were described as fragmented and largely manual.

First, the AI tool reduces manual reporting effort. Before implementation, teams spent significant time extracting data from different systems, cleansing it and compiling slide decks or static reports. The AI platform automates much of this work by continuously

collecting data, applying analytics and providing configurable dashboards. This frees up time for teams to focus on analysis, decision-making and customer-facing activities.
Second, the solution improves the speed and granularity of insight. Real-time or near real-time dashboards enable quicker detection of anomalies and trends, while AI-driven correlations help identify root causes that would be difficult to detect manually. This is particularly valuable in large, complex infrastructures where incident patterns span multiple layers or services.
Third, the unified observability platform enhances cross-team collaboration. When different functions (e.g. operations, security, risk, finance) use the same tool and share a common set of KPIs, discussions become more data-driven and less reliant on isolated, department-specific reports. Interviewees reported that this facilitated alignment between IT and business stakeholders.
Fourth, the AI tool supports compliance and auditability. Automated logging of events, alerts and KPI histories creates a traceable record that can be used to demonstrate compliance with ISO/IEC 27001:2022 and EU cybersecurity regulations. Interviewees stressed that this not only reduces the effort required for audits but also improves the quality and consistency of evidence.
Finally, the tool was seen as helping to bridge skill gaps in AI, ML and observability. For teams that lack deep technical expertise in these areas, the platform and the associated consult-led service provide ready-made analytics capabilities and best-practice guidance. While this does not eliminate the need for skilled staff, it lowers the barrier to entry and accelerates learning.
Taken together, these perceived benefits explain why stakeholders consider the AI-driven solution superior to the traditional monitoring approach in terms of efficiency, responsiveness, alignment with business goals and regulatory readiness.

5.5 Perceived risks, costs and limitations

Despite the perceived advantages, interviewees also highlighted several disadvantages, risks and open issues associated with the AI reporting and monitoring tool.
A first concern relates to cost and integration effort. Implementing the AI tool requires investment in licenses or service fees, integration work to connect data sources, and internal resources for configuration and adoption. For some accounts and customers, particularly smaller ones, this may be a significant barrier. Moreover, not all accounts allow their data to be ingested into the tool, which limits its coverage and may lead to a patchwork of monitored and non-monitored environments.
A second challenge involves data governance and trust. Some stakeholders expressed reservations about centralizing large volumes of operational data in a single platform,

especially when it is operated by a service provider. Ensuring appropriate data segregation, access controls and compliance with data protection regulations is therefore crucial. In addition, trust in AI-generated recommendations is not automatic: users need time and experience to understand how the models work, which signals they emphasize and how reliable the alerts are in practice.

Third, the AI-enabled approach has implications for roles and workforce. While the tool reduces manual reporting workload, it also requires new skills in interpreting analytics, configuring dashboards and designing automations. Some interviewees noted that traditional reporting tasks may diminish, potentially affecting roles built around these activities. At the same time, new opportunities emerge in areas such as data engineering, AI operations and service analytics. Managing this transition requires careful communication, upskilling and workforce planning to prevent fears of layoffs and resistance to adoption.

Fourth, the KPI framework itself is still evolving. Common KPIs across all accounts have not yet been fully established, and different stakeholders sometimes prioritize different metrics. As a result, there is a risk of KPI proliferation or misalignment if the AI tool is configured in an ad-hoc manner. Interviewees stressed the need for governance mechanisms to ensure that KPIs remain coherent, strategically relevant and manageable.

Finally, the early stage of implementation means that robust statistical evidence on efficiency gains is not yet available. While the first-year SMART KPIs provide clear targets and the AI tool supports ongoing monitoring, the actual realization of these improvements requires more time and likely depends on complementary changes in processes and behavior.

6 Conclusion

This study set out to explore how an AI-based reporting and monitoring tool affects IT service process monitoring and KPI management (RQ1), and how organizational stakeholders perceive its benefits and drawbacks compared with traditional approaches (RQ2). Based on a literature review and six semi-structured interviews within a multinational IT company's Hungarian subsidiary and its collaboration with a banking sector client, several conclusions can be drawn.

Regarding RQ1, the AI tool is perceived as a powerful enabler of more efficient, KPI-driven monitoring. By consolidating data from heterogeneous sources into a unified observability platform and applying AI and ML algorithms for anomaly detection and pattern recognition, the tool reduces manual reporting effort and shortens the time from event to insight. It supports the construction and operation of a SMART-based KPI scheme by providing continuous measurement of clearly defined strategically relevant, time-bound targets. First-year success metrics such as targeted incident reductions, increased corrective automation potential and high levels of compliance adherence illustrate how the AI tool can be embedded in a structured performance management framework.

At the same time, the analysis underscores that human expertise remains essential. Stakeholders are responsible for defining what should be monitored, setting realistic targets, ensuring alignment with business and regulatory objectives, and interpreting AI-generated insights. The AI tool excels in the "Measurable" aspect of SMART and in surfacing complex patterns, but it does not replace human judgement in areas such as prioritization, trade-off decisions or ethical and regulatory considerations.

With respect to RQ2, the AI-driven solution is considered superior to the previous, more traditional monitoring approach in several respects. It offers faster and more granular insights, supports cross-functional collaboration through shared dashboards and KPIs, and strengthens compliance and auditability. These features collectively enhance the organization's ability to manage complex IT services and to demonstrate the value of IT investments to business stakeholders.

However, the AI-enabled approach also introduces new risks and disadvantages. Implementation requires financial and organizational investment, and some accounts may be reluctant to share data. Data governance and trust in AI recommendations must be carefully managed, especially in regulated environments. The redistribution of work from manual reporting to analytics and configuration tasks can cause uncertainty about roles and may raise concerns about workforce reductions if not addressed proactively. Finally, the evolving KPI framework and the early stage of implementation mean that the anticipated efficiency gains and cost reductions remain, at this stage, expectations rather than empirically confirmed outcomes.

From a practical standpoint, the findings suggest several recommendations for organizations considering similar AI-based monitoring solutions:

1. Design KPI schemes explicitly according to the SMART framework and use AI primarily to strengthen measurability and timely feedback, while keeping KPI definition and interpretation under human control.
2. Clarify human–AI task allocation early, specifying where AI should automate data collection, anomaly detection and alerting, and where human actors must retain decision-making authority.
3. Invest in data governance, transparency and explainability to build trust in AI-generated insights among different stakeholder groups.

4. Anticipate workforce and skill implications, providing upskilling and clear communication to mitigate fears of layoffs and to leverage new roles in AI-enabled operations.
5. Start with focused BYOD-type engagements to build experience and demonstrate value before scaling to fully integrated, continuous monitoring implementations.

This study has several limitations. It is based on a single case in one organizational context and draws on a small number of qualitative interviews. The results therefore cannot be generalized statistically and should be interpreted as exploratory. Furthermore, the tool was still in an early implementation phase, so no longitudinal performance data were available to confirm the expected KPI improvements. Future research could complement this work with quantitative analyses of incident rates, response times, automation volumes and financial impacts before and after implementation, as well as comparative case studies across different industries and regulatory environments.

Despite these limitations, the study contributes to the emerging understanding of AI-driven monitoring solutions in IT services by showing how such tools can be integrated into a SMART-based KPI framework, how they reshape the relationship between human and machine in monitoring processes, and which organizational trade-offs accompany their adoption.

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