Beyond Black Boxes: Adaptive XAI for Dynamic Data Pipelines

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Abstract: The increasing use of real-time data streams in application areas such as the Internet of Things (IoT), financial analytics, and social media demands highly flexible and self-adaptive data pipelines. Modern AI techniques enable the automatic adjustment of these pipelines to dynamically changing data landscapes; however, their decision-making processes often remain opaque and difficult to interpret. This paper presents and evaluates novel approaches for integrating Explainable Artificial Intelligence (XAI) into self-adaptive real-time data pipelines. The goal is to ensure transparent and interpretable data processing while meeting the requirements of real-time capability and scalability. The proposed methods aim to strengthen trust in automated systems and simultaneously address regulatory demands. Initial experimental results demonstrate promising improvements in both explainability and adaptivity without significant performance degradation.

1 INTRODUCTION

The rapid increase in data—especially in the form of real-time data streams—is increasingly shaping a wide range of industries and applications. With the emergence of technologies such as the Internet of Things (IoT), social media platforms, and high-frequency financial trading, vast volumes of data are being continuously and rapidly generated (Cacciarelli & Kulahci, 2024). The analysis and processing of this data in real time is essential for enabling swift decision-making and automation across various domains, from industrial manufacturing to cybersecurity (Zaharia et al., 2016). In this context, self-adaptive data pipelines are gaining growing importance, as they are capable of dynamically responding to changing conditions and adjusting the data flow accordingly (Sresth et al., 2023).

However, while many systems are able to autonomously adapt to changing data streams, they often lack the ability to make these adaptations transparent and understandable. This raises the central research question of this work: How can explainability be integrated into self-adaptive data pipelines without compromising real-time capabilities?

Self-adaptive data pipelines are systems that not only continuously ingest and process data but also autonomously adjust their internal structure, parameters, and algorithms in response to changing data conditions or environmental factors (Zaharia et al., 2016). This is particularly relevant when dealing with so-called concept drift effects, where the underlying data distribution changes over time (Gama et al., 2014). Such changes can significantly impair model performance if not detected and addressed promptly. Traditional, static pipelines that operate without adaptive mechanisms are at a disadvantage in such scenarios and may quickly produce outdated or incorrect results (Krawczyk, 2016).

The integration of artificial intelligence (AI)—and especially machine learning methods—into these adaptive systems makes it possible to manage the complexity and dynamics of streaming data. AI models can detect patterns, make predictions, and automatically implement adjustments to optimize data processing (Gomes et al., 2023). This automation enhances not only the efficiency and accuracy but also the scalability of data pipelines in real-time environments. In addition, self-learning algorithms allow systems to proactively respond to new data

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characteristics without requiring human intervention (Gama et al., 2014).

Despite the obvious advantages of AI-powered adaptive pipelines, significant challenges remain—particularly regarding the transparency and interpretability of their automatic adjustments (Azeroual, 2024). Modern AI models are often perceived as black-box systems, with internal decision-making processes that are difficult to understand and explain (Adadi & Berrada, 2018). This lack of transparency hampers error diagnosis, debugging, and user acceptance by both end-users and decision-makers (Doshi-Velez & Kim, 2017). Moreover, regulatory requirements—such as those mandated by the General Data Protection Regulation (GDPR)—are becoming increasingly stringent, making explainable and traceable data processing essential (Rudin, 2019).

Against this backdrop, the research field of Explainable Artificial Intelligence (XAI) has emerged, aiming to design models whose decisions and adjustments are understandable and interpretable by humans (Arrieta et al., 2020). However, many existing XAI methods focus on static, batch-based models and fail to consider the specific requirements of real-time streaming and adaptive systems (Guidotti et al., 2018). In real-time environments, explanations must be delivered quickly, dynamically, and contextually, supporting users in interpreting model behavior without compromising system latency or efficiency (Abbas & Eldred, 2025).

The integration of XAI into self-adaptive real-time data pipelines thus represents a timely and critical research challenge. The objective is to develop approaches that not only maintain the adaptability of pipelines but also provide transparent and comprehensible explanations for their dynamic adjustments. Key challenges include minimizing latency, ensuring scalability, and handling continuously changing data contexts (Ribeiro et al., 2016). Addressing these aspects is crucial for building user trust and enabling the deployment of AI-based systems in safety-critical and regulated application domains.

This paper presents a novel system architecture that integrates XAI into self-adaptive real-time data pipelines. The goal is to combine adaptivity and explainability to enable transparent, interpretable, and high-performing data processing. The modular pipeline handles concept drift and is evaluated through empirical experiments and user feedback, aiming to strengthen trust in AI while meeting practical and regulatory requirements.

2 THEORETICAL BACKGROUND/ FOUNDATIONS

2.1 Data Pipelines: Structure, Function, and Challenges in Real-Time Streaming

Data pipelines are structured sequences of processing steps that guide data from acquisition through transformation to analysis (Hashem et al., 2015). In modern applications, these pipelines often need to handle large volumes of data streams in real time, which imposes specific requirements on latency, scalability, and fault tolerance (Zaharia et al., 2016). Real-time streaming pipelines enable the continuous processing of data in motion, for example through frameworks such as Apache Kafka, Apache Flink, or Apache Spark Streaming (Kreps et al., 2011; Carbone et al., 2015). A central challenge lies in ensuring data consistency and quality despite high data rates and potential failures (Liu et al., 2021).

2.2 Self-Adaptivity: Concepts and Mechanisms

Self-adaptivity refers to a system's ability to autonomously adjust its behavior to changing environmental conditions without human intervention (Salehie & Tahvildari, 2009). In data-driven pipelines, this is especially relevant when data distributions change—a phenomenon known as concept drift (Gama et al., 2014). Concept drift describes the temporal shift in the underlying data distribution, which can lead to performance degradation of static models (Widmer & Kubat, 1996). Adaptive mechanisms such as online learning or model retraining are used to detect and compensate for such changes (Krawczyk, 2016). Automated machine learning (AutoML) supports these processes by autonomously optimizing model parameters and generating new models (He et al., 2021).

2.3 Artificial Intelligence (AI) and Machine Learning (ML) in Adaptive Systems

AI, particularly ML, enables adaptive systems to learn from data and dynamically improve decision-making (Russell & Norvig, 2016). In real-time streaming scenarios, online learning methods are frequently applied to incrementally update models and reflect current data (Bifet et al., 2018). Concept drift detection techniques are essential to maintain model accuracy over time (Lu et al., 2018). Combinations of supervised, unsupervised, and reinforcement learning methods are employed to address various challenges in self-adaptive systems (Mohammadi et al., 2018).

However, the integration of ML into adaptive systems also increases complexity, making it harder for users to understand why specific adaptations occur—especially in real-time environments. This highlights the need for mechanisms that make such dynamic decisions transparent, which is where XAI becomes crucial.

2.4 Explainable AI (XAI): Definitions, Methods, Limitations

XAI refers to methods and techniques that make the decisions of AI systems understandable and transparent to humans (Doshi-Velez & Kim, 2017). The goal is to enhance trust in AI, especially in safety-critical applications (Arrieta et al., 2020). XAI methods can be categorized into intrinsic models (e.g., decision trees) and post-hoc explanations (e.g., LIME, SHAP) (Ribeiro et al., 2016; Lundberg & Lee, 2017). Despite recent advances, limitations remain regarding scalability, interpretability, and applicability to complex, dynamic systems (Adadi & Berrada, 2018). Furthermore, ensuring explanation stability over time and mitigating the risk of misleading or inconsistent explanations in self-adaptive models remain open research questions.

2.5 Specific Challenges of XAI in Real-Time and Streaming Contexts

The application of XAI in real-time streaming and self-adaptive systems imposes additional requirements: explanations must be provided with low latency, continuously updated, and adapted to changing data contexts (Abbas & Eldred, 2025). This places high demands on the efficiency of explanation methods and their ability to interpret dynamic models (Guidotti et al., 2018). Research shows that many established XAI techniques cannot be directly applied to real-time data streams, as they are often batch-oriented and computationally intensive (Molnar, 2020). New approaches aim to develop adaptive, lightweight, and context-sensitive explanations for streaming data (Lundberg et al., 2020).

The need for lightweight, adaptive explanation mechanisms in streaming contexts underscores the research gap this work aims to address—namely, the lack of integrated solutions that combine real-time adaptivity with explainability in a coherent, scalable system.

3 STATE OF RESEARCH

The rapid development of data-driven systems and the increasing importance of real-time streaming data have led to intensified research on adaptive data pipelines in recent years. These pipelines are designed to autonomously adjust to changing data environments in order to continuously deliver accurate and reliable results (Gama et al., 2014; Kiran et al., 2021). In particular, the challenge of concept drift—i.e., the temporal change in the underlying data distribution—requires flexible and adaptive approaches capable of continuously updating models and responding to new conditions (Widmer & Kubat, 1996; Krawczyk, 2017). The integration of AI and ML plays a central role in enabling automated decision-making within the pipeline and ensuring autonomous adaptation to shifting data streams (He et al., 2021; Bifet et al., 2018).

Many existing adaptive systems rely on online learning techniques, which allow models to be incrementally trained with new data, thereby maintaining model performance during live operation (Lu et al., 2018). Additionally, AutoML techniques are integrated to automate the processes of model selection and optimization, reducing the need for human intervention (He et al., 2021). Despite these advances, most studies focus on individual aspects of the pipeline—such as model updating or data preprocessing—and tend to neglect a holistic perspective that includes the explainability and transparency of automatic decisions (Kiran et al., 2021).

XAI is a growing research field aimed at increasing trust in AI systems, particularly in safety-critical and regulated application areas (Doshi-Velez & Kim, 2017; Arrieta et al., 2020). XAI encompasses methods that make the internal decision processes of often complex black-box models comprehensible (Molnar, 2020). Broadly speaking, XAI methods can be divided into intrinsically interpretable models and post-hoc explanation techniques (Ribeiro et al., 2016; Lundberg & Lee, 2017). While intrinsic models such as decision trees or linear regression are transparent by design, post-hoc approaches like LIME or SHAP provide explanations for arbitrary models without modifying the underlying architecture (Ribeiro et al., 2016; Lundberg & Lee, 2017).

However, most established XAI methods have been developed for static, batch-oriented data environments. Real-time streaming contexts pose new challenges: data distributions may change dynamically, models need to be continuously adapted, and explanations must also be delivered rapidly and adaptively to ensure transparency in decision-making at all times. Providing explanations in real time further requires resource-efficient algorithms that are compatible with high data throughput and low-latency requirements (Guidotti et al., 2018). Current research efforts therefore focus on developing incremental and lightweight XAI methods specifically tailored for streaming data (Lundberg & Lee, 2017). However, these approaches are still in an early stage and often address only partial aspects—such as the explanation of individual predictions—without fully covering the complex adaptation mechanisms of entire pipelines.

An analysis of current research clearly reveals a significant gap: there are very few integrated approaches that combine self-adaptive data pipelines with XAI methods to ensure continuous transparency and traceability in real-time streaming environments (Arrieta et al., 2020; Zhou et al., 2022). Most studies focus either on the adaptivity of the pipeline or the explainability of individual models, but not on the combination of both aspects in a dynamic, stream-based context. What is missing is an end-to-end approach that simultaneously ensures (1) continuous model adaptation, (2) timely and relevant explanations, and (3) seamless integration into real-time data pipelines.

Table 1: Classification of Existing Approach.

Study / Work	Adaptive Pipeline	AI Integration	XAI Methods Integrated	Real-Time / Streaming Capable	Main Contribution
Gama et al. (2014)	Yes	Partial (ML)	No	Yes	Concept drift detection and adaptation
Kiran et al. (2021)	Yes	Yes	No	Yes	Survey on streaming ML
Ribeiro et al. (2016)	No	Yes	Yes (LIME)	No	Post-hoc explanations for black-box models
Lundberg & Lee (2017)	No	Yes	Yes (SHAP)	Limited	Model-agnostic explanations
Guidotti et al. (2018)	No	Yes	Yes	No	Comprehensive overview of XAI methods

Table 1 provides an overview of selected relevant research works, classifying them according to their approaches to adaptive pipelines, AI integration, application of XAI methods, and real-time capabilities.

This overview illustrates that while substantial work exists on adaptive pipelines and XAI models individually, the fusion of both domains in real-time environments remains largely unexplored. This research gap represents a critical barrier to the acceptance and broader deployment of automated, self-adaptive systems, as transparency and traceability are essential prerequisites for trust and compliance (Arrieta et al., 2020).

The present paper addresses this intersection and aims to develop novel approaches that seamlessly integrate XAI methods into adaptive real-time data pipelines to ensure both high performance and transparency.

4 METHODOLOGY / CONCEPT DEVELOPMENT

This paper focuses on the development of an innovative approach for implementing explainable, self-adaptive real-time data pipelines, aiming to close existing research gaps at the intersection of adaptivity and explainability. The methodology is based on the design and implementation of a modular, dynamically adjustable system capable of continuously and autonomously responding to changes in incoming data streams, while simultaneously providing understandable explanations for its decisions and adaptations at any time. The concept is designed to enhance transparency and traceability of self-adaptive processes without compromising key real-time requirements such as latency and performance.

The proposed approach relies on a tightly integrated combination of advanced ML techniques and explainable AI (XAI) technologies. At its core, the system uses online learning algorithms that continuously update model parameters based on new incoming data, maintaining model accuracy even as data distributions shift. These methods are particularly well-suited for reacting to *concept drift*—i.e., changes in the statistical structure of the data—that would otherwise significantly degrade model performance without automatic adaptation. In addition, AutoML techniques are integrated to automate the selection and optimization of model hyperparameters, enabling the pipeline to operate largely autonomously. This reduces the need for human intervention and allows for flexible and scalable model maintenance in productive real-time environments.

LIME and SHAP were selected due to their wide acceptance, ability to generate local feature attributions, and extensibility. Despite their original design for batch scenarios, we extend them to operate in a streaming context by implementing window-based updates and approximation strategies.

Parallel to adaptive modeling, the integration of XAI methods is a central element of the design. Resource-efficient, incremental explanation approaches are developed, tailored to continuous data streams, enabling timely generation of explanations. In contrast to traditional post-hoc explanation methods, which are often computationally intensive and designed for static datasets, this methodology supports ongoing explanation generation that reflects the dynamics of the data stream and transparently illustrates changes in decision-making logic. For instance, feature importance scores and local surrogate models are incrementally updated to provide fast yet precise and context-sensitive insights into the behavior of adaptive models. Explanations are hierarchically structured to offer different levels of detail suited to various stakeholders—from technical experts to domain users—thereby enhancing both comprehensibility and relevance.

The technical realization of the approach is based on a modular system architecture that integrates components for data ingestion, preprocessing, model training and updating, explanation generation, and monitoring/control. For data ingestion and processing, established streaming frameworks such as Apache Kafka or Apache Flink are employed, ensuring high throughput and low latency as a robust foundation for real-time operations. The adaptive modeling module implements both online learning algorithms and AutoML components, which automatically determine suitable model configurations and seamlessly integrate them into operation. In parallel, a dedicated explanation module operates as a lightweight microservice, tightly coupled with the adaptive models to access relevant contextual information required for explanation generation. The monitoring component continuously evaluates data distribution, model quality, and explanation performance, controlling the adaptive pipeline by triggering model updates or issuing alerts in case of potential misadaptations. This establishes a closed feedback loop that ensures both the automation and transparency of data processing.

The modular architecture of this system is illustrated in Figure 1. It highlights the close integration of individual components—from data ingestion and adaptive modeling to explanation generation and pipeline monitoring/control. The diagram particularly emphasizes the closed control loop that enables continuous self-adjustment of the models and the ongoing generation and provision of explanations in real time. This forms a critical foundation for ensuring high adaptability and comprehensive transparency in dynamic, data-intensive environments, while also facilitating scalability, fault tolerance, and ease of maintenance—key requirements for deploying robust, trustworthy AI solutions in real-world streaming applications.

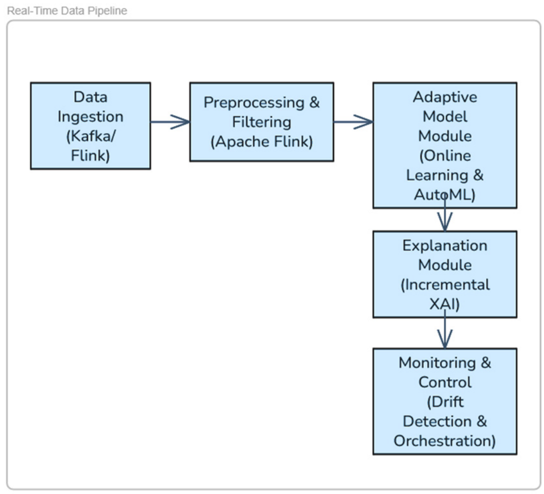

Figure 1: Modular architecture of the proposed explainable, self-adaptive real-time data pipeline.

As part of the development, specific criteria for explainability and real-time capability are also defined and systematically evaluated. The generated explanations must be comprehensible and traceable for various user groups and provide both local and global insights into model decisions and adaptations. At the same time, the pipeline must not delay data stream processing, requiring all components to be optimized for efficiency and resource usage. Through this integrative and iterative approach, a robust, scalable, and trustworthy real-time data processing system is created that addresses the demands of modern data-driven systems.

Success of the system is defined along three core criteria: (1) accuracy and adaptability of the model under concept drift, (2) latency of both predictions and explanations, and (3) user-perceived clarity and usefulness of the explanations across different stakeholder groups.

5 IMPLEMENTATION AND EXPERIMENTAL EVALUATION

To validate the proposed concept of an explainable, self-adaptive real-time data pipeline, a prototype system was designed, implemented, and rigorously evaluated using realistic application scenarios that reflect practical challenges in dynamic environments. The implementation emphasized a modular and extensible architecture that incorporates dedicated components for data ingestion, real-time processing, adaptive modeling, explainability, as well as continuous monitoring and control. This modular design allows for flexible integration and dynamic combination of various state-of-the-art AI and XAI methods, enabling comprehensive testing and optimization under stringent real-time conditions.

The overall system architecture is depicted in Figure 2. Data ingestion is managed through an Apache Kafka cluster, which ensures reliable, scalable, and fault-tolerant distribution of incoming high-velocity data streams. For preprocessing, Apache Flink is employed to perform essential real-time operations such as data cleansing, feature extraction, and feature scaling, thereby preparing the raw data for downstream modeling tasks without introducing significant latency. The adaptive modeling module incorporates incrementally learning algorithms—primarily Online Random Forests and Hoeffding Trees—combined with a lightweight AutoML mechanism that continuously optimizes hyperparameters to maintain model performance. This setup enables the system to dynamically adapt to evolving data distributions, with a particular focus on effectively detecting and reacting to concept drift.

To address the critical aspect of explainability, a dedicated module was integrated that leverages streaming-capable variants of popular explanation methods like SHAP and LIME. Explanations are generated for every individual prediction in real-time and presented through an interactive web interface, offering users transparent insights into the model's decision-making process. Complementing these components, the "Monitoring & Control" subsystem, built on Prometheus and a rule-based engine, continuously supervises system health, evaluates model quality, and triggers adaptive adjustments to modeling parameters as necessary to maintain optimal performance.

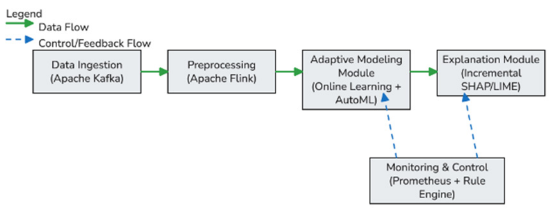

Figure 2: System Overview with Data Flow.

Figure 2 illustrates the data and control flow between system components: solid lines represent the continuous data flow (e.g., from Kafka → Flink → Modeling → Explanation), while dashed arrows depict feedback and control relationships—especially from the monitoring unit back to the modeling and explanation modules. This feedback enables demand-driven adjustments without restarting the system, which is crucial for meeting real-time requirements.

Two application scenarios were chosen for evaluation: an industrial IoT scenario with simulated machine data, and a financial scenario using modified real-time credit card transaction data. The industrial IoT case simulates predictive maintenance on streaming sensor data from manufacturing machines. This scenario reflects a typical real-time environment where early detection of equipment faults can prevent costly downtimes. The financial scenario uses anonymized credit card transaction streams to detect anomalies indicative of fraudulent activities. Both scenarios are characterized by stringent latency requirements and dynamic data distributions, making them ideal testbeds for evaluating adaptive modeling and explainability under realistic operational conditions.

The impact of concept drift on model performance is illustrated in Figure 3. The figure shows the model's accuracy over time. A significant drop in performance is observed immediately after the simulated drift point (marked by a red vertical line). However, due to the system's automatic adaptability, accuracy quickly recovers. This pattern demonstrates that the system not only responds to drift events but is also capable of restoring model quality within short timeframes.

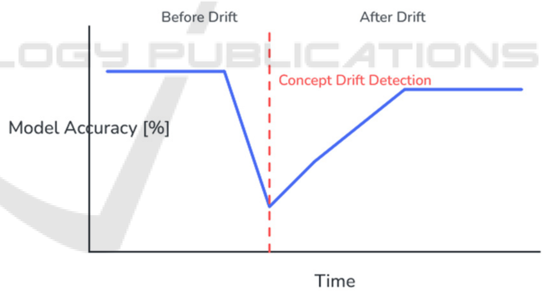

Figure 3: Model Performance Before and After Concept Drift.

Another focus was the evaluation of the model decision explainability. To this end, a real-time dashboard was developed that displays the top contributing features for each prediction as well as a locally approximated decision structure. Figure 4 illustrates a typical output from this dashboard: on the left, feature importances are shown in a bar chart; on the right, a simple decision logic is visualized using a surrogate model to explain the specific model decision. These explanations were continuously generated and updated for each data point.

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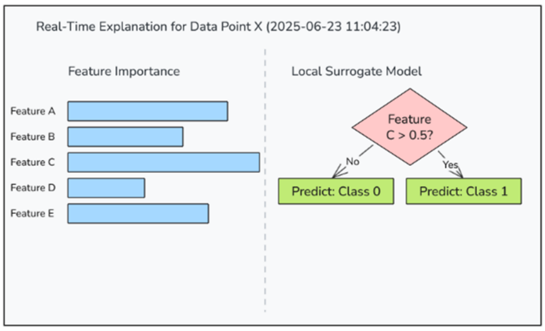

Figure 4: Example Real-Time Explanation Output.

To qualitatively assess the explanations, a user study was conducted with twelve participants from data science and domain expert backgrounds. Participants rated the explanations on a five-point Likert scale in terms of clarity, usefulness, and trust.

On average, the explanations were perceived as helpful (M = 4.3) and understandable (M = 4.5). Participants particularly appreciated the visual representation of feature importances and the ability to trace model behavior changes caused by concept drift.

Overall, the study suggests that even lightweight, incremental explanation mechanisms can meaningfully support user understanding and trust in adaptive AI systems. Several participants expressed interest in being able to adjust the depth and detail of explanations to match their level of expertise. This indicates that configurable explanation interfaces could improve usability and acceptance across diverse user groups.

In summary, the developed system is capable of adaptively responding to data changes while providing explainable decisions—without significant performance losses in terms of response time or model quality. Thus, the proposed pipeline contributes to trustworthy AI in the context of dynamic, high-frequency data streams.

6 DISCUSSION

The results presented in the previous section (Section 5) offer well-founded insights into the behavior of explainable, self-adaptive real-time data pipelines under realistic conditions. The core objective of the evaluation was to assess the extent to which XAI methods can be meaningfully integrated into adaptive streaming systems without significantly compromising real-time capability or model performance. The findings suggest that such integration is not only technically feasible but also functionally beneficial. Notably, combining adaptive learning with dynamic explainability yields substantial improvements in trust, transparency, and system control.

Performance analysis (cf. Figure 3) shows that the system was able to quickly stabilize its predictive performance following a detected concept drift. On average, the model regained acceptable accuracy within fewer than ten data windows—an efficiency considered suitable for real-time systems. These results support the assumption that AutoML-supported online models are a powerful foundation for self-adaptive architectures in streaming environments. Moreover, the concurrent integration of explainability modules did not lead to a significant increase in inference latency (≤ 60 ms), demonstrating that real-time capability can be preserved despite the added interpretability.

A particularly noteworthy aspect is the system's ability to adapt not only its models but also the associated explanations continuously in response to changing data distributions. This capability represents a clear advantage over traditional XAI approaches, which are typically designed for static or batch-oriented settings. The user study confirmed that the real-time visualization of feature importances and local decision structures (cf. Figure 4) significantly enhanced model interpretability—for both technical and non-technical users.

Despite these positive outcomes, the proposed approach also presents certain limitations. A key challenge lies in the temporal stability of explanations: since the models are constantly updated, the generated explanations may vary even for similar input data. This temporal inconsistency can lead to user uncertainty and highlights the need for further research in explanation-stable model adaptation. Another concern is the scalability of explainability in ultra-high-frequency data streams: at inference rates exceeding 10,000 events per second, even incremental XAI methods require substantial computational resources. Innovative strategies are needed here—such as selective or approximate explanation techniques that maintain interpretability without overwhelming system performance.

In addition, the current evaluation does not yet cover all relevant dimensions of system robustness and generalizability. Specifically, the adversarial sensitivity of on-the-fly explanations remains unexplored: since local explanation methods like SHAP and LIME are known to be vulnerable to input perturbations, their reliability under adversarial conditions should be further investigated. Moreover, the impact of high-dimensional input data and complex model architectures on the fidelity and stability of explanations was not explicitly benchmarked. Addressing these open issues requires more comprehensive evaluations using standardized datasets, adversarial scenarios, and controlled variation of model and data complexity.

Furthermore, the absence of standardized evaluation metrics and publicly available benchmarks for explainability in streaming settings presents a methodological gap. Community-driven efforts toward shared testbeds and multidimensional performance indicators—including latency, stability, interpretability, and adversarial robustness—would significantly enhance comparability and reproducibility in this emerging field.

In practical applications, the proposed approach opens up a range of possibilities, particularly in mission-critical domains such as predictive maintenance, real-time financial analytics, or medical telemetry. The ability to make adaptive decisions transparent not only supports regulatory compliance (e.g., in line with the EU AI Act) but also strengthens end-user trust in AI-driven systems. At the same time, the modular architecture allows for flexible adaptation to various data sources, model types, and deployment environments.

This work also raises several important questions for future research. First, there is the question of how generalizable the approach is to more complex model architectures, such as deep learning in streaming contexts. Furthermore, combining the system with reinforcement learning strategies for policy adaptation presents a promising extension. Lastly, there is a clear need for standardized metrics to evaluate explainability in dynamic, non-deterministic settings—an open challenge that has yet to be fully addressed by either the XAI or the stream processing research communities.

In conclusion, this study demonstrates that combining self-adaptivity with explainability in streaming environments is far more than a technical exercise. It represents a strategically significant step toward responsible, trustworthy AI systems for real-time applications.

7 CONCLUSIONS

This paper addresses the design, implementation, and evaluation of an explainable, self-adaptive real-time data pipeline based on modern AI and XAI methods. The starting point was the observation that existing data processing systems in streaming contexts increasingly rely on ML for autonomous model adaptation, but often without adequate consideration of explainability and transparency of the decisions made. This represents a significant limitation, especially in sensitive application domains where both regulatory requirements and end-user trust play a central role.

By integrating incrementally learning models with automated model selection (AutoML) and dynamically adaptable XAI techniques, an architectural approach was developed that operates both adaptively and interpretable—while simultaneously meeting real-time requirements. Experimental evaluation using realistic scenarios (IoT and financial data) demonstrated that the proposed pipeline can efficiently detect concept drift and adapt accordingly. At the same time, the system provided understandable and visually prepared explanations of model decisions without significantly impacting system latency or predictive quality.

The contribution of this paper lies both conceptually and methodologically. On the one hand, an architectural framework was created that explicitly enables the coupling of self-adaptivity and explainability in streaming contexts. On the other hand, existing XAI methods were examined and adapted for their suitability in streaming environments. Moreover, the developed system offers a practical reference implementation realized with common open-source technologies such as Apache Kafka, Flink, Prometheus, and SHAP/LIME, making it applicable for industrial use as well.

Nonetheless, essential challenges remain that should be addressed in future research. In particular, stable interpretability over time—i.e., consistency of explanations amid evolving models—remains an unresolved issue. There is also a need for standardizing metrics to systematically evaluate explainability in dynamic contexts. The use of deeper neural networks combined with XAI for real-time systems—for example, via distilled surrogate models—represents another promising direction for further investigation.

To build on these findings, future research must also include comprehensive, multi-dimensional evaluations—covering adversarial robustness, explanation consistency, and scalability across different data rates and dimensionalities. Comparative studies with related architectural approaches are necessary to further validate effectiveness and identify best practices.

Furthermore, future work could extend the system architecture with active learning mechanisms, self-explaining user interfaces, or semantically grounded model feedback systems to enable even closer integration between users, the system, and explanations. Finally, a long-term user acceptance study under real-world conditions (e.g., in Industry 4.0 environments) would be highly valuable to capture the actual impact of dynamic explainability on trust and system control.

The results presented here illustrate that explainable, self-adaptive AI systems in real-time data contexts are not just a theoretical vision but a practically implementable reality—provided that methodological robustness, system scalability, and human-centered perspectives are given equal consideration.

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